UNIVERSITÉ DE NEUCHÂTEL

FACULTÉ DES SCIENCES ÉCONOMIQUES ET SOCIALES

REGULAR PATTERNS IN THE GROUP PROCESS: HOW THEY ARE DETECTED, WHAT THEY TELL US, AND HOW THEY ARE RELATED TO PERFORMANCE

THÈSE

PRÉSENTÉE A LA FACULTÉ DES SCIENCES ÉCONOMIQUES ET SOCIALES
POUR OBTENIR LE GRADE DE DOCTEUR EN PSYCHOLOGIE DU TRAVAIL

PAR

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Monsieur Christof NAEGELE STALDER est autorisé a imprimer sa thèse de doctorat en Psychologie du travail intitulée :

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Il assume seul la responsabilité des opinions énoncées.

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APPENDIX

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1 Vorspann - Preface

Es ist mein Anliegen in diesem kurzen Kapitel die wichtigsten Aspekte meiner Dissertation zusammenzufassen und wichtige Etappen in der Entstehung aufzuzeigen. Dann möchte ich mich bei allen Personen bedanken, die mich in irgendeiner Form unterstützt haben.

1.1 Zusammenfassung

Meine Dissertation beruht auf Daten aus zwei von Prof. F. Tschan (Neuchâtel) und Prof. N. K. Semmer (Bern) initiierten Projekten.[1] In einem ersten Projekt wurde untersucht, wie computergestützt arbeitende Gruppen Strategien entwickeln. Im zweiten, wie eine Reflexion über den Gruppenprozess nach einer ersten Phase der Zusammenarbeit die geteilten mentalen Modelle zu beeinflussen vermag und wie sich dies schlussendlich auf die Leistung auswirkt.

In beiden Projekten wurde eine von Gareth Gabrys (1994) entwickelte Simulation einer Flugraumüberwachungsaufgabe eingesetzt. Diese Simulation, in der drei Personen in unterschiedlichen Rollen (ein Chef/eine Chefin und zwei SpezailistInnen) eine gemeinsame Aufgabe lösen müssen, begleitet mich nun schon während fast 10 Jahren. In den von uns durchgeführten Experimenten arbeiteten die Teams an je zwei Tagen während je drei bis vier Schichten zu 15 Minuten an der Aufgabe. Das faszinierende an dieser Simulation ist, dass die Aufgabe, die den Teams gestellt wird, nicht banal ist und durchaus reellen Aufgaben entspricht. Die Aufgabe ist nicht banal, da die Teams einerseits optimale Arbeitsstrategien entwickeln müssen, um sich zu befähigen, eine optimale Leitung überhaupt erreichen zu können. Andererseits ist der virtuelle Luftraum kontinuierlich zu überwachen und jegliche Veränderungen der Lage der Flugzeuge muss registriert werden, um je nach Grad der Veränderung die richtigen Entscheidungen zu treffen. Es zeigte sich denn auch, dass die rund 300 Personen, die sich zwischen 1996 und 2000 an den Experimenten beteiligten, von der gestellten Aufgabe begeistern liessen. Wichtig für meine Dissertation war insbesondere, dass jegliche Aktivität der Teams in automatisch generierten Log-

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[1] Die Projekte wurden vom Schweizerischen Nationalfonds (SNF) finanziell mit unterstützt:
Strategieentwicklung in computerunterstützter Gruppenarbeit, Projekt 11-43472.95 sowie Fortsetzungsprojekt 11-52861.97
Individual and group reflexivity, and its influence on shared mental models and performance in computer mediated groups, Projekt 1114-056997.99

Dateien protokolliert wurde. Alles was die Teams sagten und taten (Kommunikation und aufgabenbezogene Tätigkeiten) wurde vollständig protokolliert.

Die im Rahmen der beiden Projekte zur spontanen Entwicklung von Strategien und des Einflusses der Reflexion auf die Entwicklung geteilter mentaler Modelle durchgeführten Analysen fassen die Daten des ersten Tages (Schicht 1 bis Schicht 3)[2] und des zweiten Tags (Schicht 4 bis Schicht 6) je zu einer Einheit zusammen (Berechnung der Summe aller Häufigkeiten bestimmter Ereignisse oder Tätigkeiten pro Tag) (Gurtner, 2003; Tschan, Semmer, Nägele, & Gurtner, 2000).

Dadurch, dass die Aktivitäten des ersten und auch des zweiten Tages je zusammengefasst werden, wird eine Zeitdauer von je minimal 45 Minuten als eine Einheit betrachtet. Und hier beginnt meine Dissertation. Der Grundgedanke ist eigentlich einfach: Wenn Teams während drei Mal 15 Minuten zusammenarbeiten, geschieht in dieser Zeit mehr als in der Summe aller Aktivitäten dargestellt werden kann. Es ist wichtig, auch die Reihenfolge (Sequenz) anzuschauen, in der die Teams gewisse Aufgaben erledigen, also die Art und Weise, wie die Teams miteinander umgehen (interagieren). Sendet ein Chef/eine Chefin während den ersten 45 Minuten seinen/ihren MitarbeiterInnen 10 Instruktionen, ist nicht nur diese Zahl von Interesse. Es kommt doch auch darauf an, ob diese Instruktionen in den ersten Minuten der ersten Schicht erfolgen oder aber erst in den ersten Minuten der dritten Schicht. Es ist auch wichtig, ob und wie die MitarbeiterInnen darauf reagieren, was auch heissen kann, ob sie die Instruktion überhaupt zur Kenntnis nehmen. Für mich wurde eine Analyse dessen, was die Teams tatsächlich tun, immer wichtiger. Um das zu erreichen, muss die Abfolge der einzelnen Tätigkeiten, d.h. deren Sequenzierung mit analysiert werden.

In der Tradition der Kleingruppenforschung wird viel über Gruppenprozesse geforscht und geschrieben. Auch in theoretischen Überlegungen zum Thema Team oder Gruppe spielt der Prozess eine wichtige Rolle. Viele dieser Gruppenprozessdefinitionen beschreiben allerdings nicht das, was ich unter einem Prozess verstehen möchte: Ein Prozess ist eine zeitlich organisierte Abfolge von Ereignissen mit einem bestimmten Ziel.

Zugespitzt formuliert lässt der/die typische KleingruppenforscherIn Teams diskutieren, lässt sie ein Problem lösen, lässt sie ein Konzept ausarbeiten, einen Gegens-

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[2] Mit *Tag* ist nicht ein Arbeitstag gemeint. Die Experimente wurden an zwei Tagen durchgeführt. eine Sitzung dauerte ca. 2 Stunden, insgesamt 4 bis 5 Stunden.

tand konstruieren usw., um sie nachher in einem Fragebogen zu Fragen: Wie war der Prozess? Man kann sich natürlich auf den Standpunkt stellen, dass die Teammitglieder, da sie ja mit dabei waren, sicherlich als ExpertInnen für den eben abgelaufenen Prozess angesprochen werden können. Das ist so auch berechtigt. Aber: Wie man den Prozess beurteilt, hängt zum Beispiel sehr stark vom Ergebnis ab. Und da diese Fragebogen oft nur ein Mal eingesetzt werden, bilden sie die zeitliche Dynamik nicht ab.

Ich denke deshalb, dass diese Art von Forschung ergänzt werden muss mit einer Forschung, die den Teams auf die Finger schaut. Es müssen Analysen durchgeführt werden, die auf einer Akt für Akt Kodierung beruhen unter Berücksichtigung der zeitlichen Abfolge.

Ich wählte drei Methoden aus, die es ermöglichen, die Abfolge von Ereignissen zu analysieren: Lag-Sequenzanalyse, procedural network representation, KDD/ Data Mining. In der Tradition der Kleingruppenforschung gibt es nur sehr wenige mir bekannte Beispiele, die Sequenzanalysen durchführen (Becker-Beck, 2001; Brauner, 2002; Kanki & Foushee, 1989; Tschan, 2000a; Tschan, Semmer, Nägele et al., 2000; Weingart, 1997). So war denn meine erste Frage: Wie lassen sich dieses drei Methoden auf die vorliegenden Daten anwenden? Es geht also um einen „Transfer“ dieser Methoden aus anderen Wissenschaftsbereichen in die Kleingruppenforschung. Die meisten Studien aus der Kleingruppenforschung, die eine Form von Sequenzanalysen anwenden, sind zudem Einzelfallstudien. Es geht also auch um die Frage, wie diese Methoden bei einer grösseren Anzahl von Gruppen durchgeführt werden können. Die Methoden des Data Mining wurden entwickelt, um sehr grosse Datenbestande (z.B. jeder Einsatz einer Kreditkarte, alle PatientInnendaten eines grossen Krankenhauses) halb-automatisch nach interessanten Mustern zu durchkämmen. Im Vergleich dazu fallen in der ATC Simulation wenig Daten an. Eine Frage lautet deshalb, ob sich Data Mining Methoden dennoch anwenden lassen. Für meine Analysen stehen mir die Daten von 109 Teams zur Verfügung und es zeigte sich, dass auch für Data Mining Analysen genügend Interaktionen protokolliert wurden.

Neben diesem eher handwerklichen Teil der Anwendung der Methoden auf die vorliegenden Daten geht es auch um inhaltliche Aspekte. Jede der drei Methoden ist zuerst einmal dazu geeignet den Datensatz erkundend (explorativ) nach unbekannten und interessanten Abfolgen und Mustern zu durchsuchen. In den beiden eingangs erwähnten Projekten entwickelten wir aufgrund einer Aufgabenanalyse und auf Grund theoretischer Überlegungen eine Vorstellung darüber, was es bräuchte, die Teams zu gut funktionierenden Teams zu machen. Das ist nicht in dem Sinne zu verstehen, dass wir den einen besten Weg suchten, den wir dann den Teams vorschreiben könnten in der Meinung, dass sie dann besonders gut sind. Vielmehr geht es um ein Bündel von Strategien, von Vorgehensweisen, die je nach Situation und Reifegrad des Teams eingesetzte werden können. So entstanden die Kategorien des task adaptive behaviors (Tschan, Semmer, Nägele et al., 2000). Die von mir eingesetzten Methoden erlauben es, genau andersherum vorzugehen. Basierend auf einer grundlegenden Kodierung einzelner Akte, also einer Beschreibung dessen wer was wann mit wem macht, werden Sequenzen gesucht, die überzufällig häufig vorzufinden sind.

Wenn man diese Sequenzen gefunden hat, stellt sich natürlich die Frage, wie sinnvoll diese sind. Beschreiben sie also eine Art und Weise der Aufgabenerfüllung, die man als Empfehlung für andere Teams formulieren könnte? Beschreiben Sie eine Art der Aufgabenerfüllung, die es ermöglicht leistungsschwache und leistungsstarke Teams zu unterscheiden? Es zeigte sich, dass diese Fragen positive beantwortete werden können. Es kommt also darauf an, in welche Abfolge man etwas macht. Es genügt nicht, nur zu zählen, wie oft ein Team etwas macht, es muss auch danach gefragt werden, wie ein Team die einzelnen Akts kombiniert.

Die Lag-Sequenzanalyse ist eine Methode, die in der Entwicklungspsychologie oder in der Verhaltenbeobachtung schon lange eingesetzt wird. Zugespitzt formuliert könnte man fast sagen, dass diese Methode dort eingesetzt wurde und wird, wo die beobachteten Personen (noch) nicht fähig sind, Fragebogen auszufüllen. Es wird gefragt: Was geschieht unmittelbar nach einen bestimmten Ereignis (lag 1 Analysen). Oder: Was ist zweite Ereignis das nach einem bestimmten Ereingis folgt (lag 2). Es werden also immer Paare von einem auslösenden Ereignis und einem mit einer bestimmten Verzögerung nachfolgenden Ereignis betrachtet. Diese Methode ist zuerst einmal beschreibend. Sie zeigt zum Beispiel die Unterschiedlichkeit der unmittelbaren Reaktion der Chefs und Chefinnen leistungsschwacher und leistungsstarker Teams sehr schön auf. Es ist ein ideales Instrument, um den Gruppenprozess zu visualisieren. So zeigt sich zum Beispiel, dass ChefInnen nach dem Eintreffen einer neuen Nachricht im Email-Eingang ein starke Tendenz haben zu lesen. Auf den ersten Blick unterscheiden sich ChefInnen leitungsschwacher und leistleistungsstarker Teams in diesem Verhalten nicht gross voneinander. Es zeigt sich dann aber zusätzlich, dass ChefInnen leistungsstarker Team dies konsequenter machen. Dies zeigt sich unter anderem darin, dass die Wahrscheinlichkeit nach einem Email-Eingang andere Dinge zu tun als Nachrichten zu lesen bei den ChefInnen der leistungsstarken Teams viel geringer ist (stärker gehemmt ist). Es zeigt sich also bei den Chefinnen der leistungsstarken Team eine stärkere Fokussierung auf die momentan wichtige Aufgabe.

Die Analysen mit ProNet (procedural network representation) sind in einem ersten Schritt sehr ähnlich wie die Lag-Sequenzanalysen. Sie basieren auf denselben Kodierungen und derselben Logik der der Darstellung der Sequenzen. Anders ist die Art und Weise, wie diese Information graphisch dargestellt wird. Insbesondere ist spannend, dass diese Methode den numerischen Vergleich graphischer Repräsentationen des Gruppenprozesses erlaubt. Es wird eine Masszahl berechnet, die ausdrückt, wie ähnlich zwei Prozesse sind. Diese Masszahl eignet sich dann für weitere Analysen. Diese Methode zeigt zum Beispiel, dass die Reaktion der ChefInnen leistungsschwacher und leistungsstarker Teams auf das Eintreffen eines neu zu beobachtenden Flugzeugs im Luftraum ganz unterschiedlich sind. So kann in der ersten Schicht am ersten und zweiten Tag nie beobachten, dass ChefInnen leistungsschwacher Teams die Gefährlichkeit des Flugzeugs sofort provisorisch festlegen. Das ist etwas, was bei ChefInnen leistungsstarker Teams beobachtet werden kann.

Data Mining Analysen suchen nach Sequenzen beliebiger Länge in den Daten, die mit einer bestimmten minimalen Wahrscheinlichkeit zu finden sind. Aufgrund der Analysen kann zum Beispiel gesagt werden, dass es leistungsmindernd sein kann, wenn ein Chef oder eine Chefin sich zu lange nur mit dem Lesen von Nachrichten beschäftigt, die er/sie von den SpezialistInnen erhält und darob seine anderen Aufgaben vernachlässigt[3]. Oder dass es in einer ersten Phase der Zusammenarbeit durchaus sinnvoll sein kann, seinen SpezialistInnen auch über eigentlich selbstverständliches (noch einmal) zu informieren[4]. Wie diese beiden Beispiele zeigen, sind die Sequenzen sehr aufgabenspezifisch und konkret. Dies hat den grossen Vorteil, dass diese Ergebnisse zum Beispiel in einer Teamintervention eine sehr gute Rückmeldung erlauben würden und so ein grosser Beitrag zur Optimierung der Zusammenarbeit geleistet werden könnte. In der Aufgabe, die ich für meine Arbeit analysieren konnte zeigte sich zudem, dass sich die Sequenzen von Schicht zu Schicht verändern können. Je nach Komplexität der Aufgabe und je nach Reife des Teams verändert sich die Art und Weise der Bearbeitung der Aufgabe, was sich nicht unbedingt

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3 Sequenz von sechs aufeinander folgenden Read Message

4 Sequenz Handle Threat – Send Message with task related content

in der Summe der Aktivitäten abbildet, sehr wohl aber darin, wie diese aufeinander folgen, also in der Sequenz.

Die Unterschiede in der Art und Weise wie die leistungsschwache und leistungsstarke Teams die Aufgabe bearbeiten ist sind mit jeder der gewählten Methoden darstellbar. Es wäre aber falsch, sich diese Unterschiede riesengross vorzustellen. Die verschiedenen Teams machen sehr vieles sehr ähnlich. Umso spannender ist es, genau diese feinen Unterschiede darstellen zu können.

Zudem helfen die mit allen drei Methoden dargestellten Ergebnisse die Vorhersage der Leistung der Teams in den einzelnen Schichten zu verbessern (Regressionsmodelle). Das zeigt ganz deutlich, dass es wichtig ist, auch das Verhalten der Teams auf der konkreten Verhaltens- und Interaktionsebene anzuschauen und Informationen zur Abfolge der einzelnen Tätigkeiten zu analysieren.

All diese Analysen verlangen eine gute Computerinfrastruktur, genügend Rechenleistung und Speicherplatz. Für die PRONET Analysen konnte ich dasselbe Programm KNOT verwenden wie in den beiden Projekten, für die Lag-Sequenzanalyse gibt es von Bakeman und Quera (1995a) eine frei erhältliche Software. Die Data Mining Analysen wären ohne die sehr grosse Hilfe von Paul Cotofrei und Prof. K. Stoffel, Institut interfacultaire d'informatique, Université de Neuchâtel nicht möglich gewesen. Sie führten die gesamten Analysen durch, wofür ich ihnen sehr dankbar bin.

Die Auseinandersetzug mit dieser Thematik war für mich sehr spannend und lehrreich. Ich denke, dass es auch sehr relevant ist, methodische Werkzeuge zur Verfügung zu haben, die helfen, die Verhaltenssequenzen in Teamprozesse zu analysieren, und so Informationen zur Verfügung zu stellen, die eine weitere Optimierung der Teamarbeit ermöglichen. Ich denke, dass überall dort, wo Menschen gemeinsam eine Aufgabe auch unter enormem Druck erledigen müssen, Analysen dieser Art gewinnbringend eingesetzt werden können.

1.2 Danke!

Ohne die beiden von Prof. F. Tschan (Neuchâtel) und Prof. N. K. Semmer (Bern) initiierten Projekte gäbe es meine Dissertation in der vorliegenden Form nicht. Darüber hinaus unterstützen mich Franziska Tschan und Norbert Semmer in meiner Arbeit immer wieder. Sie setzten die Ziele in der inhaltlichen und fachlichen Diskussion hoch an und forderten deren Einhaltung konsequent ein. Franziska Tschan initiiert auch die Kooperation mit Kilian Stoffel und Paul Cotofrei, welche es erst ermöglichte, Data Mining Analysen mit den ATC-Daten durchzuführen. Die Diskussionen mit Franziska Tschan und ihre Vorschläge bei der Formulierung des projet de thèse[5] trugen viel zur Präzisierung der inhaltlichen Ausrichtung meiner Dissertation bei. Dankbar war ich auch für Hinweise, die es mir erlaubten, meine Arbeit trotz grossem Umfang nicht noch umfangreicher werden zu lassen. Wann immer ich inhaltlichen Rat brauchte, wusste ich, dass ich mich an Franziska Tschan und Norbert Semmer wenden konnte.

In diesen beiden Projekten zur spontanen Entwicklung von Strategien und zum Einfluss der Reflexion auf die Entwicklung geteilter mentaler Modelle waren neben Franziska Tschan und Norbert Semmer auch Andrea Gurtner, und in einer ersten Phase Christian Jaeggi tätig. Arie Abraham, Mirco Cecato, Lukas Meier und Silvia Stutz danke ich für ihre wertvolle Hilfe bei der Durchführung der Experimente.

Bedanken möchte ich mich bei Andrea Gurtner, maître-assistante, Groupe de Psychologie Appliquée, Université de Neuchâtel. Ich durfte mit ihr in den beiden Projekten zusammenarbeiten. Dies war für mich nicht nur eine Bereicherung in fachlicher Hinsicht. Seit dieser Zeit korrigiert sie mich dort, wo ich zu schnell generalisiere, zu schnell eine Schlussfolgerung ziehe und fordert die dem Gegenstand angemessene Präzision ein. Das Kodiersystem in meiner Arbeit basiert zu einem wesentlichen Teil auf dem in ihrer Diplomarbeit (Gurtner, 1997) und Dissertation (Gurtner, 2003) entwickelten System. In manchen Diskussionen haben wir auch die Daten „unserer“ Teams auseinanderdividiert, neu zusammengefügt und Strategien und Wege entwickelt, wie eine optimale Analyse der Daten aussehen könnte. In der Aufbereitung der Daten für die Projekte und ihre Dissertation ist denn auch mein Unbehagen gegenüber der Summenbildung der einzelnen Akts über ganze Schichten oder gar Tage entstanden.

Manchmal sind es auch kurze Augenblicke, die eine Blockade lösen können. Ein solcher Moment war die gemeinsame rund 10-minütige Bahnfahrt mit Elisabeth Brauner von Dresden Hauptbahnhof nach Dresden Neustadt, bei der mir klar wurde, wo meine damalige Blockade in der Anwendung der Lag-Sequenzanalyse lag. Elisabeth Brauner gab mir da den richtigen Hinweis zur richtigen Zeit.

[5] Das projet de thèse ist ein ca. 10-seiteiges Dokument, eine Art Projektantrag. Auf Grund dieses Dokuments entscheidet die Universität Neuchâtel über die Zulassung der Arbeit als Dissertation.

Zu wissen, dass die Herausforderungen, vor die einen eine solche Arbeit stellt, nichts aussergewöhnliches sind, dass Tiefs und Hochs sich abwechseln und man am Schluss alles irgendwie doch überstanden haben wird, ist gut. Noch besser ist es, wenn man dies in einer Gruppe diskutieren kann. Diesen Beitrag hat das Diss-Qaurtett mit Wolfgang Kälin, Alexandra Kunz und Fabienne Amstad geleistet.

Ganz wichtig waren für mich die Diskussionen mit Wolfgang Kälin. Sein fachlich brillantes, messerscharfes Argumentieren, seine Null-Toleranz gegenüber nicht präzisen Aussagen und Gedankengängen, zwangen mich immer wieder zur Reflexion meiner Arbeit. Wichtig war aber auch die soziale Unterstützung durch Wolfgang Kälin. Die positive Wirkung sozialer Unterstützung ist in vielen Studien belegt, hier durfte ich sie selber erfahren. Danke.

Ich weiss, dass diese Aufzählung nicht vollständig ist. Es gab zahlreiche andere Personen, die ebenfalls einen wichtigen Beitrag zur Vollendung dieser Arbeit leisteten. Dazu gehört Prof. A. Flammer, der mich auf eine Assistenz anstellte in dem Moment, in dem absehbar war, dass ein beim SNF eingereichtes Forschungsgesuch, das die beiden eingangs erwähnten Projekte mit Daten echter Teams (Notfallabteilung eines Spitals) hätte fortführen sollen, abgelehnt wird. Hätte ich da einen unifernen Job suchen müssen, wäre meine Dissertation wahrscheinlich nie fertig geworden. Aber es waren auch die Verwandten, Freunde und Freundinnen, KollegInnen und NachbarInnen die immer wieder fragten: Ist sie nun fertig?

Ohne die hoch stehende fachliche Unterstützung durch meine Frau Barbara Stalder, ihre oft gnadenlose Kritik und die vielen spannenden Diskussionen, sähe diese Arbeit ganz anders aus. Sie hat meine neuen Ideen oft als erste gehört, hat die Phasen mit erlebt, in denen nichts mehr ging, sie hat mich motiviert und unterstützt. Sie hat auch die ganze Arbeit sprachlich und inhaltlich gelesen und korrigiert.

Mein Dank gilt ganz im Besonderen meinen Kindern Pascal, Max und Ana-Lea, die einige Nachteile ertragen müssen wegen meinem Projekt, eine Dissertation zu schreiben. Viel Freizeit habe ich in diese Arbeit investiert und darob weniger Zeit gehabt Fussball zu spielen, eine Seifenkiste zu bauen usw. Ein ganz besonderer Dank gilt zum Schluss meinen Eltern. Sie ermöglichten mir das Studium und ich weiss, dass sie bis heute da sind und uns helfend zur Seite stehen, wenn immer es notwendig ist.

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2 Summary

Teams have the potential to perform much better than many individual does. However, often teams do not reach their full potential. It is often reported that teams use inefficient strategies to accomplish a task. It is also reported that teams are often very resistant to the (spontaneous) development of new and better strategies.

It is important to understand the team process. In small group research, the interaction process is a hot topic. Almost in all perceptions on small groups, the process is implicitly or explicitly mentioned (Poole et al., 2004). But if one looks at how ‘process’ is defined and operationalized in empirical studies a great diversity becomes apparent.

Three types of measures on group processes were distinguished: (i) e*valuative measures on the group process* (typically questionnaire based data, where team members are asked to evaluate the group process), (ii) frequencies of behaviors (coding and counting approaches), and (iii) measures reflecting temporal sequences in the group process. It is argued that evaluative measures and summaries of frequencies cannot represent all aspects of the group process and that an analysis of the temporal micro-behavioral organization of the group process offers additional information. This information can then be used for an effective coaching of co-acting teams.

Data of 109 teams of three persons were analyzed. An air-traffic control (ATC) simulation was used. The teams had to observe an airspace and keep track of the changing positions of the airplanes. Every single act was coded such that its type and its meaning were captured together with its time stamp. Sequential analyses were run to gain gaining insight into the group process.

Three methods are discussed and applied to the ATC-data: (i) lag sequential analysis, (ii) procedural network representation, (iii) data mining techniques. These methods are never (data mining) or seldom used in small group research.

Results show that either of these methods can be used to analyze the group process on a micro-behavioral level. They can be used as exploratory tools and aids to visualize the group process. Several examples are shown. All these sequential patterns must be evaluated in the context of the concrete task. This is perfect for team coaching or the development or refinement of categories developed in a top down process (like for example the task adaptive behaviors in Tschan, Semmer, Nägele et al., 2000).

There are also concrete recommendations to commanders of co-acting virtual teams: Use the information from the specialists, read what they are writing. Do not send task or strategy related messages if the message content is too old. Nevertheless, commanders should not stay too long in a mode of just reading messages.

Measures form sequential analyses were used in regression models to predict the team performance. This was done separately for every of the seven work-shifts of at least fifteen minutes. Results show that using this information on the sequential patterns in regression models explains additional variance in performance per shift in the range from 16% to 35% (additionally to input factors, preceding performance and frequencies of behaviors). The information extracted with sequential analyses is relevant to performance.

To improve the group process in co-acting teams detailed analyses of the temporal sequences on a micro-behavioral level is indispensable. It was shown that lag sequential analysis, procedural network representations (PRONET), and data mining techniques can be used. It is also demonstrated how this methods can be applied to the ATC-data.

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3 Introduction

> The USS *Vincennes* is a United States Navy cruiser that gained notoriety for shooting down a civilian Iranian A300 Airbus on July 3 1988 over the Strait of Hormuz, killing all 290 people on board. The *Vincennes* had been engaged in fighting Iranian gunboats at the time. Iran Air Flight 655, taking off on a routine 140-mile flight from its coastal city of Bandar Abbas southwest to Dubai in the United Arab Emirates, was mistaken for an Iranian F-14 jet fighter. A warning was transmitted, and after failing to receive a response, the *Vincennes* launched two surface-to-air missiles (see also Collyer & Malecki, 1998).

One reason for the misinterpretation of the situation was an unresolved IFF problem (Identification Friend or Foe). At the time when the firing order was given by the commander of the Vincennes, the information was ambiguous and not confirmed independently. In fact, on another ship nearby the same plane was identified as a commercial airliner. Analyses of the incident revealed that the main problems were an erroneous transmission of the information, not taking into account all available information, and no independent confirmation of the information. At the time the decision was made, the USS Vincennes was engaged in a fight with Iranian gunboats, which increased the tension on the vessel. The decision was made under high time pressure (Cannon-Bowers & Salas, 1998). The team members reporting information about the aircraft to the commander were located at different places, communication was restricted and access to information was distributed in the group (Hinds & Kiesler, 2002).

The Air Traffic Control (ATC) Simulation

In order to gain more knowledge about team decision making in such hierarchically structured teams with distributed knowledge, Gabrys (1994) programmed an air traffic control computer simulation *(*ATC simulation*)* at the University of Pittsburgh under the auspices of John Levine. In this ATC simulation, a hierarchical structured team of three persons (commander and two specialists) works in different rooms, without any face-to-face contact. All communication within the team is done through an e-mail system that allows sending and receiving typed text messages. The team observes planes in an air space and has to determine the threat level of each plane at each moment during fifteen-minute work shifts. Up to four planes moving in the airspace can be present during a shift. Each of the two specialists observes each different parameter (like speed, height, distance, ...) of the plane. This parameter information needs to be transmitted to the commander. The commander only has the knowledge how to calculate the threat level of a plane out of this parameter information. The task is both complex and dynamic. Team members work together on two days. On each day they work on four to five shifts. A detailed description of the ATC simulation is given in chapter 6.1. This simulation is similar to TIDE (Hollenbeck et al., 1997).

Although the design of the ATC simulation is based on a military catastrophe, its explanatory power is not limited to this specific incident. Hierarchically structured groups with distributed knowledge and communication restrictions which have to take decisions under time pressure can be found in many fields, for example in rescue situations or in the medical field (Marsch et al., 2004). Therefore, the Air Traffic Control simulation is a generic model for distributed work.

Prior Research Projects using the ATC simulation

We[6] used the ATC simulation in two research projects which examined spontaneous development of strategies in groups and the effect of a reflexivity instruction (West, 1996a) on the development of shared mental models and performance (Gurtner, 2003; Tschan, Semmer, Nägele et al., 2000). Both projects were supported by the Swiss National Science Foundation[7] and were run under the auspices of Prof. F. Tschan, University of Neuchâtel and Prof. N. Semmer, University of Berne.

The data I use in my thesis comes from these two research projects. The air traffic control (ATC) simulation was programmed such that the team members' behavior and communication was automatically recorded in log-files. In addition, questionnaire data, related to motivation and evaluation of the other team members and performance data is available.

Group Process

The focus of my dissertation is on an analysis of the temporal patterns in the behavior and communication within a shift. This is an analysis of the group process on a micro-behavioral level. In chapter 4 and chapter 5 I describe how the group proc-

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6 "We" refers to the project team: Andrea Gurtner, Franziska Tschan, Norbert Semmer and Christof Nägele.

7 Spontaneous development of strategies in groups, SNF, project 11-43472.95 and 11-52861.97 Individual and group reflexivity, and its influence on shared mental models and performance in computer mediated groups, SNF, project 1114-056997.99

ess is discussed in theories in small group research and how it is operationalized in empirical studies. I distinguish three types of group process measures: (i) evaluative measures of the group process, (ii) coding and counting approaches calculating summaries of the frequencies of certain behaviors, and (iii) measures taking into account the temporal organization of the group process.

Group Process Analysis: Methods, Research Questions, and Results

Methods used to analyze the temporal patterns in the group process are discussed in chapter 5.3: (i) lag sequential analyses, (ii) procedural network representations (PRONET), and (iii) data mining techniques.

The research questions are presented in chapter 7. There are three basic assumptions: (i) The activities of commanders and specialists have a certain regularity and temporal organization. Therefore, it is possible to identify meaningful patterns in the micro-behavioral organization of the groups' activities. (ii) Low and high performing teams show different patterns. (iii) Information on the temporal organization of the group process on the micro-behavioral level helps to predict performance (regression models).

In chapter 6 I present the air traffic control (ATC) simulation en detail. In chapter 7 the research questions are formulated.

Chapter 8 presents the results. In chapter 8.1 to chapter 8.5 descriptive statistics are given for input, process (summary level process variables and task adaptive behaviors) and output variables. It is also shown how these variables change over time (from shift 1 to shift 8), and which variables differ between the different experimental conditions. In chapter 8.6 these input and process variables are then used as predictors of performance (regression models).

Using the process variables this way does not take into account the temporal dependencies of the single coded acts. Therefore these measures were submitted to the three methods discussed for sequential analysis: lag sequential analyses in chapter 8.7, procedural network representations (PRONET) in chapter 8.8 , and data mining techniques in chapter 8.9. Data mining techniques can be seen as part of a procedure that tries to discover hidden knowledge in databases (KDD). Each of these three chapters is organized in four parts: (i) description of the method, (ii) use of the method as a descriptive and exploratory tool, (iii) deducing measures that are then used in regression models to predict performance and running these regression analyses, and (iv) integration and discussion of the findings.

Chapter 9 integrates and discusses the findings.

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4 Research on Small Groups[8]

Groups and teams are important in every respect. We live in groups, work in groups and play in groups (Poole, Hollingshead, McGrath, Moreland, & Rohrbaugh, 2004). Groups have become a hot topic in the business and academic worlds (Jordan, Feild, & Armenakis, 2002). A growing interest on group and team performance has lead to many publications (Wittenbaum et al., 2004) and within the last fifty years thousands of studies on many aspects of groups have appeared (Poole et al., 2004).

However, all those publications remain fragmented and discipline bound (Poole et al., 2004). There seems to be no common conception of relevant aspects as for example the team process (Marks, Mathieu, & Zaccaro, 2001). Furthermore, it is stated that relevant research has not (yet) been conducted, namely on the measurement of team process and outcome (Fleishman, 1997). It is criticized that groups are often seen as isolated from the environment, instead of taking into account their complexity (Arrow et al., 2000). Other authors find groups tantalizing and yet so disturbing (Turner, 2001), because teams often do not perform to their potential.

There is no common paradigm on how to look at groups. However, often the work of Kurt Lewin and his colleagues is seen as constitutive for many studies of the last decades, as soon as group dynamics are of interest (Lewin, 1969). A growing number of publications tries to combine ideas about groups across disciplinary and geographical as well as cultural boundaries (McGrath, 1997a; McGrath & Tschan, 2004a; Poole et al., 2004) or to fit existing research into a broader perspective of groups (Wittenbaum et al., 2004).

Poole et al. (2004) describe different perspectives from different disciplines, which have a distinctive view of groups, group processes and group outcomes (see Table 1). One of those perspectives, the functional perspective, is especially important for my work. The functional perspective focuses on input and processes as predictors of group performance. One of the most widely cited models belonging to this perspective stems from Hackman and Morris (1975) and is summarized in Figure 1. The functional perspective builds on three basic assumptions: (i) groups are goal oriented, (ii)

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[8] *Teams or groups?* Individuals working interdependently on a task, holding specific roles and responsibilities to achieve a common goal are labeled *groups* (Arrow, McGrath, & Berdahl, 2000), *co-acting work groups* (Dyer, 1997) or *teams* (Hackman, 2002; Salas, Dickinson, Converse, & Tannenbaum, 1992). I will use the terms group and team interchangeably in my thesis.

group performance varies and can be evaluated and (iii) internal and external factors influence group performance via the interaction process.

Input factors are characteristics of team members (e.g., gender, age, personal skills, …), team level factors (e.g., team composition, team skills, history, leadership structure,…), and contextual factors (e.g., organizational embedding, resources, relations with other groups, …). It is important to note that under this functional perspective the input-output relation is mediated by processes that occur during group interaction such as communication, conflict management, or behavioral acts. Effectiveness, performance, but also member satisfaction are seen as output factors (Hackman, 2002; Krech, Crutchfield, & Ballachey, 1962; McGrath, 1964; Poole et al., 2004; Steiner, 1972; Tajfel & Fraser, 1978; Tschan, 2000a).

Table 1 Perspectives on small groups.

<table>
<tr><td colspan="3"><u>psychodynamic perspective</u>
Interplay of deep psychological or sociopsychological dynamics underlying surface behavior. Main focus is on affective and emotional side of groups.</td></tr>
<tr><td>Input. History of individuals and group, mainly unresolved problems/projects</td><td>Process. Leader-member dynamics; member position in group, with differential possibility to address problems and needs</td><td>Output. Individual and group growth and development; satisfaction</td></tr>
<tr><td colspan="3"><u>functional perspective</u>
Inputs and/or processes that influence group effectiveness; groups have goals. Equal priority is given to input, process and output.</td></tr>
<tr><td>Input. Nature of group task; internal structure of group; group composition; group environment; cohesiveness</td><td>Process</td><td>Output. Productivity; efficiency; quality; leadership effectiveness; satisfaction with outcome</td></tr>
<tr><td colspan="3"><u>temporal perspective</u>
Development and change over time. Time is seen either as a context, as a resource, as a mediator, or moderator of other processes. Main focus on process.</td></tr>
<tr><td>Input. Input factors influence how the process unfolds.</td><td>Process. Process is emphasized in this perspective.</td><td>Output. Products of the process</td></tr>
<tr><td colspan="3"><u>conflict-power-status perspective</u>
Dynamics of power, status, resources, and social relationships and group structures. Often it is assumed that there are inequalities among members. Main focus is on input and process</td></tr>
<tr><td>Input. Status outside of group, resources, existing status and power structures, type of interdependence among members</td><td>Process. Influence, conflict management, negotiation, consensus building, distribution of resources.</td><td>Output. Distribution of valued outcomes, realization of members' interests, group performance, member satisfaction and changes in power and status</td></tr>
<tr><td colspan="3"><u>symbolic-interpretive perspective</u>
Social construction of groups, groups have specific meanings for their members</td></tr>
<tr><td>Input. Mainly seen as stimuli for symbolic and interpretive processes.</td><td>Process. Fantasy chaining, structuration, dialectic, sense making underlie the creation, growth, maintenance, and demise of groups.</td><td>Output. Common vision, group identity, internal group structures, and group boundaries. Also effectiveness, group cohesion, member satisfaction – mediated by the former.</td></tr>
<tr><td colspan="3"><u>social identity perspective</u>
Social Identity of individuals, constructed based on an identification with a certain group, dynamics between in-groups and out-groups. Main focus is on relations between different social groups.</td></tr>
<tr><td>Input. Structure of surrounding society, society, culture, member characteristics, cues making group identity salient.</td><td>Process. Self-categorization, depersonalization, inclusion/exclusion, social influence, stereotyping, intergroup conflict.</td><td>Output. Member self-concept, group cohesiveness, loyalty, turnover, conformity, social loafing.</td></tr>
<tr><td colspan="3"><u>social-evolutionary perspective</u>
Group structure and interaction reflect evolutionary forces. Main focus is input.</td></tr>
<tr><td>Input. People/cultures have inherent tendencies toward a certain group behavior.</td><td>Process. Influenced by input.</td><td>Output</td></tr>
<tr><td colspan="3"><u>social network perspective</u>
Groups are interlinked structures embedded in larger social networks. Main focus on network structures and the processes enabled/inhibited by certain structures.</td></tr>
<tr><td>Input. Member attributes, properties of pre-existing networks (density, centralization), resource distributions and interdependencies.</td><td>Process. Affiliation, exchange, influence, information flow, diffusion.</td><td>Output. Task effectiveness and efficiency, cohesiveness, attitude and believe convergence, change in the network</td></tr>
</table>

Note. Based on Poole et al. (2004, p. 7-11)

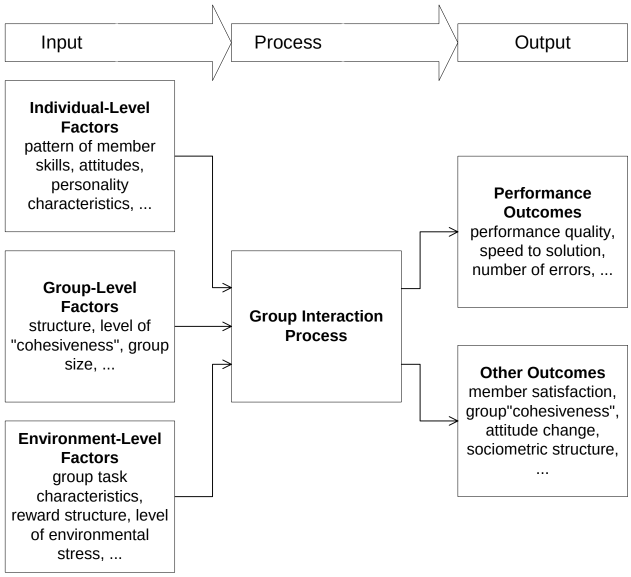


Figure 1 Framework for research on teams: Input -> Process -> Output model (Hackman & Morris, 1975).

The functional perspective links performance more or less directly and in a linear way to *input* and *process* factors. Thus, cyclical and non-linear group dynamics cannot be explained. The limits of the functional perspective are reached if there are changes over time (e.g., the development of strategies over time Tschan, Semmer, Nägele et al., 2000). In this perspective there is for example no feedback-loop from the *process* to *input*-factors, neither from the *output*-factors to the *input*-factors. But often teams show some development, individuals acquire new skills, the group climate changes (a change that is often bound to the performance) – thus the whole process is often not a straightforward *input* -> *process* -> *output* sequence. Groups have a history and an anticipated future. Groups often learn and some development takes place. Thus groups should be regarded as complex, adaptive and dynamic systems, as they are described in the CAST – Complex Action Systems Theory (McGrath & Tschan, 2004a, 2004b).

Nevertheless, the basic *input-process-output* model serves as basis for my work. The unit of analysis is a set of behavioral and communicational acts within each single shift of fifteen minutes. Each of the seven fifteen minutes shifts can then be analyzed using the *input-process-output* model. I assume that group learning and development during a single shift has just a small influence on the process within that shift. However, it has a impact on the following shifts, which can not be neglected. Thus, the performance a group achieved and the experience that a group gained in prior shifts have to be taken as *input*-factors in later shifts.

The main focus of my work is on the group process. The term ‘process’ is used by different authors with different meanings. In the next chapter I give an overview on different meanings of ‘process’ and explain my own understanding of the term.

5 The Group Process

The group process is often seen as an important agent between input variables and the outcome. McGrath (1964) and Hackman and Morris (1975) were some of the first researchers, who described the group process as equally important as the input factors to predict performance or work group effectiveness. Since then, many authors have acknowledged the importance of examining the group process more closely (Griffith & Neal, 2001; Weingart, 1997).

Hackman: Leading Teams

Hackman's (2002) book on "Leading teams. Setting the stage for great performances" is a typical example of how group research is often done. Big emphasis is put on input factors, here summarized as factors that set the stage for a team's performance. Process factors, linking input and performance, are seen as important. However, they are rarely discussed as extensively as the input factors.

Hackman discusses three conditions, which increase the probability of a team to be effective: enabling structure, compelling direction, building a real team (i.e., clear boundaries, a specified authority and membership stability). All those factors are typical input factors, although important ones. However, the group process is not neglected. Referring to Steiner (1972), Hackman discusses three aspects of group interaction which can influence team effectiveness: the members' effort to solve the task, the employment of appropriate strategies and the knowledge and skills applied. All of them are associated with process losses and gains (Table 2).

Effort. There is always some overhead cost, always some process loss. In bigger groups social loafing and motivational problems can become a problem, especially if the task is boring. Process gains appear if members become highly committed to the group, are proud of it, and are willing to work hard for the groups' task; in short: if team members "have developed 'team spirit'" (p. 171).

Performance Strategy. A process loss occurs when there is too much reliance on (habitual) routines. A well documented example for a habitual routine which led to a catastrophe is the case of the Air Florida flight 90 (Gersick & Hackman, 1990). When the external environment and the groups resources are scanned for problems and opportunities, a group can develop innovative performance strategies. In this case process gain is evident.

Knowledge and skill. The main reason for process loss is the inappropriate weighting of members' contributions (due to demographic attributes, position in the organization or behavioral style). Often, groups do not act in consideration of all potentially available information.

Therefore, for a process gain it is important that team members develop a pattern of interaction which fosters learning from one another.

"Task-performing teams are always at risk of falling victim to process losses that compromise their potential – but they also always have the chance to generate synergistic process gains" (p. 175). These gains are achieved, if the team processes are well managed. This happens sometimes spontaneously, but in the view of Hackman most often expert coaching is needed.

Table 2 Characteristic process losses and gains for performance (Hackman, 2002, p. 170).

Effort	Process loss:	Social loafing of team members, low motivation
	Process gain:	Development of high shared commitment to the team and its work
Performance Strategy	Process loss:	Mindless reliance on habitual routines
	Process gain:	Invention of innovative, task-appropriate work procedures
Knowledge and skill	Process loss:	Inappropriate weighting of member contributions
	Process gain:	Sharing of knowledge and development of member skills

My point is that the focus of interest is often more on input variables than on process variables. And the process is then often described in terms of the social exchange of information, influence attempts, expression of feelings, formation of coalitions, leadership efforts, supporting or rejecting a group leader or expressions of approval or disapprovals of fellow group members (Guzzo & Shea, 1992).

Group process measures are often evaluative reports. They do not consider what the group members actually do. However, I think that if we conceptualize the group process as being important for a teams functioning and performance, we must have a closer look at the micro-behavioral organization of this group process. We have to consider the dynamic, on-going interaction of group members with one another, with their technology and with their task. In other words: we have to look at what teams really do.

Group Process Measures

The term "process" is used to describe different aspects of what is going on between the *input* and the *output*. In the following section I give an overview of different conceptualizations and define *process variables* as variables that describe the micro-structure of the process, either as aggregates of the frequency of some behaviors or communications or as temporal sequences.

Group process. The group process can be mapped as a sequence of behavioral units or as a sequence of verbal utterances, dependent on the coding scheme available (Figure 1, elements A, B, C).

Evaluation of the group process. Measurements of social loafing, cohesion, social support or similar concepts provide an overall evaluation of the groups' status. Instead of observing the process directly, the group members are asked to report their impression of the process (Weingart, 1997). Although these variables do not really capture the real process, but rather an evaluation oft it, they are labeled process variables. Questionnaires or expert ratings are used to gather this information on the group process. This is often done retrospectively and often just once (one-shot measure).

One-shot measures are like fixed-images from a movie. We get some impression of the story, but we will never fetch the real story behind those pictures. Exactly the same is true for the group process. What we get is a picture of how the group evaluates the process. A big advantage of this approach is that a huge inventory of approved instruments (questionnaires, rating scales) as well as established procedures (from data collection to data representation and interpretation) are available. But all those methods do not allow fine grade analyses of the group process and miss to touch its micro-structure (Brauner, 1998). This is illustrated in Figure 1, arrow labeled "overall evaluation". See the discussion in chapter 5.1 for examples.

In Figure 1 the single coded micro-behavioral acts are represented as A, B, and C. Person 1 , person 2 and person 3 show a different temporal organization (the length and the succession of the acts is different). Measures on the level of the "overall evaluation" are for example cohesion, potency or the group climate. How these concepts are evaluated certainly reflects some aspects of the group process. But this macro perspective does not inform us on what the teams really do on the micro-behavioral level (the A, B, and C).

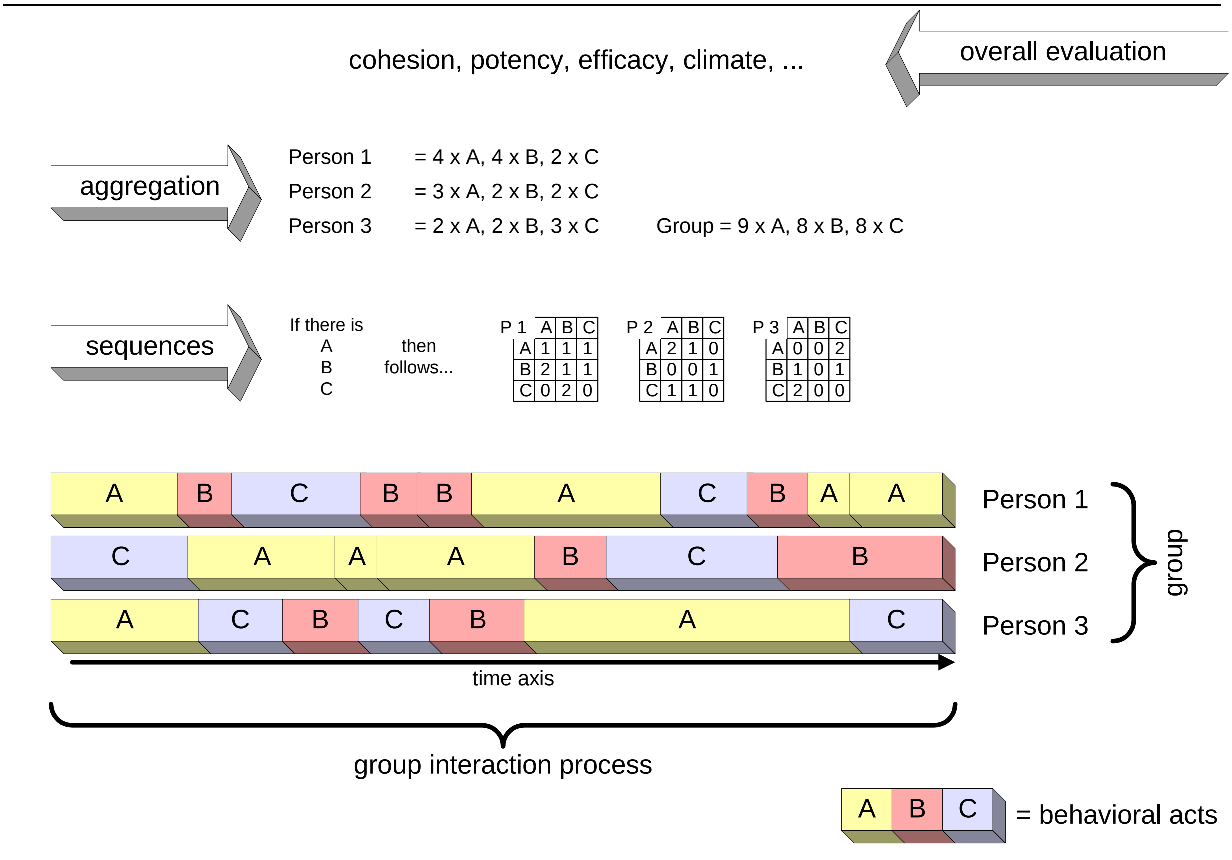


Figure 2 Framework for discussing several types of group process variables.

Coding and counting. There is a growing number of studies that represent group process as frequencies of behaviors (Weingart, 1997). These studies can describe *what* groups do. Typically frequencies or proportions of specific behaviors across the whole process are calculated. Yoder and Feurer (2000) describe this type of variables as summary-level variables. Examples can be found in research on aviation crew member communications (Brannick, Roach, & Salas, 1994). Based on a coding scheme communication acts were counted and set into relation with team performance. In research on crew resource management in aviation behavioral marker systems are used (Helmreich & Foushee, 1993; Klampfer et al., 2001). Summary level approaches are illustrated in Figure 1, arrow labeled “aggregation”.

In Tschan et al. (2000) these summary level variables were labeled as *general process variables*. The amount of communication, of strategic communication, of motivational remarks in the communication, and of specific task related operations are all examples of summary level variables. It could be shown that all these variables were bad predictors of the groups’ performance in different phases of the collaboration. More examples are given in chapter 5.2.

Temporal sequences. Interaction processes are cyclic and dynamic. They change over time. The beginning of a meeting may be dominated by planning efforts, the end of a meeting may contain more evaluation and implementation aspects; conflicts may wax and wane over time in a group, and so forth. What a lot of studies investigating group processes are unable to tell, is *how* groups interact, how groups do their job, and how behavior changes over time. Thus, sequential aspects of the group process are badly needed in team research (Arrow et al., 2000; see for an example Futoran, Kelly, & McGrath, 1989; Hackman & Morris, 1975; McGrath & Tschan, 2003; Tschan, 2002). This is illustrated in Figure 1, arrow labeled “sequences”. See the discussion in chapter 5.3 for examples.

Lack of a Standard Method for the Analysis On-Going Group Process

Reasons why there is so little research on the real group process are manifold (McGrath, 1997b; Tschan, 2000a; Weingart, 1997). First, analyses of team processes, which do not rely on retrospective perception of team members, but take into account communication or behavior variables, are time consuming and cumbersome to do (Sackett, 2000). Then, only newer technologies such as video-recording or automatically generated computer logs allow to reliably observe group processes; such technologies are not always available, and cannot be used in all situations. Third, the methods traditionally used for data analyses in psychology are not suited to examine temporal and dynamic processes (McGrath & Tschan, 2003). One exception is the work of Bales (1950; 2002). He developed his system for a multiple level observation of groups based on a meticulous analyses of the group process.

Up to now there is no standard method in small group research to analyze the ongoing team process (Becker-Beck, 1997, 2001; Brauner, 1998). However, many authors try to find new approaches to data analysis, combining them with the existing body of knowledge in small group research. For example, Boos, Morguet, and Meier used time series analyses (1989; 1990). Gockel and Brauner (2002) and Brauner (2002) employed lag-sequential analyses to investigate the development of transactive memory systems (Wegner, 1987). Brauner and Orth (2002) used monotonic network analyses to represent the structure of group discussions and to investigate and extract social representations in groups. Becker-Beck (1997) analyzed a group discussion and found that different sequential structures inhibit or promote task completion. However, such attempts are still scarce.

In my view one of the main reasons group processes have not been investigated more often with regards to sequential, temporal and dynamic aspects is - beside of the time and technology needed - primarily the lack of familiarity of (group) psychologists with methods that would allow conducting such analyses. In other fields of psychology (e.g. health psychology or family psychology), such methods are used more often. For example, Reicherts and Pihet (2000) conducted a micro-analysis relating stress episodes, coping and well-being, using time series analyses. Bakeman and Gottman (1986) investigated interactions in families with lag-sequential analyses. They explained the difference of non-sequential and sequential analyses as follows: “(…) a nonsequential analysis could tell us that distressed husbands and wives complain more than nondistressed ones do, but only a sequential analysis could tell us that distressed couples, but not nondistressed ones, tend to react to each other’s complaints with additional complaints. Similarly, a nonsequential analyses can tell us that 3-year-olds engage in less parallel play than 2-year-olds, but only a sequential analyses can tell us if, in the moment-by-moment stream of activity, young children use parallel play as a bridge into group activity” (p. 9).

In the following chapters I present some studies which use “process” (i.e. evaluation) or process (aggregations or sequences) variables to explain performance or effectiveness. I will show, that most of those studies do not hold the promise to map the group process. Then I present some studies using summary level variables (coding and counting approach) and I discuss some studies which have a closer look at the micro-structure of the group process.

Process variables are variables that describe the micro-structure of the process, either as aggregates of the frequency of some behaviors or communications or as temporal sequences.

Variables describing for example the group climate, roles, potency and similar constructs that are often labeled as group process variables in the literature are referred to as *evaluative measures of the group process*, or as “process” measures.

5.1 Evaluative Measures of the Group Process: “Process” Variables

There are many examples in the literature taking as a group “process” measure group cohesiveness, group longevity, collective efficacy (González, Burke, Santuzzi, & Bradley, 2003), potency, social support, workload sharing (Campion, Medsker, & Higgs, 1993; Campion, Papper, & Medsker, 1996), team-member exchange (Jordan et al., 2002), team communication, cohesion, and coordination (Brannick et al., 1994).

As the example of group cohesiveness shows, some constructs are used both as input variables and group “process” variables. In the model of Hackman and Morris (1975) (Figure 1), cohesion is an input variable. For González et al. (2003) cohesion is part of a social-motivational construct, representing the “process”. This is not necessarily a contradiction, because group cohesion can be either seen as a prerequisite for group functioning or as an evolving quality when people work together for some time. In the latter case it is an evaluative component of the group process. An example of a team cohesion questionnaire (Group Environment Questionnaire GEQ Carless & Paola, 2000; Carron, Bray, & Eys, 2002) illustrates this remark (Table 3). It highlights also the limits of the input – process – output model in the framework of the functional perspective, as the actual development of group cohesion can not be explained with this model.

Table 3 Group cohesion from the Group Environment Questionnaire GEQ (Carless & Paola, 2000; Carron et al., 2002).

concept	Items
task cohesion	• Our team is united in trying to reach its goals for performance. • I am unhappy with my team's level of commitment to the task. • Our team members have conflicting aspirations for the team's performance. • This team does not give me enough opportunities to improve my personal performance.
social cohesion	• Our team would like to spend time together outside of work hours. • Members of our team do not stick together outside of work time. • Our team members rarely party together. • Members of our team would rather go out on their own then get together as a team.
individual attraction to the group	• For me this team is one of the most important social groups to which I belong. • Some of my best friends are in this team.

Campion et al. (1993; 1996) show, how work team characteristics can be related to work group effectiveness (productivity, satisfaction, and manager judgments). As indicators of the group process they use potency, social support, workload sharing and communication/cooperation within the team. Process is defined as “those things that go on in the group that influence effectiveness” (Campion et al., 1993, p. 829). As the definitions in Table 4 show, all those concepts assess the group process in an evaluative way and do not really fetch the group process.

It was found that beside of concepts related to the job design, interdependence (task and goal), the groups' composition, and the context also the four group “process” variables showed in most cases positive correlations with all three performance measures. However, they were mainly related to productivity and manager judgments and not to group members satisfaction. All in all “process” characteristics had more and higher correlations with all performance measures than any other work team characteristic. Due to the small sample size of approximately 80 participants in the first study and 50 in the second study no regression models could be run. Therefore the mediational effect of the group “process” variables could not be tested. But nevertheless those two studies show that group “process” variables show high and significant relations to performance measures. Although they are labeled as process variables by the authors: no information on the real group process is collected using the four concepts presented in Table 4.

Table 4 Work group "process" variables used by Campion et al. (1993; 1996).

concept	description	items
potency	the belief by a group that it can be effective, similar to team spirit	• Members of my team have great confidence that the team can perform effectively. • My team can take on nearly any task and complete it. • My team has a lot of team spirit.
social support	Social support can be described as a group maintenance behavior. Effectiveness may be enhanced when members help each other and have positive social interactions	• Being in my team gives me the opportunity to work in a team and provide support to other team members. • My team increases my opportunities for positive social interaction. • Members of my team help each other out at work when needed.
workload sharing	Prevention of social-loafing. Sharing is enhanced, if members believe that their performance can be distinguished from the group's.	• Everyone in my team does their faire share of the work. • No one in my team depends on other team members to do the work for them. • Nearly all the members of my team contribute equally to the work.
communication/cooperation within the work group	Communication and collaboration have the potential to influence effectiveness.	• Members of my team are very willing to share information with other team members about our work. • Teams enhance the communication among people working on the same product. • Members of my team cooperate to get the work done.

In a similar study on the relationship between work group characteristics and performance Hyatt and Ruddy (1997) use six items to measure the group "process", which they call interpersonal work group process (Table 5).

Table 5 Work group “process” variables used by Hyatt and Ruddy (1997),

concept	description	items
interpersonal work group process	Factor derived from an exploratory factor analysis	• engage in open and honest communication • recognize individual’s unique contributions to the group • share and accept constructive criticisms without making it personal • have expectations about how we should behave with one another • respect each others opinions and feelings • value diversity in group members

Jordan et al. (2002) discussed three group “process” variables as predictors of performance: group potency, social cohesion, team-member exchange. In accordance with Guzzo et al. (1993) and Campion et al. (1993) group potency is defined as the belief a group has about its general effectiveness across multiple tasks. A sample item is “My team believes it can become unusually good at producing high quality work” (p. 130). Social cohesion is defined as “synergistic interactions between team members, including positive communication, conflict resolution, and effective workload sharing” (Barrick, Stewart, Neubert, & Mount, 1998, p. 382). A sample item is “The members of this team get along with each other” (p. 130). Finally, team-member exchange is defined as the quality of the exchange relationships between a team member and the rest of the team. A sample item is “The members of this team get along well with each other” (p. 130).

All measures were taken on an individual level. Then all data was aggregated on the group level. Results showed that especially group potency could explain unique variance in all performance measures (physical and mental task performance, commander ratings of team performance).

In two studies Gibson (1999) looked at the relation of group efficacy and group effectiveness with task uncertainty, task interdependence and cultural factors as moderating effects. I will focus on the group efficacy measure which can also be seen as a group process variable, related to group potency. Gibson defines group efficacy as a group's belief in its ability to perform effectively and defined similarly to self-efficacy (Bandura, 1997). Before team members started working together on a task, they were asked, (i) how certain the group is that it can complete the task (0% to 100%) and (ii) whether the group can complete the task at all (yes – no). The certainty scores were obtained through open discussion until a group consensus was reached. The decisions were made by reviewing previous experiences. A main finding was that group efficacy predicted a significant portion in the variance of group effectiveness (assessed by two expert observers looking at the video tapes).

In a later study of Gibson, Randel and Earley (2001) group efficacy was measured with three methods: (i) group potency, (ii) an aggregation of group member's certainty ratings, (iii) a group discussion (like in the studies of 1999). Group potency was measured with eight items (Guzzo et al., 1993), which are presented in Table 6. Group efficacy is conceptualized as a factor that underlies group activities. Although the focus of the study was on the assessment of several methods of group efficacy the following results are reported in relation to process variables: There are relations between group efficacy, group potency and group performance (time to finish the task, degree of intragroup agreement, personal assessment of groups ability to work productively and perceived effectiveness). The authors conclude that assessments of group efficacy using group discussion are better predictors than the aggregated efficacy score or the group potency, but neither measure was really a powerful predictor (R^2 in the range of .04 to .32).

Table 6 Group potency (Gibson, 2001; Guzzo et al., 1993).

Concept	items
Potency	• My group has confidence in itself. • My group believes it can become unusually good at producing high-quality work. • My group expects to be known as a high-performing team. • My group feels it can solve any problem it encounters. • My group believes it can be very productive. • My group can get a lot done when it works hard. • No task is too tough for my group. • My group expects to have a lot of influence around here.

Evaluation

There are several other studies using a definition of the group “process” that is similar to the examples shown in this chapter. A common characteristic of all those variables is that they are based on a overall evaluation of the group process. They do not map what is going on whilst the teams are doing their job. Furthermore, most often these processes variables are measured just once, ignoring any temporal changes. If those measurers are applied repeatedly, reactivity and measurement problems arise due to memory effects. Most important is however, that all these variables do not capture the real group process at all.

Nevertheless, all these measures provide us with valuable information on the team process on a general level. They are often easy to use and it was repeatedly shown that those measures are correlated with team performance.

5.2 Group Interaction: Coding and Counting Approaches

There are many attempts to break up either streams of communication or behavior into distinguishable categories. These approaches may be very distinct with respect to theoretical anchoring and the intention they follow – but they all share one common characteristic: Typically the observed categories are aggregated over time periods such that information on the temporal sequences is lost.

A growing number of studies represent group processes as frequencies of behaviors (Gurtner, 2003; Marks et al., 2001; Marks, Sabella, Burke, & Zaccaro, 2002; Mathieu, Heffner, Goodwin, Salas, & Cannon-Bowers, 2000; Stout, Cannon-Bowers, Salas, & Milanovich, 1999). Studies that use frequencies, sums across people, probabilities or mean differences between different conditions use *summary-level variables* (Yoder & Feurer, 2000).

In this chapter examples of studies are presented that can be summarized under the heading of coding and counting approaches.

Bales: Interaction Process Analysis (IPA)

Interaction process analysis (IPA) from Bales (Bales, 1950, 2002) is a system that uses quantitative analysis to examine interaction, most often applied to problem solving groups. It is a standard methodology in small group research and cited in many textbooks (Forgas, 1995; Forsyth, 1999; Gergen & Gergen, 1981; Manstead & Semin, 2001). During a group discussion it is recorded how often a particular type of behavior has occurred, allowing for a classification of the group members according to their particular styles of relating to statements of other group members. The IPA coding categories are presented in Table 7.

Table 7 IPA categories used for direct observation of the interaction process (adapted from Bales, 2002, p. 165).

problem areas	observation categories	
expressive-integrative social-emotional area positive reactions	1 shows solidarity	raises other's status, gives help, reward
	2 shows tension releases	jokes, laughs, shows satisfaction
	3 agrees	shows passive acceptance, understands, concurs, complies
instrumental-adaptive task area attempt answers	4 gives suggestion	direction, implying autonomy for other
	5 gives opinion	evaluation, analysis, expresses feeling, wish
	6 gives orientation	evaluation, analysis, expresses feeling, wish
instrumental-adaptive task area questions	7 asks for orientation	information, repetition, confirmation
	8 asks for opinion	evaluation, analysis, expression of feeling
	9 ask for suggestion	direction, possible ways of action
expressive-integrative social emotional area negative reactions	10 disagrees	shows passive rejection, formality, withholds help
	11 shows tension	asks for help, withdraws out of field
	12 shows antagonism	deflates other's status, defends or asserts self

The basic idea of the IPA is to categorize behavior and to count it, to determine how frequently actions belong to each category (Peräkylä, 2004). Therefore, this approach is a perfect example of a method using – in the terms of Yoder and Feurer (2000) - summary level process variables. An example, taken from Bales (2002), further illustrates this aspect. In early studies of Bales and colleagues a standard task (examination and discussion of a human relations case) was used. The communication was coded according to the IPA categories (Table 7). Frequency profiles were built (Table 8), comparing a group which was satisfied to a group which was dissatisfied with the solution they reached in the task. The examination of the percentages for two groups gives some insight into the different group processes. The interpretation Bales offers is that the satisfied group shows a model of an effective interaction process. They have a good profile. The high rates of *giving suggestion* is followed by high rates of *agreement* and low rates of *disagreement*. In contrast the dissatisfied group has a lower rate of *giving suggestions* followed by low rates of *agreement* but high rates of *disagreement*. The information on the sequence is not derived from an analysis of the sequential ordering of statements but is already embedded in the IPA categories. How the IPA categories can be used in sequential analysis is discussed in the chapter on sequential analysis, especially with reference to the work of Becker-Beck (Becker-Beck, 1997, 2001; Becker-Beck & Fisch, 1987).

Table 8 IPA profile of a satisfied and dissatisfied group on a case discussion task (adapted from Bales, 2002, p. 226).

observation categories	satisfied*	dissatisfied**
1 shows solidarity	0.7	0.8
2 shows tension releases	7.9	6.8
3 agrees	24.9	9.6
4 gives suggestion	8.2	3.6
5 gives opinion	26.7	30.5
6 gives orientation	22.4	21.9
7 asks for orientation	1.7	5.7
8 asks for opinion	1.7	2.2
9 ask for suggestion	0.5	1.6
10 disagrees	4.0	12.4
11 shows tension	1.0	2.6
12 shows antagonism	0.3	2.2
percentage total	*100*	*100*
raw total	*719*	*767*

* The highest of sixteen groups. The members rated their own satisfaction with their solution after the meeting at an average of 10.4 on a scale running from 0 to highest possible rating of 12

** The lowest of sixteen groups. Comparable satisfaction rating in this group was 2.6.

Aviation: Crew Resource Management

In research on crew resource management (CRM) behavioral marker systems are used. Behavioral marker systems focus on sets of behaviors indicative of some aspect of performance. The finding that 60% of all aviation accidents are due to human error led to big efforts to understand those crews better (Prince, Brannick, Prince, & Salas, 1997). A lot of research in this area is on crew members communication (Brannick et al., 1994). It could be shown that pilot error was more likely to reflect failures in team communication and coordination than deficiencies in technical proficiency (Sexton & Helmreich, 1999). But also other behaviors than just communication is important. This is described in behavioral marker systems and then used in crew training (Flin & Martin, 2001).

Aviation: Analyses of Communication

In team tasks communication is seen as part of the process that leads to task performance (Stroomer & Oosterdrop, 2003). Studies on aircrew performance showed repeatedly that – under most circumstances - crews with a higher performance communicate more often than crews with a lower performance (Bowers, Jentsch, Salas, & Braun, 1998; Foushee, Lauber, Baetge, & Acomb, 1986; Sexton & Helmreich, 1999).

Foushee et al. (1986) and Kanki and Foushee (1989) analyzed video-taped communication of a simulator study. In their scenario a hydraulic failure lead to a reduced braking and thrust reverse effectiveness. The crew had to decide on landing on another airport with a long enough runway. The primary interest of the study was the decision-making process of the crew and not the manual skills. Each statement was coded into one of eighteen categories: command, observation, suggestion, statement of intent, inquiry, agreement, disagreement, acknowledgement, answer, supplying information, response uncertainty, tension release, frustration/anger/derisive remark, embarrassment, repeats, checklist, non-task related, non-codable, air traffic control communication. Analyses were run calculating the mean number of events for every category for commanders or first officers for specific periods of the simulation and comparing the means running analyses of variance. One of the main findings of this study was that the amount of communication is a good predictor of overall crew performance.

In another publication of Kanki, Lozito, and Foushee (1989) communication patterns (sequences of initiation and response) were the topic.

Prinzo (1998) analyzed air traffic control communication in a simulated terminal radar approach. The coding of the speech acts were based on the aviation topics speech acts taxonomy (ATSAT Prinzo, Britton, & Hendrix, 1995). This taxonomy distinguishes six categories: address/addressee (speaker, receiver), courtesy (thanks, greetings, apology), instruction/clearance, advisory/remark, request, and non-codable remarks. Furthermore, it is coded for each speech act, whether it confirms to the standard phraseology (FAA Order 7110.65G or Airman's Information Manual) or shows some deviation from it (Table 9). The study aimed to highlight differences in communication between simulation and field communication. It showed that the communication was alike. The highest percentage of irregular communication was found in the speech act category instruction (55%), in advisory (24%), and address (14%). But again, all analyses are based on summary scores, comparing taped communication from a field and simulation recordings.

Table 9 Types of irregular communications in ATC/pilot transcripts (Prinzo et al., 1995, p. 4).

Types of irregular communication	Definition
Non-Standard Phraseology	
Grouped	Grouping of numerical information contrary to paragraph 2-85, FAA Order 7110.65G.
Sequential (Non-grouped)	Failure to group numbers in accordance with paragraphs 2-87, 2-88, 2-90, and non-use of the phonetic alphabet in accordance with paragraph 2-84, FAA Order 7110.65G.
Omission	Leaving out number(s), letter(s), word(s), prescribed in communication requirements in FAA Order 7110.65G.
Substitution	Use of word(s) or phrases(s) in lieu of communication outlined in FAA Order 7110.65G (e.g., “verify altitude” vs. “say altitude”).
Transposition	Number(s) or word(s) used in the improper order (e.g., “Universal six forty-five” instead of “Universal five forty-six”).
Excessive Verbiage	Adding word(s) or phrase(s) to communication outlined in FAA Order 7110.65G, and the communication suggested in the Aeronautical Information Manual (e.g., “Universal the number one airline six forty-five”).
Partial Readback	Pilot report or readback that does not include specific reference to a topic subject (e.g., altitude topic “out of six for four” would be recorded as a P.).
Delivery Technique	
Dysfluency	Pause(s), stammer(s), utterance(s), that add no meaning to the message (e.g., “uh,” “ah,” or “OK” when not used as a General Acknowledgment.
Misarticulation	Improperly spoken words (i.e., slurs, stutters, mumbling, etc.).

Aviation: Behavioral Marker Systems

Behavioral markers are defined as, “Observable, non-technical behaviors that contribute to superior or substandard performance within a work environment (for example, as contributing factors enhancing safety or in accidents and incidents in aviation“ (Klampfer et al., 2001, p. 10). In any case behavioral markers are observable behaviors of teams or individuals. Most often they are applied in a training or assessment situation or to explain accidents. One behavioral markers system is the European taxonomy of pilots' non-technical skills (NOTECHS). The system has four categories: co-operation, leadership and managerial skills, situation awareness and decision making (Table 10). But again, the interpretation and analyses are most often done on summarizing observations of specific periods (for example in a flight scenario predeparture, takeoff and climb descent, approach and land) (Klampfer, Häusler, Amacher, & Naef, 2002).

Table 10 NOTECHS behavioral markers (Klampfer et al., 2001, p. 26).

categories	elements	example behaviors
COOPERATION	Team building and maintaining	Establishes atmosphere for open communication and participation
	Considering others	Takes condition of other crew members into account
	Supporting others	Helps other crew members in demanding situation
	Conflict solving	Concentrates on what is right rather than who is right
LEADERSHIP & MANAGERIAL SKILLS	Use of authority and assertiveness	Takes initiative to ensure involvement and task completion
	Maintaining standards	Intervenes if task completion deviates from standards
	Planning and co-ordinating	Clearly states intentions and goals
	Workload management	Allocates enough time to complete tasks
SITUATION AWARENESS	System awareness	Monitors and reports changes in system's states
	Environmental awareness	Collects information about the environment
	Anticipation	Identifies possible future problems
DECISION MAKING	Problem definition / diagnosis	Reviews causal factors with other crew members
	Option generation	States alternative courses of action - Asks other crew member for options
	Risk assessment / Option choice	Considers and shares risks of alternative courses of action
	Outcome review	Checks outcome against plan

Task Adaptive Behaviors

Task adaptive behaviors are specific measures of the group process (Tschan, Semmer, Nägele et al., 2000). Based on a task analysis categories were developed that represent either communication or operations that are supposed to foster or hinder the teams to perform well. A detailed description of the task adaptive behaviors in the ATC simulation is given in chapter 6.9.

The basic idea is, that the coding takes into account the specific properties of the task. On an very general level it could be assumed that teams with more communication perform better. However, in the ATC simulation one important aspect of the communication is that the commander gets the information fast and correctly. Thus, it is not only the amount of communication that is important. It is a combination of the frequency and the quality of the communication. This is then reflected in a task adaptive behavior named *unambiguous and timely communication*. It is defined as a message that is easy to read, contains only necessary information and is up-to-date.

In order to contribute to the prediction of performance, task adaptive behaviors have to occur regularly. Therefore they are constructed by summarizing different variables. The "…number (or percentage) of such behaviors is then regarded as an indicator of a task adaptive behavior pattern, and it is this pattern that should be related to performance" (Tschan, Semmer, Nägele et al., 2000, p. 368). It was shown that these task adaptive behaviors are much better predictors of performance than general group process measures.

Evaluation

All studies presented in this chapter code either streams of communication or behavior with the intention to aggregate the data by counting the frequencies of certain codes in specific periods. This is on the one hand a very economic procedure, because standard statistical techniques (Chi-Square, ANOVA or regression analyses) can be used to analyze the data. In many studies frequencies of some kind of speech acts or behavioral acts are related to performance. But there are also studies showing that it is not only the number of certain acts, which is important. Rather it seems to be decisive that the sequence of certain acts is such, that it helps fulfill the task requirements.

5.3 Beyond Counting Acts

Dynamics of people interacting unfold in time, a obvious fact, if one observes social interactions, for example children's play. Children's play seems on first sight probably chaotic, unorganized, wild and loud. But even as a naïve observer of the play, after some time, repeating patterns can be detected, interactions that seem to follow rules. Another example could be to look at a couple starting an argument, and "(…) what happens after one spouse disagrees or after one spouse complains. Are there characteristic ways the other spouse responds? Are these ways different for husband and wives? Are they different for distressed and nondistressed couples?" (Bakeman & Gottman, 1986, p. 9).

In this chapter I present methods and studies, which take the sequentiality of the group process into account. The basis is always an act by act coding of the single acts of communication and behavior, together with the information on the temporal succession of the acts. The studies presented employ three different methods: data mining, sequential data analyses, and procedural network representation.

The group process is the instance where performance is "made". As I pointed out in the previous chapters, studies looking at the group process are rare. Although theory clearly postulates the importance of the process, to date it is empirically often neglected. However, Abott (1995) writes: "A quiet revolution is underway in social science. We are turning from units to context, from attributes to connections, from causes to events" (p. 93). Abott emphasizes that this kind of analyses have become possible because of the development of new technologies and methods. He distinguishes two types of methods to analyze sequence data: step-by-step methods (like time series, markov chains, event history methods) and whole sequence methods.

In the next three chapters the selected methods are described: sequential data analyses, procedural network representation and data mining. Certainly other methods exist, which contribute to the analysis and understanding of group processes, such as event-history methods (Blossfeld & Rohwer, 1995) or time series-analysis (Boos et al., 1989, 1990; Janoski & Isaac, 1994; Schmitz, 1989).

Sequential data analysis has a long standing tradition in research on behavioral observation (Gottman & Roy, 1990; van Hooff, 1982). It was often used to analyze children's play or interaction with some others (mostly mothers) (Bakeman & Brwonlee, 1980; Girbau, 2002; Martin, Maccoby, Baran, & Jecklin, 1981). Furthermore, the publication of Bakeman and Quera (1995a) along with the GESQ-SDIS computer program (http://www.ub.es/comporta/sg.htm) makes it quite convenient to run lag sequential analyses.

Procedural network representation was selected because the use of the Pathfinder algorithm (Schvaneveldt, 1990) not only visualizes dependencies between different concepts or categories. Furthermore, it is possible to directly compare different network representations and to calculate their similarity. We already used the Pathfinder algorithm to describe and compare shared mental models (Gurtner, 2003; Tschan, Semmer, Nägele, & Gurtner, 1999). Cooke et al. (1996) used Pathfinder to represent sequential data from a software usability study. Thus, it should be possible to also represent the ATC data by the use of Pathfinder algorithm.

Knowledge discovery in databases and data mining were chosen because the methods are new and hardly ever applied to psychological data. Also, there was an opportunity for a cooperation with Kilian Stoffel and Paul Cotofrei (Institut interfacultaire d'informatique, Université de Neuchâtel).

The following three chapters on lag sequential analyses (chapter 5.3.1), procedural network representations (PRONET) (chapter 5.3.2), and knowledge discovery in databases / data mining (chapter 5.3.3) highlight the main features of the method and show some examples of it's application. More information to the methods is provided in the chapters 8.7, 8.8, and 8.9 when the three methods are applied to the ATC data.

5.3.1 Lag Sequential Analyses

Lag sequential analysis has been used in studies on family interactions (Hofer, Pikowsky, Fleischmann, & Spranz-Fogasy, 1993), on mother-child interactions (Angeles Verezo & D'Ocon, 1999; Cohn & Tronick, 1987; Martin et al., 1981), in the observation of developmental disabilities (Thompson, Felce, & Symons, 2000), in research on children's play (Bakeman & Brownlee, 1980; Robinson, Anderson, Porter, Hart, & Wouden-Miller, 2003), in research on animals (for example in primatology: van Hooff, 1982). In group and team research, lag sequential analysis is less well known (examples in Becker-Beck, 1997; Brauner, 2002).

Lag sequential analysis is always based on transition frequency or contingency tables. In their raw form, contingency tables map the frequency of how often a certain given behavior (also criterion or initial behavior) is followed by a specific other target behavior (also matching behavior). A lag 1 contingency table consists of all frequencies of directly adjacent behaviors. Lag 2 contingency tables map the frequencies of the second event after a given event. See also chapter 8.7.1 (p. 158ff.), in which I show how the lag sequential method can be applied to the ATC data.

Behavioral observation and sequential analysis are often used as soon as the participants of a study are not capable to read and understand questionnaires. Because small group research is most often done with (young) adults, questionnaire based methods are easy to apply and it does not seem to be necessary to use methods like lag sequential analyses. However, this standpoint contradicts the importance that is given to the group process by many conceptions on how teams function and perform. Nevertheless, there are a few studies using lag sequential analysis. I present them in the following chapter.

Studies Using Lag Sequential Analysis in the Context of Small Groups

Putnam: Procedural Messages

In the early 1980's, Putnam (1981; 1983) published two articles on team member's use of procedural messages in a discussion (statements about what the group is doing, where it is going, and what it should do, this is a kind of a meta-communication). Teams of three participants had to plan a party and to prepare a written report on their plan. Each team was assigned either to an experimental group, that preferred that the group work was tightly structured, or to an experimental group that preferred a free-associative type of work (Putnam, 1979). She worked on three main questions: (i) Which communication patterns show some regularity? (ii) What follows after a procedural statement at lag 1? (iii) Are there differences in the profiles of the two experimental groups?

Nine categories were used to code the communication, four of them dealing with procedural matters (Table 11). Results show that there were lag 1 auto-contingencies for seven out of nine categories. This means that a certain behavior was often immediately followed by itself. But only the category *task implementation* showed this cyclical patterns for lag 2 to lag 4 behaviors. The strongest lag 1 auto-contingency was found for *digression*, *task implementation* and *continued discussion: detailed*. No auto-contingency was found for *abstract topic change* and *detailed topic change*. This means that there is a certain probability that certain behaviors show a tendency to repeat themselves. In the case of *digression* the lag 1 probability was .82. This indicates: if someone in the group starts with a multiple conversations, interrupts, or expresses some non-task related, socio-emotional issues then the next behavior in the group will most probably be of the same type.

Table 11 Nine categories used by Putnam (1981, p. 336; Putnam, 1983, p. 474) to code communication.

concept/category	items
1 PM procedural direction	messages that request, suggest, or produce deadlines, agendas, outlines, lists, and procedural guidelines
2 PM group goals	contributions that clarify group purpose or group objectives; use of a signpost at the beginning of a meeting to orient group members
3 PM task implementation	messages that request or suggest plans for implementing a course of action; contributions that propose or develop division of labor for working on a task
4 PM summaries and integration	acts that link comments together, those that summarize previous group talk and pull together the thinking of the group in terms of procedural issues or group goals
5 digression	contributions that digress from the immediate task discussion to socio-emotional issues; multiple conversations within the group; successful interruptions and talkovers
6 topic changes: abstract label	messages that change the topic of discussion by introducing an abstract label or general heading
7 continue discussion: abstract label	contributions that follow the abstract heading and do not introduce a procedural issue or a digression
8 topic change: detailed issue	contributions that change the topic of discussion by introducing a detailed issue on a new topic
9 continue discussion: detailed topic	messages that follow detailed topic change and do not initiate a procedural activity or a digression

Note. PM = category dealing with procedural matters.

For a detailed analysis of all nine categories eighty-one plots, representing the conditional probabilities for lag 1 to lag 25 contingencies were drawn for each experimental group (example in Figure 3). Eight profiles were chosen for further analyses. This choice was based on two criteria. First, there had to be “an observable difference in the rise and fall of the lag probabilities” (Putnam, 1983, p. 481) between the two experimental conditions. Second, the mean probability across all lags had to be greater than 0.1. On each profile a repeated measures ANOVA was run. One result was that the probabilities from lag 1 to lag 25 for *continue discussion: abstract label* followed by a *PM group goals* is higher for teams preferring a tightly structured (mean probability lag 1 to lag 25 is .233) than for teams preferring a free-associative work-style (mean probability for lag 1 to lag 25 is .167). Another result: *continue discussion: detailed topic* followed by *PM summaries and integration* was lower for teams preferring a tightly structured work-style (mean probability lag 1 to lag 25 is .290) than for teams preferring a free-associative work-style (mean probability for lag 1 to lag 25 is .359).

teams with a preference for a tightly structured group work | teams with a preference for a free-associative type of work

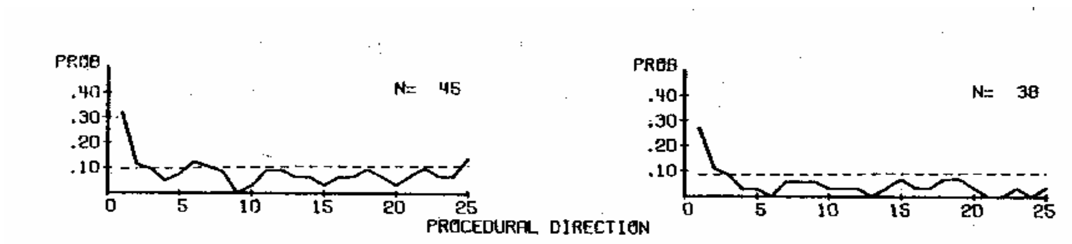


Figure 3 Example of a lag profile taken from Putnam (1983, p. 478).

Putnam (1983) summarizes her results as follows: Teams whose members preferred a tightly structured group work “organize group talk in a deductive pattern by following procedural activity with general headings that categorize substantive matters (…)” (p. 487). Teams whose members preferred a free-associative type of work “move from procedural talk to content themes via an inductive process (…)” (p. 487).

All in all the study of Putnam (1981; 1983) is an early and rare example of how lag sequential analysis can be used to analyze the group process.

The focus of Putnam’s work was on communication styles and work climate. There are some weaknesses in this study. Putnam uses solely conditional probabilities to run the analyses. This measure is very sensible to changes in the base rate of the occurrence of an event (see the discussion in chapter 8.7): if the frequency of an event is low the conditional probability is most likely also low. However, since the early 1980’s the appropriate measures for lag sequential analyses have been discussed intensively and in more recent publications, Bakeman and Quera (1995a) recommend to not use conditional probabilities any more for the kind of analysis Putnam did.

Becker-Beck and colleagues: SYMLOG coded interaction

Becker-Beck and Fisch (1987) used lag sequential analysis to detect patterns in a SYMLOG (Bales, Cohen, & Williamson, 1979) coded interaction process. One of their aims was to "achieve a more dynamic analysis of group interaction processes than the use of field diagrams allows" (p. 198). A problem-solving discussion of a group of four students was analyzed. Two types of analyses were made: (i) analyses of behavioral sequences without differentiating between group members, and (ii) analyses of interaction patterns for any combination of group members.

In SYMLOG twenty-seven behavioral categories were distinguished, which were reduced for this study to four basic behavioral types: *withdrawal*, *conflict*, *sympathy*, and *accomplishment*. Based on the frequencies in the contingency table conditional probabilities and *z*-scores (as defined in Bakeman & Gottman, 1986) were calculated for lag 1 to lag 20. First results described the conditional probabilities for lag 1 to lag 20 (Figure 4). The graph shows that after an *accomplishment* the probability that another *accomplishment* will follow is increased at lag 1, lag 2, lag 3, lag 5, and lag 11. The graph also shows that after an *accomplishment* the probability decreases that the next behavior is a *conflict* for lag 1, lag 2, lag 3, lag 5 and lag 12. Such graphs can be drawn for every behavioral type. Becker-Beck and Fish showed that the behavioral category *conflict* has the most enduring effect on the interaction. If the given behavior is a *conflict* the conditional probabilities are increased or decreased for a longer time than given any of the other behaviors. A longer time means that significant changes in the conditional probabilities and in lags higher than lag 3 or lag 4 occur more often.

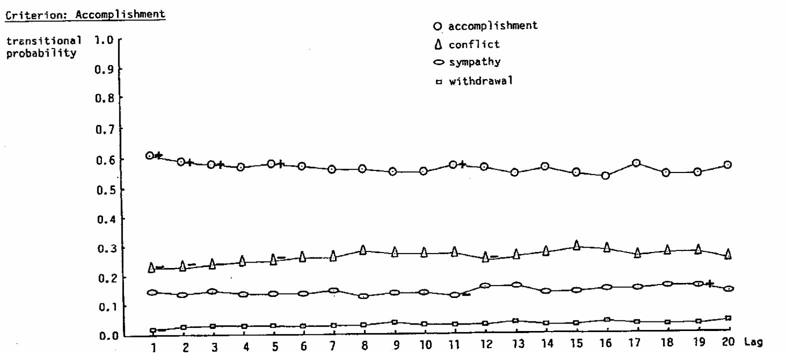


Figure 4 Conditional probabilities for the four behavioral types *withdrawal*, *conflict*, *sympathy*, and *accomplishment* given the criterion *accomplishment*. + and – indicate stat. significantly increased or decreased conditional probabilities (Becker-Beck & Fisch, 1987, p. 203).

In the words of Becker-Beck and Fisch the more interesting part of sequential analysis is “the description of differential interactional patterns between specific group members” (p. 202). The authors are especially interested in reciprocity (how often a particular type of behavior of actor A is followed by a particular behavior of actor B and vice-versa), and in dominance (the asymmetry in the mutual predictability in the behavior of two interacting individuals). These concepts are further described in Becker-Beck (1997), the formulas to calculate indices for the concepts can be found in Wampold and Margolin (1982) and Wampold (1984). The described analyses go beyond those I plan to do with the ATC-data. Nevertheless it’s important to know that lag sequential analysis can be used for very fine graded analyses of the group process.

In another paper, Becker-Beck (1994) presents a structural analysis of an interaction. Group discussions of nine teams of four persons were coded using the twenty-six SYMLOG categories. Analyses were run to identify how the categories were embedded in the sequential process. In a second step to those sequences that showed a similar temporal patterning were put together by means of a cluster analysis. Finally six classes of functionally similar categories were identified: accomplishment, complementary accomplishment, reinforcement, tension release, conflict and withdrawal.

Later, Becker-Beck (2001) demonstrated, how lag sequential analysis can be used to analyze a conflict situation in a group discussion. Two groups of four members had to discuss conflicting topics (“…exchange one’s own personal views on male and female gender roles, on the compatibility of employment and family, and one’s own personal plans for life” (p. 264)). The group composition was as follows: group A was composed of two men with traditional views on gender roles and two women with progressive views on gender roles, and group B was composed of a man and a woman with traditional and a man and a woman with progressive views on the gender role. It was hypothesized that group members having the same sex and the same attitude towards the gender roles (group A) would show more mutual support than members of the group with the same attitudes but a different gender (group B). The coding of the acts was based on Bales’ twenty-seven SYMLOG categories which were – as in Becker-Beck and Fisch (1987) – grouped into the four categories *withdrawal*, *conflict*, *sympathy*, and *accomplishment*.

Becker-Beck distinguished different strategies in conflict situations: (i) confrontation, (ii) analysis and problem solving, (iii) yielding and conciliation, (iv) withdrawal and avoidance, (v) mutual support.

The different strategies can be identified by the probability of different sequential behavioral patterns. Confrontation (conflict escalation) for example is: person's A act is *conflict* and there is a high probability that person's B reaction is also *conflict*. Avoidance of a conflict is: person's A act is *conflict* and there is a high probability that person's B reaction is not *conflict*. Lag sequential analyses was used to detect non-random behavioral enhancing or inhibiting sequences.

Mutual support was defined as an enhanced probability of a sequence of *accomplishment* (person one) followed by *sympathy* (person two). Results show that there was a higher mutual support in group A (same gender, same attitude) than in group B (different gender, same attitude).

In a second step, Becker-Beck (2001) combined a content analysis of the discussion with sequential analysis. The group consisted of two men with traditional attitudes and two women with progressive attitudes (group A). The SYMLOG-based content analysis showed for one group that there "exists a clear polarization between group members on the content level" (p. 274).

Given the limited space of this thesis, it's impossible to fully describe Bales SYMLOG system and the modifications and extensions used by Becker-Beck (2001). In the context of my discussion of lag sequential analysis the important point is, that the representation of the positions of the team members in the SYMLOG space show some polarization. Taking this information as given, one could expect that this kind of group would have to solve the content problem by "strategies of confrontation, analysis, and problem solving" (p. 277). At this point the content coding is combined with the information on the group process. A confrontation strategy is mapped on the behavioral level in an enhanced probability of a sequence of accomplishment -> conflict or conflict -> conflict. In the study of Becker-Beck the group with the strong content polarization avoided to use exactly those two strategies. In her interpretation this group failed to accomplish the task.

Browner: Transactive Memory Systems

A third example how to use lag sequential analysis can be taken from Brauner (2002). She uses this method to analyze the development of transactive memory systems (Wegner, 1987), i.e. what "knowledge about other people's knowledge is stored as metaknowledge in individual memories. Thus, other people are used as external knowledge storage devices similar to libraries or computer databases" (p. 103). Over four months a project group was tracked in twelve session and it was assessed how they developed a "concept for consulting firms regarding the implementation of information technology with respect to organizational and personnel development" (p. 106). The central interest was on how the four team members encoded, stored and retrieved own and shared knowledge. Storing new knowledge about other peoples knowledge develops new transactive knowledge, whereas the retrieval of that knowledge means using the transactive memory.

To run the analyses over 5'000 coded communication acts were available. Two tasks were compared: organizing (reporting the progress of projects) and exchange (developing consulting concepts). As expected, there was more reference to the shared knowledge in the exchange task. The sequential analyses presented refer to this task-type. There are strong auto-contingencies (i.e. the probability that a category follows itself was higher than expected at lag 1) for all four categories (storing own or other's knowledge, retrieving own or other's knowledge) (Table 12). Additionally there are positive (enhancing) contingencies between the two storing categories. All other contingencies are negative (inhibiting), some of them however statistically not significant. Storing knowledge either as own knowledge or as meta-knowledge is mutually enhanced. Brauner interprets it as "mutual alignment of knowledge" (p. 121). This is quite different if it comes to knowledge retrieval. This process is distinct from the storing process as no or inhibiting contingencies are found. Also, the negative (inhibiting) contingency between retrieving own knowledge and retrieving other's knowledge indicates that these are also two distinct processes. It can be concluded that "storing and retrieving knowledge are quite divergent processes as they reflect the input into memory and the output from memory" (p. 121).

Table 12 Storing and retrieving own knowledge and knowledge about other people's knowledge (Brauner, 2002, p. 118).

		successing category			
		Storing own knowledge	Storing other's knowledge	Retrieving own knowledge	Retrieving other's knowledge
preceding category	Storing own knowledge	**8.69**	**6.42**	**-4.44**	-1.78
	Storing other's knowledge	**4.65**	**8.48**	**-3.58**	-2.78
	Retrieving own knowledge	**-4.13**	**-4.68**	**3.59**	-1.26
	Retrieving other's knowledge	-0.85	-1.42	-2.07	**7.12**

Note. Significant residuals after Bonferroni-correction are in bold ($\alpha_{adj,}$ = .0031; z_{crit} = 2.96).

Brauner (2002) shows that there are sequential patterns in the process of storing and retrieving own or meta-knowledge. The mechanism how transactive memory systems are built in a project team is described.

5.3.2 Procedural Network Representation (PRONET) / Pathfinder

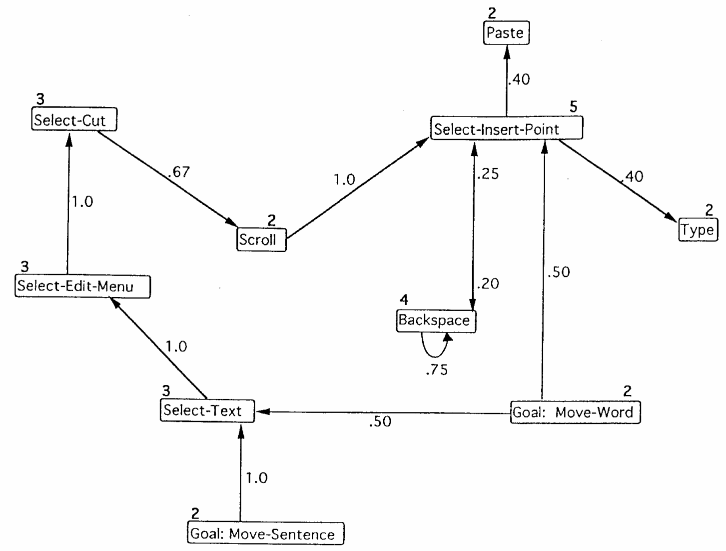
PRONET is a method for summarizing and representing sequential data. It is based on the Pathfinder algorithm (Schvaneveldt, 1990). The Pathfinder network scaling algorithm is a modeling technique, like multidimensional scaling, that is often used to map structural knowledge of a domain and to visualize changes in the knowledge organization over time or between novices and experts (Cooke et al., 1996; Cooke, Stout, Rivera, & Salas, 1998; Goldsmith & Johnson, 1990). In recent studies the Pathfinder network scaling algorithm was used to evaluate the outcomes of a cognitive training (Davis, Curtis, & Tschetter, 2003), to map the development of memory structures for homographs[9] in children and adults (Nievas & Justicia, 2003), to measure the complexity of the semantic memory organization in schizophrenic subjects (Vinogradov et al., 2003) or to map the importance of flight information in different phases made by novice and expert pilots (Schvaneveldt, Beringer, & Lamonica, 2001). The Pathfinder network scaling algorithm is also used to assess shared mental models (Cooke, Salas, Cannon-Bowers, & Stout, 2000). We have already used Pathfinder in our research on shared mental models (Gurtner, 2003; Christof Nägele, Andrea Gurtner, Franziska Tschan, & Norbert Semmer, 2002a; Christof Nägele, A. Gurtner, F. Tschan, & N. Semmer, 2002c). In comparison to other methods used to compare shared mental models (for example correlations (Smith-Jentsch, Campbell, Milanovich, & Reynolds, 2001), or r_{wg} (James, Demaree, & Wolf, 1984, 1993), Pathfinder yielded more reliable results.

Cooke, Neville, and Rowe (1996) applied the Pathfinder algorithm to sequential behavioral data in order to highlight frequently occurring transitions. This application of Pathfinder is called PROcedural NETwork representations of sequential data (PRONET). Cooke et al. use an example from the field of human computer interaction: While writing a text on a word processor system one has to move sentences or words. Moving a sentence can result in the following sequence: load document into

---

[9] Homographs are those words which have one spelling but two pronunciations and two distinct meanings or usages. A classic case would be a word like wound, which as a noun means injury and with a different pronunciation is the past tense of the verb wind, itself a homograph. http://www.marlodge.supanet.com/wordlist/homogrph.html

word processor -> point to text -> highlight text -> select edit menu -> select cut option -> scroll -> select insert point -> paste. Alternative sequences (more or less efficient) are possible. The cut and paste events were recorded, transitional probabilities were calculated and then submitted to the pathfinder algorithm (Schvaneveldt, Durso, & Dearholt, 1989), resulting in a network, representing proximity of acts for this problem (Figure 5). A detailed description on how Pathfinder networks are calculated and interpreted is given in chapter 8.8.



Numbers beside the nods are action/node frequencies. numbers attached to the arrows are transition probabilities.

Figure 5 Example Pathfinder network (*r* = infinity, *q* = 9) based on conditional transition probabilities (Cooke et al., 1996, p. 42).

As PRONET uses conditional probabilities as input for the calculation of the networks, the question is: what is the difference between lag sequential analyses and PRONET? First, PRONET uses the Pathfinder algorithm to visualize the result. Second, an advantage of the Pathfinder algorithm is that it can "handle asymmetries and nonhierarchical structures" (Cooke et al., 1996, p. 61). 'Nonhierarchical' means that there is no assumption of a underlying hierarchical structure as in MDS procedures. In MDS procedures items are represented in a tree-structure in which related items are clustered before this is done with less related items. The links in a Pathfinder network are relations, as shown in Figure 5. Items are represented as nodes with their relations expressing the distance between them, but no tree-like structure or hierarchical ordering is done. It is possible that a Pathfinder network can have directed links (point from one node to another node but not vice-versa) as soon as the proximity estimates are asymmetrical. Un-connected nods emerge if proximity estimates between an item and all other items do not meet a minimum strength criterion (*r*). Furthermore, it is easily possible to compare two network representations (by calculating Pathfinder *C*) or to summarize two or more networks. As we could show in our work on shared mental models (Gurtner, 2003; Nägele et al., 2002a; Nägele et al., 2002c) Pathfinder *C* is a measure that allows to compare two or more networks within a team or to compare expert networks with networks of novices. The same procedure can be followed if two networks have to be compared that map sequential behavioral data. Pathfinder *C* expresses the closeness or similarity of the networks. An example of how this value is calculated is presented in chapter 8.8 (p. 188ff.).

5.3.3 Knowledge Discovery in Databases (KDD) / Data mining

The term *data mining* is synonymous with *data dredging* or *fishing* (Hand, 1998). At first sight, data mining is nothing more than exploratory data analysis. Hand distinguishes primary and secondary data analysis. Psychologists are used to do primary data analysis: data are collected with an idea (question, theory) in mind and then analyzed accordingly. It is a top down ("hypotetico-deductive" (p. 112)) approach. In contrast, data mining is then defined as "*the process of secondary analysis of large databases aimed at finding unsuspected relationships which are of interest or value to the database owners*" (p. 112). Data mining is a bottom up (inductive) approach. Knowledge discovery in databases and data mining addresses problems that arise when the amount of data is huge (millions of customer calls or credit card transactions per day; tremendous amounts of data gathered for example in the NASA Earth Observing System, in the human genome project and so on). As it is impossible to run traditional statistical analyses in these cases, there is a big need for data mining algorithms that can find interesting patterns automatically or semi-automatically.

According to Fayyad, Piatetsky-Shapiro, and Smyth (1996) *data mining* is a part of the larger process of *knowledge discovery in databases (KDD)* (Figure 6). KDD aims to find useful knowledge from large databases, to extract meaningful patterns and to provide new insights. It is a process which describes the selection of data, the preprocessing and transformations necessary to apply data mining algorithms, in order to eventually find some "hidden" patterns, relationships or rules, and the interpretation of the results.

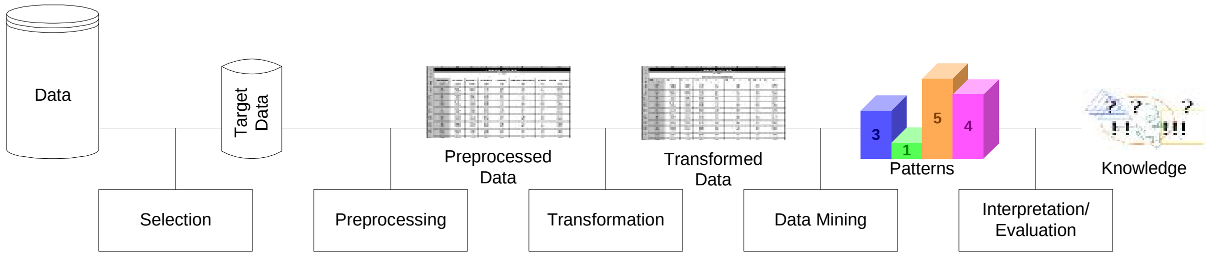


Figure 6 Knowledge Discovery in Databases (KDD) Process.

Data mining has been used to identify shopping patterns in supermarkets, to optimize website profitability by making appropriate offers to each visitor, to predict customer response rates in marketing campaigns, to define new customer groups for marketing purposes, to predict customer defections (which customers are likely to switch to an alternative supplier in the near future), to distinguish between profitable and unprofitable customers, or to identify suspicious (unusual) behavior, as part of a fraud detection process and so on.

Descriptive data mining is used to learn from and to understand the data. An example is the identification and description of customers with common buying behaviors.

Predictive data mining aims to develop models to foresee future events. A internet solutions provider could build a predictive model, which estimates the risk that a customer will leave the contract after the first 12 months. Benefits could then be offered to those customers with the highest risk to leave the contract. Or a model could try to predict, based on the customer's characteristics, how much he or she will spend on the next order.

The methods used in *descriptive data mining* are clustering (grouping together similar data into clusters), summarization (putting together data with similar characteristics, also generalizing), deriving association rules (an analysis of the links, uncovering relationships) and sequence discovery (as a special case of a link analysis). Methods in *predictive data mining* are classification, regression, time series analyses and the development of models to predict future states.

Data Mining in Psychology

Using the keywords *knowledge discovery* and *data mining*, in the field of business economics and business management, many publications can be found. In psychology, however, the same keyword search generates hardly any hits. To my knowledge, in small group research, nobody has yet applied this method to group process data. This is due to at least three factors: (i) often data sets collected in psychology are rather small so that there is no need for KDD, (ii) most often the data are collected theory based and with a particular question in mind, and (iii) psychologist have already used data mining tools (cluster analysis, factor analysis, regression analysis, discriminant function analysis or profile analysis) for a long time.

Mining the Data

Data mining can be used to extract information on a workflow *(process mining,* or *workflow mining,* or *process discovery)*. If there is for example a database with records on single actions of employees, it is reasonable to assume that it should be possible to extract information on how the employees typically proceed. The better a work process is structured, the higher is the probability to extract a small number of workflow models. An example is the workflow in a call center: answering the phone starts a sequence of well defined further steps. However, if the process is weakly structured, it is less likely to extract a single workflow model (Schimm, 2004). In those cases, Van der Aalst and Weijters (2004) propose to search for patterns and temporal association rules.

Basically, there are two types of temporal rules, that can be extracted from the data: (i) temporal association rules (5% of customers bought ‘Foundation’, then ‘Foundation and Empire’ and ‘Ringworld’, then ‘Second Foundation’), and (ii) event rules (If yesterday was a sunny day, with a maximum temperature of 35°, and today is an overcast day, with a wind blowing between 40 and 60 Km/h, then tomorrow will be a rainy day).

The aim of all data mining techniques is to find “hidden” patterns in the data. Such patterns can be a succession of events, described as workflow. But it can also be a temporal rule. There is a lot of research done in the development of data mining algorithms that find the really interesting patterns in the data (Cotofrei & Stoffel, 2002a, 2002b, 2002c, 2003; Hwang, Wei, & Yang, 2004).

What is an Interesting Pattern?

An important task in KDD and data mining is to decide whether a pattern is interesting or not. It is not a single statistical that helps to decide this question. There are several criteria that have to be fulfilled to make a pattern an interesting pattern (Klösgen, 1996):

- *Evidence*
  The significance of a finding is indicated by a statistical criterion.
- *Redundancy*
  This is the similarity of a finding with respect to other findings.
- *Usefulness*
  Are the results useful for the user? Are the findings related to the goals of the user?
- *Novelty*
  Is there some deviation from prior knowledge of the user?
- *Simplicity*
  Refers to the syntactical complexity of the presentation of a finding.
- *Generality*
  Is it possible to generalize the results?

To run data mining analyses I could count on the help of Paul Cotofrei. He ran all the data mining analyses. My task as a psychologist was then to find reasonable explanations for the identified patterns. The algorithm used to mine the ATC data is presented in chapter 8.9.1.

5.4 Integration and Discussion

Research on small groups often follows a functional perspective (Poole et al., 2004), where *input* factors lead to a certain *performance*, mediated by the group *process*. This framework is rooted in the work of McGrath (1964) and Hackman and Morris (1975).

One of the features of this *input-process-output* model is the strong emphasis placed on the group process. The process is conceptualized as important instance that “creates” performance. However, in empirical studies the group process is often neglected.

I distinguished three types of group process research. There are studies that…

- …take evaluative measures of the group process as process variables.
- …code and count acts of communication or (seldom) behavior.
- …use methods to analyze the sequential structure of the process.

I define process variables as variables that describe the micro-structure of the process. These variable are either aggregated and summarized (summary level variables in the coding and counting paradigm) or analyzed with methods that take into account the sequential nature of every process.

Up to date, a lot of published studies do not touch the micro-structure of group processes. Although several studies use the label ‘process variable’ for their measures, they do not meet the criteria of my definition. Questionnaire data gathered on various topics like task cohesion, social cohesion, potency, social support provide valuable information on the group process from a retrospective and evaluative perspective of the team members. But all these measures do not tell us how the team interaction was on a micro-behavioral level. It must be considered that retrospective measures risk to be heavily biased. In a study of Staw (1975) teams got false feedback about their performance. Then team members were asked to describe objectively how the team had functioned. Teams with a poor performance but a false positive feedback described the group process as more harmonious and the communication as better than teams with a false negative feedback on their good performance. Furthermore, especially if these measures are taken only once, they are a rather bad indicator of a group process. Above all, all those measures do not touch the micro-structure of the group process. They contain no information on what groups really did.

Coding and counting approaches go a step further. Often, they are based on a act by act coding of some communication or behavior. But as soon as summary level process variables are built any information on the temporal sequence is lost. Often this loss is compensated by splitting the process in phases (early and late), comparing the frequencies before and after some intervention, some learning experience or the like. An example of this approach is our own work on task adaptive behaviors (Tschan, Semmer, Nägele et al., 2000).

However, the group process is more than just a sum of acts or events. The information on the temporal sequence, the order how certain things are done, is important. Until now research on the group process is done with a limited set of methods. There is a clear lack of methods which allow to describe the group process not only by aggregating behaviors and communication but by analyzing the process as it unfolds moment by moment (Brauner, 1998; McGrath & Tschan, 2003).

I discussed three methods to run sequential analyses: lag sequential analyses, procedural network representations, and knowledge discovery in databases/data mining.

Lag sequential analysis was introduced by Sackett (1979) and promoted by Bakeman and Gottman (1986), Gottman and Roy (1990) and Bakeman and Quera (Bakeman & Quera, 1995a). The method is often used in behavioral research, but seldom in small group research. One of the rare examples is the work of Becker-Beck and colleagues (Becker-Beck, 2001; Becker-Beck & Fisch, 1987) who analyzed SYMLOG coded communication with lag sequential analysis.

Lag sequential analysis is a well suited for the analysis of sequential, categorical event-based data. The method can already be used with relatively few observations. The studies I presented showed convincingly that process characteristics on a micro-behavioral level can be detected, described and used in further analysis. The lag sequential method analyses every lag independently of the other lags. The sequence of all events is always broken up in dyadic sequences of one given event followed by another event at lag 1, lag 2 or lag n. As a consequence we do not know what happened at lag 1 or lag 2 when we look at a lag 3 contingency. Lag sequential analysis is further discussed in chapter 8.7, p. 158ff.).

Procedural network representations is a method proposed by Cooke and Neville (1996) to represent sequential behavior based on the Pathfinder algorithm (Schvaneveldt, 1990). The networks are calculated using conditional probabilities and can be read as if – then relations. This easily readable graphical representation is one of the big advantages PRONET has. Furthermore, there is an easy way to compare two or more graphical representations by calculating the Pathfinder *C* index. PRONET is further discussed in chapter 8.8 (p. 188ff.).

Knowledge discovery in databases is a process that describes the selection of data, the preprocessing and transformations necessary to apply data mining algorithms. The aim is to eventually find some “hidden” patterns, relationships or rules, and to meaningfully interpret the results. In psychology almost no publications can be found on *knowledge discovery* and *data mining* . A picture that is completely different in business economics and business management.

Data mining can be seen as a form of *data dredging* or *fishing*. In psychology, this approach is rather disdained. Psychologist prefer data collection and analysis, which are guided by theory and predefined questions. Data mining is just the opposite. However, thinking of the huge data sets generated e.g. by credit card companies logging all transactions, or data available from the NASA earth observing system, this approach seems to be more than legitimate. KDD is further discussed in chapter 8.9 (p. 208ff.).

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6 Method

Experiments using the Air Traffic Control simulation have been conducted between 1996 and 2002 at the Universities of Berne and Neuchâtel. During those years 196 teams (or 588 persons) participated (details in Table 13).

In my analyses I will use the data of 109 teams (327 persons). I excluded all teams from the TIK - Training of interpersonal knowledge condition from my analyses because the task structure was different in several shifts (Gurtner, 1997). For the same reason all teams from the COMP – Complexity condition were excluded from my analyses. Additional planes in the airspace changed the task structure and made it hardly comparable to the other experimental conditions. The task in all other experimental conditions was alike.

Due to technical problems several teams had to be excluded from the analyses. I used only data from teams with no drop-outs. The weak point of the computer program we used to run the simulation is that data is lost as soon as a slight problem with one of the machines or in the network occurs. The ATC simulation we used has no backup During a shift no backup copies are made. A problem five seconds before the end of a shift can result in a complete loss of data of the whole shift. This is the major reason why we had to exclude many groups from our analyses.

Table 13 Overview of all experiments in the period of 1996 to 2002 using the ATC simulation[10].

	Experimental condition	Dates	Total number of teams	Groups in analyses	% in analyses
1	BC - Base Condition	7.5.1996 – 27.9.1996	38	20	53%
2	TIK - Training of interpositional knowledge	29.7.1996 – 7.11.199 und 29.10.1998 – 18.11.1998	17	0	0%
3	COMP - Complexity	18.9.1997 – 28.1.1999	21	0	0%
4	Goal	13.11.1997 – 12.12.1997 und 18.11.1998 – 19.11.1998	17	9	53%
5	CHAT	2.12.1998 – 28.1.1999	18	14	78%
-	Pre-test	23.6.2000 – 7.7.2000	4	0	0%
6	CC-1 - Control Condition 1	21.9.2000 – 3.5.2001	18	15	83%
7	CC-2 - Control Condition 2	1.12.2000 – 2.5.2001	19	17	89%
8	IR - Individual Reflexivity	19.2.2001 – 2.5.2001	21	17	81%
9	GR - Group Reflexivity	15.1.2001 – 18.5.2001	23	17	74%
			196	109	55%

Note. I do not use data from the experimental conditions 2 TIK and 3 COMP in my thesis.

10 The experiments were carried out by Arie Abraham, Mirco Cecato, Andrea Gurtner, Christian Jaeggi, Christof Nägele and Silvia Stutz.
Arthur Wyss (technical assistent) and Rudolf Marti (computer support) helped us to solve many technical and organisational problems.

6.1 The Air Traffic Control Simulation

In the Air Traffic Control simulation hierarchical teams of three (commander, two specialists) observed an airspace with incoming and passing aircrafts. The main task of the team was to assess the threat level of each plane at each moment of observation.

The task was complex and dynamic: (i) planes could change their threat levels several times while moving in the airspace, (ii) the group members had to learn how to best organize their individual work, (iii) how to coordinate the efforts in the group, (iv) and up to six planes were in the airspace at the same time.

Plane information and formula. Nine pieces of information about a plane were available to assess the threat level of a plane, access to plane characteristics is distributed in the group: Only specialist A had access to information about *height* (feet), *distance* (distance from base in miles), *corridor* (being in, at the edge, or out of a prescribed corridor) and *size* (size of plane: small, medium, large). Only specialist B had access to information about *speed* (miles per hour), *angle* (flight angle in degrees), *direction* (flight direction in degrees) and *radar* (type of radar: weather, none, weapon). Depending on the raw values of these characteristics, their danger potential was either low (1), medium (2), or high (3) for height, distance, size, speed, angle, and radar, and no (0), medium (1) or high (2) for corridor and direction. The specialists observed raw values of plane and flight characteristics. They had information sheets allowing them to transform raw values into danger potential values. So they could either send raw values or danger potential values to the commander. Only the commander had access to information about IFF information (identify friend or foe: friend, civilian, foe plane), with threat values of 0, 1, and 2.

It was the commander's task to calculate the threat level for each plane. Only the commander knew about and was trained in the use of a formula that integrated the various pieces of information. In the formula, total threat was the result of three subtypes of threat. *Position_threat* was calculated out of the information available to specialist A by adding the danger potential of height (1-3) and distance (1-3), and multiplying that sum by the value for corridor (0-2). Because of the multiplicative formula, a value of 0 for corridor yielded an overall result of 0 for position threat. Corridor therefore was the critical parameter. *Maneuverability threat* was calculated by adding the danger potential of the plane characteristics available to specialist B: speed (1-3) and angle (1-3), and multiplying that sum by direction (0-2). Maneuverability threat was 0 if the plane was flying away from the base (multiplication by 0), direction here was the critical parameter. *Plane type threat* was calculated by summing the danger potential of size (1-3) and radar type (1-3). The values of these three threat subtypes were then added and finally multiplied by the danger potential of IFF (0-2). Because of this multiplication, the threat level of friends was always 0, regardless of the other characteristics. See Figure 7.

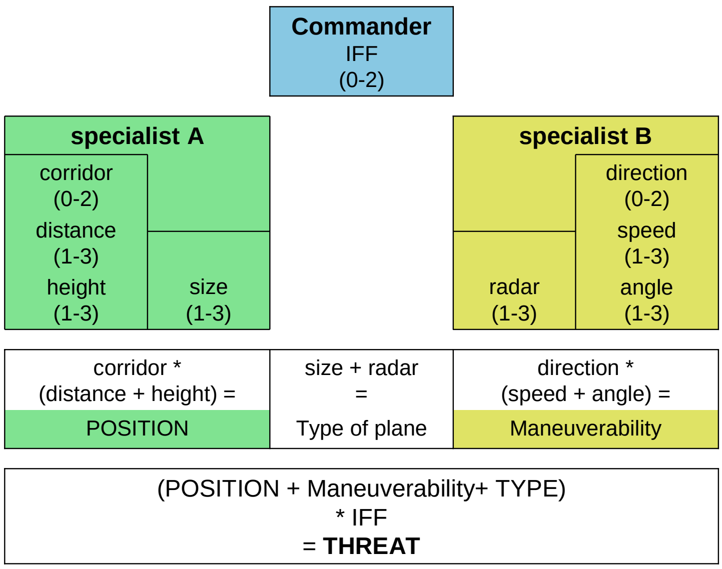

Figure 7 Schematic representation of the formula to calculate threat (Tschan, 2000b).

The two specialists sent information about plane characteristics to the commander via the e-mail system. The commander calculated the threat level for each plane and then assigned it to the plane by clicking the respective buttons on the screen. The result of the commander's assignment appeared on the screens of the specialists, represented by stars (one star for lowest, seven stars for highest threat level). Feedback about performance was given to everyone automatically after each 15-minute shift, with a score of 100 indicating absolute accuracy in threat assignment.

Written communication was indispensable for task fulfillment. The experts had to inform the commander about the values of their parameters. Without this information the threat could not be calculated. All communication was done through an e-mail system. Participants could use predefined report forms or a blank email form to send messages. The email facility was very convenient because it offered quick access to predefined forms and to address information. All information was available by pointing and clicking.

6.2 Training

Information about the task was presented to each team using a standardized procedure, both verbally and graphically (slides). An explanation of plane characteristics and their levels of potential danger was followed by an introduction to the computer facilities. During training, team members were in the same room, working on different computers in their specific roles. Special emphasis was put on using the message facilities, on learning how to look up information and on understanding the basic idea of the air traffic control simulation (see Table 14).

Table 14 Written instruction handed out to the specialist A or specialist B.

Specialist A

YOUR TASK IS TO MONITOR ALTITUDE, RANGE, CORRIDOR, AND SIZE OF THE AIRPLANES.

* ALTITUDE REFERS TO HOW HIGH THE AIRPLANE IS FLYING. LOWER FLYING AIRPLANES ARE MORE THREATENING.
* RANGE REFERS TO HOW CLOSE THE AIRPLANE IS TO THE BASE. CLOSER PLANES ARE MORE THREATENING.
* CORRIDOR REFERS TO WHETHER THE AIRPLANE IS IN ITS CORRIDOR. PLANES OUTSIDE THE CORRIDOR ARE MORE THREATENING.
* SIZE REFERS TO THE SIZE OF THE AIRPLANE. SMALLER AIRPLANES BEING MORE THREATENING.

Specialist B

YOUR TASK IS TO MONITOR AIRSPEED, ANGLE, DIRECTION, AND RADAR OF THE AIRPLANES.

* AIRSPEED REFERS TO HOW FAST THE AIRPLANE IS FLYING. FASTER PLANES ARE MORE THREATENING.
* ANGLE REFERS TO ALTITUDE CHANGE OF THE AIRPLANE. RAPIDLY DESCENDING PLANES ARE MORE THREATENING.
* DIRECTION REFERS TO THE AIRPLANE'S HEADING RELATIVE TO THE BASE. AIRPLANES HEADING TOWARDS THE BASE ARE MORE THREATENING.
* RADAR REFERS TO THE TYPE OF RADAR AN AIRPLANE HAS. PLANES WITH WEAPONS RADAR ARE MORE THREATENING.

The feedback screen was explained (see Figure 10). After team training, only the commander was shown an additional slide-show on how to work with the formula and assign threat values (see Table 15).

Table 15 Paper given to commanders to calculate the threat level of planes.

POSITION THREAT

ALTITUDE		+	RANGE		=		x	CORRIDOR		=	
> 30000 = 1			> 80 = 1					IN = 0			
15-30000 = 2			40 - 80 = 2					EDGE = 1			+
< 15000 = 3			< 40 = 3					OUT = 2			

MANEUVERABILITY THREAT

AIRSPEED		+	ANGLE		=		x	DIRECTION		=	
< 435 = 1			≥ 2 = 1					> 120 = 0			
435-570 = 2			-1 to 1 = 2					60-120 = 1			+
> 570 = 3			≤ - 2 = 3					< 60 = 2			

TYPE OF PLANE THREAT

SIZE		+	RADAR		=	
LARGE = 1			WEATHER = 1			
MEDIUM = 2			NONE = 2			
SMALL = 3			WEAPONS = 3			

=

IFF		x		=	
FRIENDLY = 0					
CIVILIAN = 1					
ENEMY = 2					

LOW			THREAT ASSIGNMENT			HIGH
0-9	10-18	19-27	28-36	37-45	46-54	55-60
*	**	***	****	*****	******	*******

The *basic training instruction* was made in 1996 and was used without any change until 2001. It was a self-running PowerPoint presentation with recorded speech.

The structure of the presentation: (i) presentation of the cover story, (ii) remarks to the program, (iii) general description of the task: decide on the threat level of a plane in the airspace, (iv) communication via email, (iv) some definitions (dimension of air-space, terminology), (v) a remark that the threat level is changing second by second, (vi) explanation of all 9 parameters to observe and their importance (vii) introduction and description of each single parameter in the same form, i.e. height: a plane higher than 30’000 feet is not dangerous, (low threat level), a plane between 15’000 and 30’000 feet is of medium threat, a plane below 15’000 feet is dangerous (high threat level), (viii) it was again said that all information on a plane is important, that the threat level can change continuously and that it is important to work together. The detailed instruction can be found in a working paper (Nägele, Jaeggi, Gurtner, & Tschan, 1996a).

The second part was the *training on the computer*. This was done directly using the ATC-simulation.

The structure of the presentation was as follows: All participants sit in front of one computer, the screen is explained, the left side of it related to the planes and the observational task, the right side combining the tools for communication. Then it is explained how information on planes can be requested, how the threat level is assigned and how the communication system is used. After approximately five minutes participants started to work on their own computers where they had to write messages, reply to messages, request information, assign the threat level (only commander).

The third element was the *commander’s training*. This was again a self-running PowerPoint presentation with speech. The main goal was to teach the commander how to use the formula to calculate the threat level out of the 9 parameters. This was done step-by-step to be sure that any commander understood the formula. The detailed script can be found in a working paper (Nägele, Jaeggi, Gurtner, & Tschan, 1996b).

6.3 Procedure

The experiments were conducted in the laboratory of the Institute of Psychology, University of Berne. The computers were installed in three separate rooms. These rooms were also used by other research teams for their experiments, as storage rooms or as a workplace for students.

In 1996 we started with three computers and had to rely on the internal network of the University of Berne. As computers got more powerful and cheaper we continuously "inherited" additional machines from the institute. Additionally, we installed our own server and our own local network to increase the reliability of the technical installation.

We used a simulation of an air-traffic-control task written by Gabrys (1994). The ATC-program runs on computers using the operating system DOS and a Novell-network protocol.

Room 1[11] was equipped with four computers. One computer was used as server and as workplace in the training session. The second computer was used as workplace in the training session, the third as workplace in the training session and during the simulation. On all those machines the operating system DOS was running (the one with: c:\>). The fourth computer was a Windows 95 based machine and was only used to present the instructions (self running PowerPoint presentations).

In one experimental condition (Individual Reflexivity, see chapter 6.6.4) there was an additional computer which served as archive (mailbox) for the participants.

Rooms 2 and 3 were equipped with one computer each: the workplace for one person during the simulation.

As soon as a person applied for participation she or he was registered in a database (Microsoft Access). Then we called every person to fix a date. To compose a group of three persons we carefully checked that we did not put people into the same group who lived together, were close friends or relatives or attended the same class at school before university.

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11 I describe the final state. We started with only three computers – as mentioned in the text – and it worked. But we had to change computers on the fly, we had to shut down and restart computers in presence of the participants and so on. It delayed the experiments and so we were happy to inherit old machines.

As soon as a date was fixed, it was confirmed with a letter. On the evening before the first appointment all participants were reminded by telephone.

Upon arrival, participants completed an informed consent form and were informed about the general procedure for the experiment. Then they were seated before a PC-screen and the standardized training procedure began (12 minutes in room 1).

Then the group members were assigned to the three roles at random.

A practical training on the computer followed (shift 0, 15 minutes). All participants were still in the same room. The handling of the software was explained and it was ascertained that all participants knew how to request information about the planes and how to use the email system. This instruction was done according to the assigned roles, the commander working as commander, the experts working as experts. Any discussion on strategies between the participants was stopped immediately, arguing that they must concentrate on the technical aspect of the program or that they could talk about strategies later.

After this shift 0 the (first) electronic questionnaire started. It was explained how to fill it out. In the first questionnaire we asked for birth date, gender and computer related expertise. Afterwards, the performance feedback was given and explained.

At this point the participants had the last possibility to ask questions. Only questions related to technical aspects were answered. Questions related to strategies were not answered. It was said that this was the duty of the group, that this was not the right place or we answered like politicians (using a lot of words without saying anything relevant or of importance).

After this training, team members were led to different rooms, each equipped with a computer connected to the other computers. It was assured that they had turned off their mobile phones. Then the specialists had to fill in another questionnaire and had to wait until the commander finished his additional training.

In the meantime the commander was given an extra training. A standardized presentation was used to explain the threat calculation en detail. Because it was very important that any commander mastered the threat calculation a concrete example was given and worked trough.

The participants also got water and a bar of chocolate.

After this extensive introduction and training the experiment started with shift 1 (15 minutes). An example of the screen is given in Figure 8.

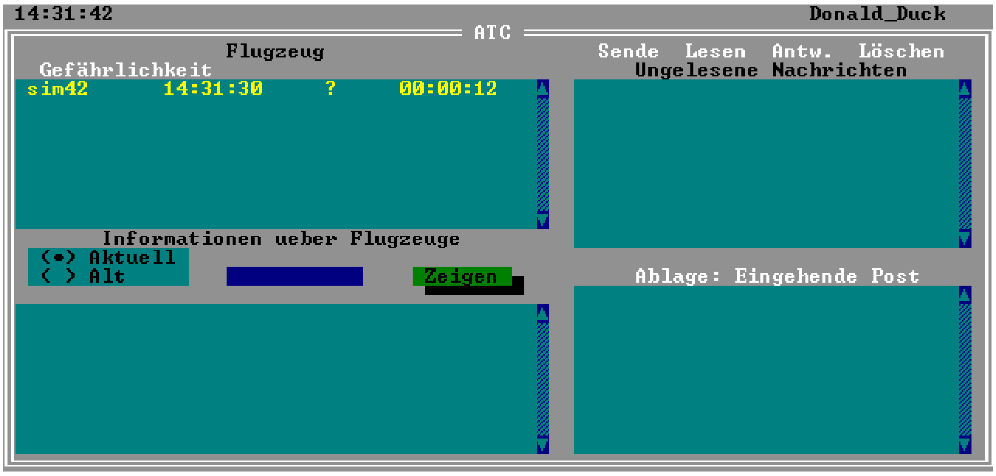

Figure 8 Screen of the ATC simulation.

After shift 1 there was a questionnaire (mainly questions evaluating the performance, the group climate, the own contribution to the work) and then the performance feedback was given. Right from the beginning of our project we used electronic questionnaires (assessment of group climate, group and own performance etc.). In those days it was not common practice to use online questionnaires and there was a certain skepticism against it. Questions concerning the technical feasibility and the reliability of the data were raised. A detailed description of the questionnaire is given in Nägele (in prep.). The electronic questionnaire was running on Dbase IV (a database program running under DOS). Figure 9 gives an example how the questionnaire was presented to the participants.

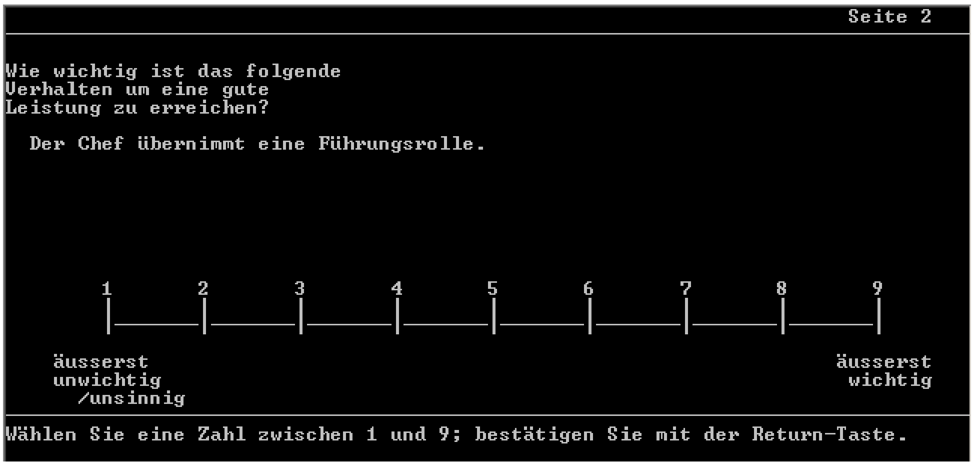

Figure 9 Screen shot of the electronic questionnaire applied after each shift.

The air-traffic control simulation was programmed to run in an unattended mode. Once shift 1 had started, the program automatically saved the data after the shift, started the electronic questionnaire, gave the performance feedback (Figure 10) and then started the next shift. This was realized with a series of DOS batch files.

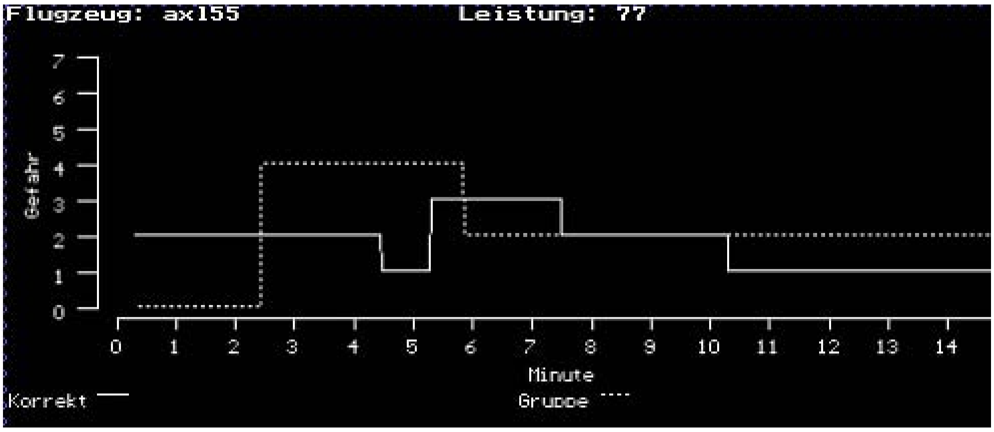

Figure 10 Example of performance feedback after a shift.

On the first day shifts 1 to 3 had to be worked through. After shift three an additional questionnaire was presented to the participants. The content of the questionnaire depended on the experimental condition. It was either a questionnaire on strategies and strategy development, a questionnaire on shared mental models or on coping strategies, stress and some personality variables.

The participants could take notes on paper, they had a pencil and a rubber during a shift. On one A4-sheet the parameters that had to be observed were documented for expert A and expert B. The commander had a paper where all nine parameters were listed (Table 15).

On the threat sheet there was additional information for the experts. This information was given to ensure that the experts understood their basic task and to summarize the information given during the instruction (Table 14).

At the end of the first day the participants were asked to come back one week later. The were instructed not to talk to anybody about the ATC simulation. We said that we were going to check for this, that we could see it in the data and above all that the effort they made, the time they spent would be lost if they started to talk about strategies, about the simulation. We emphasized that our interest was to see how groups work together in the setting of our air-traffic-control simulation and that we knew it would often be easier to sit together and talk about the simulation. Generally, people stack to the instruction. People talked about the simulation but all they said was that it had something to do with planes, that it was fun and that there were chocolate bars for free.

After a week the participants showed up at the same time at the same place.

On the second day the participants were directly brought into their rooms and the simulation was started with shift 4. If no technical problems occurred the simulation ran through in the unattended mode to shift 8. In some experimental conditions shift 7 was skipped. Every ten to fifteen minutes it was checked whether the simulation was still running. After shift 8 an additional questionnaire was presented. Again, the content varied according to the experimental condition.

After the last questionnaire the participants were debriefed. It was noted whether the students wished to be paid by money or signatures (credits).

6.4 Participants

Participants were recruited from the Psychology subject pool at the University of Berne. We used flyers, went to lectures and seminars to campaign for our experiment and counted on mouth-to-mouth propaganda. Additionally, we twice published a small ad in a local newspaper.

The students could apply by phone (answering machine), by email or they could fill in the name and address in a list on a notice board. In the beginning it was a rather hard to convince people to take part in our experiment (we could offer only 15.- sFr. per hour to our participants). We asked them to participate four to five hours on two days. Thus – from a students' perspective -, it was not very attractive to participate in our experiment. In the years 1999 to 2001 the recruiting was much easier. We could offer four to five credits instead of money, which made participation more attractive.

6.5 The ATC log-file

Data available. As mentioned, a computer log of each act of each person is available and serves as basis for data analyses. A log-file contains 2500 to 4500 lines for each team, each line representing an event. Events can be actions of team members (e.g. sending a message or reading a message) or system-related events (e.g. a new plane coming into the airspace). Table 16 shows and excerpt of such a log.

Table 16 Excerpt of automatically stored log-file, commander, team 113, shift 1 (Gabrys, 1994).

s1g113	command	12:59:35	12:59:35	GameBegins				
s1g113	command	12:59:35	12:59:35	PlyrBegins				
s1g113	command	12:59:45	13:00:02	SendMsg	M16	Deleted	Niedrig	FT
					ExpertInA	Hallo, seid ihr alle da ?		
s1g113	command	12:59:52	12:59:52	NewPlane	axl55			
s1g113	command	13:00:18	13:00:18	ShowInfo	axl55	Current	Identitaet	ZIVIL
s1g113	command	13:00:25	13:00:49	SendMsg	M18	Deleted	Hoch	VI
					ExpertInA	Identitaet	axl55	1
s1g113	command	13:00:29	13:00:29	NewMsg	M0			
s1g113	command	13:00:57	13:01:08	ReadMsg	M0	Saved	Niedrig	FT
					ExpertInB	bezeichne Gefährlichkeit jeweils		
					mit Hoch, mittel und gering			
s1g113	command	13:01:34	13:01:34	ShowInfo	axl55	Current	Identitaet	ZIVIL
s1g113	command	13:01:35	13:01:35	ShowInfo	axl55	Current	Identitaet	ZIVIL
s1g113	command	13:01:36	13:01:36	ShowInfo	axl55	Current	Identitaet	ZIVIL
s1g113	command	13:01:40	13:01:40	ShowInfo	axl55	History	Identitaet	
s1g113	command	13:01:41	13:01:41	NewMsg	M1			
s1g113	command	13:01:43	13:02:04	ReadMsg	M1	Saved	Niedrig	VI
					ExpertInB	Geschw.	axl55	mittel
s1g113	command	13:01:46	13:01:46	NewMsg	M2			
s1g113	command	13:02:05	13:03:25	ReadMsg	M2	Saved	Mittel	FT
					ExpertInA	axl55		
					Grösse: Gering			
					Distanz: Gering			
					Korridor: Im => Gering			
					Höhe: Gering			
s1g113	command	13:02:44	13:02:44	NewMsg	M3			
s1g113	command	13:03:27	13:03:38	ReadMsg	M3	Saved	Niedrig	VI
					ExpertInB	Winkel	axl55	mittel
s1g113	command	13:03:41	13:03:41	NewMsg	M4			
s1g113	command	13:03:42	13:04:01	ReadMsg	M3	Quit	Niedrig	VI
					ExpertInB	Winkel	axl55	mittel
s1g113	command	13:04:03	13:04:24	ReadMsg	M4	Saved	Niedrig	VI
					ExpertInB	Richtung	axl55	hoch
s1g113	command	13:04:11	13:04:11	NewMsg	M5			
s1g113	command	13:04:26	13:04:36	ReadMsg	M5	Saved	Niedrig	VI
					ExpertInB	Radar	axl55	mittel
s1g113	command	13:04:42	13:05:18	SendMsg	M25	Deleted	Hoch	FT
					ExpertInB	was meint Richtung hoch?		
					Ich brauche den Winkel			
s1g113	command	13:05:08	13:05:08	NewPlane	tam66			
etc.								

6.6 Experimental Conditions

In this chapter I present all experimental conditions from which I use data (Table 13). The task structure is the same in all these experimental conditions. We started with the Base condition in 1996. All other experimental conditions are variants form the Base Condition.

6.6.1 Base Condition (1)

We designed the base condition with a total of eight working shifts and one training shift (referred to as shift 0). Shift 1 to 3 on day one where equal to shift 4 to 6 on day two with regard to the number of planes to observe, the plane characteristics, and their movements in the airspace. Only the names of the planes were changed. Shift 7 was more difficult, shift 8 was based on shift 7 but with one additional plane. The number of planes and their names is given in Table 17.

I shift 1 the teams had to observe two planes: axl55 and tam66. The exact behavior of the planes was programmed in the air traffic control simulation (time entering the airspace, change of the parameter values). In shift 4 the teams had also to observe two planes: ora330 and sum34. The behavior of these two planes in the airspace was exactly the same as for the two planes in shift 1. We only changed the names of the planes! The same was done for shift 2 and shift 5, for shift 3 and shift 6. In shift 7 we used three new planes (res18, zec14, hun88). In shift 8 the same planes were used (but renamed: ant55, pol45, dese5). Additionally a friendly plane was introduced as third plane (kom44).

Table 17 Planes in the Base Condition.

shift	Number of planes	planes			
Shift 0	2	CIVIL sim42	FRIEND bega33		
Shift 1 = 4	2	CIVIL axl55 ora330	CIVIL tam66 sum34		
Shift 2 = 5	3	CIVIL kla34 rim66	ENEMY blue7 sub89	CIVIL ala4 kum57	
Shift 3 = 6	3	ENEMY bib32 bob65	FRIEND urt222 erto555	ENEMY asug333 ola222	
Shift 7	3	ENEMY res18	CIVIL zec14		ENEMY hun88
Shift 8	4	ENEMY ant55	CIVIL pol45	FRIEND kom44	ENEMY dese5

The groups were working on eight shifts, each shift was followed by an questionnaire and the performance feedback (see chapter 6.3 for details). An overview is given in Figure 11.

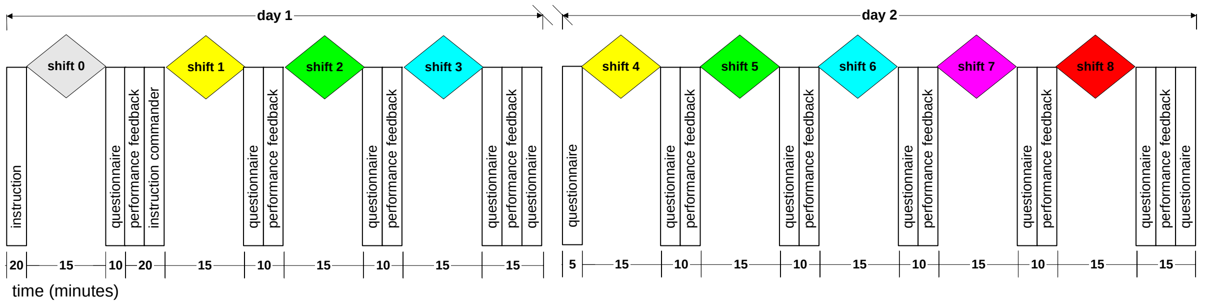

Figure 11 Schematic representation of the Base Condition.

6.6.2 Goal (4)

Goal setting theories show that specific, difficult goals lead to higher performance than just telling people to do their best (Locke & Latham, 1990, 2002). In our base condition we just mentioned that the group has to assign the threat level to each plane and that this has to be done as best they can. Therefore, we expected to increase performance by setting the 80% percentile of the performance of all groups of the base condition as specific and demanding goal. This goal was given to the groups before the start of each new shift.

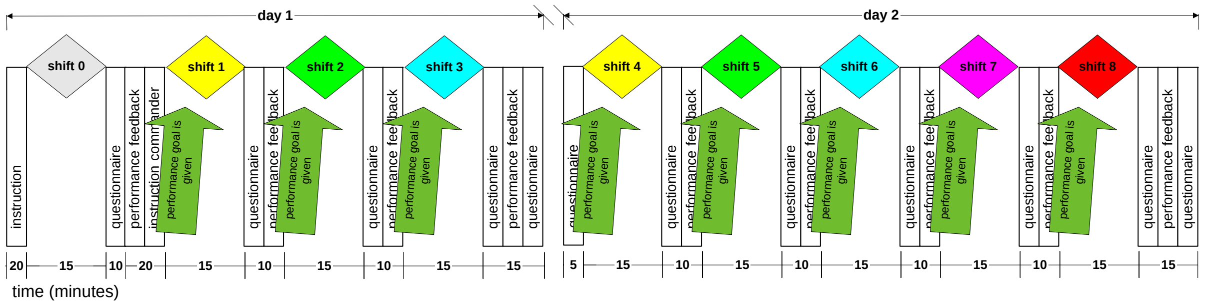

Figure 12 Schematic representation of the Goal Condition.

6.6.3 CHAT condition (5)

We saw that the groups had some difficulties to spontaneously develop new and better strategies (Tschan, Nägele, Gurtner, Semmer, & Jaeggi, 1998; Tschan, Semmer, Gurtner, & Nägele, 2000). Possibly, the groups had simply not enough time to discuss strategies and to find a common understanding of the task. Reflection on what one is doing often needs an extra effort and extra time (West, 1996b). Therefore we added five minutes before shift 2 and shift 5 (Figure 13). In shift 2 nothing happened during the five minutes. In shift 5 a friendly plane entered into the airspace (Table 18). Friendly planes are not dangerous and there is no need to observe them anymore after they are identified.

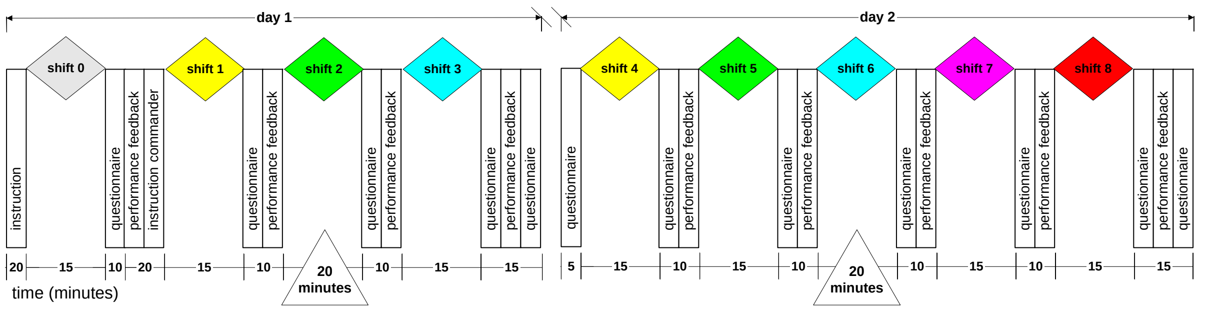

Figure 13 Schematic representation of the CHAT Condition.

Table 18 Planes in the CHAT Condition.

shift	Number of planes	planes			
Shift 0	2	CIVIL sim42	FRIEND bega33		
Shift 1 = 4	2	CIVIL 11 axl55 41 ora330	CIVIL 12 tam66 42 sum34		
Shift 2 = 5	4	FRIEND -- 54 hurt12	CIVIL 21 kla34 51 rim66	ENEMY 22 blue7 52 sub89	CIVIL 23 ala4 53 kum57
Shift 3 = 6	3	ENEMY 31 bib32 61 bob65	FRIEND 32 urt222 62 erto555	ENEMY 33 asug333 63 ola222	
Shift 7	3	FEIND 71 res18	CIVIL 72 zec14	ENEMY 73 hun88	
Shift 8	4	ENEMY 81 ant55	CIVIL 82 pol45	FRIEND 83 kom44	ENEMY 84 dese5

6.6.4 Reflexivity Conditions (6, 7, 8, 9)

We used a reflexivity instruction (West, 1996b) to activate the development of shared mental models (Gurtner, Tschan, Nägele, & Semmer, submitted; Tschan & Semmer, 1999). It is assumed that teams that have good shared mental models are able to perform better than teams holding imperfect or no shared mental models (Cannon-Bowers, Salas, & Converse, 1993; Kraiger & Wenzel, 1997; Langan-Fox, Wirth, Code, Langfield-Smith, & Wirth, 2001). The reflection phase was in the beginning of day two. It was either an individual reflection or a reflection in the group (using the email system of the air Traffic control simulation).

The reflexivity conditions were programmed like the base condition with the following changes: (i) we skipped shift 7 to save time, (ii) day two starts with the reflexivity-shift (shift r), (iii) at the end of day one and day two questionnaires to measure mental models were used. To conduct those experiment we used a enlarged Solmon-Four-Group design (details in Tschan & Semmer, 1999). A consequence for all my analyses is, that I will can not use data from shift 7.

There are four reflexivity conditions. There is no reflexivity intervention is n the two control conditions (CC-1 and CC-2). Instead of reflecting on the task the participants were asked to discuss factors that lead to a successful career. In CC-1 the questionnaire to measure the mental models was applied at the end of day one and at the end of day 2. In CC-2 the mental models were only measured at the end of day two. In tie individual reflexivity condition (IR) the team members had to reflect on their own, in the group reflexivity condition they were allowed to use the email system and reflect together (Christof Nägele, A. Gurtner, F. Tschan, & N. Semmer, 2002b).

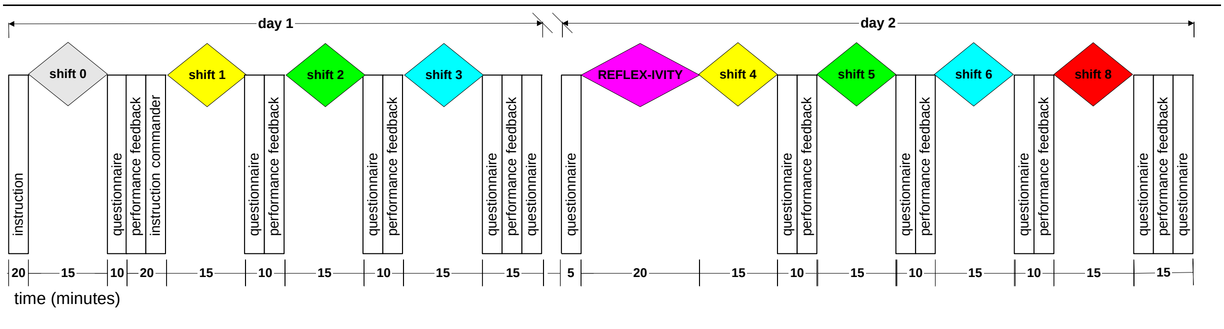

Figure 14 Schematic representation of the Reflexivity Conditions.

6.7 Calculation of the Performance Measure

The ATC-program automatically calculates an overall performance measure for each shift (details in: Stutz, Abraham, Nägele, & Gurtner, 2002). The overall performance measure is based on a threat calculation that compares second by second the real threat level (as programmed in the control files of the simulation) and the threat assignment of the team. This momentary performance is calculated according to Table 19.

Table 19 Formula to calculate the performance at a certain point in time.

$$P-ATC=\left(\frac{Maximal\ Possible\ Error\,(MPE)\quad -\quad True\ Error\,(TE)}{Maximal\ Possible\ Error\,(MPE)}\right)*100$$

To calculate the maximal possible error (MPE):

If threat level < 4: $MPE = 7 - True\ Error$

If threat level ≥ 4: $MPE = True\ Error$

Calculation of true error (TE): $TF = \left|\ real\ threat\ level - threat\ assignment\ of\ group\ \right|$

Overall performance of one plane (*P-ATC, plane in shift*):

$$P-ATC,\ plane\ in\ shift=\frac{\sum_{1-n} P-ATC}{n}$$, (n = time, seconds plane is in airspace)

Performance of one shift (all planes):

$$P-ATC,\ shift=\frac{\sum_{1-m} P-ATC,\ plane\ in\ shift}{m}$$, (m = number of planes in shift)

THREAT	*TE* true error	*MPE* Maxyimal possible error	
7 ******		If threat = 7:	**7**
6 ******	**plane**	If threat = 6:	**6**
5 *****		If threat = 5:	**5**
4 ****	*difference*	If threat = 4:	**4**
3 ***	= *TE*	If threat = 3:	**4**
2 **		If threat = 2:	**5**
1 *	**threat assignment**	If threat = 1:	**6**
0			**-**

6.8 Definition of Process Variables

This chapter gives an overview of the process-variables used in lag sequential analyses, procedural network representations PRONET, and data mining analyses. The definition of the process variables is a crucial step. With this coding it is defined how the single acts of the commanders and specialists can be used in the analyses.

An excerpt of a automatically stored log-file is shown in Table 16. The activities of the commander and the two specialists are stored in separate log-files.

The coding scheme includes codes for operations like setting the threat level and also codes for the content of the communication. There is only one way to communicate within the team: the email system of the ATC simulation. This constraint in the communication channels has the advantage, that all communication is visible in the log files of the sender (coded in the log-file as SendMsg) as well as in the log files of the recipient. On the side of the recipient all communication attempts of the sender are in a first step messages in the inbox (coded in the log-file as NewMsg). Only if the recipient opens the message he gets access to the message content (coded in the log-file as ReadMsg).

Due to the nature of the ATC task in this simulation it is enough to analyze either a commanders' or a specialists' behavior and communication to gather the group process. This is best reflected by extracting two behavioral streams from the raw data. A behavioral stream is a sequence of distinct, not co-occurring events:

Stream 1 contains all events initiated by a team member (e.g., looking up the plane information or sending a message).

Stream 2 contains all events that happen without the intervention of a team member (e.g., new planes coming into the airspace, new messages in the inbox).

Stream 1: Initiated Events of Commanders or Specialists

There are several events which can be initiated by a commander or a specialist: reading or sending messages, request plane information and some other events like moving the window on the screen, or deleting messages in the archive. The coding scheme is presented in Table 20.

Table 20 Coding scheme of all initiated events (ie), commander and specialists.

ieR[XXX]	reading an incoming message, [XXX] = content of message, see Table 21
ieS[XXX]	sending a message [XXX] = content of message, see Table 21
ieSi[Z]	request information on planes z = 1 information on critical parameter (IFF, corridor, direction) z = 0 information on any other parameter
ieH[YY]	setting the threat level of a plane (only commander, and specialists in experimental condition 2 in shift 1 and 2) [YY] = number of plane and change in threat level, see Table 22
ieOTHER	there are some rare events in this category like moving a window on the screen, deleting a message from the inbox or archive, or using the reply button (this does not result in a message sent to the other team members).
00.00-00.00	time an event starts - time an event ends

Stream 1 Coding: Message Content

The message content is coded using the coding scheme of Gurtner (1997; 2003). The coding scheme was however simplified, describing three aspects of the communication: (i) task related communication, (ii) strategy related communication, and (iii) nontask / nonstrategy related communication.

Task related communication contains all communication on parameter information (position, maneuverability, type and identification of plane). Strategy related communication is communication on the use and development of (better) strategies. Nontask / nonstrategy related communication contains all communication that could not be coded in the other two categories. If commanders or specialists used the free form text tool, it was quite common that more than one statement was made in a single message. This is reflected in the codes presented in Table 21. Additionally, the onset and offset time of any event is recorded.

In Table 21 all possible combinations of the three different message types are listed. The team members could use a predefined message form to send task related messages. However, with this form it was only possible to send one bit of information on a plane in a message. Most communication was done using a free message form. The length of this message type was limited to approx. 200 characters. But within this limit it was possible to combine task, strategy and nontask/non-strategy related contents. The codes in Table 21 are used for the coding of read messages as well as sent messages (R/S).

Examples: *R111* is coded if a read message contains task related, strategy related and non-task/non-strategy related information. A *S100* is coded if the message contains only task related information. A code *R000* or *S000* is not possible.

Table 21 Coding of message content [XXX].

	X	X	X	Task-Related Communication	Strategy-Related Communication	Nontask-/Nonstrategy-Related Communication
R/S	1	1	1	yes	yes	yes
R/S	1	1	0	yes	yes	no
R/S	1	0	0	yes	no	no
R/S	1	0	1	yes	no	yes
R/S	0	1	1	no	yes	yes
R/S	0	0	1	no	no	yes
R/S	0	1	0	no	yes	no

R = Read Message with content as coded
S = Send Message with content as described

Stream 1 Coding: Threat Assignment

The threat assignment can only be done by the commander. The coding of the threat assignment contains information on the plane (number of plane in shift (cf. Table 17)), and the newly assigned threat level. The threat level varies from 1 to 7 (as shown in Table 19). A new plane has no threat assignment until the commanders assign the threat for the first time. All possible codes are described in Table 22.

Example: A handle threat in shift 1 coded as *H13 10.00* has to be read as: The threat assignment of the first plane (axl44, see Table 17) was changed to 3. This threat assignment was done in second 10.00 after the shift started.

As the threat assignment can only be done by the commander it must be coded as system event for specialists.

Table 22 Coding scheme of Threat Assignment.

H[YY]	
H	handle threat
Y	number of plane in shift (1 to 4)
Y	new threat level (1 to 7)

Stream 2: System Events

System events happen without the direct intervention of a commander or specialist. There are two types of system events: new message in inbox, and a new plane in the airspace. The coding scheme is presented in Table 23.

Example: A system events coded as *seNP1,17.00 seNewMsg,78.00 seNewMsg,126.00* …have to be read as: The first new plane enters the airspace at second 17.00. At second 78.00 a new message is in the inbox, at second 126.00 the next message arrives in the inbox. All those events have no duration.

Table 23 Coding scheme of all system events (se), commander and specialists.

seNewMsg	indicates that a new message is in the inbox
seNP[Z]	indicates that a new plane entered the airspace z = plane in shift, 1 to 4
00.00-00.00	time an event starts - time an event ends

Summary

These codes are used in all analyses. They describe the behavioral units used in the analyses of the micro-behavioral organization of the group process. All these variables can be used in a coding and counting approach. Then summaries of the frequencies are calculated. The same variables can also be used in sequential analyses, taking into account the time stamp included in all codes (start and end time of an event).

6.9 Task Adaptive Behavior

Task adaptive behaviors are measures of specific aspect of the group process (Tschan, Semmer, Nägele et al., 2000). Based on a task analysis categories were developed that represent either communication or operations that are supposed to foster or hinder the teams to perform well. In Tschan et al. (2000) it was demonstrated that task adaptive behaviors better predict performance than more general group process measures.

General measures of the group process were (1) the amount of communication, (2) the number of messages containing strategy propositions, (3) the number of messages containing motivational remarks, (4) the amount of plane information sent to commander, and (5) the number of plane characteristics searched for during a shift (number of Show Information).

Task adaptive behaviors focus on critical elements of the task and are assessed on a task specific level. We distinguished seven domains of task adaptive behaviors, each one based on several indicators (a detailed description can be found in: Tschan, Semmer, Nägele et al., 2000, p. 375): (1) Basic Task Mastery, summarizes the number of times team members missed to do some basic tasks, (2) strategic leadership commander, summarizes how many of four specific strategies a commander communicated at least once, (3) motivational and corrective leadership commander, is the information on whether or not the commander sent messages with motivational remarks, (4) unambiguous and timely communications specialists A and B, contains the information on the quality of the messages sent by the specialists, (5) plane handling commander, includes information on the timing and accuracy of the threat assignment, (6) message handling commander, is the mean time elapsed until an incoming message is opened and read, (7) plane observation specialists A and B, is an index on how reliable the specialists plane observations are. All seven domains of task adaptive behavior combine information from different variables.

In order to contribute to the prediction of performance, task adaptive behaviors have to occur regularly. Therefore they are constructed by summarizing different variables. The "…number (or percentage) of such behaviors is then regarded as an indicator of a task adaptive behavior pattern, and it is this pattern that should be related to performance" (Tschan, Semmer, Nägele et al., 2000, p. 368). It is important to note that this pattern is not a sequential pattern but a frequency count of a certain type of behavior.

Task Adaptive Behaviors in Single Shifts

In Tschan et al. (2000) all these task adaptive behavior variables were calculated on the aggregated data from shift 1 to shift 3 (day one) and shift 4 to shift 6 (day two). As the task adaptive behaviors turned out to be strong predictors of the teams' performance I calculated all these task adaptive behaviors for every single shift in the air traffic control simulation. This allows to compare the effects of variables derived with sequential analyses with the task adaptive behaviors. The definition of the task adaptive behaviors is given in Table 24.

Table 24 Definition of the Task Adaptive Behavior (TAB) for commanders and specialists (based on Tschan, Semmer, Nägele et al., 2000).

Basic Task Mastery BTM		Index representing the minimal competencies and behaviors that ensure that participants understood the fundamental role specific task requirements.
	commander	sum of number of planes commander missed IFF and number of planes commander missed threat assignment
	specialists	sum of number of plane characteristics missed to look up and number of messages not read
Plane Handling PLH		Index representing the task to observe planes and to set their threat level.
	commander	sum of *z*-transformed values for shift 1, shift 2 to 8 values were standardized on shift 1: time to identify plane, recoded: the faster the better time to set initial threat level, recoded: the faster the better number of threat assignments friendly planes, recoded: the less the better number of threat assignments civil planes number of threat assignments enemy plane
	specialist	sum of *z*-transformed values: continuous observation of planes (=mean number of plane information's looked up per plane) weighting of critical information (corridor for specialists A, direction for specialist B) (Proportions were arcsine-transformed, sum of *z*-transformed values for shift 1, shift 2 to 8 values were standardized on shift 1.)
Message Handling MSH		Index representing a good message handling.
	commander specialists	sum of *z*-transformed values: time elapsed until a message is read for the first time, recoded: the slower the worse time spent reading messages, recoded: the longer the worse (Sum of *z*-transformed values for shift 1, from shift 2 to 8 values were standardized on shift 1.)
Strategic Leadership STL		Index representing commanders taking seriously their task-related leadership function and using their additional knowledge to gear the process by means of communicating critical information to the specialists and to teach them more complex strategies.
	commander	sum of frequencies of the four variables: propose to pre-process information propose to weight critical parameter information more heavily inform specialists about friendly planes instruct specialists to use threat formula on their own
Motivational and Corrective Leadership MCL		Index representing commanders taking seriously their relationship-orientated leadership function.
	commander	number of motivational and supporting comments in messages of commanders

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7 Research Questions

I argued that investigating group processes with regards to sequential, temporal and dynamic aspects will give us insights about *how* groups work, but that suitable methods are rarely used in team research. My thesis therefore has the following aspects:

1. The first topic of my thesis is to apply methods to the ATC data that allow an investigation of the group process. I want to go a step further than just coding and counting acts to compute summary-level variables. Methods discussed are:, (i) lag sequential analysis, (ii) procedural network representation, and (iii) knowledge discovery in databases (KDD) and data mining techniques. So far, those methods are most often used for single case description (Brauner & Orth, 2002) or with very small data sets (Cooke et al., 1996). One aim of my work is to demonstrate how those methods can be used with a big sample as ours that includes more than 100 groups.
2. Doing that first requires the 'transfer' of those methods to the field of small group research. I do not attempt to do this as statistician or as mathematician would. My aim is to use those methods as an advanced user – this is, the methods and the algorithms in the methods will not be changed, but I will investigate how and under what circumstances and with what result those methods can be used for team process research.
3. With the methods found, I will analyze the process data of the Air Traffic Control simulation. A main focus will be on the description of the process for low and high performing teams, a comparison of the predictive power of input variables, summary-level process variables and task adaptive behavior variables with variables derived from an analysis of the group process.

The framework for all my analyses is the *input* -> *process* -> *output* model as it was postulated by Hackman and Morris (1975) (Figure 1, p. 24). The discussion of this model in chapter 4 showed that a lot of research relying on this model focuses only on *input* variables to predict group success (the *output*). If the group process is part of the analyses, it is most often captured as sums of certain events (*summary-level process variables*) or as recapitulatory, evaluative statements of team members on their perception of the process (e.g., team climate, fairness, quality of social interaction, etc.).

My point is that it is not enough to look only at *input* and/or *summary-level process* variables to predict performance. *Process* variables are very important because they reflect a team's struggle with the concrete task and this determines the final performance.

Participants in the Air Traffic Control Simulation Studies

First I am going to present some results describing the participants. We gathered information on the age, gender, education and computer expertise in a questionnaire at the end of shift 0 (the training shift).

P I. No differences in computer expertise are expected for commanders and specialists.

P II. But it is expected that males report a higher computer expertise than females, independent of age and experimental condition.

P III. The age of the participants is expected to be alike in all experimental conditions. Although the experiments were running from 1996 to 2001.

P IV. The air traffic control simulation is a computer-based task oriented technical simulation. The cover story positioned the task in the context of a military operation lead by the UN. It could be expected that all this leads to a reduced interest of females to participate in the study.

P V. Most participants are university students but there are also some college students and other participants. They should be evenly distributed on the different experimental conditions.

Performance of the Teams

The performance of the teams is calculated per shift and is an indicator of the quality of the overall threat assignments. The performance measure is discussed in chapter 6.7.

PERF I. It is expected that performance increases from shift 1 to shift 8.

PERF II. There are performance differences between the experimental conditions. The overall lowest performance is found for teams of the Base Condition.

Process Variables: Counting

The process variables are the coded acts of the team members as they are defined in chapter 6.8. All these variables are coded per shift and role. Following a coding and counting approach (see chapter 5.2) the sum of the frequencies of these variables is calculated.

C I. Read Message, Send Message, Show Information and Handle Threat show some variation over time.

C II. The number of Read Message of commanders should go up if there are more planes in the shift because specialists send more parameter information.

C III. The number of Read Message of specialists should be higher in shifts with less planes, because then time is available for commanders to teach the specialists.

C IV. The Send Message of commanders should be higher in early shifts (giving instructions) and in shifts with less planes (shift 2, shift 4).

C V. The Send Message of specialists should be higher as more planes are in the airspace.

C VI. The mean number of Show Information per plane of commanders should be constant over time. Commanders have only one parameter to observe (plane identification) and it is enough to look up this information just once because it never changes.

C VII. The number of Show Information of specialists should be higher if there are more planes in the airspace.

C VIII. The number of Handle Threat per plane of commanders should be higher if there are dangerous planes (often and quickly changing the threat value, shift 3, shift 6, shift 7 and shift 8) in the airspace.

Process Variables: Task Adaptive Behaviors

The task adaptive behaviors are task specific coded acts of the team members. These variables are defined in chapter 6.9. In Tschan et al. (2000) it was shown that these task adaptive behaviors differ for day one (aggregate of shift 1 to shift 3) and day two (aggregate of shift 4 to shift 6). It is now tested how these task adaptive behaviors change if they are calculated per shift.

TAB I. Basic Task Mastery of commanders and specialists is expected to be highest on day one (the higher the value the worse!) and has no more significance on day two.

TAB II. Plane Handling should become better from shift to shift and have the highest value in shift 8, for commanders as well as for specialists.

TAB III. Message Handling also should become better from shift to shift, having the highest value in shift 8, for commanders and specialists.

TAB IV. Strategic Leadership of commanders should be present right from the beginning, reaching its peak around shift 4 when there is a greater familiarity with the task then in the first shifts.

TAB V. Motivational and Corrective Leadership is a rarely done. No differences between different experimental conditions and no time effects are expected.

Predicting Performance

Input Variables as Predictors of Performance

Based on the *input – process – output* model presented in chapter 4 it is expected, that these variables explain a certain amount of variance in performance.

IN I. Input variables predict performance.

IN II. But they are better predictors in early shifts than in late shifts (in later shifts group processes and other factors should become better predictors than input variables).

IN III. It is expected that mainly the commanders' gender, education and computer expertise can predict performance. The effect of the same variables for specialists is expected to be weaker. This is due to the hierarchical structure of the task in the air traffic control simulation.

Summary Level Process Variables and Task Adaptive Behavior Variables as Predictors of Performance

Frequencies of behaviors per shift are used as predictors of performance. It is the coding and counting approach described in chapter 5.2.

SUM I. Adding summary-level process variables results in a better prediction of performance than just looking at the input variables.

SUM II. Task adaptive behaviors alone explain more variance in performance than any input variable or any summary-level process variable.

SUM III. Also controlling for preceding performance, for input and summary-level process variables task adaptive behaviors still contribute additionally to the prediction of performance.

Sequential Analyses

Then I will have a closer look at *process* variables. Because any activity unfolds in time, information from the sequences must be extracted in a way that represents this aspect. In a sequence of events, the probability that a certain succeeding event occurs also depends on the previous events (Pötter & Blossfeld, 2000). In the ATC simulation: A Handle Threat of a plane is only possible if there is actually a plane in the airspace. Commanders can only calculate the correct threat level of a plane if they have got the information from the specialists.

Process variables can be defined top-down: Based on theoretical assumptions which take the task itself and the activities of individuals or the team as starting point of the analyses (Frese & Zapf, 1994; Hacker, 1998; Tschan, 2000a; von Cranach, 1994) critical sequences are defined that are hypothesized to lead either to a low or high performance. Tschan (2000a) proposes that teams following ideal communication cycles (orienting and planning before evaluation) perform much better than teams neglecting this sequence or even skipping orientation, planning, or evaluation. The innovative aspect of this research is the integration of tools of cognitive task analyses (Vicente, 1999) and hierarchical task analyses (Shepherd, 1998) into the framework of action psychology (Hacker, 1986) on the level of the concrete operations and actions.

I will discuss the three methodological approaches showing different ways to extract knowledge on the group process in a more automated way. Chapter 8.7 describes lag sequential analyses (also ESD, exploratory sequential data analyses). In chapter 8.8 I discuss a method proposed by Cooke and Neville (1996): PROcedural NETwork representations. In chapter 8.9 I will introduce and discuss data mining technologies to extract meaningful patterns automatically from the data.

The basic assumptions, discussing the three methods proposed, are:

SEQ I. The activities of commanders and specialist have a certain regularity. It is possible to identify meaningful patterns.

SEQ II. Moreover, low and high performing teams show different patterns.

SEQ III. It is possible to predict performance if the identified patterns are entered as predictors in a regression model.

SEQ IV. Due to the nature of the ATC task and how it is implemented, patterns of directly adjacent events are better predictors of performance than either patterns combining events that follow one another after some other events happened or patterns of long sequences (six or more succeeding events).

This process is mainly exploratory and data driven. This fact has to be kept in mind when reading all the tables and figures.

8 Results

All variables were carefully screened (as proposed by Tabachnick & Fidell, 2001). There is no missing data in the automatically recorded log-files, neither in the electronic questionnaires, but there were participants who skipped some items in the paper-pencil questionnaires.

The total N is 109 teams. If N is smaller this is caused by missing values in questionnaire data.

8.1 Participants in the Air Traffic Control Simulation Studies (Input Variables)

The following chapters give an overview on computer expertise, age, gender and the education of the participants.

Computer Expertise

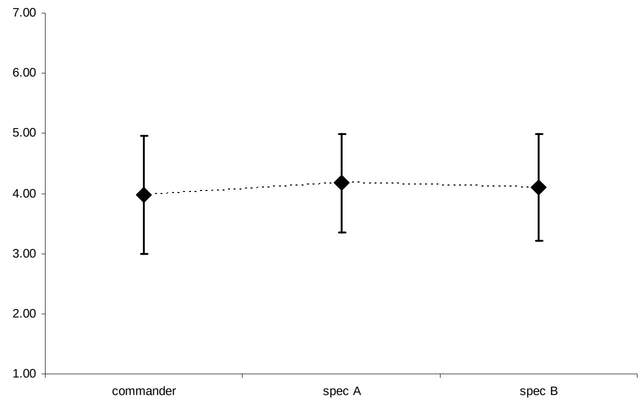
Computer expertise was measured in the beginning after the training shift (shift 0). It was measured with two items (“My computer related knowledge is” … and “I am experienced user of computers…”) on a seven point Likert-type scale (1 = not at all, 7 = completely).

Table 25 Means and Standard Deviations for Computer Expertise[12].

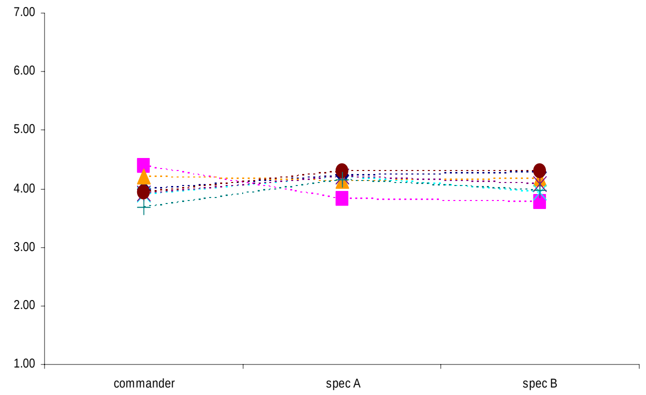
YOMPER		commander	spec A	spec B
all teams	mean	3.97	4.17	4.10
	stdv	0.98	0.82	0.89
BC - Base Condition	mean	4.00	4.23	4.29
	stdv	1.28	0.94	0.98
Goal	mean	4.39	3.83	3.78
	stdv	0.96	1.00	1.09
CHAT	mean	4.21	4.14	4.18
	stdv	0.80	0.86	0.85
CC-1 - Control Condition 1	mean	3.90	4.20	3.93
	stdv	1.02	0.80	0.96
CC-2 - Control Condition 2	mean	3.91	4.21	4.09
	stdv	0.91	0.75	0.80
IR - Individual Reflexivity	mean	3.94	4.29	4.29
	stdv	0.85	0.83	0.90
GR - Group Reflexivity	mean	3.68	4.15	3.97
	stdv	0.92	0.68	0.80

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17

12 There are two cases with missing values, both for specialist B of the Base Condition. The missing values were replaced with the mean for the entire series.



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✳) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 15 Means and standard deviations for Computer Expertise.

ANOVA results show that the means are not different for the three roles ($F(2, 204) = 0.67$, $p = .51$), and there is also no interaction of roles and experimental conditions ($F(12, 204) = 0.58$, $p = .86$). There is no overall difference in the mean of computer expertise for the different experimental conditions ($F(6, 102) = 0.56$, $p = .77$).

Computer Expertise and Gender

The mean computer expertise for males is $M_{male} = 4.51$, $SD_{male} = 0.91$. For women the value is much lower $M_{female} = 3.77$, $SD_{female} = 0.76$. This effect is statistically significant ($F(1,327)=62.83$, $p < .01$, controlling for experimental conditions).

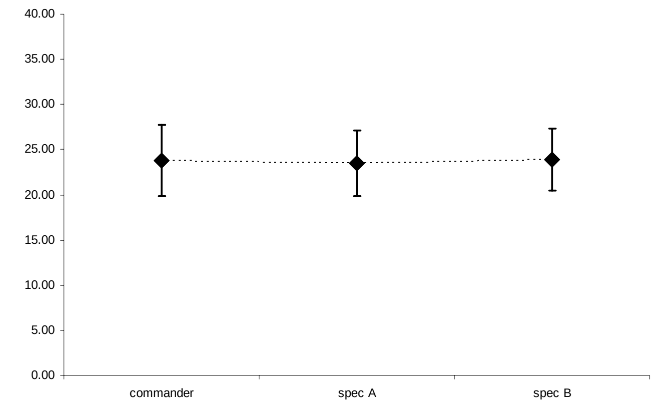
Age

The mean age is around 24 years. There were some persons responding to our adds in the newspapers. Typically they were much older. We have missing data for 5 participants (1 commander, 1 specialist A, 3 specialist B). The missing values were replaced with the mean for the entire series.

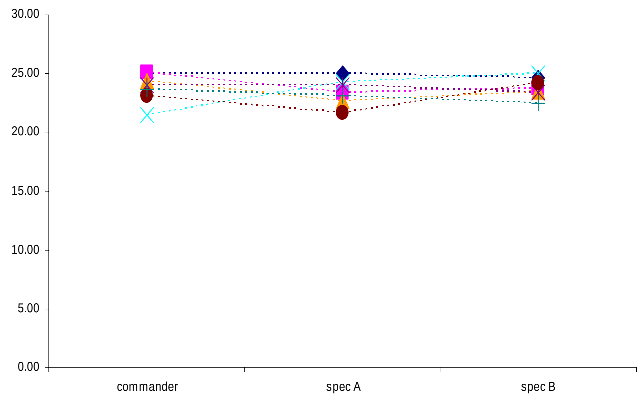
Table 26 Means and standard deviations of the age of the participants in years.

ylter		commander	spec A	spec B
all teams	mean	23.78	23.49	23.87
	stdv	3.92	3.67	3.42
BC - Base Condition	mean	25.00	24.98	24.66
	stdv	4.15	3.49	3.65
Goal	mean	25.08	23.43	23.74
	stdv	4.87	3.37	4.01
CHAT	mean	24.34	22.70	23.52
	stdv	2.95	2.55	3.77
CC-1 - Control Condition 1	mean	21.46	24.27	25.01
	stdv	2.31	4.21	3.64
CC-2 - Control Condition 2	mean	24.01	24.01	23.42
	stdv	4.62	3.44	2.74
IR - Individual Reflexivity	mean	23.11	21.62	24.16
	stdv	4.46	4.30	3.94
GR - Group Reflexivity	mean	23.66	23.10	22.46
	stdv	3.15	3.41	2.12

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✳) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 16 Means and standard deviations of the age of the participants in years.

ANOVA results show that the means are not different for the three roles ($F(2, 204) = 0.46$, $p = .63$), and there is also no interaction of roles and experimental conditions ($F(12, 204) = 1.45$, $p = .13$). There is no overall difference in the mean of the age for the different experimental conditions ($F(6, 102) = 1.36$, $p = .07$).

Gender

We got an almost even distribution of the gender: female participants N = 188 (57%), male participants N = 139 (43%).

Gender and Experimental Conditions

As the results in Table 27 show there females and males are evenly distributed on the different experimental conditions for every role. The number of commanders participating in different experimental conditions did not differ by gender, $\chi^2(6) = 6.98$, $p = .32$. The number of specialists A participating in different experimental conditions did not differ by gender, $\chi^2(6) = 2.18$, $p = .90$. The number of specialists B participating in different experimental conditions did not differ by gender, $\chi^2(6) = 9.50$, $p = .15$.

Table 27 Crosstable of gender of participants and experimental conditions.

	experimental condition							*Total*
commander	BC	Goal	CHAT	CC-1	CC-2	IR	GR	
female	**10**	**3**	**6**	**11**	**10**	**8**	**12**	***60***
male	**10**	**6**	**8**	**4**	**7**	**9**	**5**	***49***
Total	*20*	*9*	*14*	*15*	*17*	*17*	*17*	*109*
specialist A								
female	**10**	**4**	**9**	**8**	**8**	**9**	**11**	***59***
male	**10**	**5**	**5**	**7**	**9**	**8**	**6**	***50***
Total	*20*	*9*	*14*	*15*	*17*	*17*	*17*	*109*
specialist B								
female	**10**	**4**	**6**	**11**	**12**	**12**	**14**	***69***
male	**10**	**5**	**8**	**4**	**5**	**5**	**3**	***40***
Total	*20*	*9*	*14*	*15*	*17*	*17*	*17*	*109*

Note. Number of participants.

Gender and Education

Participants were mainly psychology students. Some participants were recruited in colleges or through an ad in a local newspaper. All in all 66 (20%) participants were college students or professionals and 261 (80%) of the participants were university students. The number of commanders participating in different experimental conditions did not differ by education, $\chi^2(6) = 2.78$, $p = .83$. But there are more specialists A college students or professionals than expected ($\chi^2(6) = 15.13$, $p = .02$). In all other cases the distribution is as expected. The number of specialists B participating in different experimental conditions did not differ by education, $\chi^2(6) = 8.53$, $p = .20$. Details see Table 28.

Table 28 Crosstable of education of participants and experimental conditions.

	experimental condition							*Total*
commander	BC	Goal	CHAT	CC-1	CC-2	IR	GR	
college studnet or professional	**4**	**2**	**1**	**4**	**3**	**4**	**2**	***20***
university student	**16**	**7**	**13**	**11**	**14**	**13**	**15**	***89***
Total	*20*	*9*	*14*	*15*	*17*	*17*	*17*	*109*
specialist A								
college studnet or professional	**4**	**3**	**1**	**6**	**2**	**9**	**2**	***27***
university student	**16**	**6**	**13**	**9**	**15**	**8**	**15**	***82***
Total	*20*	*9*	*14*	*15*	*17*	*17*	*17*	*109*
								Total
specialist B								
college studnet or professional	**6**	**0**	**4**	**4**	**1**	**2**	**2**	***19***
university student	**14**	**9**	**10**	**11**	**16**	**15**	**15**	***90***
Total	*20*	*9*	*14*	*15*	*17*	*17*	*17*	*109*

Note. Number of participants.

Review of the Research Questions to Input Variables

P I. No differences in computer expertise are expected for commanders and specialists.

The means of computer expertise do not differ for the three roles, neither for the different experimental conditions.

P II. But it is expected that males report a higher computer expertise than females, independent of age and experimental condition.

In fact, male participants report a much higher computer expertise than females.

P III. The age of the participants is expected to be alike in all experimental conditions. Although the experiments were running from 1996 to 2001.

There are no age differences observed between the different experimental conditions.

P IV. The air traffic control simulation is a computer-based task oriented technical simulation. The cover story positioned the task in the context of a military operation lead by the UN. It could be expected that all this leads to a reduced interest of females to participate in the study.

There are more female than male participants but because females are dominant in psychology they are nevertheless underrepresented in the ATC study. However, the distribution to the different experimental conditions shows no bias insofar that females and males are evenly distributed to the experimental conditions.

P V. Most participants are university students but there are also some college students and other participants. They should be evenly distributed on the different experimental conditions.

For all three roles the participants are evenly distributed to the different experimental conditions. There is only one exception. There are more professionals or college students specialists A in the Individual Reflexivity condition.

8.2 Performance Measure

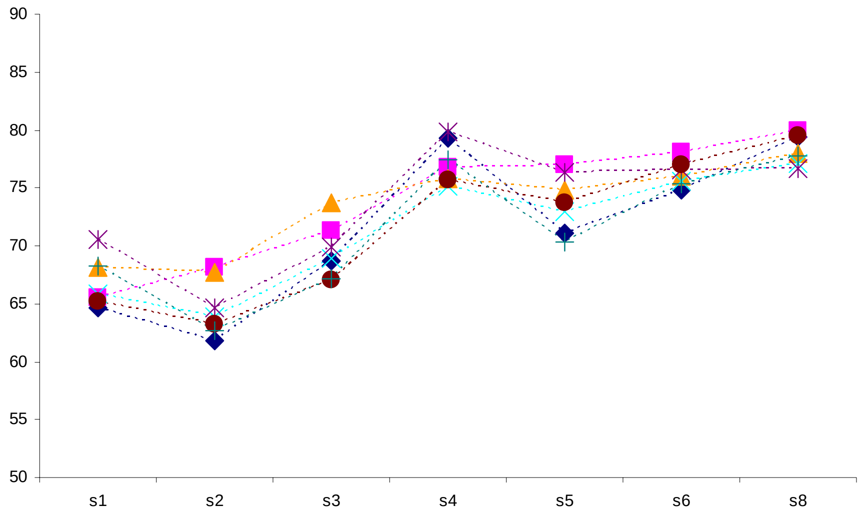
There are no overall performance differences between the teams of the different experimental conditions ($F_{between}(6,102) = 0.42$, $p = .86$). But there are changes over time ($F_{within}(6, 612) = 57.01$, $p = .00$). The teams perform better on day two than on day one (Table 29 and Figure 17).

This results was not expected. We thought that the different interventions should also lead to performance differences. However, a detailed analysis of the performance measure and the development of alternative measures showed that there is no reliable alternative solution to the performance calculation presented in chapter 6.7 (Stutz et al., 2002).

Table 29 Means and standard deviations of performance, shift 1 to shift 8, all experimental conditions.

Condition	N	shift 1		shift 2		shift 3		shift 4		shift 5		shift 6		shift 8	
	teams	Mean	stdv	Mean	stdv	Mean	stdv	Mean	stdv	Mean	stdv	Mean	stdv	Mean	stdv
1 BC	20	64.68	11.99	61.80	14.16	68.67	11.07	79.28	7.25	71.13	9.07	74.78	7.99	79.45	4.96
4 Goal	9	65.56	13.05	68.11	10.20	71.26	6.13	76.72	9.57	77.00	3.89	78.07	5.87	79.92	4.13
5 CHAT	14	68.14	11.15	67.69	8.06	73.67	7.83	75.82	10.63	74.83	10.17	76.02	8.22	77.95	12.05
6 CC-1	15	65.90	7.69	63.87	11.75	68.87	11.83	75.10	11.33	72.98	7.12	75.53	10.46	77.15	5.59
7 CC-2	17	70.56	8.93	64.63	12.66	69.84	9.10	79.79	6.61	76.29	4.92	76.55	7.03	76.63	6.59
8 IR	17	65.24	9.92	63.20	10.26	67.06	10.88	75.65	10.47	73.75	8.23	77.00	5.86	79.46	6.49
9 GR	17	68.24	10.72	62.71	13.94	67.16	9.81	77.44	8.54	70.27	13.28	75.39	10.49	77.79	6.82
Total	109	66.92	10.40	64.16	11.89	69.25	9.92	77.28	9.10	73.43	8.92	76.03	8.11	78.28	6.93

Note. Performance CHAT-condition, shift 5 without the first plane. Performance is between 0 (low) and 100 (high). N is the number of teams. Shift 7 is omitted as there is no data available for the reflexivity conditions. BC = Base Condition, Goal = Goal condition, CHAT = chat condition, CC-1 = Reflexivity: Control Condition 1, CC-2 = Reflexivity: Control Condition 2, IR = Reflexivity: Individual Reflexivity, GR = Reflexivity: Group Reflexivity.



Note. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ∗) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 17 Mean performance shift 1 to shift 8.

Review of the Research Questions to the Performance Measure

PERF I. It is expected that performance increases from shift 1 to shift 8.

Performace does not increase steaely from shift 1 to shift 8. On day two the performacne in shift 4, shift 5, shift 6 and shift 8 is more or less constant. But performace on day 2 is significantly higher than performance on day one.

PERF II. There are perfomance differnces between the experimental conditions. The overall lowest performance is found for teams of th Base Cndition.

There are no effects of the experimental conditions at all.

8.3 Process Variables: Counting

In this chapter I present results of the frequencies of the process variables (as defined in chapter 6.8). Descriptive statistics are presented for shift 1 to shift 6, and for shift 8. Shift 7 is omitted because in specific experimental conditions this shift was skipped in favor of the measurement of shared mental (see chapter 6.6).

The presentation is restricted to the main categories of the coding scheme: Read Message, Send Message, Show Information for commanders and specialist and the Handle Threat of commanders. The detailed information available from the coding of Send Message or Read Message related to the message content and the timing is skipped for these summary level analyses. he same is done for the details in the coding of ShowInformation and Handle Threat.

Means and standard deviations are presented together with an analysis of variance with repeated measure to test for differences over time. To run ANOVA analyses GLM procedure of SPSS 10.0 was used. Contrast analyses were run for the time factor (within-subject contrasts) usually taking shift 8 as reference category. To specify overall differences between the experimental conditions contrast analyses were run, comparing each level (between-subject contrasts) with the grand mean. In all analyses the Mauchly's sphericity tests was significant, thus values reported are from the more conservative Greenhous-Geisser test.

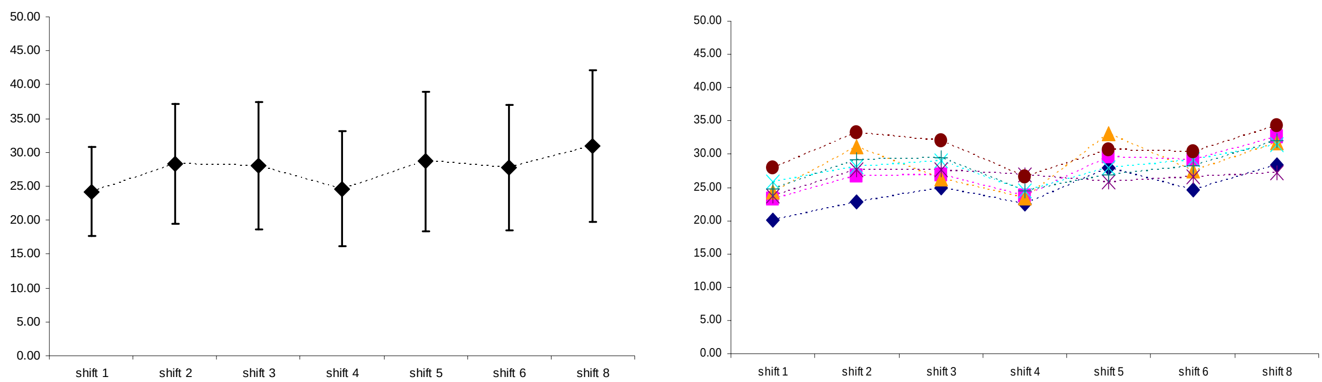
Means, Standard deviations and ANOVA results for the frequency of Read Message Commander shift 1 to shift 8

Read Message Commander is the the number of messages a commande reads per shift. The average commander reads 20 to 34 messages per shift. The lowest mean is found for commanders of the Base Condition in shift 1 (mean = 20.10), the highest mean for commanders of the Individual Reflexivity in shift 8 (mean = 34.29). See Table 30 and Figure 18.

Table 30 Means and standard deviations for Read Message commander shift 1 to shift 8.

FIR_C1 # of Read Message - shift 1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	24.19	28.32	28.05	24.61	28.68	27.76	30.88
	stdv	6.57	8.80	9.38	8.47	10.30	9.28	11.19
BC - Base Condition	mean	20.10	22.85	24.85	22.45	27.90	24.65	28.45
	stdv	4.93	6.23	8.24	10.14	11.46	9.50	11.11
Goal	mean	23.22	26.78	26.89	23.67	29.67	29.11	32.56
	stdv	5.04	8.32	8.87	8.38	10.48	9.49	12.91
CHAT	mean	24.36	31.14	26.21	23.43	33.14	27.43	31.71
	stdv	9.71	11.84	9.49	8.75	12.60	10.98	11.83
CC-1 - Control Condition 1	mean	25.80	28.07	28.93	24.53	28.00	29.13	31.40
	stdv	6.42	7.81	9.31	7.74	10.29	10.84	13.96
CC-2 - Control Condition 2	mean	23.71	27.71	27.71	26.88	25.76	26.59	27.12
	stdv	5.07	7.86	9.13	7.31	6.05	6.75	7.97
IR - Individual Reflexivity	mean	27.88	33.24	32.06	26.59	30.71	30.41	34.29
	stdv	5.66	6.44	10.90	10.49	11.38	7.51	10.57
GR - Group Reflexivity	mean	24.76	29.18	29.47	24.47	26.88	28.29	32.06
	stdv	6.37	9.93	9.26	5.65	9.08	10.11	10.85

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.

Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17

Figure 18 Means and standard deviations for Read Message commander shift 1 to shift 8.

ANOVA results show that the mean of Read Message changes over time (F(3.23, 329.47) = 19.45, p < .01). There is no interaction of shifts and experimental conditions (F(19.38, 329.47) = 1.33, p = .16). Overall the means of Read Message do not differ for different experimental conditions (F(6, 102) = 1.13, p = .35). Contrast analyses show that all shifts differ statistically significant from shift 8 (weakest effect $F_{\text{shift 2 - 8}}$ (1, 102) = 7.28, p = .01, strongest effect $F_{\text{shift 4 - 8}}$ (1, 102) = 77.52, p < .01).

The means of Read Message of commanders go up from shift 1 to shift 3. In shift 4 on day two the mean is relatively low but then goes up again until shift 8. That the mean number of Read Message goes back for commanders in shift 4 may have several reasons. In shift 4 there are only two planes in the airspace, therefore the specialist send less messages. And some commanders sent in shift 4 messages to their to instruct them and they had therefore less time to read messages.

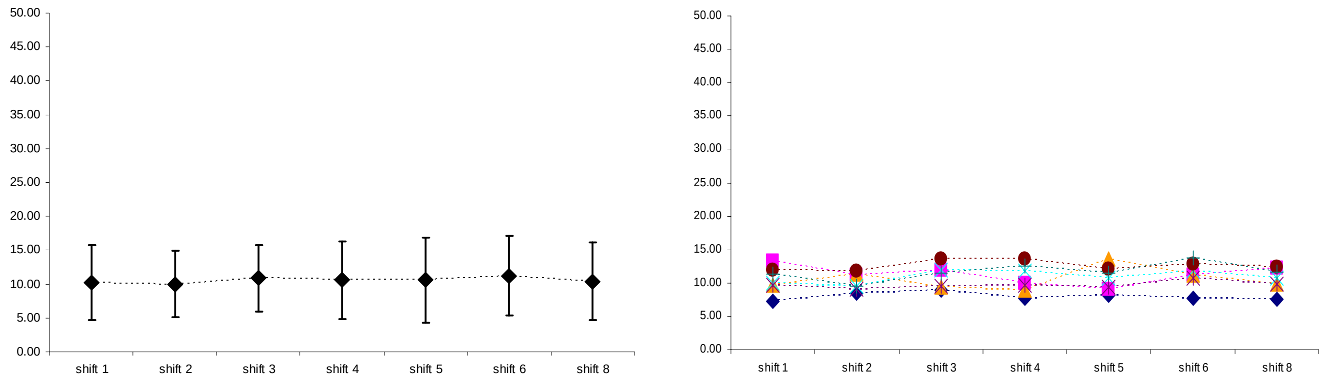
Means, Standard deviations and ANOVA results for the frequency of Read Message Specialist A shift 1 to shift 8

Read Message specialist A is the the number of mesages a specialist A reads per shift. The lowest mean for Read Message of specialist A is found in the Base Condition in shift 1 (mean = 7.20), the highest mean for Specialists A of the Group Reflexivity condition in shift 6 (mean = 13.76). See Table 31 and Figure 19.

Table 31 Means and standard deviations for Read Message specialist A shift 1 to shift 8.

FIR_A1 # of Read Message - shift 1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	10.17	9.97	10.84	10.58	10.61	11.21	10.41
	stdv	5.52	4.88	4.95	5.68	6.29	5.88	5.76
BC - Base Condition	mean	7.20	8.50	8.90	7.70	8.15	7.65	7.60
	stdv	3.96	4.43	4.04	4.44	5.82	4.16	4.41
Goal	mean	13.22	11.11	11.89	10.00	9.11	11.22	12.22
	stdv	6.42	5.60	6.17	7.19	6.43	8.21	7.74
CHAT	mean	9.64	11.29	9.43	8.86	13.64	11.14	9.86
	stdv	4.94	3.47	3.37	4.09	5.67	4.38	3.98
CC-1 - Control Condition 1	mean	10.00	9.47	11.87	11.80	10.80	11.80	10.67
	stdv	4.54	4.69	4.96	4.54	6.26	6.64	6.88
CC-2 - Control Condition 2	mean	9.65	9.06	9.47	9.65	9.35	10.71	9.76
	stdv	5.30	4.96	4.47	4.15	4.74	4.73	4.59
IR - Individual Reflexivity	mean	12.00	11.82	13.53	13.65	12.06	12.88	12.41
	stdv	6.75	5.66	5.65	6.63	8.23	5.31	6.09
GR - Group Reflexivity	mean	11.29	9.53	11.53	12.47	11.41	13.76	11.65
	stdv	5.74	5.12	5.10	6.83	5.87	6.93	6.32

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.

Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17

Figure 19 Means and standard deviations for Read Message specialist A shift 1 to shift 8.

ANOVA results show that the mean of Read Message does not change over time (F(3.74, 381.90) = 1.04, p = .38). There is no interaction with the experimental condition (F(22.46, 381.90) = 1.14, p = .30). Overall the means of Read Message differ for different experimental conditions (F(6, 102) = 2.36, p = .04). Contrast analyses show that compared to the Grand Mean of Read Message (mean = 10.66) specialists A of the Base Condition have a significantly lower mean of Read Message (mean = 10.43), and specialists A of the Individual Reflexivity condition have a significantly higher mean of Read Message (mean = 11.3).

The number of messages read by specialists A is constant from shift 1 to shift 8. Specialists A of the Base Condition read (on the average) less messages then all other groups, specialists A of the Individual Reflexivity condition read more messages.

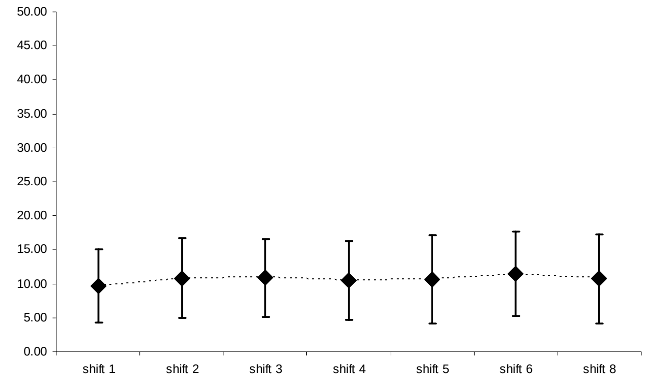
Means, Standard deviations and ANOVA results for the frequency of Read Message Specialist B shift 1 to shift 8

Read Message specialist B is the the number of mesages a specialist B reads per shift.The lowest mean for Read Message of specialist B is found in the Base Condition in shift 4 (mean = 6.70), the highest mean for specialists B of the Group Reflexivity condition in shift 6 (mean = 14.76). See Table 32and Figure 20.

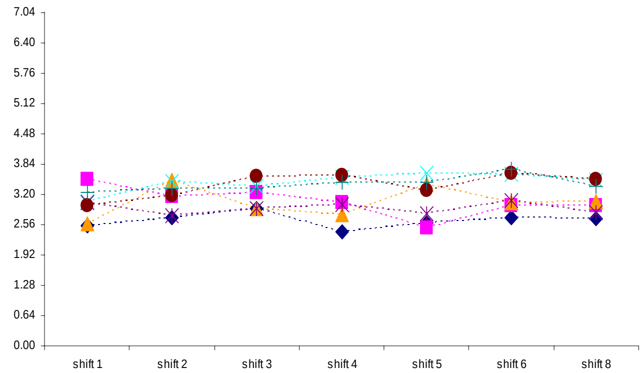
Table 32 Means and standard deviations for Read Message specialist B shift 1 to shift 8.

FIR_B1 # of Read Message - shift 1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	9.62	10.82	10.84	10.50	10.64	11.50	10.74
	stdv	5.38	5.91	5.77	5.81	6.43	6.24	6.55
BC - Base Condition	mean	7.80	8.75	9.25	6.70	7.65	8.40	8.30
	stdv	5.64	6.05	5.09	4.99	5.54	6.34	6.55
Goal	mean	13.44	10.22	10.89	10.00	6.78	9.78	9.33
	stdv	8.11	3.19	4.14	6.32	4.15	7.05	4.85
CHAT	mean	6.86	12.43	9.00	8.14	12.21	9.64	9.86
	stdv	2.03	3.57	4.72	4.24	5.74	4.05	5.42
CC-1 - Control Condition 1	mean	10.80	13.20	12.33	13.33	14.00	13.73	13.33
	stdv	6.30	7.20	6.98	6.48	6.45	5.84	7.47
CC-2 - Control Condition 2	mean	9.71	8.06	9.06	9.35	8.29	9.88	8.41
	stdv	4.31	3.86	4.51	3.72	4.03	4.14	3.61
IR - Individual Reflexivity	mean	9.47	11.59	13.71	13.65	12.12	14.00	13.53
	stdv	4.65	6.91	7.02	5.84	7.33	6.13	7.28
GR - Group Reflexivity	mean	11.06	12.12	11.82	12.65	12.82	14.76	12.35
	stdv	4.85	6.70	5.79	5.62	7.45	7.06	7.47

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17. Square root transformed values (Levene's test was significant).

Figure 20 Means and standard deviations for Read Message specialist B shift 1 to shift 8.

ANOVA results show that the mean of Read Message is constant from shift 1 to shift 8 (F(4.03, 411.24) = 1.81, p = .13). There is an interaction of shifts and experimental conditions (F(26.04, 411.24) = 1.97, p < .01). Overall the means of Read Message differ for different experimental conditions (F(6, 102) = 3.26, p = .01). Contrast analyses show an interaction effect (only trend) for shift 5 compared to shift 8 ($F_{\text{shift 5 - 8}}$ (6, 102) = 2.02, p = .07). This is due to the CHAT condition in which specialists A have remarkably more Read Messages in shift 5 than in shift 4 or shift 6. Contrast analyses also show that compared to the Grand Mean of Read Message (mean

$_{SQRT}$= 3.14)[13] only specialists A of the Base Condition have significantly lower means (mean $_{SQRT}$ = 3.00).

The mean number of messages read by specialists B is constant from shift 1 to shift 8. The overall lowest frequencies is found for specialists B of the Base Condition.

Means, Standard deviations and ANOVA results for the frequency of Send Message Commander shift 1 to shift 8

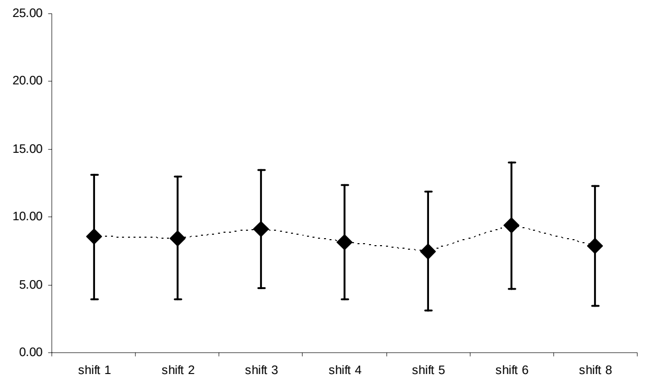
Send Message commander is the the number of mesages a commander sends per shift. Commanders send an average of 5 to 12 messages per shift. The lowest mean is found for commanders of the Base Condition in shift 5 (mean = 4.95), the highest mean for commanders of the Goal condition in shift 3 (mean = 12.33). See Table 33 and Figure 21.

Table 33 Means and standard deviations for Send Message commander shift 1 to shift 8.

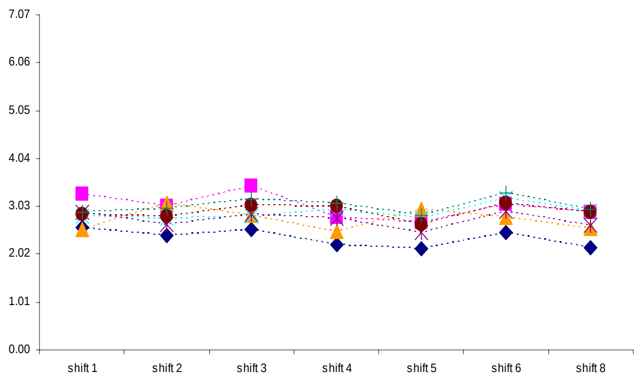
FIS_C1 # of Send Message - shift 1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	8.54	8.44	9.12	8.16	7.49	9.36	7.87
	stdv	4.58	4.51	4.33	4.19	4.37	4.66	4.44
BC - Base Condition	mean	7.25	6.30	7.05	5.40	4.95	6.45	5.00
	stdv	4.20	3.73	3.95	3.55	2.86	2.93	2.60
Goal	mean	11.44	9.56	12.33	8.44	8.00	10.22	9.22
	stdv	5.10	4.19	4.33	4.69	5.05	5.87	5.47
CHAT	mean	6.79	9.79	8.50	6.43	9.21	8.29	6.86
	stdv	2.89	2.64	3.67	1.91	3.98	3.75	2.77
CC-1 - Control Condition 1	mean	8.53	8.07	8.27	9.20	8.07	10.60	9.00
	stdv	4.55	3.37	3.41	3.55	3.49	3.78	3.91
CC-2 - Control Condition 2	mean	9.18	8.12	8.94	8.35	7.18	9.24	7.82
	stdv	5.08	5.97	4.96	4.90	6.26	5.82	5.79
IR - Individual Reflexivity	mean	9.00	8.88	9.76	9.76	7.59	10.12	9.00
	stdv	5.41	5.60	4.07	4.71	4.37	4.04	4.23
GR - Group Reflexivity	mean	8.88	9.47	10.65	9.94	8.47	11.47	9.29
	stdv	4.15	4.46	4.58	3.60	3.48	5.14	4.73

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17

13 As the Levene's test was significant, the values were square-root transformed (Tabachnick & Fidell, 2001).



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ∗) = 17, N(IR ●) = 17, N(GR +) = 17. Square root transformed values (Levene's test was significant).

Figure 21 Means and standard deviations for Send Message commander shift 1 to shift 8.

ANOVA results show that the mean of Send Message varies within shifts (F(3.70, 377.83) = 7.61, p < .01). There is an interaction of shifts with the experimental condition (F(22.25, 377.83) = 1.80, p = .02). Overall the means of Send Message differ between experimental conditions (F(6, 102) = 2.51, p = .03). Contrast analyses show, that only shift 3 and shift 6 differ statistically significant form shift 8 – the mean of Send Message is higher ($F_{\text{shift 3 - 8}}$ (1, 102) = 16.57, p < .01, $F_{\text{shift 6 - 8}}$ (1, 102) = 36.07, p < .01. Contrast analyses show also that compared to the Grand Mean of Send Message (mean = 2.82) only commanders of the Base Condition have a significantly lower means of Send Message (mean = 2.36).

The mean of Send Message of commanders is highest in shift 3 and shift 6. Overall the mean of Send Message is lowest for commanders of the Base Condition.

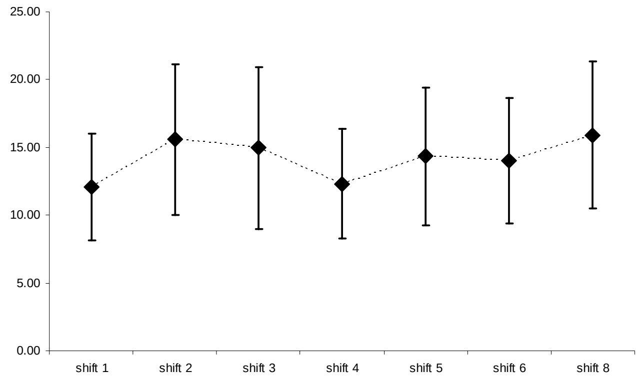
Means, Standard deviations and ANOVA results for the frequency of Send Message Specialist A shift 1 to shift 8

Send Message specialist A is the the number of mesages a specialist A sends per shift. Specialists A send an average of 10 to 20 messages per shift. The lowest mean is found for specialists A of the Goal condition in shift 1 (mean = 10.33), the highest mean for specialists A of the Group Reflexivity condition in shift 3 (mean = 18.94). See Table 34 and Figure 22.

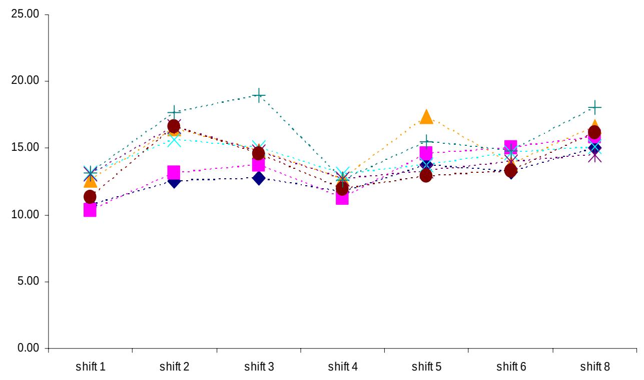
Table 34 Means and standard deviations for Send Message specialist A shift 1 to shift 8.

FIS_A1 # of Send Message - shift 1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	12.11	15.60	14.97	12.32	14.34	14.02	15.89
	stdv	3.94	5.56	5.96	4.02	5.09	4.61	5.43
BC - Base Condition	mean	10.70	12.55	12.80	11.70	13.75	13.20	15.00
	stdv	3.50	3.61	3.85	4.95	5.16	4.64	6.58
Goal	mean	10.33	13.11	13.78	11.22	14.56	15.00	15.89
	stdv	3.39	4.76	4.58	2.59	2.96	4.42	5.58
CHAT	mean	12.64	16.43	14.79	12.71	17.36	13.79	16.64
	stdv	3.88	5.75	6.83	4.84	6.38	5.18	4.63
CC-1 - Control Condition 1	mean	13.13	15.67	15.00	13.07	13.73	14.67	15.13
	stdv	4.53	6.35	6.22	4.32	5.28	5.41	6.24
CC-2 - Control Condition 2	mean	13.06	16.65	14.71	12.71	13.29	14.00	14.53
	stdv	4.28	6.47	6.23	3.85	3.42	4.17	4.27
IR - Individual Reflexivity	mean	11.35	16.65	14.59	11.94	12.88	13.29	16.18
	stdv	3.28	5.12	5.88	3.27	4.44	3.50	4.67
GR - Group Reflexivity	mean	13.18	17.65	18.94	12.65	15.47	14.82	18.06
	stdv	4.10	5.41	6.55	3.66	6.01	5.31	5.57

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17

Figure 22 Means and standard deviations for Send Message specialist A shift 1 to shift 8.

ANOVA results show that the mean of Send Message varies over time (F(3.61, 367.71) = 21.65, p < .01). There is an interaction of shifts and experimental condition (F(21.63, 367.71) = 1.62, p = .04). Overall the different experimental conditions do not differ (F(6, 102) = 1.07, p = .39). Contrast analyses show that all shifts expect of shift 2 and shift 3 differ statistically significant from shift 8 – the mean of Send Message is lower (weakest effect: $F_{\text{shift 4 - 8}}$ (1, 102) = 883.25, p < .00, strongest effect $F_{\text{shift 5 - 8}}$ (1, 102) = 19.20, p < .01).

In shift 2 and shift 3 the mean of Send Message is as high as in shift 8. In all other shifts the mean is lower. In shift 3 the mean of Send Message is highest for specialists A of the Control Condition 1, in shift 5 for specialists A of the CHAT condition.

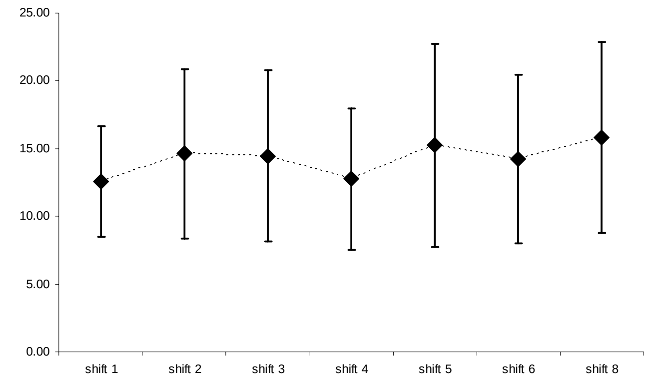
Means, Standard deviations and ANOVA results for the frequency of Send Message Specialist B shift 1 to shift 8

Send Message specialist B is the the number of mesages a specialist B sends per shift. Specialists B send an average of 11 to 18 messages per shift. The lowest mean is found for specialists B of the Base Condition in shift 1 (mean = 10.85), the highest mean for specialists B of the Control Condition 1 in shift 8 (mean = 18.13). See Table 35 and Figure 23.

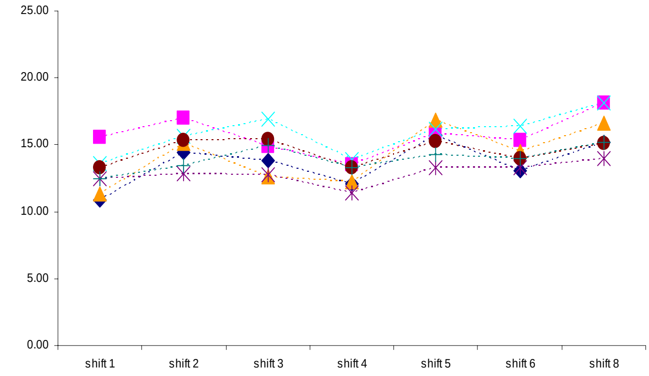
Table 35 Means and standard deviations for Send Message specialist B shift 1 to shift 8.

FIS_B1 # of Send Message - shift 1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	12.57	14.61	14.44	12.74	15.26	14.22	15.83
	stdv	4.08	6.27	6.32	5.19	7.49	6.20	7.06
BC - Base Condition	mean	10.85	14.40	13.80	12.10	15.70	13.10	15.20
	stdv	3.39	7.16	6.76	6.47	9.36	5.98	5.68
Goal	mean	15.56	17.00	14.89	13.56	15.89	15.33	18.11
	stdv	4.64	6.96	6.19	6.31	9.78	7.11	9.48
CHAT	mean	11.36	15.07	12.64	12.21	16.86	14.50	16.64
	stdv	4.62	6.88	6.85	5.82	8.53	7.78	8.52
CC-1 - Control Condition 1	mean	13.60	15.60	16.93	13.87	16.13	16.40	18.13
	stdv	5.05	7.25	7.47	5.25	8.90	8.11	10.07
CC-2 - Control Condition 2	mean	12.47	12.82	12.76	11.41	13.29	13.29	14.00
	stdv	3.61	5.08	5.82	3.59	4.04	5.34	5.74
IR - Individual Reflexivity	mean	13.29	15.35	15.41	13.29	15.24	13.94	15.12
	stdv	3.20	5.56	5.28	4.33	6.07	4.12	4.53
GR - Group Reflexivity	mean	12.47	13.41	14.94	13.29	14.29	14.00	15.18
	stdv	3.68	5.37	5.85	4.90	6.05	5.61	6.21

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17

Figure 23 Means and standard deviations for Send Message specialist B shift 1 to shift 8.

ANOVA results show that the mean number of Send Message varies over time (F(3.07, 312.90) = 12.72, p < .01). There is no interaction of shifts and experimental condition (F(18.41, 312.90) = 0.95, p = .53). Overall the means of Send Message do not differ (F(6, 102) = 0.59, p = .74). Contrast analyses show that all shifts expect shift 5 differ statistically significant form shift 8 – the mean number of Send Message is lower (weakest effect $F_{\text{shift 2 - 8}}$ (1, 102) = 3.80, p < .54, strongest effect to $F_{\text{shift 4 - 8}}$ (1, 102) = 57.55, p < .00).

The mean of Read Message of specialist B is constantly increasing from shift 1 to shift 3, decreases in shift 4 to reach in shift 5 the same value as in shift 8. There is no effect of the experimental conditions at all.

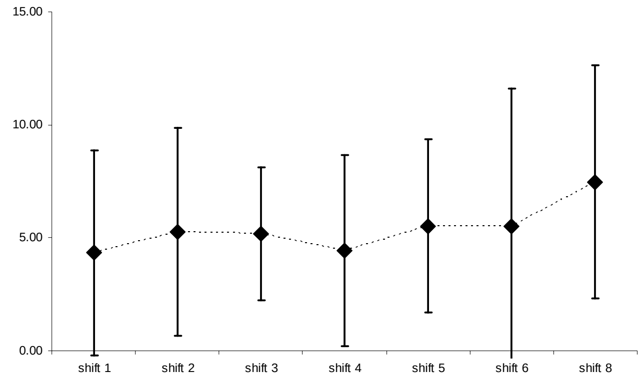
Means, Standard deviations and ANOVA results for the frequency of Show Information Commander shift 1 to shift 8

Show Information comander is the the number of times a commander looks up in-foration on a plane per shift. Commanders have 3 to 9 Show Information on average per shift and plane. The lowest mean is found for commanders of the Goal condition in shift 1 (mean = 2.56), the highest mean for commanders of the Individual Reflexivity condition in shift 8 (mean = 8.94). See Table 36 and Figure 24.

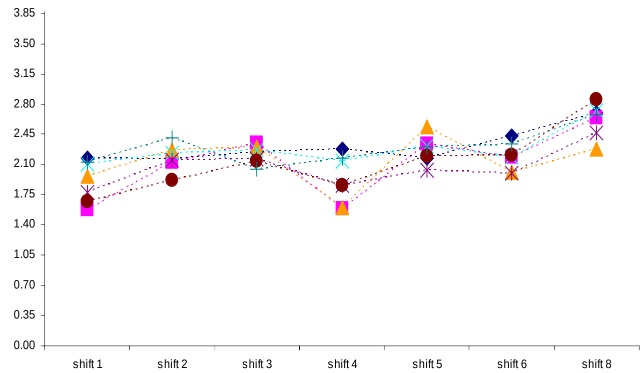
Table 36 Means and standard deviations for Show Information commander shift 1 to shift 8.

FIESI_C1 # of Show Information - shift		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	4.34	5.28	5.17	4.43	5.52	5.52	7.48
	stdv	4.55	4.59	2.95	4.21	3.82	6.10	5.17
BC - Base Condition	mean	6.10	5.55	5.70	6.15	5.15	7.50	8.10
	stdv	7.85	5.43	4.68	5.71	3.69	11.53	6.98
Goal	mean	2.56	4.67	5.67	2.67	5.89	5.11	7.33
	stdv	1.01	1.80	2.00	1.41	3.82	3.18	3.35
CHAT	mean	4.14	5.36	5.50	2.64	6.79	4.14	5.29
	stdv	2.44	2.44	2.28	1.15	3.95	1.35	1.73
CC-1 - Control Condition 1	mean	5.13	5.27	5.60	4.93	6.07	5.53	8.27
	stdv	5.19	2.58	3.79	2.74	5.44	5.93	6.95
CC-2 - Control Condition 2	mean	3.29	4.94	4.94	3.65	4.24	4.06	6.35
	stdv	1.45	2.77	2.30	1.90	1.52	1.20	2.85
IR - Individual Reflexivity	mean	2.94	3.82	4.76	3.65	5.24	5.12	8.94
	stdv	1.39	1.74	2.14	1.73	3.80	2.26	6.13
GR - Group Reflexivity	mean	5.12	7.00	4.29	5.94	5.82	6.41	7.59
	stdv	4.83	8.86	1.49	7.34	4.00	6.26	4.15

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ∗) = 17, N(IR ●) = 17, N(GR +) = 17. Square root transformed values (Levene's test was significant).

Figure 24 Means and standard deviations for Show Information commander shift 1 to shift 8.

ANOVA results show that the mean of Show Information varies with time (F(5.07, 517.45) = 20.68, p < .01). There is an interaction of shifts and experimental condition (F(30.44, 517.45) = 1.59, p = .03). Overall the means of Show Information do not differ for the experimental conditions (F(6, 102) = 0.62, p = .72). Contrast analyses show that all shifts differ statistically significant form shift 8 (weakest effect $F_{\text{shift 5 - 8}}$ (1, 102) = 24.47, p < .01, strongest effect $F_{\text{shift 4 - 8}}$ (1, 102) = 78.83, p < .01. Contrast analyses show an interaction effect for shift 5 ($F_{\text{shift 5 - 7}}$ (6, 102) = 2.43, p = 0.03). In shift 5 the mean of Show Information is higher for commanders of the CHAT condition.

The mean of Show Information is in all shifts lower than the mean of Show Information in shift 8.

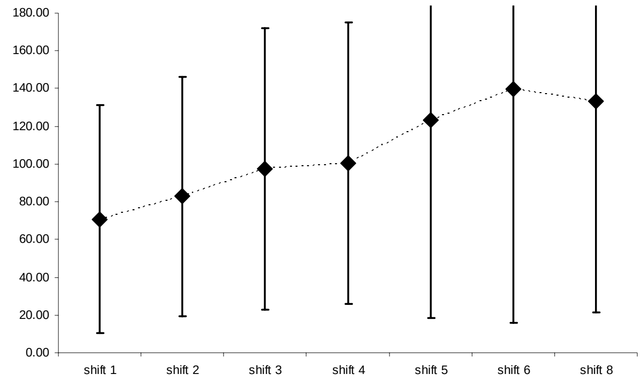
Means, Standard deviations and ANOVA results for the frequency of Show Information Specialist A shift 1 to shift 8

Show Information specialist A is the the number of times a specialist A looks up inforation on a plane per shift. Specialists A have 43 to 184 Show Information on average per shift. The lowest mean is found for specialists A of the Goal condition in shift 1 (mean = 43.44), the highest mean for specialists A of the CHAT condition in shift 5 (mean = 183.5). See Table 37 and Figure 25.

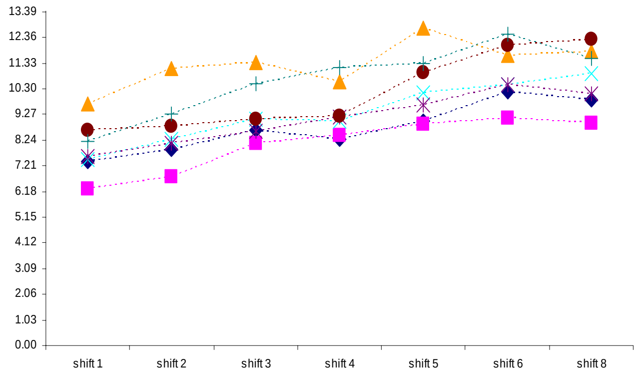
Table 37 Means and standard deviations for Show Information specialist A shift 1 to shift 8.

FIESI_A1 # of Show Information - shift		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	70.76	82.84	97.55	100.58	123.47	139.70	133.14
	stdv	60.35	63.36	74.53	74.62	105.11	124.02	111.91
BC - Base Condition	mean	59.95	66.40	80.40	73.75	85.80	113.20	107.45
	stdv	42.67	37.25	46.79	48.13	45.88	77.23	80.13
Goal	mean	43.44	49.78	71.78	78.67	85.11	91.22	88.67
	stdv	24.44	29.04	41.84	46.79	49.98	53.72	57.43
CHAT	mean	114.14	143.71	151.79	129.93	183.50	145.79	151.14
	stdv	125.81	123.56	134.44	99.98	127.12	78.13	90.74
CC-1 - Control Condition 1	mean	61.93	73.73	88.93	90.93	119.80	128.60	136.00
	stdv	50.02	48.96	53.42	68.01	110.47	116.46	108.46
CC-2 - Control Condition 2	mean	58.71	68.29	79.06	92.88	103.18	125.76	112.00
	stdv	20.54	28.70	44.37	58.55	69.84	107.24	77.85
IR - Individual Reflexivity	mean	81.65	84.00	89.00	97.41	145.29	175.65	178.88
	stdv	52.29	54.17	55.67	72.36	165.71	199.07	194.95
GR - Group Reflexivity	mean	71.18	91.00	121.35	138.94	140.35	179.29	144.94
	stdv	36.78	46.90	85.71	96.23	87.58	147.48	95.63

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17. Square root transformed values (Levene's test was significant).

Figure 25 Means and standard deviations for Show Information specialist A shift 1 to shift 8.

ANOVA results show that the mean number of Show Information changes over time (*F*(2.73, 278.27) = 37.54, p < .01). There is no interaction of shifts and experimental condition (*F*(16.37, 278.27) = 1.04, p = .42). Overall the means of Show Information do not differ for different experimental conditions (*F*(6, 102) = 1.90, p = .08). Contrast analyses show that shift 1 to shift 5 differ statistically significant from shift 8 (weakest effect $F_{\text{shift 5 - 8}}$ (1, 102) = 3.82, p = .05, strongest effect $F_{\text{shift 1 - 8}}$ (1, 102) = 82.62, p < .01).

Specialist A have much more Show Information than commanders. The number of Show Information is increasing from shift 1 to shift 6. There are no differences between the experimental conditions.

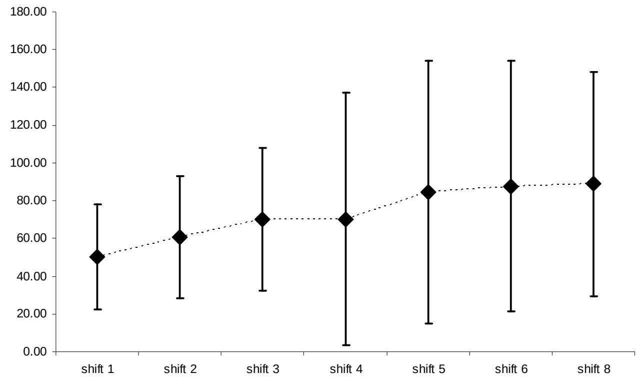
Means, Standard deviations and ANOVA results for the frequency of Show Information Specialist B shift 1 to shift 8

Show Information specialist B is the the number of times a specialist B looks up inforation on a plane per shift. Specialists B have 35 to 111 Show Information on average per shift. The lowest mean is found for specialists B of the Goal condition in shift 1 (mean = 34.89), the highest mean for specialists B of the CHAT condition in shift 5 (mean = 111.21). See Table 38 and Figure 26.

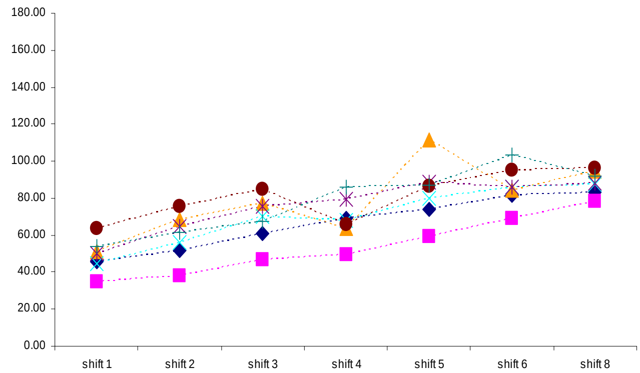
Table 38 Means and standard deviations for Show Information specialist B shift 1 to shift 8.

FIESI_B1 # of Show Information - shift		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	50.18	60.66	70.17	70.24	84.61	87.71	88.95
	stdv	28.03	32.46	37.86	66.79	69.53	66.27	59.45
BC - Base Condition	mean	45.95	51.90	61.10	68.90	74.10	81.70	83.35
	stdv	24.21	25.45	26.63	32.96	37.62	42.39	30.67
Goal	mean	34.89	38.33	46.56	49.56	59.11	68.89	78.11
	stdv	21.38	14.87	14.44	27.59	27.67	32.08	36.35
CHAT	mean	51.00	68.57	77.21	63.50	111.21	84.07	94.50
	stdv	16.63	20.45	31.94	26.31	67.20	47.08	40.70
CC-1 - Control Condition 1	mean	44.73	56.20	70.13	67.73	79.80	85.87	87.40
	stdv	33.05	43.61	43.90	73.23	84.75	94.43	96.79
CC-2 - Control Condition 2	mean	50.29	64.94	75.47	79.41	88.82	85.94	88.00
	stdv	21.14	33.89	38.93	55.59	58.43	54.13	47.80
IR - Individual Reflexivity	mean	63.88	75.35	85.00	65.71	86.41	95.35	96.35
	stdv	33.85	34.35	48.10	49.87	61.11	47.65	44.79
GR - Group Reflexivity	mean	53.59	61.24	67.47	85.88	86.82	103.47	91.65
	stdv	34.81	34.67	40.65	130.18	110.89	107.74	89.70

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 26 Means and standard deviations for Show Information specialist B shift 1 to shift 8.

ANOVA results show that the mean of Show Information changes over time (F(2.08, 211.69) = 25.25, p < .01). There is no interaction of shifts and experimental condition (F(12.45, 211.69) = 0.79, p = .67). Overall the means do not differ for different experimental conditions (F(6, 102) = 0.49, p = .82). Contrast analyses show that shift 1 to shift 5 differ statistically significant from shift 8 (weakest effect $F_{\text{shift 3 - 8}}$ (1, 102) = 19.97, p < .01, strongest effect $F_{\text{shift 1 - 8}}$ (1, 102) = 74.92, p < .01).

The mean of Show Information of specialists B is increasing from shift 1 to shift 6. There are no differences between the experimental conditions.

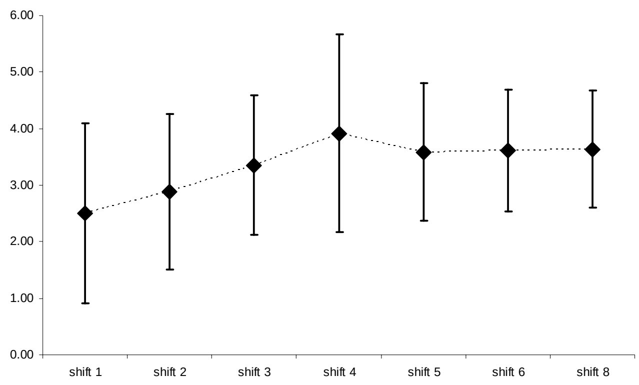
Means, Standard deviations and ANOVA results for the frequency of Handle Threat Commander shift 1 to shift 8

Handle Threat commander is the number of threat assignments a commander makes per shift. The results presented in this chapter are based on the number of Handle per plane. The lowest mean is found for commanders of the Base Condition in shift 1 (mean = 1.53), the highest mean for commanders of the Goal condition in shift 4 (mean = 5.22). See Table 39 and Figure 27.

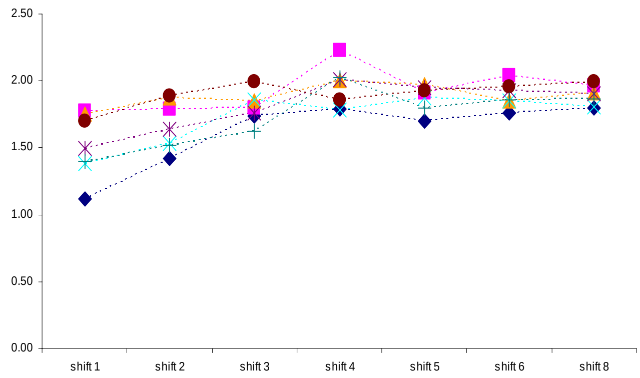
Table 39 Means and standard deviations for Handle Threat commander shift 1 to shift 8.

FIEH_C1R		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	2.51	2.89	3.35	3.92	3.58	3.61	3.63
	stdv	1.59	1.38	1.24	1.75	1.22	1.07	1.04
BC - Base Condition	mean	1.53	2.15	3.10	3.30	2.98	3.18	3.30
	stdv	1.09	1.10	1.08	1.23	1.00	1.08	0.93
Goal	mean	3.22	3.26	3.33	5.22	3.78	4.19	3.92
	stdv	1.06	0.89	1.22	2.69	1.45	0.80	1.15
CHAT	mean	3.54	3.71	3.50	4.18	3.95	3.48	3.71
	stdv	2.28	1.69	1.17	1.60	1.12	0.82	0.80
CC-1 - Control Condition 1	mean	2.17	2.44	3.56	3.23	3.60	3.51	3.38
	stdv	1.23	0.92	1.20	0.96	1.07	0.98	1.11
CC-2 - Control Condition 2	mean	2.41	2.84	3.14	4.21	3.86	3.78	3.66
	stdv	1.38	1.34	0.81	1.84	1.11	1.03	0.79
IR - Individual Reflexivity	mean	3.03	3.69	4.10	3.71	3.84	3.92	4.04
	stdv	1.33	1.34	1.54	1.95	1.40	1.15	1.22
GR - Group Reflexivity	mean	2.32	2.51	2.80	4.26	3.33	3.55	3.59
	stdv	1.74	1.40	1.30	1.71	1.34	1.29	1.21

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17. *Square root transformed values (Levene's test was significant).*

Figure 27 Means and standard deviations for Handle Threat commander shift 1 to shift 8.

ANOVA results show that the mean number of Handle Threat changes over time ($F(3.74, 381.17) = 29.11$, $p < .01$). There is an interaction of shifts and experimental conditions ($F(22.42, 381.17) = 1.83$, $p = .01$). Overall the means of Handle Threat differ for different experimental conditions ($F(6, 102) = 3.13$, $p = .01$). Contrast analyses show that only shift 1, shift 2, and shift 3 differ statistically significant from shift 8 ($F_{\text{shift 1 - 8}}(1, 102) = 54.53$, $p < .01$, $F_{\text{shift 2 - 8}}(1, 102) = 39.28$, $p < .01$; $F_{\text{shift 3 - 8}}(1, 102) = 6.42$, $p = .01$). Contrast analyses show also that compared to the Grand Mean of Handle Threat (mean = 1.8) only the teams of the Base Condition have a significantly lower mean (mean = 1.52). This effect is due to the low mean of Handle Threat of commanders of the Base Condition in shift 1 and shift 2.

The mean of Handle Threat is going up on day one, has its peak in shift 4 and then goes slightly down and stays stable from shift 5 to shift 8. Commanders of the Base Condition have a very low mean of Handel Threat in shift 1 and shift 2.

Review of the Research Questions to Process Variables: Counting

C I. Read Message, Send Message, Show Information and Handle Threat show some variation over time.

Almost all variables change over time. There are however two exceptions: Read Message of specialists A and B do not change over time.

C II. The number of Read Message of commanders should go up if there are more planes in the shift because specialists send more parameter information.

No effects can be found for the frequency of Read Message for commanders.

C III. The number of Read Message of specialists should be higher in shifts with less planes, because time is available for commanders to teach the specialists.

For specialists A there is an effect of the experimental condition but also no time effect. However, my expectation that specialists A of the CHAT condition read more messages than all others is not met. It is the specialists A of the Individual Reflexivity condition that read most messages.
For specialists B there is also no time effect, but at least specialists B - as expected - read more messages in shift 2 and shift 5 than in any other shift.

C IV. The Send Message of commanders should be higher in early shifts (giving instructions) and in shifts with less planes (shift 2, shift 4).

The data does not support this assumption. It can be observed that commanders send more messages in shifts with more dangerous planes (shift 3 and shift 6) than in any other shift.

C V. The Send Message of specialists should be higher if there are more planes are in the airspace.

The Send Message for specialists A is higher on day one than on day two - but is highest in shift 8. But it is not higher in shifts with more planes.
The Send message of specialists B also varies over time. The highest mean can be found in shift 5 (due to the specialists B of the CHAT

condition) Specialists B. It is remarkable that specialists B of the GOAL condition have overall rather high frequencies of Send Message.

C VI. The mean number of Show Information per plane of commanders should be constant over time. Commanders have only one parameter to observe (plane identification) and it is enough to look up this information just once because it never changes.

Commanders have much more Show Information per plane than theoretically required. The highest value can be found in shift 8. The number of Show Information per plane varies over time, therefore not supporting the assumption.

C VII. The number of Show Information of specialists should be higher if there are more planes in the airspace.

This is not the case for specialists A and specialists B: the number of Show Information steadily goes up from shift 1 to shift 8.

C VIII. The number of Handle Threat per plane of commanders should be higher if there are dangerous planes (often and quickly changing the threat value, shift 3, shift 6, shift 7 and shift 8) in the airspace.

This is not the case. The highest number of Handle Threat a commander makes is in shift 4 in which we find no dangerous plane

The result of all ANOVA analyses are summarized in Table 40 showing significant main effects and interaction effects.

Table 40 Summary of ANOVA (GLM repeated) analyses for summary-level process variables, shift 1 to shift 8.

	changes over time	interaction shifts x experimental conditions	overall differ-ences be-tween ex-perimental conditions
Read Message commander	yes	no	no
Read Message specialist A	no	no	yes
Read Message specialist B	no	yes	yes
Send Message commander	yes	yes	yes
Send Message specialist A	yes	yes	no
Send Message specialist B	yes	no	no
Show Information commander	yes	yes	no
Show Information specialist A	yes	no	no
Show Information specialist B	yes	no	no
Handle Threat Commander	yes	yes	yes

Note. N = 109 teams, changes over time = within subject effects, interaction shifts x experimental conditions = within subject contrasts, overall differences between experimental conditions = between subject effects, yes = statistically significat effect, no = no statistically sigificant effect.

8.4 Process Variables: Task Adaptive Behaviors

Means, Standard deviations and ANOVA results for the frequency of Basic Task Mastery Commander shift 1 to shift 8

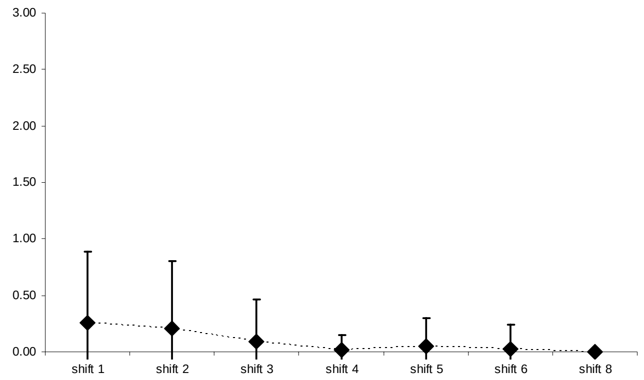
Basic Task Mastery commander is an index representing the minimal competencies and behaviors that ensure that a commander understood the fundamental role specific task requirements. Lower values of Basic Task Mastery stand for a better mastery of the basic task requirements.

The mean of Basic Task Mastery is between 0 and 0.7 on average. The lowest mean is found for example for all commanders in shift 8 (with a standard deviation of 0, indicating that all commanders perfectly mastered the Basic Task Mastery). The highest mean is for commanders of the Base Condition in shift 1 (mean = 0.70). See Table 41 and Figure 28.

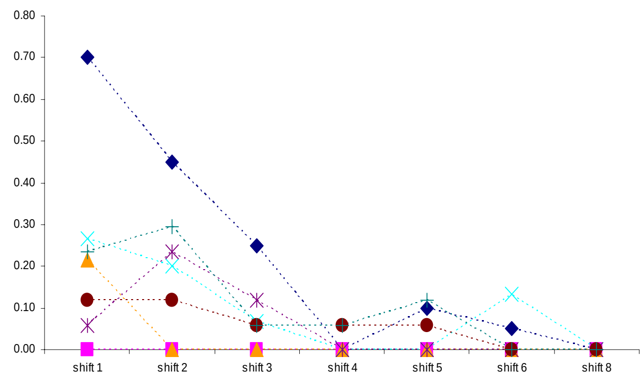
Table 41 Means and standard deviations Basic Task Mastery commander shift 1 to shift 8.

BTMC_S1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	0.26	0.21	0.09	0.02	0.05	0.03	0.00
	stdv	0.63	0.59	0.37	0.13	0.25	0.21	0.00
BC - Base Condition	mean	0.70	0.45	0.25	0.00	0.10	0.05	0.00
	stdv	0.92	0.83	0.64	0.00	0.31	0.22	0.00
Goal	mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	stdv	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CHAT	mean	0.21	0.00	0.00	0.00	0.00	0.00	0.00
	stdv	0.58	0.00	0.00	0.00	0.00	0.00	0.00
CC-1 - Control Condition 1	mean	0.27	0.20	0.07	0.00	0.00	0.13	0.00
	stdv	0.80	0.56	0.26	0.00	0.00	0.52	0.00
CC-2 - Control Condition 2	mean	0.06	0.24	0.12	0.00	0.00	0.00	0.00
	stdv	0.24	0.75	0.49	0.00	0.00	0.00	0.00
IR - Individual Reflexivity	mean	0.12	0.12	0.06	0.06	0.06	0.00	0.00
	stdv	0.33	0.49	0.24	0.24	0.24	0.00	0.00
GR - Group Reflexivity	mean	0.24	0.29	0.06	0.06	0.12	0.00	0.00
	stdv	0.56	0.59	0.24	0.24	0.49	0.00	0.00

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 28 Means and standard deviations for Basic Task Mastery commander shift 1 to shift 8.

ANOVA results show that the mean number of Basic Task Mastery changes over time ($F(3.17, 323.42) = 6.60$, $p < .01$). There is no interaction of shifts and experimental conditions ($F(19.03, 323.42) = 1.29$, $p = .19$). Overall the means of Basic Task Mastery differ for different experimental conditions ($F(6, 102) = 2.48$, $p = .03$). Contrast analyses show that shift 1, shift 2 and shift 3 differ statistically significant from shift 8 ($F_{\text{shift 1 - 8}}(1, 102) = 14.60$, $p < .01$, $F_{\text{shift 2 - 8}}(1, 102) = 10.10$, $p < .01$, $F_{\text{shift 3 - 8}}(1, 102) = 4.56$, $p = .04$).

Especially commanders of the Base Condition have some troubles to fulfill the Basic Task Mastery on day one (shift 1 to shift 3). From shift 4 to shift 8 almost all commanders mastered the basic requirements of the task, the mean goes towards 0.

Means, Standard deviations and ANOVA results for the frequency of Basic Task Mastery Specialist A shift 1 to shift 8

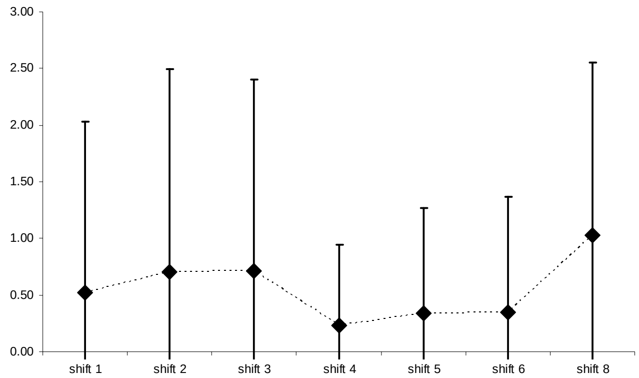
Basic Task Mastey specialist A is an index representing the minimal competencies and behaviors that ensure that a specialis A understood the fundamental role specific task requirements. Lower values of Basic Task Mastery stand for a better mastery of the basic task requirements.

The mean of Basic Task Mastery of specialists A is between 0 and 2 on average. The lowest mean is found for specialists A of the Group Reflexivity condition in shift 4 (mean = 0), the highest mean for specialists A of the Goal condition in shift 3 (mean = 2.33). See Table 42 and Figure 29.

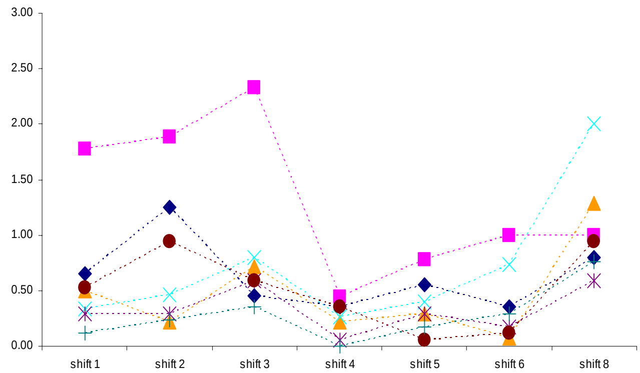
Table 42 Means and standard deviations for Basic Task Mastery specialist A shift 1 to shift 8.

BTMA_S1 BTMA_s1: Basic Task Mast		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	0.52	0.71	0.72	0.23	0.34	0.35	1.03
	stdv	1.51	1.79	1.69	0.72	0.93	1.02	1.52
BC - Base Condition	mean	0.65	1.25	0.45	0.35	0.55	0.35	0.80
	stdv	1.63	1.94	1.00	1.18	1.43	0.93	1.67
Goal	mean	1.78	1.89	2.33	0.44	0.78	1.00	1.00
	stdv	3.63	3.79	4.27	1.01	1.39	1.58	1.58
CHAT	mean	0.50	0.21	0.71	0.21	0.29	0.07	1.29
	stdv	1.34	0.58	1.07	0.43	0.61	0.27	1.59
CC-1 - Control Condition 1	mean	0.33	0.47	0.80	0.27	0.40	0.73	2.00
	stdv	0.62	0.64	1.26	0.80	1.06	1.91	1.85
CC-2 - Control Condition 2	mean	0.29	0.29	0.59	0.06	0.29	0.18	0.59
	stdv	0.59	0.69	1.23	0.24	0.69	0.53	1.12
IR - Individual Reflexivity	mean	0.53	0.94	0.59	0.35	0.06	0.12	0.94
	stdv	1.46	2.54	1.70	0.61	0.24	0.33	1.43
GR - Group Reflexivity	mean	0.12	0.24	0.35	0.00	0.18	0.29	0.76
	stdv	0.33	0.75	0.70	0.00	0.53	0.77	1.20

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 29 Means and standard deviations for Basic Task Mastery specialist A shift 1 to shift 8.

ANOVA results show that the mean of Basic Task Mastery changes over time (F(3.06, 311.88) = 7.20, p < .01). There is no interaction of shifts and experimental conditions (F(18.35, 311.88) = 1.29, p = .71). Overall the means of Basic Task Mastery do not differ for different experimental conditions (F(6, 102) = 1.74, p = .12). Contrast analyses show that shift 1, shift 4, shift 5, and shift 6 differ statistically significant from shift 8 (weakest effect $F_{\text{shift 1 - 8}}$ (1, 102) = 4.80, p < .03, strongest effect $F_{\text{shift 4 - 8}}$ (1, 102) = 25.89, p < .01).

Basic Task Mastery of specialists A is best in shift 4, shift 5 and shift 6 on day two but it gets worse in shift 8. On day one Basic Task Mastery is in shift 2 and shift 3 as high as in shift 8.

Means, Standard deviations and ANOVA results for the frequency of Basic Task Mastery Specialist B shift 1 to shift 8

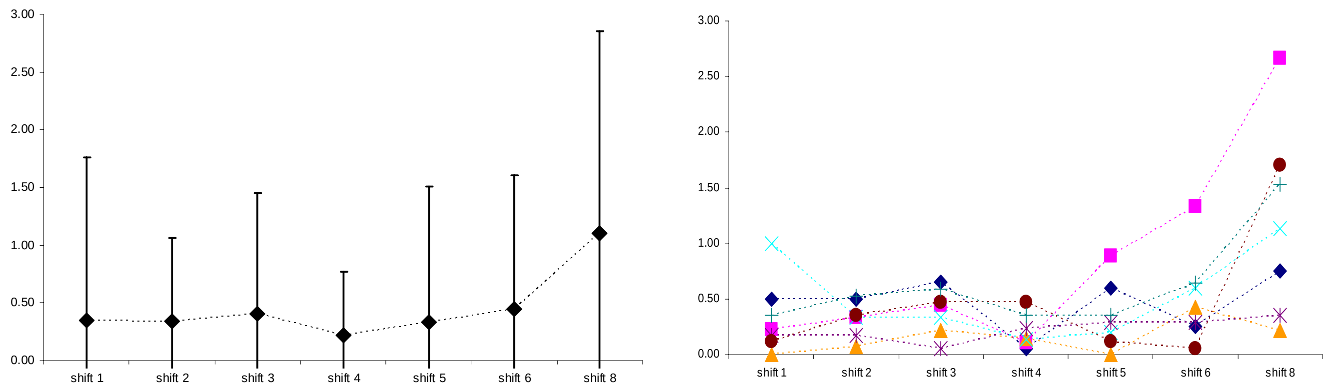
Basic Task Mastery specialist B is an index representing the minimal competencies and behaviors that ensure that a specialist B understood the fundamental role specific task requirements. Lower values of Basic Task Mastery stand for a better mastery of the basic task requirements.

The mean of Basic Task Mastery of specialists B is between 0 to 3 on average. The lowest mean is found for specialists B of the CHAT condition in shift 1 and shift 5 (mean = 0), the highest mean for specialists B of the Goal condition in shift 8 (mean = 2.67). See Table 43 and Figure 30.

Table 43 Frequencies and standard deviations for initiated event: Handle Threat commander shift 1 to shift 8.

BTMB_S1 BTMB_s1: Basic Task Mast		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	0.35	0.34	0.40	0.22	0.33	0.45	1.10
	stdv	1.41	0.72	1.05	0.55	1.18	1.16	1.75
BC - Base Condition	mean	0.50	0.50	0.65	0.05	0.60	0.25	0.75
	stdv	1.28	1.00	1.79	0.22	1.88	0.72	1.33
Goal	mean	0.22	0.33	0.44	0.11	0.89	1.33	2.67
	stdv	0.44	0.71	1.01	0.33	1.96	2.18	2.24
CHAT	mean	0.00	0.07	0.21	0.14	0.00	0.43	0.21
	stdv	0.00	0.27	0.58	0.36	0.00	1.34	0.43
CC-1 - Control Condition 1	mean	1.00	0.33	0.33	0.13	0.20	0.60	1.13
	stdv	3.34	0.82	0.62	0.35	0.56	0.91	1.51
CC-2 - Control Condition 2	mean	0.18	0.18	0.06	0.24	0.29	0.29	0.35
	stdv	0.53	0.53	0.24	0.97	1.21	0.77	1.06
IR - Individual Reflexivity	mean	0.12	0.35	0.47	0.47	0.12	0.06	1.71
	stdv	0.33	0.70	0.72	0.51	0.33	0.24	1.86
GR - Group Reflexivity	mean	0.35	0.53	0.59	0.35	0.35	0.65	1.53
	stdv	0.79	0.72	1.28	0.61	1.00	1.58	2.45

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.

Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 30 Means and standard deviations for Basic Task Mastery specialist B shift 1 to shift 8.

ANOVA results show that the mean of Basic Task Mastery changes over time (F(4.03, 410.55) = 10.15, p < .01). There is an interaction of shifts and experimental conditions (F(24.15, 410.55) = 1.60, p = .37). Overall the means of Basic Task Mastery do not differ for different experimental conditions (F(6, 102) = 1.74, p = .12). Contrast analyses show, that the Basic Task Mastery is constant form shift 1 to shift 6, going up in shift 8. All shifts differ statistically significant from shift 8 (weakest effect $F_{\text{shift 6 - 8}}$ (1, 102) = 16.75, p < .01, strongest effect $F_{\text{shift 4 - 8}}$ (1, 102) = 30.67, p < .01).

Specialists B have good Task Adaptive Behaviors from shift 1 to shift 6. In shift 8 the values go up, which means that the Basic Task Mastery gets worse. There are no differences between the experimental conditions.

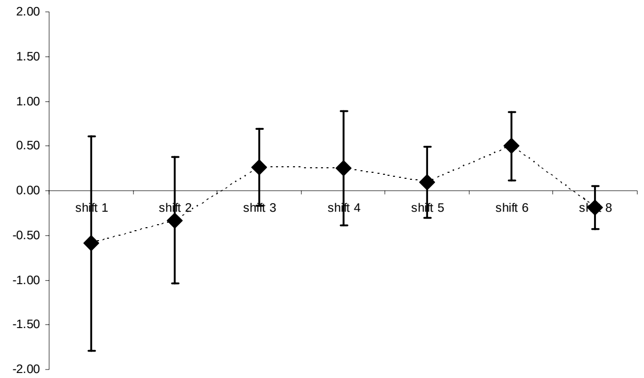
Means, Standard deviations and ANOVA results for the frequency of Plane Handling Commander shift 1 to shift 8

Plane Hanling commander is an index representing the task to observe planes and to set their threat level. The mean of Plane Handling of commanders is between -1.4 to 0.7 on average. The lowest mean is found for commanders of the Base Condition in shift 1 (mean = -1.43), the highest mean for commanders of the Goal condition in shift 6 (mean = 0.74). See Table 44 and Figure 31.

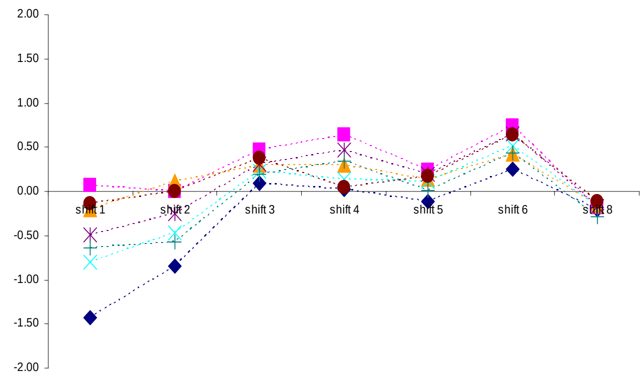
Table 44 Means and standard deviations for Plane Handling commander shift 1 to shift 8.

PLHC_S1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	-0.59	-0.33	0.26	0.25	0.09	0.50	-0.19
	stdv	1.20	0.71	0.43	0.64	0.40	0.38	0.24
BC - Base Condition	mean	-1.43	-0.84	0.10	0.02	-0.11	0.25	-0.21
	stdv	1.52	0.87	0.35	0.62	0.46	0.50	0.26
Goal	mean	0.07	0.00	0.47	0.64	0.24	0.74	-0.18
	stdv	0.63	0.29	0.28	0.65	0.43	0.25	0.25
CHAT	mean	-0.20	0.11	0.30	0.29	0.14	0.42	-0.16
	stdv	1.58	0.49	0.53	0.73	0.32	0.41	0.14
CC-1 - Control Condition 1	mean	-0.80	-0.47	0.23	0.14	0.12	0.51	-0.18
	stdv	1.13	0.79	0.52	0.37	0.42	0.31	0.41
CC-2 - Control Condition 2	mean	-0.49	-0.25	0.31	0.46	0.20	0.65	-0.17
	stdv	0.77	0.52	0.44	0.48	0.27	0.24	0.16
IR - Individual Reflexivity	mean	-0.14	0.00	0.38	0.05	0.17	0.64	-0.12
	stdv	0.57	0.41	0.35	0.83	0.38	0.26	0.15
GR - Group Reflexivity	mean	-0.64	-0.57	0.20	0.35	0.02	0.44	-0.28
	stdv	1.12	0.70	0.46	0.59	0.43	0.38	0.23

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ◆) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 31 Means and standard deviations for Plane Handling commander shift 1 to shift 8.

ANOVA results show that the mean number Plane Handling changes over time ($F(2.61, 265.94) = 52.49$, $p < .01$). There is an interaction of shifts and experimental conditions ($F(15.63, 265.94) = 2.18$, $p = .01$). Overall the means of Plane Handling differ for different experimental conditions ($F(6, 102) = 4.22$, $p < .01$). Contrast analyses show that all shifts differ from shift 8, expect shift 2 (weakest effect $F_{\text{shift 1 - 8}}(1, 102) = 3.17$, $p < .01$, strongest effect $F_{\text{shift 3 - 8}}(1, 102) = 129.87$, $p < .01$).

Plane Handling of commanders gets better until shift 6 and then drops back to the level already achieved in shift 2. Interaction effects are due to the Base Condition. Here the mean in Plane Handling is in shift 1 and shift 2 remarkably low.

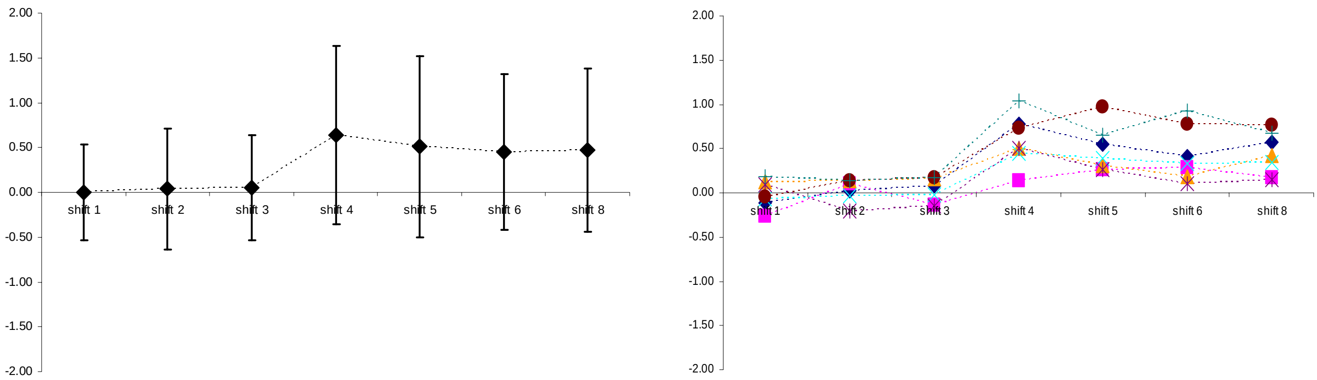
Means, Standard deviations and ANOVA results for the frequency of Plane Handling Specialist A shift 1 to shift 8

Plane Hanling specialist A is an index representing the task to observe planes and to set their threat level. The mean of Plane Handling of specialists A is between -0.3 and 1 on average. The lowest mean is found for specialists A of the Goal condition in shift 1 (mean = -0.26), the highest mean for specialists A of the Group Reflexivity condition in shift 6 (mean = 1.04). See Table 45 and Figure 32.

Table 45 Means and standard deviations for Plane Handling specialist A shift 1 to shift 8.

PLHA_S1 PLHA_s1: plane handling sp		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	0.00	0.04	0.05	0.64	0.51	0.45	0.47
	stdv	0.53	0.68	0.59	0.99	1.01	0.86	0.91
BC - Base Condition	mean	-0.11	0.02	0.08	0.78	0.55	0.41	0.58
	stdv	0.43	0.63	0.62	1.28	0.92	0.87	1.20
Goal	mean	-0.26	0.10	-0.14	0.14	0.27	0.29	0.17
	stdv	0.71	1.14	0.46	0.49	0.81	0.60	0.60
CHAT	mean	0.13	0.14	0.16	0.51	0.31	0.18	0.42
	stdv	0.82	0.57	0.66	0.54	0.73	0.50	1.01
CC-1 - Control Condition 1	mean	-0.07	-0.03	-0.02	0.44	0.38	0.33	0.35
	stdv	0.52	0.55	0.38	0.60	0.77	0.67	0.78
CC-2 - Control Condition 2	mean	0.09	-0.21	-0.15	0.51	0.27	0.11	0.15
	stdv	0.38	0.29	0.24	0.93	1.14	0.50	0.63
IR - Individual Reflexivity	mean	-0.05	0.14	0.17	0.74	0.97	0.78	0.76
	stdv	0.47	0.66	0.79	1.18	1.46	1.23	0.99
GR - Group Reflexivity	mean	0.18	0.13	0.17	1.04	0.65	0.92	0.68
	stdv	0.42	0.92	0.70	1.17	0.91	1.02	0.79

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.

Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 32 Means and standard deviations for Plane Handling specialist A shift 1 to shift 8.

ANOVA results show that the mean of Plane Handling changes over time ($F(3.67, 374.68) = 21.60$, $p < .01$). There is an interaction of shifts with experimental condition ($F(22.04, 374.68) = 1.10$, $p < .01$). Overall the means of Plane Handling do not differ for different experimental conditions ($F(6, 102) = 1.23$, $p = .30$). Contrast analyses show that shift 1, shift 2, and shift 3 differ from shift 8, but not shift 4, shift 5, and shift 6 ($F_{\text{shift 1 - 8}}(1, 102) = 27.08$, $p < .01$, $F_{\text{shift 2 - 8}}(1, 102) = 21.51$, $p < .01$, $F_{\text{shift 3 - 8}}(1, 102) = 26.60$, $p < .01$).

Plane Handling of specialists A is better on day two than on day one. But it is constant on each day. On day two Plane Handling of specialists A of the Goal condition is remarkably lower than the Plane Handling of specialists A of the Control Condition 1.

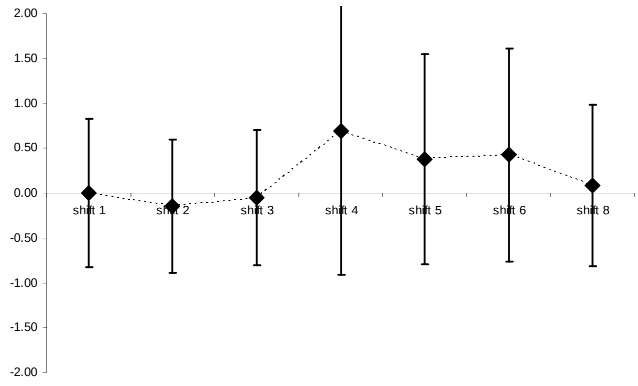
Means, Standard deviations and ANOVA results for the frequency of Plane Handling Specialist B shift 1 to shift 8

Plane Hanling specialist B is an index representing the task to observe planes and to set their threat level. The mean of Plane Handling of specialists B is between -0.3 and 1 on average. The lowest mean is found for specialists A of the Goal condition in shift 1 (mean = -0.26), the highest mean for specialists A of the Group Reflexivity condition in shift 6 (mean = 1.04). See Table 46 and Figure 33.

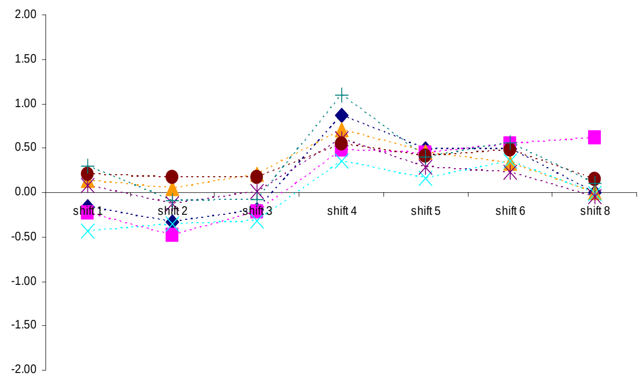
Table 46 Means and standard deviations for Plane Handling specialist B shift 1 to shift 8.

PLHB_S1 PLHB_s1: plane handling sp		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	0.00	-0.15	-0.05	0.69	0.38	0.43	0.08
	stdv	0.83	0.75	0.75	1.60	1.17	1.19	0.90
BC - Base Condition	mean	-0.16	-0.33	-0.20	0.87	0.49	0.49	0.00
	stdv	0.75	0.68	0.68	1.63	1.23	1.33	0.72
Goal	mean	-0.22	-0.48	-0.21	0.48	0.45	0.55	0.62
	stdv	0.70	0.48	0.43	0.86	1.09	1.19	1.43
CHAT	mean	0.14	0.04	0.20	0.71	0.46	0.33	0.00
	stdv	0.75	0.89	0.84	1.07	1.09	1.05	0.67
CC-1 - Control Condition 1	mean	-0.43	-0.35	-0.32	0.35	0.16	0.36	-0.01
	stdv	0.86	0.76	0.69	1.85	1.43	1.62	1.38
CC-2 - Control Condition 2	mean	0.08	-0.13	0.02	0.60	0.29	0.23	-0.05
	stdv	0.66	0.61	0.53	1.09	0.94	0.76	0.66
IR - Individual Reflexivity	mean	0.20	0.17	0.17	0.55	0.41	0.48	0.15
	stdv	0.79	0.84	0.93	1.07	0.83	0.69	0.49
GR - Group Reflexivity	mean	0.30	-0.09	-0.08	1.10	0.41	0.56	0.10
	stdv	1.07	0.76	0.92	2.66	1.57	1.53	0.97

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 33 Means and standard deviations for Plane Handling specialist B shift 1 to shift 8.

ANOVA results show that the mean of Plane Handling changes over time (F(3.67, 374.68) = 21.60, p < .01). There is an interaction of shifts and experimental conditions (F(22.04, 374.68) = 1.10, p < .01). Overall the means of Plane Handling do not differ for different experimental conditions (F(6, 102) = 1.23, p = .30). Contrast analyses show that shift 1, shift 2, and shift 3 differ from shift 8, but not shift 4, shift 5, and shift 6 ($F_{\text{shift 1 - 8}}$ (1, 102) = 27.08, p < .01, $F_{\text{shift 2 - 8}}$ (1, 102) = 21.51, p < .01, $F_{\text{shift 3 - 8}}$ (1, 102) = 26.60, p < .01).

Plane Handling of specialists B is better on day two than on day one. It is constant on day one, has the highest mean in shift 4 and then goes constantly down. On day two Plane Handling of specialists B of the Goal condition is remarkably lower than the Plane Handling of specialists B of the Control Condition 1. Specialist B of the Goal condition have on day one the lowest mean in Plane Handling, on day two they have a mean which is often the highest compared to the other experimental conditions.

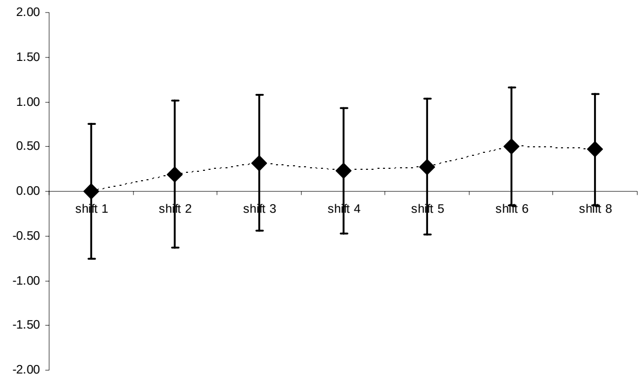
Means, Standard deviations and ANOVA results for the frequency of Message Handling Commander shift 1 to shift 8

Message Handlingcommander is an index representing a good message handling. The mean of Message Handling of commanders is between -0.4 and 0.9 on average. The lowest mean is found for commanders of the Base Condition in shift 1 (mean = -0.38), the highest mean for commanders of the Base Condition in shift 6 (mean = 0.87). See Table 47 and Figure 34.

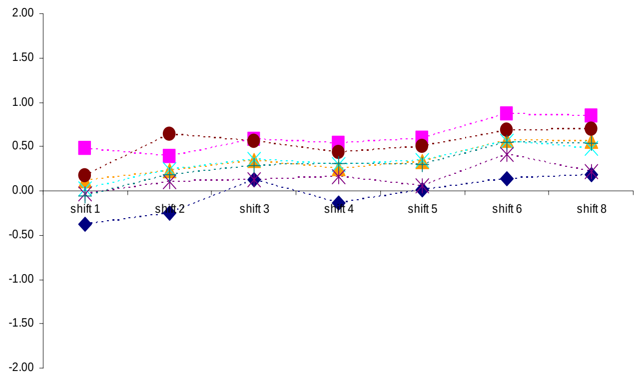
Table 47 Means and standard deviations Message Handling commander shift 1 to shift 8.

MSHC_S1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	0.00	0.19	0.32	0.23	0.27	0.51	0.47
	stdv	0.76	0.83	0.76	0.70	0.76	0.66	0.63
BC - Base Condition	mean	-0.38	-0.25	0.13	-0.14	0.01	0.14	0.18
	stdv	0.90	0.93	0.73	0.81	0.76	0.69	0.44
Goal	mean	0.48	0.39	0.58	0.54	0.59	0.87	0.85
	stdv	0.74	0.82	0.66	0.79	0.67	0.65	0.58
CHAT	mean	0.11	0.23	0.34	0.26	0.33	0.57	0.56
	stdv	0.81	0.91	0.84	0.77	0.96	0.79	0.71
CC-1 - Control Condition 1	mean	0.02	0.24	0.35	0.29	0.34	0.56	0.48
	stdv	0.94	0.65	0.83	0.56	0.69	0.67	0.75
CC-2 - Control Condition 2	mean	-0.04	0.11	0.13	0.16	0.05	0.41	0.21
	stdv	0.56	0.71	0.72	0.44	0.69	0.49	0.59
IR - Individual Reflexivity	mean	0.18	0.64	0.56	0.43	0.51	0.69	0.70
	stdv	0.39	0.49	0.57	0.63	0.68	0.58	0.53
GR - Group Reflexivity	mean	-0.05	0.18	0.29	0.31	0.30	0.55	0.54
	stdv	0.71	0.98	0.90	0.75	0.78	0.61	0.63

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 34 Means and standard deviations for Message Handling commander shift 1 to shift 8.

ANOVA results show that the mean number of Message Handling changes over time (F(3.73, 380.36) = 14.95, p < .01). There is no interaction of shifts and experimental conditions (F(22.37, 380.36) = 0.47, p = .98). Overall the means of Message Handling differ for different experimental conditions (F(6, 102) = 2.21, p = .05). Contrast analyses show that all shifts expect shift 7 have a lower Message Handling than shift 8 (weakest effect $F_{\text{shift 3 - 8}}$ (1, 102) = 6.89, p = .01, strongest effect $F_{\text{shift 1 - 8}}$ (1, 102) = 32.73, p < .01). Contrast analyses show also that compared to the Grand

Mean of Message Handling (mean = 0.32) only commanders of the Base Condition have significantly lower means (mean = 0.05).

Means of Message Handling of commanders are highest in shift 8. Overall commanders of the Base Condition have the lowest means in Message Handling.

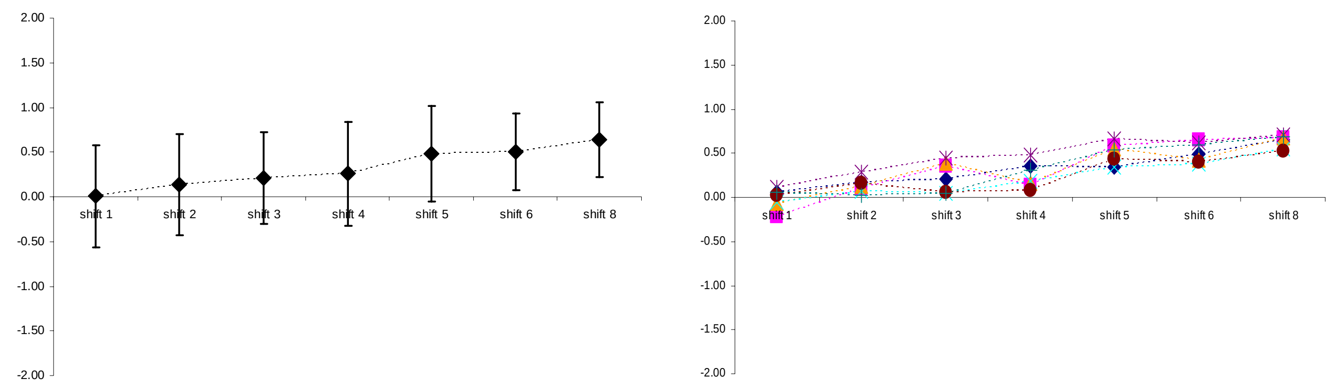
Means, Standard deviations and ANOVA results for the frequency of Message Handling Specialist A shift 1 to shift 8

Message Handling specialist A is an index representing a good message handling. The mean of Message Handling of specialists A is between -0.2 and 0.7 on average. The lowest mean is found for commanders of the Goal condition in shift 1 (mean = -0.22), the highest mean for commanders of the Control Condition 2 in shift 6 (mean = 0.71). See Table 48 and Figure 35.

Table 48 Frequencies and standard deviations for initiated event: Handle Threat commander shift 1 to shift 8.

MSHA_S1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	0.01	0.14	0.21	0.26	0.48	0.50	0.64
	stdv	0.57	0.56	0.51	0.58	0.53	0.43	0.42
BC - Base Condition	mean	0.06	0.17	0.20	0.35	0.34	0.49	0.65
	stdv	0.57	0.56	0.42	0.45	0.75	0.54	0.40
Goal	mean	-0.22	0.11	0.35	0.13	0.58	0.65	0.68
	stdv	0.60	0.49	0.34	0.76	0.21	0.26	0.33
CHAT	mean	-0.07	0.13	0.39	0.16	0.55	0.42	0.68
	stdv	0.73	0.63	0.22	0.50	0.34	0.43	0.35
CC-1 - Control Condition 1	mean	-0.06	0.07	0.05	0.19	0.34	0.37	0.55
	stdv	0.57	0.54	0.51	0.52	0.64	0.57	0.59
CC-2 - Control Condition 2	mean	0.11	0.29	0.44	0.47	0.67	0.61	0.71
	stdv	0.50	0.43	0.39	0.37	0.28	0.30	0.34
IR - Individual Reflexivity	mean	0.02	0.16	0.06	0.08	0.44	0.41	0.53
	stdv	0.50	0.67	0.67	0.71	0.50	0.33	0.48
GR - Group Reflexivity	mean	0.06	0.03	0.04	0.31	0.53	0.59	0.69
	stdv	0.56	0.64	0.67	0.74	0.60	0.41	0.39

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.

Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ∗) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 35 Means and standard deviations for Message Handling specialist A shift 1 to shift 8.

ANOVA results show that the Message Handling changes over time (F(4.41, 449.33) = 31.33, p < .01). There is no interaction of shifts and experimental conditions (F(26.43, 449.33) = 0.72, p = .85). Overall the means of Message Handling do not differ for different experimental conditions (F(6, 102) = 0.95, p = .46). Contrast analyses show that all shifts have a lower mean than shift 8 (weakest effect $F_{\text{shift } 5-8}$ (1, 102) = 11.22, p < .01, strongest $F_{\text{shift } 1-8}$ (1, 102) = 105.34, p < .01).

Means of Message Handling of specialists A constantly go up from shift 1 to shift 8. There are no overall mean differences between the experimental conditions.

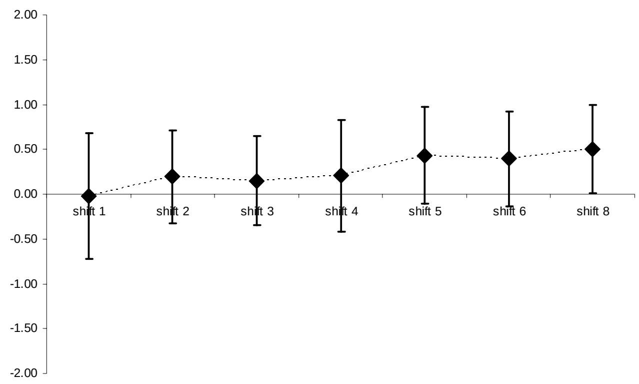
Means, Standard deviations and ANOVA results for the frequency of Message Handling Specialist B shift 1 to shift 8

Message Handling specialist B is an index representing a good message handling. The mean of Message Handling of specialists B is between -0.2 and 0.8 on average. The lowest mean is found for specialists B of the Base Condition in shift 1 (mean = -0.21), the highest mean for specialists B of the Goal condition in shift 8 (mean = 0.80). See Table 49 and Figure 36.

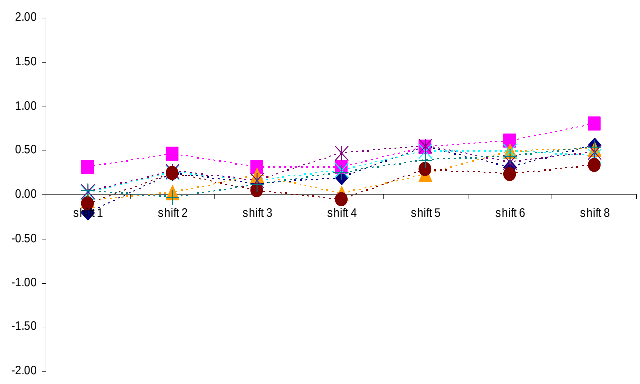
Table 49 Frequencies and standard deviations for initiated event: Handle Threat commander shift 1 to shift 8.

MSHB_S1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	-0.02	0.19	0.15	0.20	0.43	0.40	0.50
	stdv	0.70	0.52	0.50	0.62	0.54	0.53	0.49
BC - Base Condition	mean	-0.21	0.24	0.12	0.19	0.54	0.31	0.56
	stdv	1.14	0.57	0.63	0.58	0.55	0.74	0.43
Goal	mean	0.31	0.46	0.31	0.31	0.53	0.61	0.80
	stdv	0.37	0.34	0.34	0.84	0.50	0.29	0.27
CHAT	mean	-0.06	0.02	0.21	0.01	0.22	0.49	0.52
	stdv	0.53	0.56	0.45	0.50	0.46	0.37	0.39
CC-1 - Control Condition 1	mean	0.02	0.25	0.16	0.28	0.49	0.49	0.43
	stdv	0.41	0.46	0.46	0.36	0.33	0.36	0.41
CC-2 - Control Condition 2	mean	0.03	0.26	0.16	0.47	0.55	0.37	0.48
	stdv	0.54	0.33	0.57	0.34	0.41	0.51	0.46
IR - Individual Reflexivity	mean	-0.10	0.24	0.05	-0.06	0.29	0.23	0.33
	stdv	0.71	0.53	0.49	0.94	0.87	0.59	0.76
GR - Group Reflexivity	mean	0.04	-0.04	0.12	0.25	0.39	0.43	0.54
	stdv	0.63	0.62	0.44	0.59	0.45	0.53	0.46

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 36 Means and standard deviations for Message Handling specialist B shift 1 to shift 8.

ANOVA results show that the Message Handling changes over time (F(4.00, 407.51) = 18.05, p < .01). There is no interaction of shifts with the experimental conditions (F(23.97, 407.51) = 0.92, p = .57). Overall the means of Message Handling do not differ for different experimental conditions (F(6, 102) = 0.91, p = .51). Contrast analyses show that all shifts, expect shift 5, have a lower mean than shift 8 (weakest effect $F_{\text{shift } 6-8}$ (1, 102) = 5.49, p = .21, strongest effect $F_{\text{shift } 3-8}$ (1, 102) = 49.26, p < .01).

Means of Message Handling of specialists B go up from shift 1 to shift 8, although the means in shift 2, shift 3 and shift 4 are the same. There are no overall mean differences between the experimental conditions.

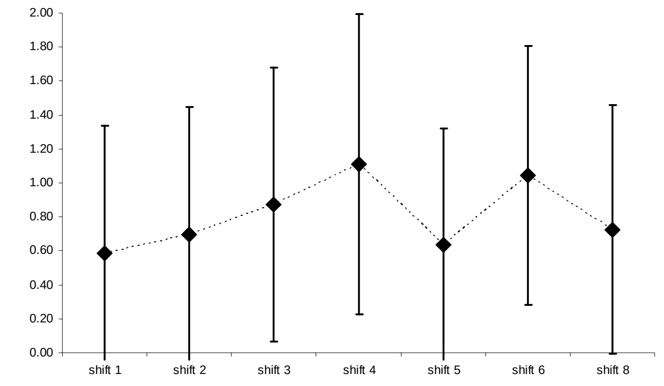
Means, Standard deviations and ANOVA results for the frequency of Strategic Leadership Commander shift 1 to shift 8

Strategic Leadership commander is an index representing commanders taking seriously their task-related leader-ship function and using their additional knowledge to gear the process by means of communicating critical information to the specialists and to teach them more complex strategies. The mean of Strategic Leadership of commanders is between 0.2 and 1.9 on average. The lowest mean is found for commanders of the Control Condition 2 in shift 1 (mean = 0.18), the highest mean for commanders of the Individual Reflexivity condition in shift 4 (mean = 1.94). See Table 50 and Figure 37.

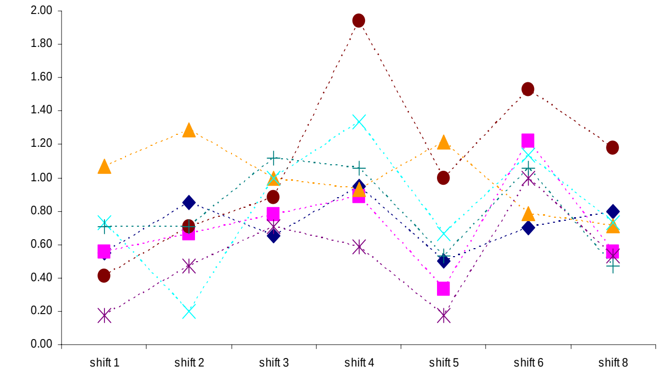
Table 50 Means and standard deviations for Strategic Leadership commander shift 1 to shift 8.

STLC_S1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	0.59	0.70	0.87	1.11	0.63	1.05	0.72
	stdv	0.75	0.75	0.81	0.89	0.69	0.76	0.73
BC - Base Condition	mean	0.55	0.85	0.65	0.95	0.50	0.70	0.80
	stdv	0.60	0.81	0.81	0.89	0.61	0.57	0.70
Goal	mean	0.56	0.67	0.78	0.89	0.33	1.22	0.56
	stdv	0.73	0.71	0.83	0.78	0.50	0.44	0.53
CHAT	mean	1.07	1.29	1.00	0.93	1.21	0.79	0.71
	stdv	1.00	0.91	0.68	0.73	0.70	0.80	0.47
CC-1 - Control Condition 1	mean	0.73	0.20	1.00	1.33	0.67	1.13	0.73
	stdv	0.88	0.41	0.85	0.72	0.62	0.74	0.80
CC-2 - Control Condition 2	mean	0.18	0.47	0.71	0.59	0.18	1.00	0.53
	stdv	0.39	0.62	0.69	0.80	0.39	0.61	0.62
IR - Individual Reflexivity	mean	0.41	0.71	0.88	1.94	1.00	1.53	1.18
	stdv	0.62	0.77	0.86	0.90	0.71	0.94	1.07
GR - Group Reflexivity	mean	0.71	0.71	1.12	1.06	0.53	1.06	0.47
	stdv	0.77	0.59	0.93	0.75	0.72	0.83	0.51

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ✱) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 37 Means and standard deviations for Strategic leadership commander shift 1 to shift 8.

ANOVA results show that the Strategic Leadership changes over time (F(5.25, 535.92) = 11.06, p < .01). There is an interaction of shifts and experimental conditions (F(31.53, 535.92) = 2.82, p < .01). Overall the means of Strategic Leadership differ for different experimental conditions (F(6, 102) = 2.86, p = .01). Contrast analyses show that in shift 4, and shift 6 Strategic Leadership is higher than in shift 8 ($F_{\text{shift } 4-8}$ (1, 102) = 17.76, p = .< .01, $F_{\text{shift } 6-8}$ (1, 102) = 18.77, p < .01). In these two shifts especially commanders of the Individual Reflexivity condition have a high mean of Strategic Leadership. Contrast analyses also show that compared to the grand mean of Strategic leadership (mean = 0.81) only commanders of the Control Condition 2 have significantly lower values (mean = 0.63).

The means for Strategic Leadership of commanders are highest in shift 4 and shift 6. Especially commanders of the Individual Reflexivity condition have very high means for Strategic Leadership in shift 4, but also in shift 6.

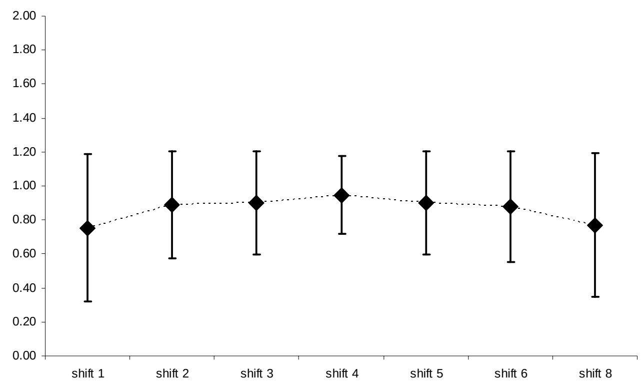
Means, Standard deviations and ANOVA results for the frequency of Motivational and Corrective Leadership Commander shift 1 to shift 8

Motivational and Corrective Leadership commander is an index representing commanders taking seriously their relationship-orientated leadership function. The mean of Motivational and Corrective Leadership of commanders is between 0.7 and 1.0 on average. The lowest mean is found for commanders of the Individual Reflexivity condition in shift 1 (mean = 0.65), the highest mean of 1 is found for commanders of the Goal condition in shift 2, the CHAT condition shift 2 to shift 5, the Control condition 1 in shift 4, the Group Reflexivity in shift 2. See Table 51 and Figure 38.

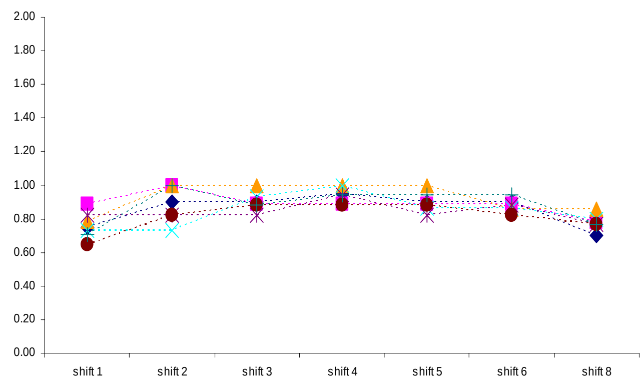
Table 51 Means and standard deviations for Motivational and Corrective Leadership commander shift 1 to shift 8.

MCLC_S1		shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
all teams	mean	0.75	0.89	0.90	0.94	0.90	0.88	0.77
	stdv	0.43	0.31	0.30	0.23	0.30	0.33	0.42
BC - Base Condition	mean	0.75	0.90	0.90	0.95	0.90	0.90	0.70
	stdv	0.44	0.31	0.31	0.22	0.31	0.31	0.47
Goal	mean	0.89	1.00	0.89	0.89	0.89	0.89	0.78
	stdv	0.33	0.00	0.33	0.33	0.33	0.33	0.44
CHAT	mean	0.79	1.00	1.00	1.00	1.00	0.86	0.86
	stdv	0.43	0.00	0.00	0.00	0.00	0.36	0.36
CC-1 - Control Condition 1	mean	0.73	0.73	0.93	1.00	0.87	0.87	0.80
	stdv	0.46	0.46	0.26	0.00	0.35	0.35	0.41
CC-2 - Control Condition 2	mean	0.82	0.82	0.82	0.94	0.82	0.88	0.76
	stdv	0.39	0.39	0.39	0.24	0.39	0.33	0.44
IR - Individual Reflexivity	mean	0.65	0.82	0.88	0.88	0.88	0.82	0.76
	stdv	0.49	0.39	0.33	0.33	0.33	0.39	0.44
GR - Group Reflexivity	mean	0.71	1.00	0.88	0.94	0.94	0.94	0.76
	stdv	0.47	0.00	0.33	0.24	0.24	0.24	0.44

Note. N = 109 teams; N(BC) = 20, N (Goal) = 9, N(CHAT) = 14, N(CC-1) = 15, N(CC-2) = 17, N(IR) = 17, N(GR) = 17



Note. Lines indicate mean +/- standard deviation. N = 109 teams.



Note. Estimated marginal means. N = 109 teams; N(BC ♦) = 20, N (Goal ■) = 9, N(CHAT ▲) = 14, N(CC-1 ×) = 15, N(CC-2 ∗) = 17, N(IR ●) = 17, N(GR +) = 17.

Figure 38 Means and standard deviations for Motivational and Corrective Leadership commander shift 1 to shift 8.

ANOVA results show that the Motivational and Corrective Leadership is changing over time ($F(4.64, 473.44) = 5.03$, $p < .01$). There is no interaction of shifts with experimental conditions ($F(27.85, 473.44) = 0.49$, $p < .99$). Overall the means of Motivational and Corrective Leadership do not differ for different experimental conditions ($F(6, 102) = 0.60$, $p = .73$). Contrast analyses show that all shifts, expect shift 1 have a higher Strategic and Motivational Leadership than shift 8 (weakest effect $F_{\text{shift } 2-8}$ (1, 102) = 5.48, p = .21, highest effect $F_{\text{shift } 4-8}$ (1, 102) = 13.79, p < .01).

Motivational and Corrective Leadership of commanders is highest from shift 2 to shift 6, lowest in shift 1 and shift 8. There are no differences between the experimental conditions.

Review of the Research Questions to Process Variables: Task Adaptive Behavior

TAB I. Basic Task Mastery of commanders and specialists is expected to be highest on day one (the higher the value the worse!) and has no more significance on day two.

As expected, commanders in later shifts have less troubles with the Basic Task Mastery. From shift 1 to shift 8 commanders get constantly better. Commanders of the Base Condition have most troubles with Basic Task Mastery.
All in all specialists have more trouble with the Basic Task Mastery than commanders. Specialists A of the Goal Condition have the poorest Basic Task Mastery of all specialists A on day one. In shift 8 all specialists A and B have more trouble with the Basic Task Mastery than in the preceding shifts. Thus Basic Task Mastery is still important on day two, especially if there are many more planes to observe as in shift 8.

TAB II. Plane Handling should become better from shift to shift and have the highest value in shift 8, for commanders as well as for specialists.

Plane Handling gets better for commanders from shift 1 to shift 6 but goes dramatically back in shift 8. For specialists A and B the Plane Handling is better on day two than on day one, but there is also a decline in shift 8. Again shift 8 distorts the picture – Plane Handling only gets better from shift to shift if the complexity of the task is stable.

TAB III. Message Handling also should become better from shift to shift, having the highest value in shift 8, for commanders and specialists.

Here the expected effect is found: Message Handling of commanders and specialists gets constantly better from shift 1 to shift 8.

TAB VI. Strategic Leadership of commanders should be present right from the beginning, reaching its peak around shift 4 when there is a greater familiarity with the task then in the first shifts.

It is found that Strategic Leadership is in fact lower in shift 1 or shift 2 than in most other shifts. There are two interesting effects of the experimental conditions. In shift 2 and shift 5 commanders of the Chat Condition have far more Strategic Leadership than all other commanders. And commanders of the Individual Reflexivity Condition show a lot of Strategic Leadership in shift 4 (the shift just after they reflected upon the task on their own). Although the value goes back for the commanders of the Individual Reflexivity Condition in shift 5, shift 6 and shift 8 it remains one of the highest values.

TAB VII. Motivational and Corrective Leadership is a rarely done. No differences between different experimental conditions and no time effects are expected.

One could say that the Motivational and Corrective Leadership is stable – if there would be no shift 1 and no shift 8. In the first and last shift the Motivational and Corrective Leadership is lowest.

The result of all ANOVA analyses are summarized in Table 52 showing significant main effects and interaction effects.

Table 52 Summary of ANOVA (GLM repeated) analyses for summary-level process variables and task adaptive behaviors, shifts 1 to 8.

	changes over time	interaction shifts x experimental conditions	overall differences between experimental conditions
Basic Task Mastery commander	yes	no	yes
Basic Task Mastery specialist A	yes	no	no
Basic Task Mastery specialist B	yes	yes	no
Plane Handling commander	yes	yes	yes
Plane Handling specialist A	yes	yes	no
Plane Handling specialist B	yes	yes	no
Message Handling commander	yes	no	yes
Message Handling specialist A	yes	no	no
Message Handling specialist B	yes	no	no
Strategic Leadership Commander	yes	yes	yes
Motivational and Corrective Leadership Commander	yes	no	no

Note. N = 109 teams, changes over time = within subject effects, interaction shifts x experimental conditions = within subject contrasts, overall differences between experimental conditions = between subject effects, yes = statistically significat effect, no = no statistically sigificant effect.

8.5 Process Variables: Counting and Task Adaptive Behaviors – an overview of the results

The overview of the ANOVA (GLM repeated) analyses shows that all measures change over time – exceptions are the Read Message of specialists A and B. Different developments can be observed: (i) the Handle Threat of the commanders is increasing on day one, reaches its peak in shift 4 and then stays on the same level up to shift 8; (ii) the Read Message of commanders goes steadily up on day one, falls back in shift 4 and then goes up again, being in shift 4 and 5 on the same level as already in shift 3 and 4 or (iii) the Show Information of specialists A which has its lowest mean in shift 1 and then goes up constantly from shift to shift to reach the highest value in shift 8.

There are interactions of the shifts and the experimental conditions. For the *summary-level process* variables in 5 of 10 cases statistically significant interactions can be found. But its hard to find some regularity and to explain why this interactions emerge. For the *task adaptive behaviors* 5 of 11 cases show statistically significant interactions. For commanders and specialists A and specialists B interactions are found for Plane Handling.

Send Message commander is a *summary-level process* variable that changes over time, differentially for the experimental conditions and with an overall difference between the experimental conditions. It can be seen that commanders of the CHAT condition send more messages in shift 2 and shift 5 than they do in other shifts. In shift 2 and 5 they had additional five minutes time in the beginning of the shift without the need to observe additional dangerous planes. Commanders of the Goal condition send more messages on day one than on day two. This might well be an effect of the specific goal setting instruction which has an impact on the commanders behavior. And finally, commanders of the Base Condition have overall the lowest rate of Send Message.

Handle Threat is also a *summary-level process* variable that changes over time. Commanders of the Base Condition have the least number of Handle Threat per plane right from the beginning in shift 1 – although the difference to the other groups gets smaller in later shifts. Commanders of the Goal and Individual Reflexivity conditions have much higher numbers of Handle Threat already in shift 1. The value of the commanders of the Goal condition in shift 4 is remarkably high.

The *task adaptive behaviors* Plane Handling commander and Strategic Leadership commander are also changing over time, differentially for the experimental conditions and with an overall difference between the experimental conditions. Plane Handling commander has the same value for all experimental conditions in shift 8. But this is the only shift with no differences. In shift 1 and shift 2 commanders of the Base Condition have remarkably low Plane Handling values. Also in shift 5 they have the lowest values of all experimental conditions. Commanders of the Goal condition on the other side have the highest values. Strategic Leadership of the commander is a rare event, but it is done. The most remarkable finding is, that commanders of the Individual Reflexivity conditions have a very high value in shift 4. This is probably an impact of the reflexivity instruction, which forced commanders and specialists to reflect on their own on the task. The effect is striking: After 20 minutes of reflection they have to give strategic instructions to their subordinates. Again commanders of the CHAT condition show a higher activity in sending messages in shift 2 and shift 5 than they do in any other shift. It is also remarkable that commanders of the CHAT condition start already in shift 1 and shift 2 with more Strategic Leadership than commanders of all other experimental conditions.

The strongest effects can be found for commanders sending messages or setting the threat level of the planes. All in all these results show that the measures are sensible to changes over time and differentiate the experimental conditions.

8.6 Predicting Performance per Shift: Input Variables, Summary Level Process Variables, and Task Adaptive Behaviors

In the following chapters results of regression analyses are presented. The dependent variable is always the teams' performance per shift (as defined in chapter 6.7).

In a first model, input factors are used to predict the teams' performance per shift. A second model controls for the effects of the preceding performance. This is done by entering the mean performance of all preceding shifts in the first step of a sequential, hierarchical regression model (Tabachnick & Fidell, 2001). There are always two regression models calculated per shift.

These regressions models test how much variance in performance can be explained by input variables. The *input-process-output* model presented in chapter 4 is thus truncated to a *input-output* model. This model assumes that already the knowledge on the group composition helps to predict the groups' performance.

In a second set of regression analyses, information on the process is added to the regression models. Again, all regression are run per shift. The first regression model uses the frequencies of the behaviors (summary level process variables) as predictors of performance. In a second hierarchical regression model per shift it is controlled for the mean performance of all preceding shifts and for the effects of the input variables. This is done by entering these variables in a first step, summary-level process variables are then entered in a second step.

In a third set of regression analyses the information on the basic task mastery (cf. chapter 6.9) is added to the regression models.

This sequence of fifty-two regression analyses follows strictly the *input-process-output* model. First those measures are used to predict performance that are easily available. This is the information on the group composition. However, it is expected that adding information on the group process to the regression models results in a better prediction of the performance.

Information on summary-level process variables is used before the information on the task adaptive behaviors. Summary-level process variables are frequencies of coded events. Taking the coding scheme presented in chapter 6.8 (main categories:

Read Message, Send Message, Show Information, Handle Threat) these variables can be derived directly from the original log-file (cf. Table 16). The definition of the task adaptive behaviors are based on a task analyses. Much more effort has to be put in the definition of these variables. It is expected, that summary-level process variables as well as task adaptive behaviors contribute significantly to the prediction of the teams' performance.

As I argued in chapter 5 neither summary-level process variables nor task adaptive behavior variables represent the temporal organization of the group process. Thus, the discussion of the techniques allowing a sequential analyses of the group process (chapter 8.7 on lag sequential analyses, chapter 8.8 on procedural network representations, chapter 8.9 on data mining techniques) include a chapter in which results are presented that use measures on the sequential organization of the group process as predictors of performance. The expectation is that these measures are even better predictors of performance than the input variables, the summary-level process variables or the task adaptive behaviors.

Although there was no overall performance difference for the experimental conditions (chapter 8.2) these information on the experimental conditions was always entered as dummy coded variables into the regression equations. The reference category was always the Base Condition (BC).

The following three chapters present regression results for input variables, summary-level process variables and task adaptive behavior variables as predictors of performance.

8.6.1 Predicting Performance: Input variables

Input variables are: computer expertise, age, gender, and education of commander and specialists.

The results are summarized in Table 53 and presented en detail in Table 82 to Table 94 (appendix). The regressions are run per shift, first taking *input* variables as predictors and the performance of the shift as dependent variable. A second regression model controls for the mean performance of all preceding shifts this information is entered in step 1 of a sequential, hierarchical regression. *Input* variables were always entered using the method forward. This explorative proceeding is often criticized (Field, 2000; Tabachnick & Fidell, 2001), but it is justified in a situation in which the best fitting (optimal) model is sought to determine the maximal contribution *input* variables can reach in predicting performance.

Input variables explain 13% of the variance of the performance in shift 1. In shift 2 the percentage goes down to 5% and stays around 20% for shifts 3 to shift 8 (Table 53, equation 1). Adding the mean performance of preceding shifts in the regression model, the explained variance is higher: the lowest value is 24% in shift 2, the highest value is 46% in shift 6 (Table 53, equation 2). The mean performance of all the shifts preceding a certain shift is a very strong predictor of performance. Preceding performance alone explains 21% of the variance in performance of shift 2 up to 41% in shift 6. Entering *input* variables into the regression model after controlling for the effects of the preceding performance, the amount of additionally explained variance is in the range of 2% in shift 2 and 12% in shift 4 and shift 8. Thus *input* variables and preceding performance share a certain amount of variance.

Table 53 Summary of results: Explained variance (R2) using only input variables as predictors of performance.

dependent variable is performance in…	Variance equation 1 *Input* factors only		equation 2 preceding performance		plus *Input* factors		change due to *Input* factors
	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	*diff.* R^2
shift 1	0.130	0.105 *	-	-	-	-	-
shift 2	0.053	0.035	0.212	0.205	0.236	0.222 **	0.024
shift 3	0.181	0.150 **	0.323	0.316	0.407	0.390 **	0.084
shift 4	0.133	0.117 *	0.235	0.228	0.353	0.314 **	0.118
shift 5	0.204	0.166 **	0.271	0.264	0.326	0.307 **	0.055
shift 6	0.188	0.165 **	0.405	0.400	0.464	0.443 **	0.059
shift 8	0.251	0.207 **	0.331	0.325	0.455	0.417 **	0.124

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first (step 1, method enter), input variables were then entered in step 2 using the method forward. Predictor variables are entered into the equation if the smallest probability of F is smaller than 0.15. Model fit: * $p < .05$, ** $p < .001$. Model in shift 2 with input variables: $p = .055$.

The *input* variables which show up as predictors of a high performance are a high computer expertise of the commander, a low age of the commander, and the commander being male (summary in Table 54, details in appendix Table 82 to Table 94).

Table 54 summarizes the significant Beta values of the second equation per shift (see Table 53) after controlling for the preceding performance. As there is no preceding performance available in shift 1 only *input* variables are used as predictors. This illustration of the results from he regression analyses facilitates the detection of important predictors across the seven shifts. It shows also that the pattern of variables predicting performance often changes from shift to shift. Nevertheless the most important contribution stems from the commander.

In the first shifts teams with commanders that are not university students perform better, but in later shifts this changes and teams with a commander who is a university students perform better than the other teams.

It is interesting to note that in shift 8 computer expertise of specialists A and B become predictors of performance ($\beta_{\text{computer expertise specialist A}} = .150$, $\beta_{\text{computer expertise specialist B}} = .128$).

Table 54 Summary of results: Input variables predicting performance in shift 1 to shift 8, after controlling for the preceding performance (except shift 1).

	shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
Base Condition (reference category)							
Goal condition (dummy coded)							
CHAT condition (dummy coded)				-			
Control Condition 1 (dummy coded)							
Control Condition 2 (dummy coded)							-
Individual Reflexivity (dummy coded)							
Group Reflexivity (dummy coded)							
age commander (in years)			-	-		-	
gender commander		+	+		+		
education commander	-			+		+	+
computer expertise commander	+			+	+	+	+
age specialist A							
gender specialist A				-			
education specialist A	+						
computer expertise specialist A							+
age specialist B							
gender specialist B							
education specialist B							+
computer expertise specialist B							+

Note. + / - direction of effect, sign of beta value. Age is in years; Gender: 1 = female, 2 = male; education: 1 = professional or college student, 2 = university student; computer expertise = higher values are better. Only statistical significant results are shown.

Conclusion. *Input* variables explain after controlling for the preceding performance[14] approximately 2% to 12% of variance of the performance in a single shift. *Input* variables best predict performance in shift 4 – the first shift on day two (variance explained 12%) and in shift 8, the last shift with additional planes to observe (vari-

[14] In shift 1 no preceding performance is available. There is no performance measure available from the training shift (shift 0).

ance explained 12%). Best performing teams have a young, male commander with a high computer expertise.

Review of the Research Questions to Input Variables

IN I. Input variables predict performance.

Input variables explain 2% (shift 2) up to 12% (shift 4 and shift 8) of variance in performance after controlling for preceding performance.

IN II. But they are better predictors in early shifts than in late shifts (in later shifts group processes and other factors should become better predictors than input variables).

This is not the case. In shift 8 input variables explain after controlling for the preceding performance 12% of variance in performance. In shift 2 it is 2%, in shift 3 8%.

The additional R^2 due to input variables after controlling for preceding performance are not statistically significant different ($\chi 2$ = 3.412, p = .637). Even the difference between the lowest value ($R^2_{\text{shift 2}}$ = .024) and the highest value ($R^2_{\text{shift 8}}$ = .124) are not different (z = 1.541, p = .061).

IN III. It is expected that mainly the commanders' gender, education and computer expertise can predict performance. The effect of the same variables for specialists is expected to be weaker. This is due to the hierarchical structure of the task in the air traffic control simulation.

A commander being male and having a high computer expertise is related to higher performance. As expected, the input variables of the specialist do not predict performance.

8.6.2 Predicting Performance: Summary-Level Process Variables

Summary-level process variables are: number of Read Message, Send Message, Show Information, and Handle Threat of commanders and specialists and the durations of Send Message and Read Message.

Summary-level process variables are calculated as frequencies of the main categories of the coding scheme presented in chapter 6.8. These variables can be extracted from the automatically recoded log-files. The duration of Send Message and Read Message is calculated as the mean duration per shift (time is in seconds), using the information on the beginning and end of the events.

The results are summarized in Table 55 and presented en detail in Table 95 to Table 108 (appendix). The regressions are run per shift, first taking *summary-level process* variables as predictors and the performance of the shift as dependent variable. A second regression model controls for the mean performance of all preceding shifts and the effect of *input* variables. This information is entered in step 1 of a sequential, hierarchical regression. *Input* and *summary-level process* variables were always entered using the method forward.

Summary-level process variables explain 7% of the variance of the performance in shift 3. In shift 6 they explain 46% of variance in performance. In most shifts the explained variance in performance is around or below 20% (Table 55, equation 1).

When additionally the preceding performance and the *input* variables are added to the regression model (equation 2) the explained variance is in the range of 32% in shift 2 to 56% in shift 8. After controlling for the preceding performance and the *input* variables the *summary level process* variables explain 5% in shift 6 to 19% in shift 1 additional variance in performance (Table 55).

Table 55 Summary of results: Explained variance (R2) using preceding performance, input and summary-level process variables as predictors of performance.

	Variance explained by equation 1		equation 2						change due to *summary level process variables*
	Summary level process variables only		preceding performance		plus *Input* factors		plus *summary level process* variables		
dependent variable: performance in…	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	*diff.* R^2
shift 1	0.229	0.191 **	-	-	0.130	0.105	0.321	0.267 **	0.191
shift 2	0.150	0.134 **	0.212	0.205	0.236	0.222	0.337	0.305 **	0.101
shift 3	0.068	0.050 *	0.323	0.316	0.407	0.390	0.468	0.443 **	0.061
shift 4	0.150	0.126 *	0.235	0.228	0.353	0.314	0.470	0.410 **	0.117
shift 5	0.149	0.125 *	0.271	0.264	0.326	0.307	0.446	0.407 **	0.120
shift 6	0.463	0.215 **	0.405	0.400	0.464	0.443	0.515	0.476 **	0.051
shift 8	0.273	0.245 **	0.331	0.325	0.455	0.417	0.563	0.518 **	0.108

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of F is smaller than 0.15. Model fit: * $p < .050$, ** $p < .001$.

The *summary-level process* variables that have a predictive power are summarized in Table 56 (details in appendix Table 95 to Table 108). In shift 1 a good performance (controlling for *input* variables) is the result of a high number of the commander's Handel Threat combined with not spending too much time sending messages, of specialists A, who also spend not too much time sending messages, and of specialists B reading messages often without spending too much time reading them. In shift 2 (controlling for the preceding performance and *input* variables) it is the number of Show Information and Handle Threat of commanders that predict performance. In shift 3 (controlling for the preceding performance and *input* variables) performance is better if commanders do not spend too much time with Send Message and if specialists B read messages often. In shift 4 (controlling for the preceding performance and *input* variables) a good performance is based on not too many Handle Threat of the commander (which is just the other way round than in shift 1) and reading messages. Additionally, specialists A should not spend too much time sending messages, specialists B not too much time reading them but looking up the plane information regularly (Show Information). In shift 5 (controlling for the preceding performance and *input* variables) a high performing team has a commander who does not spend too much time sending messages but assigns the threat level regularly (Handle Threat), specialist A should not look up plane information too often, whereas specialists B should do it more often. In shift 6 and shift 8 (controlling for the preceding performance and *input* variables) no *summary-level process* variable of the commander has some predictive power. In shift 6 specialists A of high performing teams send and read messages more often, specialists B do not spend too much time reading messages and they do not send too much new messages. In shift 8 specialists A of high performing teams spend less time reading and sending messages than specialists A of low performing teams, and specialists B have more Show Information.

Table 56 Summary of results: Summary-level process variables predicting performance in shift 1 to shift 8, controlling for preceding performance (except in shift 1) and input variables.

	shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
number Handle Threat, commander	+	+		-	+		
number Read Message, commander							
number Send Message, commander			-				
number Show Info, commander		+					
duration Read Message, commander				+			
duration Send Message, commander	-				-		
number Read Message, specialist A						+	
number Send Message, specialist A						+	
number Show Info, specialist A					-		
duration Read Message, specialist A							-
duration Send Message, specialist A	-			-		-	-
number Read Message, specialist B	+	-	+				
number Send Message, specialist B							
number Show Info, specialist B				+	+		+
duration Read Message, specialist B	-			-		-	
duration Send Message, specialist B							

Note. + / - direction of effect, sign of beta value. The coding scheme is described in chapter 6.8. Only statistical significant results are shown.

As for the input variables: The pattern of predictors is different between the shifts (Table 56). And some predictors show up in some shifts with a positive Beta value, in other shifts with a negative Beta value. One such example is the number of a commanders' Handle Threat: A good performance is often predicted by a high number of Handle Threat. However, this is not the case in shift 4!

The number of Handle Threat is rather low in shift 1 (mean number of Handle Threat = 2.51, see Table 39), indicating that some commanders missed to assign the threat level in shift 1. In shift 4 the mean number of Handel Threat is higher (mean = 3.92). But we also observe the biggest standard deviation for Handle Threat in this shift 4. As all commanders set the threat level of all planes in shift 4 there must be some commanders that exaggerate their threat assignment activities. And this behavior impairs performance.

Review of the Research Questions to Summary-level Process Variables

SUM I. Adding summary-level process variables results in a better prediction of performance than just looking at the input variables.

In all shifts performance is better predicted adding *summary-level process variables* to the regression model, after controlling for preceding performance and input variables.

8.6.3 Predicting Performance: Task Adaptive Behavior Variables

Task adaptive behavior variables are: Basic Task Mastery, Plane Handling, Message Handling, and Strategic as well as Motivational and Corrective Leadership of commanders. Task adaptive behaviors are measures of specific aspects the group process (Tschan, Semmer, Nägele et al., 2000) and are defined in chapter 6.9.

Task adaptive behavior variables alone explain 19% of variance in performance in shift 4 up to 53% in shift 2 (Table 57, equation 1). Just taking *task adaptive behavior* variables as single predictors of performance per shift gives in most shifts a better prediction of performance than using either only *input* variables (Table 53, 5% in shift 2 to 25% in shift 8, equation 1) or only *summary-level process* variables (Table 55, 7% in shift 3 to 46% in shift 6) . If *task adaptive behavior* variables are entered in the regression model after entering *input* variables and *summary-level process* variables they still explain additional 7% of the variance in performance in shift 6 up to 31% in shift 1 (Table 57, equation 2).

Table 57 Explained variance (R2) using preceding performance, input, summary-level process variables, and task adaptive behavior variables as predictors of performance.

dependent variable: performance in…	Variance explained by equation 1: *Task Adaptive Behavior* variables only		equation 2: preceding performance		plus *Input* factors		plus *summary level process* variables		plus *Task* Adaptive Behavior		change due to *Task Adaptive Behavior*
	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	*diff.* R^2
shift 1	0.245	0.223 **	-	-	0.130	0.105	0.321	0.267	0.629	0.396 **	0.308
shift 2	0.530	0.498 **	0.212	0.205	0.236	0.222	0.337	0.305	0.601	0.569 **	0.264
shift 3	0.510	0.481 **	0.323	0.316	0.407	0.390	0.468	0.443	0.637	0.612 **	0.169
shift 4	0.188	0.157 **	0.235	0.228	0.353	0.314	0.470	0.410	0.599	0.529 **	0.129
shift 5	0.480	0.444 **	0.271	0.264	0.326	0.307	0.446	0.407	0.695	0.649 **	0.249
shift 6	0.442	0.409 **	0.405	0.400	0.464	0.443	0.515	0.476	0.591	0.540 **	0.076
shift 8	0.360	0.329 **	0.331	0.325	0.455	0.417	0.563	0.518	0.642	0.593 **	0.079

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were then entered using the method forward. Independent variables are entered into the equation if the smallest probability of F is smaller than 0.15. Model fit: * p < .050, ** p < .001.

The most important *task adaptive behavior* variable is the Plane Handling of commanders. It shows up as strong predictor of performance in 5 of 7 shifts (Table 58, details in appendix Table 109 to Table 122). Plane Handling is an index representing the ability to quickly look up plane information, to make a quick initial threat assignment and to change the threat assignments in accordance with plane identification (IFF). Inconsistent with the expectations is the finding that better Basic Task Masteries of specialists B leads to a lower performance in 4 of 7 shifts (negative Beta values). It seems that it is better for specialists B not to look up all plane information and to skip reading messages from time to time.

Strategic Leadership as well as Motivational and Corrective Leadership of commanders are almost of no importance to predict performance. In shift 1 a good Motivational and Corrective Leadership of commanders even goes together with a lower performance.

In later shifts a good Message Handling of specialists B leads to high performance. Message Handling combines reading messages quickly and not spending too much time reading them. But in shift 4 the better the Message Handling is, the worse is the performance.

Table 58 Task adaptive behavior variables as predictors of performance in shift 1 to shift 8.

	shift 1	shift 2	shift 3	shift 4	shift 5	shift 6	shift 8
Basis Task Mastery, commander		-		-	-		
Plane Handling, commander	+	+	+	+		+	
Message Handling, commander					-		
Strategic Leadership, commander							+
Motivational and Corrective Leadership, com.	-					+	
Basic Task Mastery, specialist A	+						
Plane Handling, specialist A				+			
Message Handling, specialist A					+	+	
Basic Task Mastery, specialist B		+		+	+		+
Plane Handling, specialist B				-	-		
Message Handling, specialist B			+	-	+		+

Note. green = as expected, red = not as expected, + / - direction of effect, sign of beta value. The coding scheme is described in chapter 6.9. Only statistical significant results are shown.

Review of the Research Qeustions to Task Adaptive Behavior Variables

SUM II. Task adaptive behaviors alone explain more variance in performance than any input variable or any summary-level process variable.

Task adaptive behavior variables explain 19% in shift 1 to 53% of variance in performance without taking into account other variables (see Table 57**, equation 1). These numbers are higher than those typically achieved for summary-level process variables (7% in shift 3 up to 27% in shift 8, shift 6 with an explained variance of 46% is the exception, see Table 55, equation 1). Input variables alone explain between 5% in shift 2 and 25% of variance in performance (Table 53**, **equation 1).**

As already in Tschan et al. (2000) task adaptive behavior variables are again strong predictors of performance, even if they are calculated

per shift and not on the aggregated data form shift 1 to shift 3 (day 1) and shift 4 to shift 6 (day 2)

SUM III. Also controlling for preceding performance, for *input* and *summary-level process* variables task adaptive behaviors still contribute additionally to the prediction of performance.

Results show clearly that at task adaptive behavior variables add at least 8% (in shift 6 and shift 8) additionally explained variance to the regression models (Table 57, equation 2). In all other shifts this number is higher.

8.6.4 Summary

The best predictor of performance in shift n is the performance of shift n – 1.

The *task adaptive behavior* variables are the second best predictor. This is mainly due to the Plane Handling of commanders. Controlling for preceding performance, *input* variables and *summary-level process* variables, the *task adaptive behavior* variables still reach a minimal additional R^2 = 0.076 in shift 6 to a maximal additional R^2 = 0.308 in shift 1 (Table 57).

Input variables and *summary-level process* variables both are in the same range of additionally explained variance. Controlling for the preceding performance, the minimal additionally explained variance by *input* variables is R^2 = 0.024 in shift 1 to a maximal R^2 = 0.124 in shift 8 (Table 53). Controlling for preceding performance and *input* variables, the minimal additionally explained variance by *summary-level process* variables is R^2 = 0.051 in shift 6 to a maximum of R^2 = 0.191 in shift 1 (Table 55).

In the regression models in which the preceding performance, *input* variables, *summary-level process* variables and *task adaptive behaviors* are used as predictors (Table 57, equation 2) the minimal explained variance in performance is R^2 = 0.599 in shift 4 and the maximal explained variance is R^2 = 0.695 in shift 5. Explaining 60% to 70% of variance in performance per shift is a good result.

All process variables used up to this point are calculated as frequencies of coded events per shift. No information on the temporal organization, of the sequence of the events is used in the analyses. In the next three chapters methods are discussed that allow to have a closer look at sequences of events. In each chapter it is explained how the method can be used with the ATC data. Each method is then used as descriptive tool to understand and visualize the group process and finally the topic of this chapter is resumed. The question is then: How much additional variance in performance can be explained using information on the sequential organization of the group process? The base rate is set to 60% to 70% of explained variance in this chapter.

8.7 Lag Sequential Analysis

Lag sequential analysis was introduced in chapter 5.3.1 as a method that is well suited for the analysis of sequential, categorical event-based data. The method can already be used with relatively few observations. The lag sequential method analyses every lag independently of the other lags. The sequence of all events is always broken up in dyadic sequences of one given event followed by another event at lag 1, lag 2 or lag n.

In this chapter lag sequential analysis is applied to the ATC-data. The aim is to test the promise of lag sequential analysis, which is that this methods helps to detect patterns in behavior or in communication (descriptive analyses). The second question is, how the information derived from lag sequential analyses can be used in regression analyses predicting performance (regression analyses).

8.7.1 Method Subsection: Lag Sequential Data Analyses

The sequential data analysis is based on the process variables defined in chapter 6.8.: New Plane, New Message, Handle Threat, Read Message, Send Message, and Show Information. The total N is 109 teams.

Calculating the Contingency Tables

The sequential data has to be represented in contingency tables. These tables are then analyzed. In a contingency table it is counted how often a certain given behavior is followed by a next, succeeding event (tallies).

The ATC data was coded using the six main categories New Plane, New Message, Handle Threat, Read Message, Send Message, and Show Information. These events are all potential starting points (given events) for a sequence. Given one of these events the question is then: What follows next? Possible events to follow are for commanders a Handle Threat, Read Message, Send Message, or a Show Information. For specialists a Handle Threat can never be a succeeding event of any given event. Specialists have no possibility to assign the threat level of a plane. For commanders and specialists a New Plane or a New Message can never be a succeeding event (they were defined as system events in chapter 6.8). There is no way to initiate these events. A New Plane comes into the airspace according to the information in the control data used by the ATC simulation. A New Message arrives at the inbox if a commander or a specialist has written a message, but it can never be a reaction of a commander or a specialist to a given event.

A stream of events for a commander could be as follows (fictitious example):

(…) Send Message -> Show Information -> Send Message -> New Message -> Read Message -> Show Information -> Show Information -> Show Information -> Show Information -> New Message -> Read Message -> New Message -> Read Message -> New Message -> Read Message -> New Message -> Read Message -> Read Message -> New Message -> Read Message -> Send Message -> NewPlane (…)

This commander first sends a new message, then he looks up the plane information, then he sends a next message and so on. To determine lag 1 sequences and to calculate the contingency table it is counted how many times a certain event follows a preceding event. The contingency table for this commanders' sequence is (lag 1):

	Read Message	Send Message	Show Information	Handle Threat
New Plane	0	0	0	0
New Message	6	0	0	0
Handle Threat	0	0	0	0
Read Message	1	1	1	0
Send Message	0	0	1	0
Show Information	0	1	3	0

In this example lag 1 contingencies were counted. Lag 2 contingencies are counted similarly. Instead of counting the directly adjacent event one event is skipped. The lag 2 event in the sequence Send Message -> Show Information -> Send Message is the Send Message. The Show Information at lag 1 is not counted. Lag 3, lag 4 to lag n contingencies can be counted accordingly.

Data Coding: Skipping Detailed Information

The details of the coding, related to the message content of sent and read messages (defined in chapter 6.8), was skipped from the lag sequential analyses. Preliminary tests showed that the complexity of the contingency tables was difficult to handle, also the criteria that $p * (1 – p) * G$ should not be lower than 9, was often not met if too many categories from the coding scheme were used (p is the probability of an event, G is the sum of utterances in the contingency table) (Becker-Beck, 1997;

Brauner, 2002). Therefore I decided to use only the main categories of the coding scheme.

All events were coded with their onset time. According to Bakeman and Quera (1995a), the data are repeatable event sequential data (multiple state - MSD). Events are coded e.g., as *ieH12,15.00-* (initiated event Handle Threat, plane 1, commander assigns 2 stars in second 15). The next event is *ieSi1,26.00-* (initiated event Show Information, commander looks up critical parameter at second 26). No ending times are coded, e.g., *ieH12,15.00-* assuming that a single event always lasts until the next event starts.

Software used to run Lag Sequential Analysis

Software used. All lag sequential analyses were run with GESQ, a program that performs quantitative analyses of the sequences and computes sequential indices that can be used in further analyses (Bakeman & Quera, 1995a; Quera & Bakeman, 2000). Further analyses can be done using either log-linear models or regression models (Bakeman, 1991; Bakeman, Adamson, & Strisik, 1989, 1995; Bakeman & Quera, 1995b; Quera & Bakeman, 2000). Widely used statistical software packages (like SPSS) have no procedures to calculate lag-sequences directly (O'Conner, 1999).

Running Lag Sequential Analysis: Step by Step

According to Quera and Bakeman (2000), sequential data analysis always follows the following procedure:

I. Calculate initial lag sequential statistics, which is the analysis of the frequencies at lag 0 of all events that are used in lag sequential analyses.
II. Calculate overall chi-square statistics to determine if there are sequential associations in the contingency tables at all.
III. Take a look at the lag frequencies (also called joint frequencies), and
IV. the conditional probabilities.
V. Finally calculate the *z*-scores (adjusted residuals) (see Table 63) .

The aim of the analyses is to find sequential patterns that indicate an activation and inhibition (Haberman, 1978) of the succeeding event. An activating pattern has a raised probability that a certain event follows to a specific given event. A inhibiting pattern has a lowered probability that a certain event follows a specific given event.

Running Lag Sequential Analysis: (I) Initial Lag Sequential Statistics

GESQ offers the possibility to run simple statistics, like frequencies, relative frequencies or durations. These results differ of course not from the frequencies calculated with SPSS. It is just the sum of all coded events per shift or the mean duration of the events as they were presented in chapter 8.3.

Lag sequential analyses were run for low and high performing teams separately. The teams were separated using a median split of the performance for every shift. The frequencies of the coded behaviors (the lag 0 analyses) are in the appendix (Table 123).

Running Lag Sequential Analysis: (II) Chi-Square Table Statistics

The chi-square statistics is a first test that shows whether there are any sequential associations in the contingency table. The results show clearly that there are sequential associations in the contingency tables (lag 1 contingencies for commanders χ^2 (15) = 1559.41, $p < .01$, for specialists A χ^2 (10) = 2153.66, $p < .01$, for specialists B χ^2 (10) = 1714.61, $p < .01$). Even if the χ^2 values for low and high performing teams (median split of performance) are calculated, this precondition to run lag sequential analyses is always fulfilled (Table 59). In this table results for lag 1 to lag 5 contingencies are presented for shift 1 data for all three team members as well as lag 1 results for shift 4.

Table 59 Results of the chi-square analyses testing for overall sequential associations in contingency tables, shift 1 (lag 1 to lag 5), shift 4 (lag 1).

			low performing teams			high performing teams		
shift	lag		χ^2	*df*	*p*	χ^2	*df*	*p*
1	**1**	**C**	**744.02**	**15**	**.00**	**833.21**	**15**	**.00**
1	2	C	193.19	15	.00	240.16	15	.00
1	3	C	116.38	15	.00	102.33	15	.00
1	4	C	68.65	15	.00	55.24	15	.00
1	5	C	32.28	15	.01	43.49	15	.00
1	**1**	**A**	**995.39**	**10**	**.00**	**1269.05**	**10**	**.00**
1	2	A	365.77	10	.00	379.95	10	.00
1	3	A	130.31	10	.00	176.91	10	.00
1	4	A	60.07	10	.00	87.61	10	.00
1	5	A	50.41	10	.00	77.57	10	.00
1	**1**	**B**	**1004.70**	**10**	**.00**	**1183.14**	**10**	**.00**
1	2	B	297.29	10	.00	315.90	10	.00
1	3	B	96.25	10	.00	62.23	10	.00
1	4	B	54.75	10	.00	37.97	10	.00
1	5	B	41.28	10	.00	18.25	10	.00
4	1	C	909.15	15	.00	1302.92	15	.00
4	1	A	1661.07	10	.00	1754.71	10	.00
4	1	B	1318.50	10	.00	1259.70	10	.00

Note. low = low performing teams, high = high performing teams, median split (shift 1 median = 68, shift 4 median = 79). C = commander, A = specialist A, B = specialist B. **Bold numbers** correspond to the contingency tables shown in Table 60.

Running Lag Sequential Analysis: (III) Lag Frequencies

The lag frequencies show how often a given event is followed by a target event. It is the basic representation of the contingencies and the basis for further measures.

In Table 60 the absolute numbers for directly adjacent events (lag 1 frequencies) are reported for shift 1, lag 1 contingencies. The numbers are higher for specialists than for commanders. The sequence that can be observed most often for commanders is that they read a message after a new message has arrived in the inbox (New Message -> Read Message, 724 times, commanders of low performing teams, and 732 times, commanders of high performing teams).

For specialists A and B of low and high performing teams the sequence that can be found most often is a Show Information followed by another Show Information. See Table 60.

Table 60 Lag sequential analyses: Lag frequencies, lag 1, shift 1.

Commander

low

	Read Message	Send Message	Show Information	Handle Threat	
New Plane	20	14	51	5	*90*
New Message	724	106	39	101	*970*
Handle Threat	117	35	19	9	*180*
Read Message	372	199	20	108	*699*
Send Message	65	67	15	2	*149*
Show Information	29	43	70	12	*154*
	1327	*464*	*214*	*237*	*2242*

high

	Read Message	Send Message	Show Information	Handle Threat	
New Plane	10	11	55	9	*85*
New Message	732	68	44	147	*991*
Handle Threat	161	48	23	7	*239*
Read Message	298	198	36	115	*647*
Send Message	50	50	13	9	*122*
Show Information	31	49	87	21	*188*
	1282	*424*	*258*	*308*	*2272*

Specialist A

low

	Read Message	Send Message	Show Information	Handle Threat	
New Plane	7	7	81		*95*
New Message	245	43	189		*477*
Handle Threat	31	34	124		*189*
Read Message	133	81	242		*456*
Send Message	81	15	217		*313*
Show Information	104	459	2231		*2794*
	601	*639*	*3084*		*4324*

high

	Read Message	Send Message	Show Information	Handle Threat	
New Plane	6	3	84		*93*
New Message	166	49	161		*376*
Handle Threat	24	37	189		*250*
Read Message	103	46	218		*367*
Send Message	63	16	247		*326*
Show Information	95	475	2920		*3490*
	457	*626*	*3819*		*4902*

Specialist B

low

	Read Message	Send Message	Show Information	Handle Threat	
New Plane	5	7	87		*99*
New Message	206	46	159		*411*
Handle Threat	33	44	117		*194*
Read Message	88	60	215		*363*
Send Message	88	15	274		*377*
Show Information	71	519	1825		*2415*
	491	*691*	*2677*		*3859*

high

	Read Message	Send Message	Show Information	Handle Threat	
New Plane	12	6	75		*93*
New Message	193	54	135		*382*
Handle Threat	37	46	166		*249*
Read Message	120	56	221		*397*
Send Message	58	16	242		*316*
Show Information	76	467	1869		*2412*
	496	*645*	*2708*		*3849*

Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53).

However, it is tricky to interpret these numbers as they are shown in Table 60. The numbers show which contingencies are most often observed. But these numbers are biased by differences in the overall activity of teams. If we are interested in the structure of the behavior, and the sequential patterns, these numbers hide the fact that two teams can act structurally equal even if team 1 has much more event sequences than team 2. The number of tallies depends on the overall frequency of the events. Therefore it is better to look at conditional probabilities and finally at adjusted residuals.

Running Lag Sequential Analysis: (IV) Conditional Probabilities

Conditional probabilities express the probability that a certain event follows after a specific given event. The probabilities are calculated row by row using the lag frequencies (Table 60). Conditional probabilities (conp) are presented in Table 64 for shift 1, lag 1 contingencies. The table can be read as follows:

Given a New Plane commanders react most likely with a Show Information at lag 1 ($conp_{\text{low perf}} = 0.57$, $conp_{\text{high perf}} = 0.65$), which is also true for specialists A ($conp_{\text{low perf}} = 0.85$, $conp_{\text{high perf}} = 0.90$), and specialists B ($conp_{\text{low perf}} = 0.88$, $conp_{\text{high perf}} = 0.81$). Given a New Message, commanders react at lag 1 most likely with a Read Message ($conp_{\text{low perf}} = 0.75$, $conp_{\text{high perf}} = 0.74$). Specialist A react to a New Message most probably with a Read Message ($conp_{\text{low perf}} = 0.51$, $conp_{\text{high perf}} = 0.44$) or a Show Information ($conp_{\text{low perf}} = 0.40$, $conp_{\text{high perf}} = 0.43$). The same is true for specialists B, who also react to a New Message with either a Read Message ($conp_{\text{low perf}} = 0.50$, $conp_{\text{high perf}} = 0.51$), or a Show Information ($conp_{\text{low perf}} = 0.39$, $conp_{\text{high perf}} = 0.35$). The Show Information is of course not something that's influenced by the preceding New Message. But it shows that the specialists often do not react immediately to a new message in the inbox but continue their observation of planes. If the commander reads a message the most probable next event is that he reads immediately after that another message ($conp_{\text{low perf}} = 0.53$, $conp_{\text{high perf}} = 0.46$). If the specialist read a message the next event is then often a Show Information (spec A: $conp_{\text{low perf}} = 0.53$, $conp_{\text{high perf}} = 0.59$, spec B: $conp_{\text{low perf}} = 0.59$, $conp_{\text{high perf}} = 0.56$). They have often to look up information on planes the commander asks for. After a commanders Send Message follows either another Send Message ($conp_{\text{low perf}} = 0.45$, $conp_{\text{high perf}} = 0.41$) or a Read Message ($conp_{\text{low perf}} = 0.44$, $conp_{\text{high perf}} = 0.41$). The specialist, after sending a message, switch back to plane observation (spec A: $conp_{\text{low perf}} = 0.69$, $conp_{\text{high perf}} = 0.76$, spec B: $conp_{\text{low perf}} = 0.73$, $conp_{\text{high perf}} = 0.77$). And a Show Information has a high probability that the next event is another Show Information (commander: $conp_{\text{low perf}} = 0.45$, $conp_{\text{high perf}} = 0.46$, spec A: $conp_{\text{low perf}} = 0.80$, $conp_{\text{high perf}} = 0.84$, spec B: $conp_{\text{low perf}} = 0.76$, $conp_{\text{high perf}} = 0.77$). See Table 61.

Table 61 Lag sequential analyses: Conditional probabilities, lag 1, shift 1

Commander

		Read Message	Send Message	Show Information	Handle Threat	
low	New Plane	0.22	0.16	0.57	0.06	*1.00*
low	New Message	0.75	0.11	0.04	0.10	*1.00*
low	Handle Threat	0.65	0.19	0.11	0.05	*1.00*
low	Read Message	0.53	0.28	0.03	0.15	*1.00*
low	Send Message	0.44	0.45	0.10	0.01	*1.00*
low	Show Information	0.19	0.28	0.45	0.08	*1.00*
		Read Message	Send Message	Show Information	Handle Threat	
high	New Plane	0.12	0.13	0.65	0.11	*1.00*
high	New Message	0.74	0.07	0.04	0.15	*1.00*
high	Handle Threat	0.67	0.20	0.10	0.03	*1.00*
high	Read Message	0.46	0.31	0.06	0.18	*1.00*
high	Send Message	0.41	0.41	0.11	0.07	*1.00*
high	Show Information	0.16	0.26	0.46	0.11	*1.00*

Specialist A

		Read Message	Send Message	Show Information	Handle Threat	
low	New Plane	0.07	0.07	0.85		*1.00*
low	New Message	0.51	0.09	0.40		*1.00*
low	Handle Threat	0.16	0.18	0.66		*1.00*
low	Read Message	0.29	0.18	0.53		*1.00*
low	Send Message	0.26	0.05	0.69		*1.00*
low	Show Information	0.04	0.16	0.80		*1.00*
		Read Message	Send Message	Show Information	Handle Threat	
high	New Plane	0.06	0.03	0.90		*1.00*
high	New Message	0.44	0.13	0.43		*1.00*
high	Handle Threat	0.10	0.15	0.76		*1.00*
high	Read Message	0.28	0.13	0.59		*1.00*
high	Send Message	0.19	0.05	0.76		*1.00*
high	Show Information	0.03	0.14	0.84		*1.00*

Specialist B

		Read Message	Send Message	Show Information	Handle Threat	
low	New Plane	0.05	0.07	0.88		*1.00*
low	New Message	0.50	0.11	0.39		*1.00*
low	Handle Threat	0.17	0.23	0.60		*1.00*
low	Read Message	0.24	0.17	0.59		*1.00*
low	Send Message	0.23	0.04	0.73		*1.00*
low	Show Information	0.03	0.21	0.76		*1.00*
		Read Message	Send Message	Show Information	Handle Threat	
high	New Plane	0.13	0.06	0.81		*1.00*
high	New Message	0.51	0.14	0.35		*1.00*
high	Handle Threat	0.15	0.18	0.67		*1.00*
high	Read Message	0.30	0.14	0.56		*1.00*
high	Send Message	0.18	0.05	0.77		*1.00*
high	Show Information	0.03	0.19	0.77		*1.00*

Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53).

Conditional probabilities represent the sequential contingencies in the data. But as they are calculated separately row by row the overall frequency of the contingencies in the table is not taken into account. This is illustrated in the example in Table 62: Person B has ten times more events than person A. The proportion of the contingencies is however the same. This is reflected in the same values for the conditional probabilities. Thus, the information on the different number of contingencies is completely ignored in the calculation of the conditional probabilities.

Table 62 Lag frequencies and conditional probabilities and adjusted residuals (z-scores), a fictitious example.

		A	B	C	
Person A					
lag frequency	A	10	15	5	30
	B	5	15	10	30
		15	30	15	60
conditional probabilities	A	0.33	0.50	0.17	1.00
	B	0.17	0.50	0.33	1.00
adjusted residuals	A	1.49	0.00	-1.49	
	B	-1.49	0.00	1.49	

		A	B	C	
Person B					
lag frequency	A	100	150	50	300
	B	50	150	100	300
		150	300	150	600
conditional probabilities	A	0.33	0.50	0.17	1.00
	B	0.17	0.50	0.33	1.00
adjusted residuals	A	4.71	0.00	-4.71	
	B	-4.71	0.00	4.71	

Note. A, B and C represent fictitious events.

Therefore, it is recommended to calculate adjusted residuals (*z*-scores). This measure takes into account the different number of contingencies.

Running Lag Sequential Analysis: (V) Adjusted Residuals

The adjusted residuals (the *z*-scores) have “the merit of expressing the extent to which an observed value for a conditional probability differs from its expected value” (Bakeman, 2000, p. 154). The group process is represented in the adjusted residuals showing the inhibition or activation of sequences of given and target events.

The adjusted residuals presented in the (fictitious) example in Table 62 are calculated according to the formula presented in Table 63.

Table 63 Calculation of adjusted residuals (Bakeman & Quera, 1995a, p. 84).

$$adjusted\ residuals\ z(r,c) = \frac{f(r,c) - \exp f(r,c)}{\sqrt{\exp f(r,c)\,[1-p(c)]\,[1-p(r)]}}$$

Where $f(r,c)$ is the observed frequency at the intersection of row *r* and column *c*,

$$\exp f(r,c) = \frac{f(c)\ f(r)}{N},\ p(c) = \frac{f(c)}{N}, \text{ and } p(r) = \frac{f(r)}{N}.$$

Note. r = row, c = column in contingency table.

Summary

I presented the five basic steps to run lag sequential analyses from the calculation of the initial lag 0 statistics to the calculation of the adjusted residuals. A crucial and important step is the appropriate coding of the data. There is according to Bakeman and Quera (1995a) no standard to store sequential data in data bases. They propose to use the Sequential Data Interchange Standard (SDIS), that is to store single events in the form “event,time start-time end”[15], for example as “Read Message,10.00-20.00”. Data stored in this form can easily be analyzed with GESQ a generalized sequential querier, a book-ware program of Bakeman and Quera.

In the next chapter results are presented comparing lag sequences for shift 1 and shift 4. I restricted the presentation of the results to these two shifts. A lag sequential analyses always compares pairs of given and target behaviors. It is not always easy to decide on the appropriate lag to analyze.[16] This is a decision that has to be taken by the researcher. In a preliminary study I calculated lag 1 to lag 5 contingencies for shift 1 to shift 8 and for all roles for low and high performing teams. The result consisted of 210 tables each with up to twenty four *z*-scores. This summed up to over 4’000 *z*-scores. The discussion of data mining analyses in chapter 8.9 will show, that there are better techniques for this purpose.

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15 The space after the comma must be omitted!

16 Lag sequential analyses can not automatically scan the data for sequences with the optimal lag.

8.7.2 Lag 1 to Lag 5 Sequences in Shift 1

The following analyses compare the adjusted residuals for two groups: the low performing teams and the high performing teams. The median of the performance of shift 1 was used to split the teams into two groups. In shift 1 56 low performing teams are compared with 53 high performing teams. The question is: Are there any differences in the temporal organization on the micro-behavioral level between the two groups? For this analyses the data for all low and all high performing groups was aggregated (pooled).

The "standard" z-value for a statistical significant enhancing or inhibitory sequence is at the 5%-significane level z = 1.96. As the contingency tables contain twenty-four cells for commanders and 18 cells for specialists (see Table 60), a Bonferroni-corrected z-value has to be used to keep the overall significance level in spite off the numerous test at the 5%-level. For commanders this value is z_{crit} = 3.071 and for specialists z_{crit} = 2.984. In Table 64 results for lag 1 contingencies in shift 1 for commanders and specialists are presented. Statistically significant results are in bold and a minus (-) respectively plus (+) points to the direction of the association (-: inhibition; +: activation).

Lag 1 Sequences for shift 1

The lag 1 contingencies of commanders from low and high performing teams are quite similar. However, some differences can be found: (i) Given a New Message all commanders show a higher probability that the next event is a Read Message, and a reduced probability that it is a Send Message. However, this inhibition of a Read Message is much stronger for commanders of high performing teams. (ii) Given a Handle Threat the probability that the next event is a Read Message is enhanced for commanders of high performing teams, but not for commanders of low performing teams.

For specialists a New Message enhances the probability that the next event is a Read Message, and hinders a Show Information. A Show Information always hinders a Read Message. The main difference between specialists of low and high performing teams is their reaction to a New Plane. Specialists of high performing teams show no specific reaction, whereas specialists of low performing teams have an enhanced probability to react with a Show Information. Another difference is that for specialists of high performing teams a Read Message enhances itself. See Table 64.

For the graphical representation of the *z*-values only values above z_{crit} are considered. All values below z_{crit} are set to 0. The graphical representation gives an overview of inhibiting (blue, dashed lines) or activating sequences (green, solid lines), the arrow indicates the direction. Thick lines indicate that the *z*-value is greater than 10. Because New Plane and New Message are only analyzed as target and not as given events, there is never an arrow pointing towards those two boxes. For specialists Handle Threat is a system event and therefore no arrow can point to this box. A circle means that a given category activates or inhibits itself. See Figure 39.

Table 64 Lag sequential analyses: Adjusted residuals, lag 1, shift 1.

Commander

		Read Message	Send Message	Show Information	Handle Threat
s1 - low	New Plane	**-7.28 -**	-1.23	**15.53 +**	-1.58
	New Message	**13.00 +**	**-9.97 -**	**-7.77 -**	-0.21
	Handle Threat	1.65	-0.43	0.48	-2.53
	Read Message	**-3.87 -**	**6.12 +**	**-7.25 -**	**5.06 +**
	Send Message	**-4.00 -**	**7.57 +**	0.22	**-3.79 -**
	Show Information	**-10.56 -**	2.29	**15.72 +**	-1.16
		Read Message	Send Message	Show Information	Handle Threat
s1 - high	New Plane	**-8.46 -**	-1.38	**15.80 +**	-0.81
	New Message	**14.74 +**	**-12.70 -**	**-9.14 -**	1.56
	Handle Threat	**3.61 +**	0.60	-0.89	**-5.07 -**
	Read Message	**-6.29 -**	**9.22 +**	**-5.49 -**	**3.71 +**
	Send Message	**-3.54 -**	**6.51 +**	-0.25	-2.05
	Show Information	**-11.53 -**	2.72	**15.76 +**	-1.00

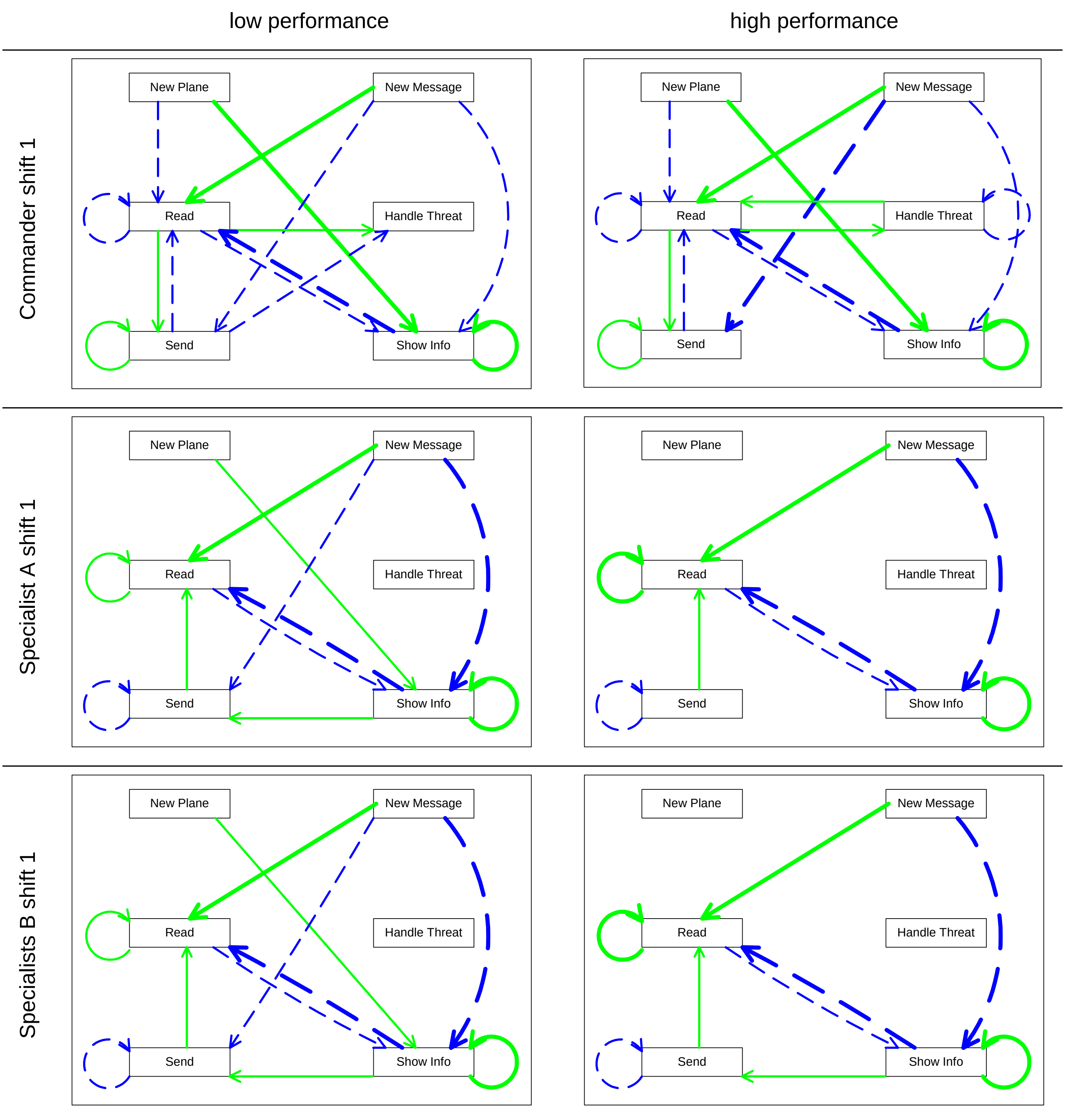
Specialist A

		Read Message	Send Message	Show Information	Handle Threat
s1 - low	New Plane	-1.86	-2.06	**3.04 +**	.
	New Message	**25.08 +**	**-3.76 -**	**-16.23 -**	.
	Handle Threat	1.02	1.27	-1.78	.
	Read Message	**9.96 +**	1.90	**-9.11 -**	.
	Send Message	**6.36 +**	**-5.17 -**	-0.81	.
	Show Information	**-26.14 -**	**4.13 +**	**16.75 +**	.
		Read Message	Send Message	Show Information	Handle Threat
s1 - high	New Plane	-0.96	-2.78	2.91	.
	New Message	**24.17 +**	0.16	**-17.07 -**	.
	Handle Threat	0.15	0.99	-0.90	.
	Read Message	**12.84 +**	-0.14	**-8.88 -**	.
	Send Message	**6.43 +**	**-4.40 -**	-0.96	.
	Show Information	**-24.99 -**	2.77	**15.28 +**	.

Specialist B

		Read Message	Send Message	Show Information	Handle Threat
s1 - low	New Plane	-2.32	-2.85	**4.05 +**	.
	New Message	**24.07 +**	**-3.76 -**	**-14.28 -**	.
	Handle Threat	1.84	1.78	-2.81	.
	Read Message	**6.92 +**	-0.72	**-4.40 -**	.
	Send Message	**6.51 +**	**-7.43 -**	1.47	.
	Show Information	**-23.59 -**	**7.51 +**	**10.80 +**	.
		Read Message	Send Message	Show Information	Handle Threat
s1 - high	New Plane	0.00	-2.69	2.20	.
	New Message	**23.13 +**	-1.45	**-15.79 -**	.
	Handle Threat	0.96	0.75	-1.32	.
	Read Message	**10.89 +**	-1.49	**-6.77 -**	.
	Send Message	**3.03 +**	**-5.81 -**	2.53	.
	Show Information	**-23.36 -**	**5.60 +**	**12.55 +**	.

Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53). Bonferroni corrected z-values for commanders $z_{crit} = 3.071$, for specialists $z_{crit} = 2.984$.



Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53); **green, bold lines** = enhancing, adj. residual > +10; green, thin lines = enhancing, adj. residual between +3.07 (commanders), respectively +2.98 (specialists) and +10; **blue, bold dashed lines** = inhibiting, adj. residual < -10; blue, thin dashed lines = inhibiting, adj. residual between -10 and -3.07 (commanders), respectively -2.98 (specialists).

Figure 39 Lag sequential analyses: Adjusted residuals, lag 1, shift 1

Lag 2 to lag 5 Sequences for Shift 1

Additionally lag 2 to lag 5 contingencies were calculated for commanders and specialists in shift 1. Results show, that there are significant lag 2 to lag 5 sequences but the effects are lower than for lag 1 sequences. All results for lag 1 to lag 5 contingencies for commanders and specialist are in the appendix (Table 126 to Table 129 and Figure 52 to Figure 55). The results for lag 2 to lag 5 analyses in shift 1 are summarized as follows:

LAG 2. The *z*-values for lag 2 contingencies are lower than for lag 1 contingencies. The highest values for commanders are the self-enhancing Show Information contingencies (a Show Information enhances the probability of another Show Information to follow at lag 2). The main differences for commanders of low and high performing teams lie in their reaction to New Message: the probability that a Read Message follows at lag 2 is enhanced but for commanders of high performing teams, and the probability of a Show Information is reduced. Commanders of low performing teams show a rather high self-enhancing contingency of Show Information.

Specialist of low and high performing teams do not differ much. The probability that given a Send Message the lag 2 event is a Read Message is higher for specialists of low performing teams. Specialists B of low performing teams have an enhanced probability that given a New Plane the lag 2 event is a Send Message.

LAG 3. For commanders there are almost no lag 3 contingencies with high *z*-values. If higher values are found they all refer to lag 3 events given a New Plane.

For the specialists the patterns diverge. Specialists A of low performing teams have an enhanced probability that a Read Message is at lag 3 followed by a Send Message. For specialists A of high performing teams its just the other way round: a Send Message enhances the probability of a Read Message at lag 3. Specialists A show no enhancing or inhibiting sequences given a New Plane. This is different for specialists B of good performing teams. Given a New Plane they have a higher probability of a Show Information at lag 3, and a reduced probability of a Read Message at lag 3.

LAG 4. Commanders have almost no lag 4 contingencies. Found contingencies are the same for commanders of low and high performing teams. Also specialists A do not differ much. Specialists A of low performing teams have a higher probability that a Read Message is followed by another Read Message at lag 4 than specialists

A of high performing teams. Specialists A of high performing teams have a hindered contingency of a given Show Information followed by a Send Message at lag 4.

Lag 5. Commanders show no lag 5 contingencies. Only for commanders of low performing teams a self-enhancing sequence of Show Information can be found. This is also the case for specialists B. The picture is completely different for specialists A. Especially, there is an enhancing contingency given a New Plane followed by a Send Message at lag 5 and a hindered sequence of New Plane followed by a Show Information at lag 5. It seems as if specialists A look up all 4 parameters of a plane and then send a message to the commander.

Conclusion. Lag 1 contingencies show clearly that commanders of low and high performing teams read messages immediately, but that commanders of high performing teams have a lower probability to respond (that means send a message) immediately. Commanders of good performing teams assign the threat level of planes and then switch back to reading messages. Specialists of high performing teams show no special reaction to a New Plane. They are either in a cycle of requesting information on planes or in a cycle of reading messages. It is necessary to read incoming messages quickly but also not to respond too immediately. Also lag 2 contingencies of specialists show clearly that specialists of good performing teams give no special attention to new planes. They have strong sequences of Show Information's which are broken up by New Messages.

The contingencies of lag 3, lag 4 or lag 5 are not easy to interpret because the strength of the association of given and target events is rather weak.

8.7.3 Comparing lag 1 contingencies of shift 1 and shift 4

Lag 1 sequences of shift 1 and shift 4 are compared because the task is the same in both shifts. Shift 1 is the first shift on the first day, shift 4 is the first shift on day 2. I expect that the comparison of these two shifts shows team development from day 1 to day 2. The adjusted residuals for shift 1 are presented in Table 64, those for shift 4 in Table 65. The graphical representation for lag 1 contingencies in shift 1 is in Figure 39, for shift 4 in Figure 40. The results are summarized as follows:

Commander. In shift 1 lag 1 not many differences can be found between the commanders of low and high performing teams. One difference is the stronger inhibition of a Send Message following a New Message and how the lag 1 Handle Threat is sequentially related to the other events. The lag 1 sequences in shift 4 are on the first sight very similar. Commanders of low performing teams have now also a stronger inhibition of the sequence New Message -> Send Message. The reaction to a New Message is a Read Message. A Send Message, a Handle Threat and especially for commanders of high performing teams, a Show Information are unlikely to follow. This example shows that the reaction of commanders of low and high performing teams is not fundamentally different. The differences lie – in technical terms – in lower *z*-values. This means that commanders of low performing teams follow the same sequences as commanders of high performing teams. They know in principle how to handle the task. But they do it with less consistency. For commanders of low and high performing teams the sequence Read Message -> Handle Threat is enhanced. This means that commanders set the threat level according to information in the messages from the specialists. But this sequence is much stronger enhanced for commanders of low performing teams, especially in shift 4. This could signify that commanders of low performing teams - because they react much faster to information from the specialists than commanders of high performing teams – either do not get as much information from the specialists or that they use the formula to calculate the overall threat level of a plane differently. An immediate reaction to a new message which is a quick adjustment of the threat level of a plane is on the first sight a good strategy, but it should not be too dominant. This could be because the plane information from the specialists is sometimes contradictory or has no direct impact on the threat level. Therefore it is sometimes very useful to set the threat level immediately and it is also sometimes very useful to integrate information from both specialists before a new threat assignment is made.

Specialists A. Comparison of the lag 1 sequences for specialists A shows clearly that in shift 4 neither specialists A nor specialists B show an immediate reaction to a New Plane. This was something that specialists A of low performing teams already did in shift 1. Again specialists A lag 1 sequences of low and high performing teams are quite similar. Some interesting differences, however, can be found as follows: specialists A of low performing teams have an increased probability to react to a Handle Threat (of the commander) with a Read Message and also an enhanced probability that a Read Message leads to a Send Message. Additionally, there is a stronger inhibition of the sequence Read Message followed by a Show Information. Taking this information together gives a picture of specialists A of low performing groups investing more in communication. That a Handle Threat activates a Read Message could signify that specialists A try to find additional information on the threat assignment of the plane. That a Read Message immediately activates a Send Message could tell us that specialist reply to the message or that they send old plane information to the commander (if the commanders request plane information the reaction should be a Show Information and then at lag 2 or higher a Send Message).

Specialists B. The sequences for specialists B are neither for the specialists of low performing teams nor for the specialists of high performing teams fundamentally different from those of specialists A. A New Message activates a Read Message and inhibits a Show Information. A Read Message inhibits a Show Information, and a Show Information activates another Show Information. Also for specialists B the inhibition that a Read Message is followed by a Show Information is stronger for specialists B of low performing teams than for specialists B of high performing teams. This means that if specialists B of low performing teams are in the mode of reading messages the probability that they stay in this mode is greater then for specialists B of high performing teams (because leaving this mode and switching to Show Information is strongly inhibited).

Conclusion. As well for commanders and specialists no fundamental differences are found in the lag 1 sequences comparing shift 1 and shift 4. Observing these teams in the natural setting might well lead to the conclusion that they do the same thing and that performance differences are not related to the observable group process. But this is not the whole story.

For specialists A and B it is better to show no immediate reaction to a New plane. This is something specialists of low performing teams do in the beginning, not often, but they do it.

Specialists A and B have mainly two tasks: reading messages and getting information about the planes. From time to time they have to send the information to the commander, something that is done right from the beginning from specialists A and B regardless of the performance level of the teams. The difference in the process is then that specialists of low performing teams show stronger contingencies of just reading messages (in shift 4). While it is certainly necessary to spend enough time to read messages, it is crucial to switch back in time to the plane observation task.

Table 65 Lag sequential analyses: Adjusted residuals, lag 1, shift 4.

Commander

		Read Message	Send Message	Show Information	Handle Threat
s4 – low	New Plane	**-6.48 -**	-1.87	**16.47 +**	-2.08
	New Message	**17.47 +**	**-13.30 -**	**-6.81 -**	**-4.28 -**
	Handle Threat	2.24	**3.81 +**	-1.07	**-5.78 -**
	Read Message	**-11.59 -**	**7.73 +**	**-6.13 -**	**11.77 +**
	Send Message	-2.14	**4.52 +**	0.72	-2.21
	Show Information	**-9.35 -**	**4.13 +**	**13.55 +**	-2.12
		Read Message	Send Message	Show Information	Handle Threat
s4 - high	New Plane	**-8.71 -**	-2.72	**18.43 +**	-0.88
	New Message	**22.31 +**	**-15.70 -**	**-11.30 -**	**-4.60 -**
	Handle Threat	1.18	**5.52 +**	-1.61	**-5.81 -**
	Read Message	**-11.12 -**	**11.38 +**	**-6.93 -**	**9.11 +**
	Send Message	**-4.34 -**	2.61	**3.10 +**	0.60
	Show Information	**-14.34 -**	2.94	**19.09 +**	0.39

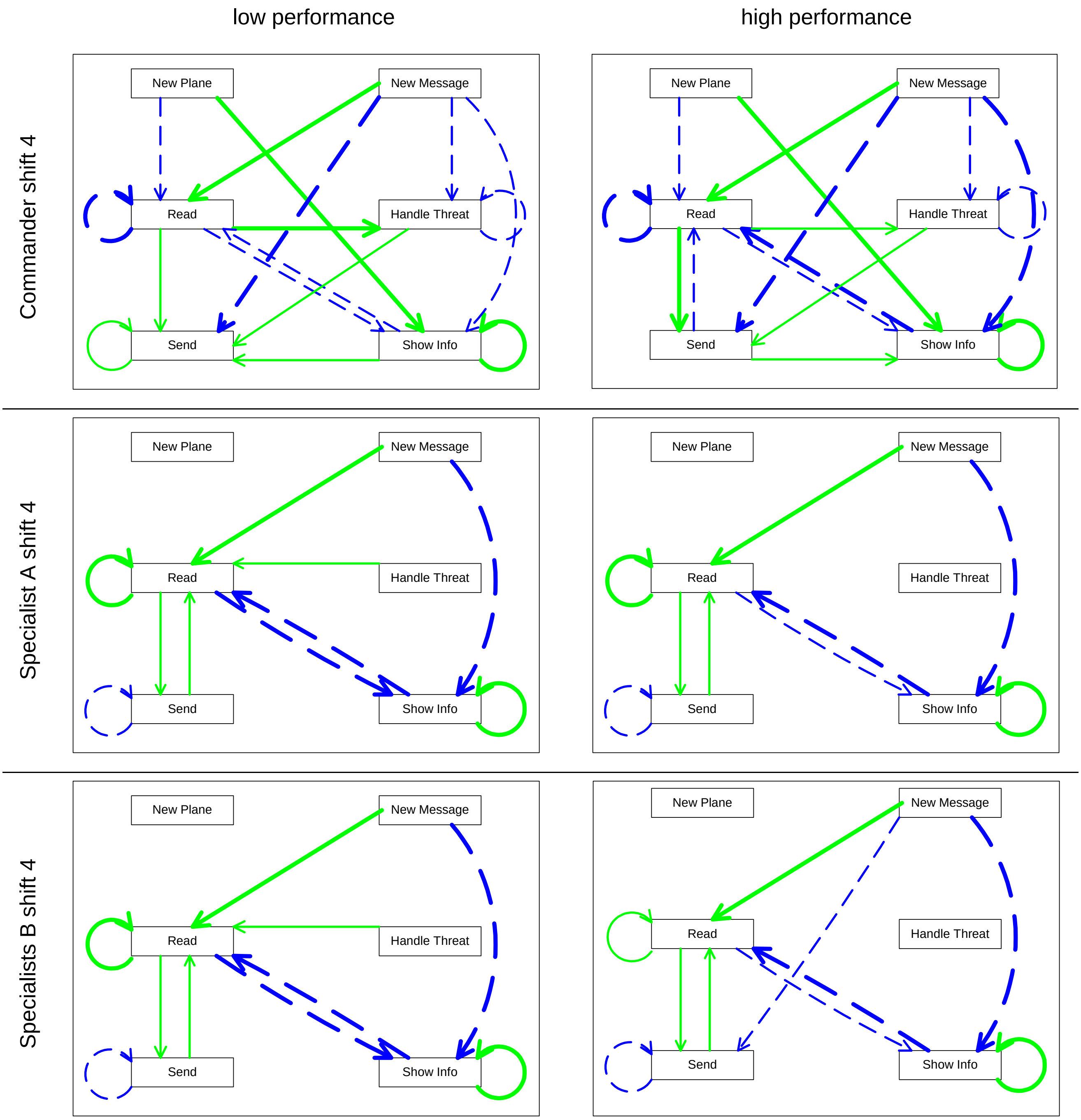
Specialist A

		Read Message	Send Message	Show Information	Handle Threat
s4 - low	New Plane	-2.05	-1.83	2.91	.
	New Message	**36.04 +**	-2.64	**-24.75 -**	.
	Handle Threat	**3.96 +**	-1.23	-2.01	.
	Read Message	**10.85 +**	**5.24 +**	**-12.04 -**	.
	Send Message	**3.13 +**	**-3.91 -**	0.65	.
	Show Information	**-31.22 -**	1.44	**22.08 +**	.
		Read Message	Send Message	Show Information	Handle Threat
s4 - high	New Plane	-0.42	-2.06	1.91	.
	New Message	**39.03 +**	**-3.65 -**	**-25.04 -**	.
	Handle Threat	1.25	1.32	-1.93	.
	Read Message	**6.94 +**	**4.83 +**	**-8.74 -**	.
	Send Message	**3.31 +**	**-4.65 -**	1.28	.
	Show Information	**-29.71 -**	1.63	**19.97 +**	.

Specialist B

		Read Message	Send Message	Show Information	Handle Threat
s4 - low	New Plane	-2.05	-1.83	2.91	.
	New Message	**36.04 +**	-2.64	**-24.75 -**	.
	Handle Threat	**3.96 +**	-1.23	-2.01	.
	Read Message	**10.85 +**	**5.24 +**	**-12.04 -**	.
	Send Message	**3.13 +**	**-3.91 -**	0.65	.
	Show Information	**-31.22 -**	1.44	**22.08 +**	.
		Read Message	Send Message	Show Information	Handle Threat
s4 high	New Plane	-0.42	-2.06	1.91	.
	New Message	**39.03 +**	**-3.65 -**	**-25.04 -**	.
	Handle Threat	1.25	1.32	-1.93	.
	Read Message	**6.94 +**	**4.83 +**	**-8.74 -**	.
	Send Message	**3.31 +**	**-4.65 -**	1.28	.
	Show Information	**-29.71 -**	1.63	**19.97 +**	.

Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance, $N_{shift\ 1} = 56$, $N_{shift\ 4} = 55$), high = high performing teams ($N_{shift\ 1} = 53$, $N_{shift\ 4} = 54$). Results shown for shift 1, lag 1 are the same as in the preceding chapter but are presented again for easier comparison.



Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance, N $_{\text{shift 4}}$ = 55), high = high performing teams (N $_{\text{shift 4}}$ = 54).

Figure 40 Lag sequential analyses: Adjusted residuals, lag 1, shift 4

8.7.4 Summarizing and Condensing Results from Lag Sequential Analyses

All the information on the lag 1 sequences of commanders and specialists is represented in *z*-scores and graphically displayed. Nevertheless, it is not that easy to see the differences in the lag 1 sequences of shift 1 and shift 4. The information is therefore additionally condensed in a summarizing representation in Table 66.

In Table 66 all given codes are listed in the first column, for example New Plane. In the last column the target codes are listed, for example Read Message. Minus (-) and plus (+) signs indicate inhibiting and enhancing sequences for low and high performing teams in shift 1 and shift 4. The colors indicate the size of the effect. A dark blue or a dark green line indicates adjusted residuals that are larger than 10 (also indicated by a ++ instead of a +, respectively a - - instead of -). The first row for lag 1 contingencies of the commander shows that the lag 1 sequence New Plane -> Read Message is inhibited for commanders of low and high performing teams in shift 1 and in shift 4. All commanders show the same contingencies. In the third row is the sequence New Plane -> Show Information. This sequence is in both shifts for commanders of low and high performing teams strongly enhanced.

Commanders of high performing teams have in shift 4 a stronger inhibition that a New Message is followed by a Show Information or that a Show Information is followed by a Read Message, but a higher probability that a Read Message is directly followed by a Send Message. Commanders of low performing have a higher probability that a Read Message is directly followed by a Handle Threat. This outline shows again that commanders of low and high performing teams handle the task more or less alike. The difference between those two performance groups is often found in the consistency or regularity of the commanders actions. The weighting of the sequences is different.

Also specialists A and specialists B show very similar lag 1 sequences. Again the main differences are due to another weighting of those sequences. For both specialists a Read Message is often followed by another Read Message. This probability is higher for high performing teams in shift 1, but higher for low performing teams in shift 4. That a New Message is followed by a Send Message is inhibited for specialists of low performing teams in shift 1, but in shift 4 its inhibited for specialists of high performing teams.

Table 66 Summary Results: Lag Sequential Analyses comparing shift 1 and shift 4 lag 1 contingencies (adjusted residuals).

lag 1, commander given	shift 1 low	shift 1 high	shift 4 low	shift 4 high	target
New Plane	-	-	-	-	Read Message
New Plane					Send Message
New Plane	++	++	++	++	Show Information
New Plane					Handle Threat
New Message	++	++	++	++	Read Message
New Message	-	--	--	--	Send Message
New Message	-	-	-	--	Show Information
New Message			-	-	Handle Threat
Handle Threat		+			Read Message
Handle Threat			+	+	Send Message
Handle Threat					Show Information
Handle Threat		-	-	-	Handle Threat
Read Message	-	-	--	--	Read Message
Read Message	+	+	+	++	Send Message
Read Message	-	-	-	-	Show Information
Read Message	+	+	++	+	Handle Threat
Send Message	-	-		-	Read Message
Send Message	+	+	+		Send Message
Send Message				+	Show Information
Send Message	-				Handle Threat
Show Information	--	--	-	--	Read Message
Show Information			+		Send Message
Show Information	++	++	++	++	Show Information
Show Information					Handle Threat
lag 1, specialists A					
New Plane					Read Message
New Plane					Send Message
New Plane	+				Show Information
New Plane					Handle Threat
New Message	++	++	++	++	Read Message
New Message	-			-	Send Message
New Message	--	--	--	--	Show Information
New Message					Handle Threat
Handle Threat			+		Read Message
Handle Threat					Send Message
Handle Threat					Show Information
Handle Threat					Handle Threat
Read Message	+	++	++	+	Read Message
Read Message			+	+	Send Message
Read Message	-	-	--	-	Show Information
Read Message					Handle Threat
Send Message	+	+	+	+	Read Message
Send Message	-	-	-	-	Send Message
Send Message					Show Information
Send Message					Handle Threat
Show Information	--	--	--	--	Read Message
Show Information	+				Send Message
Show Information	++	++	++	++	Show Information
Show Information					Handle Threat

(continued next page)

lag 1, specialists B					
New Plane					Read Message
New Plane					Send Message
New Plane	+				Show Information
New Plane					Handle Threat
New Message	++	++	++	++	Read Message
New Message	-			-	Send Message
New Message	--	--	--	--	Show Information
New Message					Handle Threat
Handle Threat			+		Read Message
Handle Threat					Send Message
Handle Threat					Show Information
Handle Threat					Handle Threat
Read Message	+	++	++	+	Read Message
Read Message			+	+	Send Message
Read Message	-	-	--	--	Show Information
Read Message					Handle Threat
Send Message	+	+	+	+	Read Message
Send Message	-	-	-	-	Send Message
Send Message					Show Information
Send Message					Handle Threat
Show Information	--	--	--	--	Read Message
Show Information	+	+			Send Message
Show Information	++	++	++	++	Show Information
Show Information					Handle Threat

Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance, $N_{shift\ 1} = 56$, $N_{shift\ 4} = 55$), high = high performing teams ($N_{shift\ 1} = 53$, $N_{shift\ 4} = 54$).

-- = inhibiting, adj. residual < -10	- = inhibiting, adj. residual between -2.98 (specialists, rsp,. 3.07 (commanders) and -10	+ activating, adj. residual between +2.98 (specialists), respectively +3.07 (commander) and +10	++ = activating, adj. residual > +10

Summary

Working with lag sequential analyses extracts a lot of information on the sequential organization of the group process, making it difficult to see relevant differences between low and high performing teams, for example. Therefore, I compacted the information available for lag 1 contingencies in shift 1 and shift 4 in a way that allows a quick comparison of the different sequential patterns – without getting lost in the details of the analyses.

8.7.5 Predicting Performance per shift: Adjusted Residuals derived from Lag Sequential Analyses

This chapter aims to describe how the information on inhibiting and activating sequences (adjusted residuals) can be used in regression analyses. The information from the lag sequential analyses is to be integrated in the input - processes - output framework proposed by Hackman and Morris (1975). The question to be answered is whether or not the information on the process shown in the adjusted residuals helps to predict performance.

All analyses in the preceding chapter were based on *z*-scores calculated either for the low performing teams or the high performing teams. Taking just these pairs of adjusted residuals to run regression analyses makes no sense. The *z*-scores have to be calculated for every team and every role. Doing this results in contingency tables with very low frequencies in the cells (tallies) and also empty cells. I will therefore shortly discuss this problem and solutions.

Preparatory Steps

To run regression analyses *z*-scores must be calculated for every single team member. Doing this often hurts the preconditions to run lag sequential analyses. A precondition to a reliable interpretation of the *z*-scores is that there are actually sequential associations in the contingency table, tested with a chi-square statistics. But a precondition for running chi-square analyses is that there are less then 20% of all cells with expected values of less than 5 and no cell with a expected frequency of 0 (Bortz, 1997; Bortz & Lienert, 1998). Consequently, the program GESQ automatically excludes all these contingency tables from further statistical testing (see Table 67).

Table 67 Observed lag frequencies and chi-square statistics, groups 412 and 507, shift 1, lag 1.

Given	Target ieH	ieR	ieS	ieSi	Totals
seNP	0	0	0	1	1
seNewMs	2	17	3	1	23
ieH	1	3	3	0	7
ieR	7	7	6	0	20
ieS	0	1	0	1	2
ieSi	0	1	0	0	1
Totals	10	29	12	3	54

Given	Target ieH	ieR	ieS	ieSi	Totals
seNP	0	1	1	0	2
seNewMs	0	16	3	0	19
ieH	0	0	1	0	1
ieR	1	2	6	1	10
ieS	0	3	7	1	11
ieSi	0	0	1	0	1
Totals	1	22	19	2	44

```
Lag 1. XSQ. Pearson's Chi-square
   Pearson's Chi-square         =     37.5163
   Degrees of freedom           =          15
   Approximative p-value        =    0.001114
   Expected frequencies < 5     =       87.5%
   Expected frequencies < 3     =       70.8%
   Expected frequencies < 1     =       50.0%
```

```
Lag 1. XSQ. Pearson's Chi-square
   Pearson's Chi-square         =     20.5228
   Degrees of freedom           =          15
   Approximative p-value        =    0.152283
   Expected frequencies < 5     =       83.3%
   Expected frequencies < 3     =       75.0%
   Expected frequencies < 1     =       70.8%
```

In order to omit this problem alternative tests are used, for example the Craddock-Flood chi-square test, the Haldane-Dawson test or exact tests (Bortz & Lienert, 1998; Bortz, Lienert, & Boehnke, 2000). I ran some analyses using Monte Carlo estimates for the likelihood-ratio chi-square exact test. For the two examples given in Table 67 this test shows is statistically significant: $\chi^2_{\text{group 412, lag1}}$ (15, N = 54) = 24.01, p = 0.03, $\chi^2_{\text{group 507, lag1}}$ (15, N = 44) = 22.30, p = 0.02.

Results from chi-square analyses (Monte Carlo simulation to calculate Fisher's exact tests) show that 61% of the commanders have overall statistically significant lag 1 associations in shift 1. This percentage goes down to 21% for lag 2 associations, 13% for lag 3 associations and then goes below 10% for lag 4 to lag 8 associations. The situation for specialists A and B is similar: most often overall statistically significant associations can be found for lag 1 and lag 2 associations. It is remarkable that only 3% of all commanders have overall statistically significant lag 4 associations. Taking this information only 61% of the commanders lag 1 contingencies in shift 1 could be used in further analyses. But Bakeman and Robinson (1994) cite Milligan (1980) with the remark that even if the overall chi-square statistic is not statistically significant one "(…) might even cautiously persevere in (the) analyses; although inadequate expected frequencies reduce power, they do not generally make type I error more likely" (p. 98).

Thus, the z-scores could be used "cautiously" in further analyses, if there would not be a further problem.

Following the discussion in the literature over some years there are phases where the use of the z-score was recommended, in other phases it was heavily questioned.

Bakeman and Gottman (1986) recommended using the *z*-score – the adjusted residuals - to run regression analyses. Yet some years later, saying that this was “not sound advice” (Bakeman, 1991, p. 272). Bakeman recommends the use of the odds-ratios or Yule’s Q for 2x2 tables (see also: Bakeman, McArthur, & Quera, 1996) or to calculate dichotomous scores, just telling if there is a negative or positive reciprocity. Quera and Bakeman (2000, p. 314) recommend using either Haberman’s adjusted residuals or Yule’s Q (which can only be calculated for 2x2 tables). Both can be interpreted as test of the deviation from the null hypothesis for some specific sequences, or as descriptive indices of sequential association.

This discussion reflects a disadvantage of the *z*-score: it is not independent of the number of tallies. If the number of tallies in the cells are doubled whilst keeping the associations the same, the *z*-score increases (see the example in Table 62). Commanders or specialists with a very low frequency also have lower *z*-scores in general, respectively those with high frequencies have much higher *z*-scores. A minimal number of tallies is a precondition for sequential associations to emerge. Having as few as 15 tallies means that this commander or specialist did almost nothing. In this case the very low *z*-scores are a good indicator that no meaningful sequences can be found. The other extreme are the commanders or specialists with a lot of tallies. This is either a sign of a strong engagement or of a more chaotic trial and error strategy (just pressing the buttons as often as possible).

Reviewing this discussion I decided to follow the suggestion not to use the raw *z*-scores. Before entering the *z*-scores into the regression analyses they were recoded following a suggestion of Bakeman (1991). Values between -1.96 and + 1.96 were recoded to 0, this is no sequential association. Values below -1.96 were recoded to -1, this is a inhibiting sequential association. Values above +1.96 were recoded to +1, that is an enhancing sequence. In my view this recoding condenses the wanted information in a reasonable way, taking into account the perils that lie in the calculation of the *z*-score.

Predicting Performance using Adjusted Residuals (lag 1)

The recoded adjusted residuals of lag 1 contingencies are used as predictors of the performance per shift. These recoded adjusted residuals express whether a lag 1 contingency is observed more often than expected (that is a enhancing sequence) or less often than expected (a inhibiting sequence). The main categories of the coding scheme (chapter 6.8) are used to calculate the adjusted residuals per team and role: Read Message, Send Message, Show Information, Handle Threat, New Plane, and New Message.

The recoded adjusted residuals alone explain 20% of variance in performance in shift 4 up to 46% in shift 3 (Table 68). Generally, the recoded adjusted residual are better predictors of performance per shift than input variables (Table 53, 5% in shift 2 to 25% in shift 8, equation 1) or *summary-level process* variables (Table 55, 7% in shift 3 to 46% in shift 6). There are in some shifts also better predictors than the task adaptive behaviors (Table 57, 19% in shift 4 to 53% in shift 2). If the recoded adjusted residuals are entered in the regression model after controlling for the preceding performance and after entering input variables and summary level process variables they still explain additional 8% of variance in performance in shift 8 to 24% in shift 2

Table 68 Summary of results: Explained variance (R2) using only input variables, summary-level process variables and recoded adjusted residuals as predictors of performance.

	Variance explained by equation 1			equation 2								
dependent variable: performance in…	*adjusted residuals (recoded) only*			preceding performance		plus *Input* factors		plus *summary level process* variables		plus *adjusted residuals (recoded)*		change due to *adjusted residuals*
	R^2	$R^2_{adj.}$		R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	*diff.* R^2
shift 1	0.401	0.319	**	-	-	0.130	0.105	0.321	0.267	0.546	0.456 **	0.225
shift 2	0.372	0.286	**	0.212	0.205	0.236	0.222	0.337	0.305	0.576	0.507 **	0.239
shift 3	0.463	0.370	**	0.323	0.316	0.407	0.390	0.468	0.443	0.640	0.587 **	0.172
shift 4	0.201	0.154	**	0.235	0.228	0.299	0.279	0.470	0.410	0.576	0.491 **	0.106
shift 5	0.361	0.302	**	0.271	0.264	0.326	0.307	0.446	0.407	0.546	0.489 **	0.100
shift 6	0.291	0.227	**	0.405	0.400	0.464	0.443	0.515	0.476	0.598	0.543 **	0.083
shift 8	0.374	0.303	**	0.331	0.325	0.455	0.417	0.563	0.518	0.713	0.648 **	0.150

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were then entered using the method forward. Independent variables are entered into the equation if the smallest probability of F is smaller than 0.15. Model fit: * $p < .050$, ** $p < .001$.

The sequences that were used in the regression models as predictors of performance are summarized in Table 69 (the details are in Table 148 to Table 161 in the appendix).

In Table 69 the given event is on the left side, for example a New Plane. The target behavior is on the right side, for example a Send Message. In between all beta values that are in the final regression model are displayed per shift. The three roles are represented in three rows (C, A, B). An example: For the commanders' lag 1 sequence New Plane -> Send Message the beta value is negative (written as red – sign in the table). If there is a positive recoded adjusted residual (+1), the probability is enhanced and this sequence New Plane -> Send Message occurs above chance. But in the end this lowers performance. If the recoded adjusted residual is negative (-1) the probability that this sequences does not occur is above chance. Thus, the performance is better if the sequence New Plane -> Send Message is inhibited. The columns labeled day 1 and day 2 poll the results from the single shifts.

It is often better that the commander does not send a new message if there is a new plane in the airspace (in shift 3, shift 4 and shift 6). If there is a new message in the inbox specialists A and specialists B should at least in shift 8 not send an own message.

Neither specialists A nor specialists B need to react immediately to a new plane. A good reaction of a commander to a new plane in the airspace is to immediately assign a threat level to the plane. The only thing a commander should not do is to send a message if there is a new plane in the airspace.

There emerges no clear picture on what to do after a new message arrived in the inbox. A new message does not need to be read immediately nor is it something that should not be done. The same is truth for the threat assignments.

However, the next step after a message is read is important. A commander should omit a sequences of reading a message after having read a message. For specialists A this is slightly different. There are shifts in which an enhanced sequence of specialists A reading a message following reading a message is fostering performance. In some shifts it is better for commanders to omit sequences of reading a message and then sending a message. This is the case in shift 3 and in shift 4. In other shifts (shift 1 and shift 6) it is exactly the other way around: commanders sending a new message after having read a message achieve a better performance. A commander should better not assign the threat level immediately after having read a message (shift 2, shift 3 and shift 6.

The next step after sending a message seems not to be of some special importance for the performance. But it is probably better to omit sequences of sending two messages one after another, to look up plane information (as specialist) after having sent the message. Also the step immediately following a Show Information is not very important for the teams performance.

Table 69 Summary of results: Adjusted residuals (lag 1), shift 1 to shift 8, controlling for preceding performance (except in shift 1), and input variables and summary level process variables.

given		shift 1	shift 2	shift 3	**day 1**	shift 4	shift 5	shift 6	shift 8	**day 2**	target
New Plane	C										Read Message
	A	+			+						
	B										
New Plane	C			-	-	-		-		-	Send Message
	A										
	B										
New Plane	C		+		+						Show Information
	A								+	+	
	B										
New Plane	C		+		+				+	+	Handle Threat
	A										
	B										
New Message	C		+		+						Read Message
	A	-			-						
	B						+			+	
New Message	C		+		+						Send Message
	A								-	-	
	B					-			-	-	
New Message	C										Show Information
	A										
	B		-		-						
New Message	C	-			-				+	+	Handle Threat
	A										
	B										
Handle Threat	C										Read Message
	A		-		-			-		-	
	B								+	+	
Handle Threat	C						+			+	Send Message
	A										
	B										
Handle Threat	C										Show Information
	A										
	B			-	-						
Handle Threat	C			+	+						Handle Threat
	A										
	B										
Read Message	C			-	-	-			-	-	Read Message
	A	-	+		+/-				+	+	
	B	+			+						
Read Message	C	+		-	+/-	-		+		+/-	Send Message
	A										
	B	+			+						
Read Message	C										Show Information
	A					+			+	+	
	B							-		-	
Read Message	C		-	-	-			-		-	Handle Threat
	A										
	B										
Send Message	C										Read Message
	A										
	B			-	-	+				+	
Send Message	C										Send Message
	A						-			-	
	B			-	-						
Send Message	C		+		+						Show Information
	A	-			-						
	B										
Send Message	C	-			-						Handle Threat
	A										
	B										
Show Information	C		+						+	+	Read Message
	A	-					-			-	
	B										
Show Information	C					-					Send Message
	A			-	-						
	B										
Show Information	C										Show Information
	A										
	B										
Show Information	C						+			+	Handle Threat
	A										
	B										

Note. + / - direction of effect, sign of Beta value. The coding scheme is described in chapter 6.8. All Beta values of the final regression model are displayed. C = commander, A = specialist A, B = specialist B .

Review of the Research Questions to Lag Sequential Analyses

SEQ I. The activities of commanders and specialist have a certain regularity. It is possible to identify meaningful patterns.

Lag sequential analysis identifies patterns.
And it is possible to meaningfully interpret the patterns.

SEQ II. Moreover, low and high performing teams show different patterns.

It is possible to show different patterns between low and high performing teams. Nevertheless, these differences are not that big that low and high performing teams show completely different patterns.

SEQ III. It is possible to predict performance if the identified patterns are entered as predictors in a regression model.

Recoded adjusted residuals were used as predictors of performance. They explain. After controlling for the preceding performance and after entering input variables and summary-level variables the recoded adjusted residuals explain still additional 8% of variance in performance in shift 8 to 24% in shift 2.

SEQ IV. Due to the nature of the ATC task and how it is implemented, patterns of directly adjacent events are better predictors of performance than either patterns combining events that follow one another after some other events happened or patterns of long sequences (six or more succeeding events).

As only lag 1 sequences were used in the regression model there is no answer to this question.

8.7.6 Evaluation of Lag Sequential Analyses Applied to the ATC Data

Lag sequential analysis is a well established method in behavioral research. There is a lot of information available on how to run lag sequential analysis. An intense discussion can be found in the literature on what preconditions must be met and what measures are best used in lag sequential analyses.

An advantage of the method is that it produces reliable results already with relatively few observations. The trick is to look either at lag 1 or lag 2 or lag 3, etc. contingencies and not to build long, continuous sequences. This is of course also one of the drawbacks of the method. A lag 2 sequence of e.g., Read Message - (…) - Read Message looks different if the lag 1 event is a Read Message or a Handel Threat.

The results are first of all descriptive. The examples given in my text show the contingencies for lag 1 to lag 5 sequences for shift 1 and lag 1 contingencies for shift 4, each separating teams of low and high performance. Numbers and figures are meaningful and allow a detailed analyses of the group process. A difficulty in lag sequential analysis is to decide on the appropriate lag to analyze. Running analyses for e.g., lag 1 to lag 5 contingencies, for low and high performing teams, for all three roles from shift 1 to shift 8 results in 210 contingency tables which are not that easy to handle.

Looking at lag 1 contingencies reveals that commanders or specialists of low and high performing teams do not differ that much in shift 1 or shift 4 if one looks only at the patterns. They are very much alike. The differences between low and high performing teams are often found in the value of the adjusted residuals. This means that although the two performance groups behave structurally almost identical, the chance that a certain sequence emerges is different.

Lag sequential analysis is a very good tool to discover contingencies in the data. Results can be visualized to help understand the group process. If the interest is on the group process the method is very feasible.

In a second step I calculated adjusted residuals for every role. Thus its possible to use the values in regression analysis or ANOVA for further analyses. There are pros and cons doing this. The main problem is that analyzing individual contingency tables instead of pooled data often hurts preconditions. Often the number of tallies in a table is too low so that the minimum number of cells with an expected frequency of 5 to run chi-square statistics is hurt. Or the number of tallies differ to such an extent that the adjusted residuals cannot be compared anymore between individuals. As I argued it is – at least in for the ATC data – in spite of this problem possible to work with the adjusted residuals.

8.8 Procedural Network Representation

Procedural network representation (PRONET) was introduced in chapter 5.3.2 as a method to represent sequential behavior based on the Pathfinder algorithm (Schvaneveldt, 1990). The Pathfinder algorithm calculates non-hierarchical networks, showing the relations between concepts and is similar to multi dimensional scaling algorithms. Pathfinder *C* can be calculated to compare different network representations.

In this chapter procedural network representation (PRONET) is applied to the ATC data. The aim is to use PRONET as a tool to visualize the different group process in low and high performing teams. The Pathfinder *C* value will be calculated to compare the different networks representing a different group process.

8.8.1 Method Subsection: Procedural Network Representation (PRONET)

The PRONET analyses is based on the same process variables as the lag sequential analyses: New Plane, New Message, Handle Threat, Read Message, Send Message, and Show Information (see definition in chapter 6.8).

Software used to run PRONET

I run the analyses using GSEQ (Bakeman & Quera, 1995a) to calculate the conditional probabilities. Further analyses are run with the Knowledge Network Organizing Tool (KNOT, Schvaneveldt, 1990). In Table 162 (appendix) I give an example of an input file for the KNOT program.

Running PRONET analysis: Step by Step

The steps in PRONET analyses are (Cooke et al., 1996, p. 37ff.):

- Collect sequential data.
- Encode data into discrete events which will become nodes in the procedural network.
- Generate transitions matrices.
- Conduct Pathfinder analyses.
- Interpret procedural networks.

The coding of the data and the calculation of the conditional probabilities is already described in the chapter on lag sequential analysis (chapter 8.7). I will only mention those points that differ.

Running PRONET analysis: Preparing the Data

PRONET analyses are based on same contingency tables as the lag sequential analyses. Conditional probabilities are submitted to the Pathfinder algorithm. However, the Pathfinder algorithm requires symmetrical tables (matrices). In lag sequential analyses the tables were calculated for six given behaviors and four target behaviors, they were asymmetrical (cf. Table 60). It is not possible that a New Plane or a New Message is a reaction to any other event. All conditional probabilities related to a sequence having a New Plane or a New Message as target are therefore set to zero (see Table 165 for an example, appendix).

Running PRONET analysis: Calculating Pathfinder *C*

To compare two or more procedural networks the *C* measure of similarity is used (Goldsmith & Davenport, 1990). *C* is calculated as the mean proportion of shared links for each pair of nodes in the two networks, not taking into account the link weight (Cooke et al., 1996).

Taking an example from Goldsmith, Johnson and Acton (1991) I will shortly illustrate the steps to calculate Pathfinder *C*. In this example five concepts (also called entities, which then will become nods in the Pathfinder network representation) are given; A, B, C, D, E and the matrix with the proximity data (Table 70). These proximities are transformed into a non-hierarchical Pathfinder network as shown in Figure 41 (right side).

The Pathfinder network scaling algorithm searches through all the nods of a network to find the closest indirect path between objects. To calculate the distances the Minkowski distance measure is used. The distance between nods is calculated as $(x^r + y^r)^{1/r}$, $x \geq 0$, $y \geq 0$, $r \geq 1$. The *r* parameter determines how the weight of a path is calculated from the weights of the links: increasing the *r* value increases the relative importance of larger link weights. In Pathfinder analyses the *r* parameter is often set to infinite, which means that maximal link weights are searched. The psychological interpretation of larger values of *r* is that the perceived dissimilarity between nods is determined by the dissimilarity of the most dissimilar relations connecting the nods. A second parameter of *q* limits the number of links which are used to find the minimal path weights. Typically, this value is set to number of nods minus 1. The *q* parameter allows to control the density of links in a network (Schvaneveldt et al., 1989)

In searching through the nods to find the closest indirect paths the following criteria are applied:
criteria 1: A direct link between two objects is only added if the closest indirect path between the two nods is greater than the proximity value for that pair of objects.
criteria 2: But this is only done, if the graph-theoretical distance is smaller than the corresponding proximity value. The graph-theoretical distance is the least number of links separating two nods (Goldsmith et al., 1991).
criteria 3: And finally the graph must be connected.

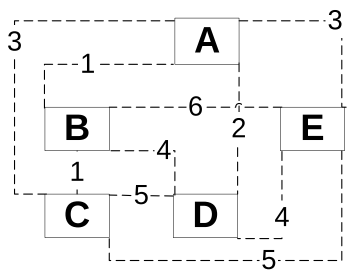
Example. The direct link from A to B has a proximity value of 1. Indirect paths from A to B are e.g., **A** -> C -> **B** with a total length of 4 (3 for A -> C plus 1 for C -> B), or **A** -> E (3) -> D (4) -> -**B (4)** with a total length of 11. There is no indirect path from A to B that is shorter than the direct path (criteria 1 is met). The proximity value for A -> B is 1, and the least number of links connecting the two nods is 1. Because 1 is not smaller than 1 a direct link is added connecting A and B (criteria 2 is met).
There is no direct path from D to E. There is no other path from D to E that is shorter than 4 (e.g., D -> A -> E = 5, D -> C -> E = 10) and so criteria 1 is met. But criteria 2 is not met: The least number of links connecting D and E is smaller than 4.
The links from A and E and A and D are added to get a connected graph (criteria 3).

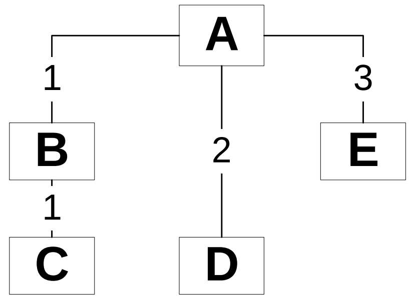
Table 70 Hypothetical proximity data (Goldsmith et al., 1991, p. 89).

	A	B	C	D	E
A	0	1	3	2	3
B	1	0	1	4	6
C	3	1	0	5	5
D	2	4	5	0	4
E	3	6	5	4	0

.

data net	Pathfinder network representation





Note. Representation on the lift side is Pathfinder network, in the right side the dashed lines represent indirect paths.

Figure 41 Pathfinder network representation of hypothetical proximity data (Goldsmith et al., 1991, p. 90)

Pathfinder *C* is calculated as the number of shared links in two networks. An example of two hypothetical networks is given in Figure 42. It is counted for each graph separately how many links go from one nod to other nod(s) as shown in columns A to C in Figure 43. Then it is counted how many links are common (columns D and F) and how many links there are all in all (columns F and G). Then the quotient is calculated (column H). Finally, Pathfinder *C* is calculated as the sum of column H divided by the sum of column G, which results in a *C* value of .43 for the two hypothetical networks presented in Figure 42.

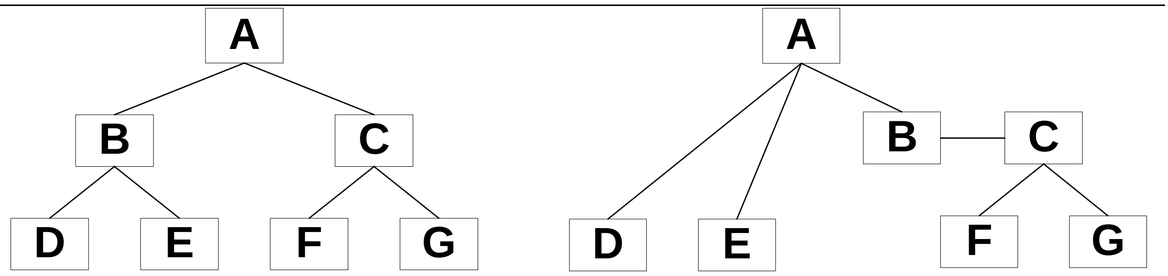


Figure 42 Two hypothetical Pathfinder network representations for two given two network representations.

A	B	C	D	E	F	G	H
nod	links to nod … in graph 1	links to nod … in graph 2	common links	number of common links	links present in graph 1 or graph 2	number of links	common links / number of links
A	**B, C**	**B, D, E**	**B**	**1**	**B, C, D, E**	**4**	**1 : 4**
B	A, D, E	A, C	A	1	A, C, D, E	4	1 : 4
C	A, F, G	B, F, G	F, G	2	A, B, F, G	4	2 : 4
D	B	A	-	0	A, B	2	0 : 2
E	B	A	-	0	A, B	2	0 : 2
F	C	C	C	1	C	1	1 : 1
G	C	C	C	1	C	1	1 : 1
					sum	**7**	**3**
					Pathfinder C		3 : 7 = **.43**

Figure 43 Calculation of Pathfinder C.

8.8.2 Results PRONET/Pathfinder Analyses

Pathfinder Networks for Lag 1 Conditional Probabilities in Shift 1 and Shift 4

Results of PRONET/Pathfinder analyses are presented in Figure 44 to Figure 46. The networks for low and high performing teams are presented, for all roles, lag 1 conditional probabilities in shift 1 and shift 4. The split criteria was the median performance in shift 1, respectively in shift 4. All results are based on analyses of the pooled data for low and high performing teams (hence two groups are compared). In chapter 0 results are presented which are based on Pathfinder network representations calculated for each person separately.

How to read the graphs. In Figure 44 there is a path for commanders of low performing teams from New Message to Send Message. The numbers beside New Message (1292) and Send Message (484) are the number of times those events can be observed. The value of .11 on the arrow is the link weight which ranges from 0 to 1. The higher the link weight the stronger the connection. The links can then be read as: if there is a new message commanders of low performing teams react in shift 1 either with a Send Message or a Handle Threat.

The graphical representations from a PRONET analysis are very similar to the graphical representations of the lag sequential analyses. Both methods use the same lag 1 contingency tables with the same frequencies (the same number of tallies). Lag sequential analyses moves then forward to calculate adjusted residuals (*z*-scores), whereas PRONET uses the conditional probabilities in a Pathfinder analyses.

Conditional probabilities express the probability that a certain event succeeds on a specific given event. Adjusted residuals express the extent to which a conditional probability differs from its expected value.

As a consequence, PRONET network representations of the group process show all paths that occurred. An example that directly compares conditional probabilities and adjusted residuals is given in Table 62.

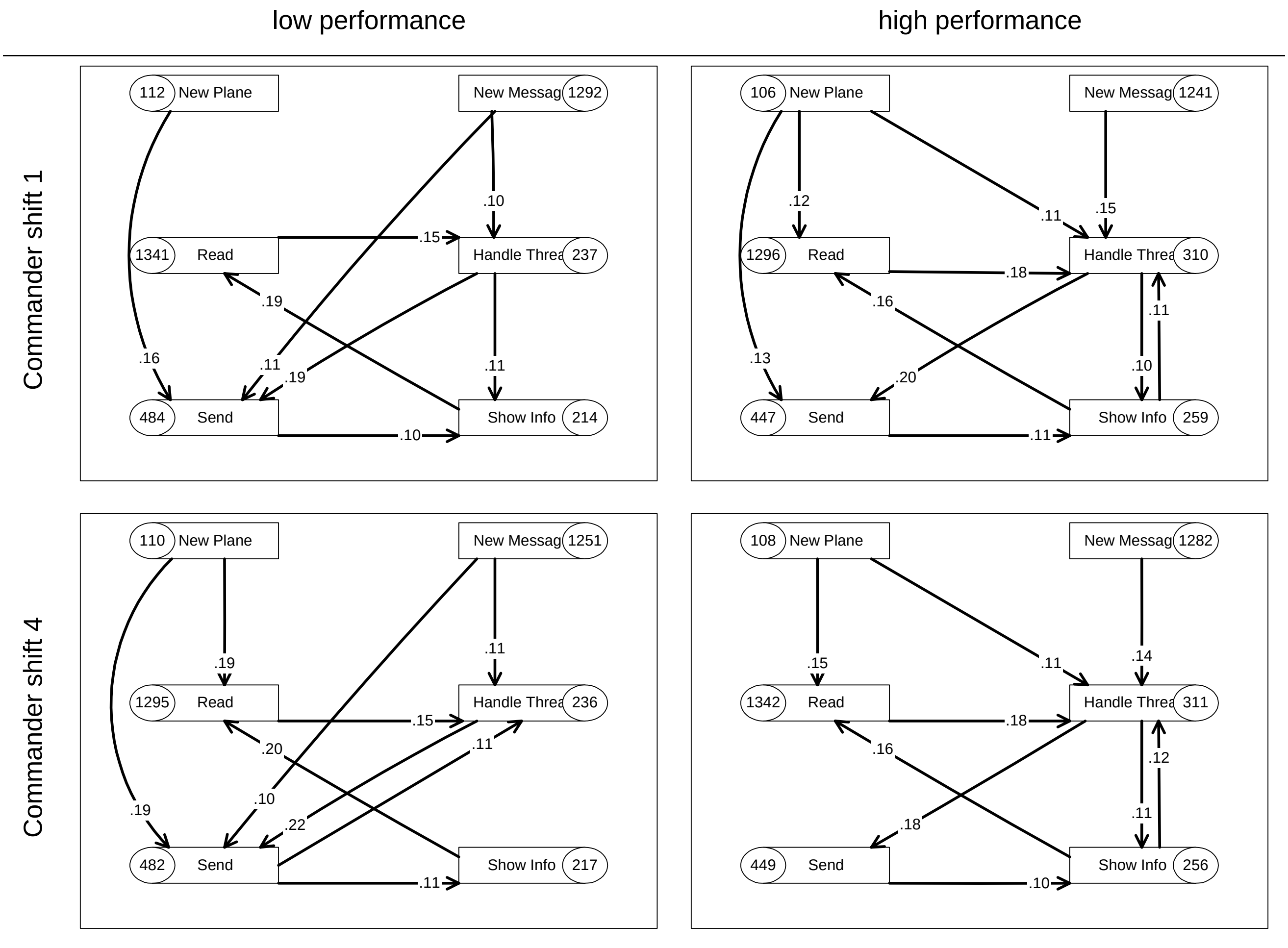
Pathfinder network relations are easy to read, but they bear the danger to read longer sequences than implied. The network in Figure 44 contains only lag 1 relations. Given a New Plane for commanders of low performing teams it is likely that a Show Information (weight of the path .88) follows. Given a Show Information it is likely that a Send Message follows (path weight = .21). However, we must not conclude that given a New Plane, the next step is a Show Information, which then is often followed by a Send Message. This second link is not related to the first link, because only lag 1 sequences are analyzed (Kiekel, Cooke, Foltz, Gorman, & Martin, n.d.).

Commanders, shift 1 and shift 4. If there is a New Plane, commanders of low performing teams in shift 1 react with a Send Message. Something that is also true for commanders of high performing teams, but they also have other reactions to a New Plane: reading a message, or setting the threat level. In shift 4 commanders of low performing teams still react with a Send Message to a New Plane or with a Read Message, whereas commanders of high performing teams react solely with a Read Message or a Handle Threat.

Commanders of low performing teams have in shift 1 and shift 4 a connection of New Message followed by a Send Message. Something that commanders of high performing teams do not show right from the beginning.

The connection of Handle Threat followed by a Show Information or vice-versa is much stronger for commanders of high performing teams. For commanders of low performing teams this contingencies are missing in shift 4.

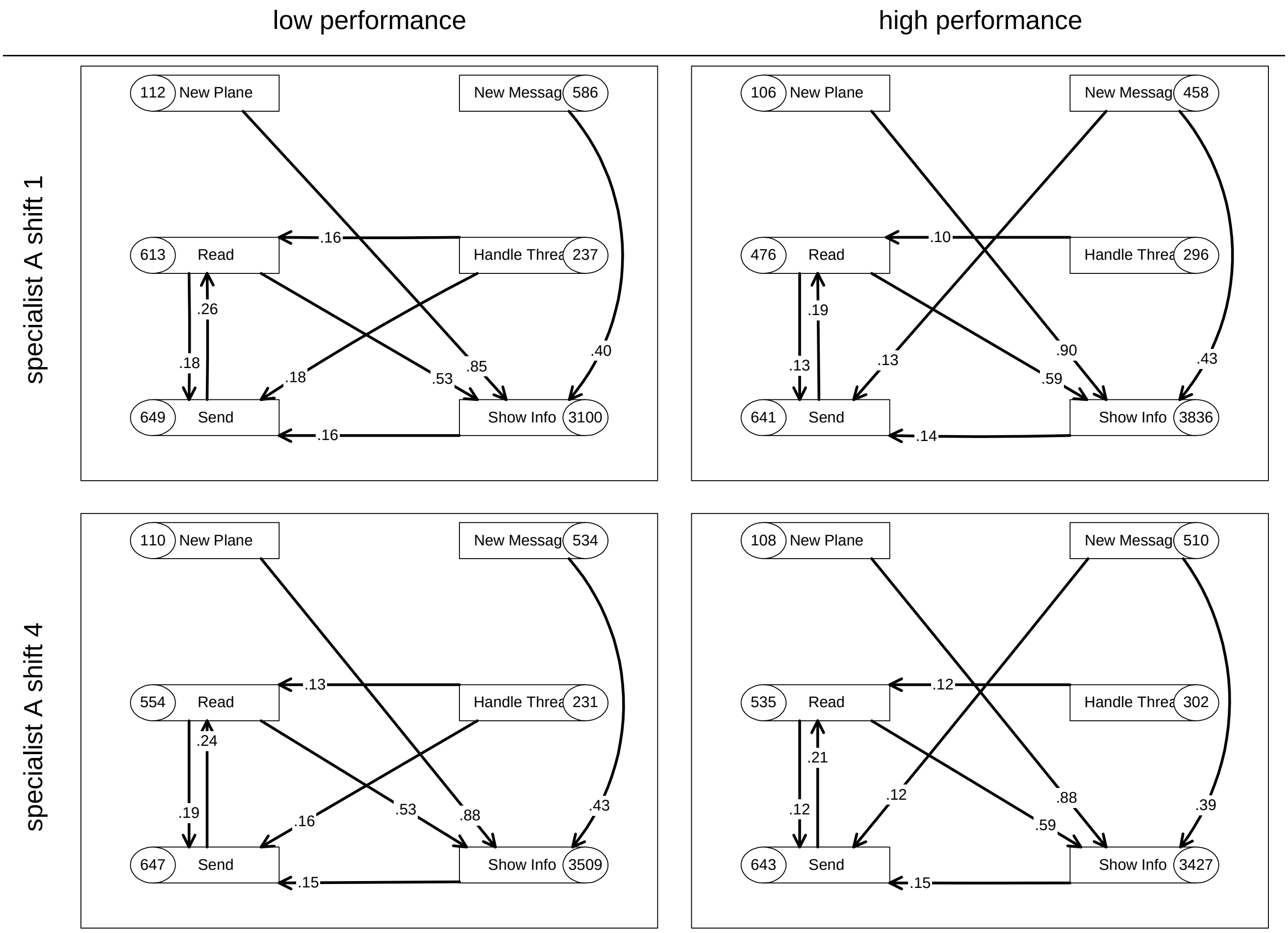
Looking at the contingencies of New Message followed by a Send Message and Send Message followed by an Handle Threat which both are only to be found for commanders of low performing teams and comparing the path weights for Read Message followed by a Handle Threat, or Show Information followed by a Handle Threat which are greater for commanders of high performing teams, leads to the assumption that commanders of high performing teams use the information they get on the planes much more intensively than commanders of low performing teams. It seems as if commanders of low performing teams must ask their specialist for information on planes, whereas commanders of high performing teams get them delivered more automatically.



Note. N = 109 teams, median split of performance: low performance N $_{\text{shift 1}}$ = 56 teams, N $_{\text{shift 4}}$ = 55 teams, high performance N $_{\text{shift 1}}$ = 53 teams, N $_{\text{shift 2}}$ = 54 teams. Numbers on arrows are path weights (from 0 to 1). Numbers in circles near to the event label are the frequencies of the events. The minimal link weight is set to 0.1.

Figure 44 PRONET: Pathfinder network representations for commanders, lag 1 conditional probabilities, shift 1 and shift 4.

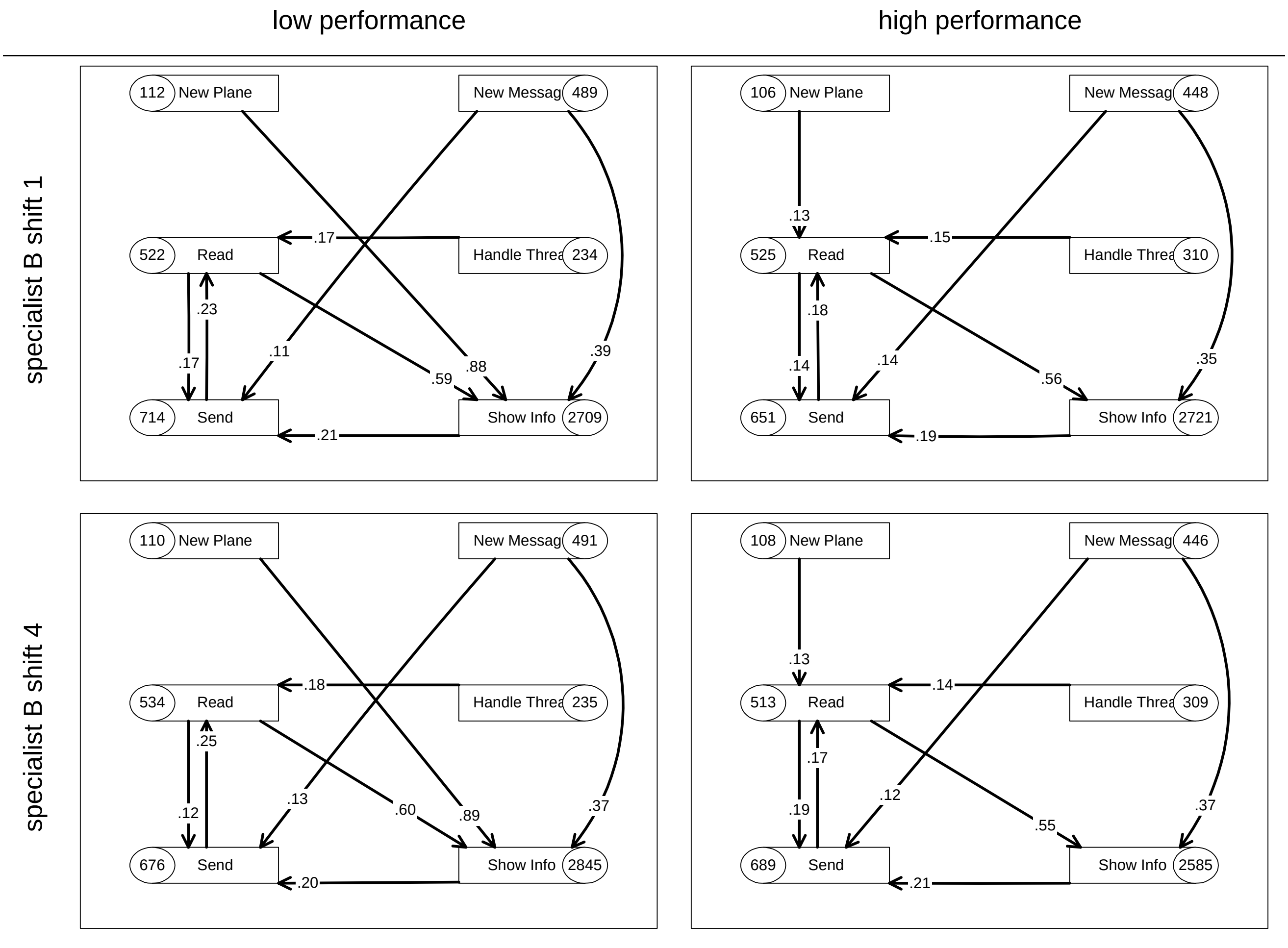
Specialists A, shift 1 and shift 4. If there is a New Plane there is a high probability that specialists A look up information on the plane (low and high performing teams, shift 1 and shift 4) . There is also a high probability that specialists A look up plane information after having read a message. Butt overall the network representations for specialists A of low and high performing teams are almost identical. The path weights are different.



Note. N = 109 teams, median split of performance: low performance $N_{shift\ 1}$ = 56 teams, $N_{shift\ 4}$ = 55 teams, high performance $N_{shift\ 1}$ = 53 teams, $N_{shift\ 2}$ = 54 teams. Numbers on arrows are path weights (from 0 to 1). Numbers in circles near to the event label are the frequencies of the events. The minimal link weight is set to 0.1.

Figure 45 PRONET: Pathfinder network representations for specialists A specialists A lag 1 conditional probabilities, shift 1 and shift 4.

Specialists B, shift 1 and shift 4. There is one striking difference: specialists B of high performing teams did not react to a Show Information with a Show Information. Specialists B of low performing teams do it as well as specialists A, regardless of their performance. Specialists B of high performing teams start reading messages when there is a New Plane in the airspace.



Note. N = 109 teams, median split of performance: low performance $N_{shift\ 1}$ = 56 teams, $N_{shift\ 4}$ = 55 teams, high performance $N_{shift\ 1}$ = 53 teams, $N_{shift\ 2}$ = 54 teams. Numbers on arrows are path weights (from 0 to 1). Numbers in circles near to the event label are the frequencies of the events. The minimal link weight is set to 0.1.

Figure 46 PRONET: Pathfinder network representations for specialists B lag 1 conditional probabilities, shift 1 and shift 4.

In the next chapter Pathfinder *C* is calculated as measure that compares different graphical representations.

Pathfinder C – The Similarity of Network Representations

Pathfinder *C* can be calculated for every pair of Pathfinder network representations. The basis for the following calculations are the Pathfinder networks presented in the precedent chapter.

Commanders, shift 1 and shift 4. The highest similarity is between the networks of commanders of high performing teams for shift 1 and shift 4 (C = .90). The similarity of the networks for commanders of low and high performing teams in shift 1 is C = .67, but goes back to C = .55 in shift 4. This means that Pathfinder networks of commanders of low and high performing teams are less similar in shift 4. The similarity of the Pathfinder networks for low performing teams is with C = .78 lower than those for commanders of high performing teams. This could indicate that low performing teams have more changes in their strategies, whereas high performing teams stick to their successful strategy which is already visible in shift 1.

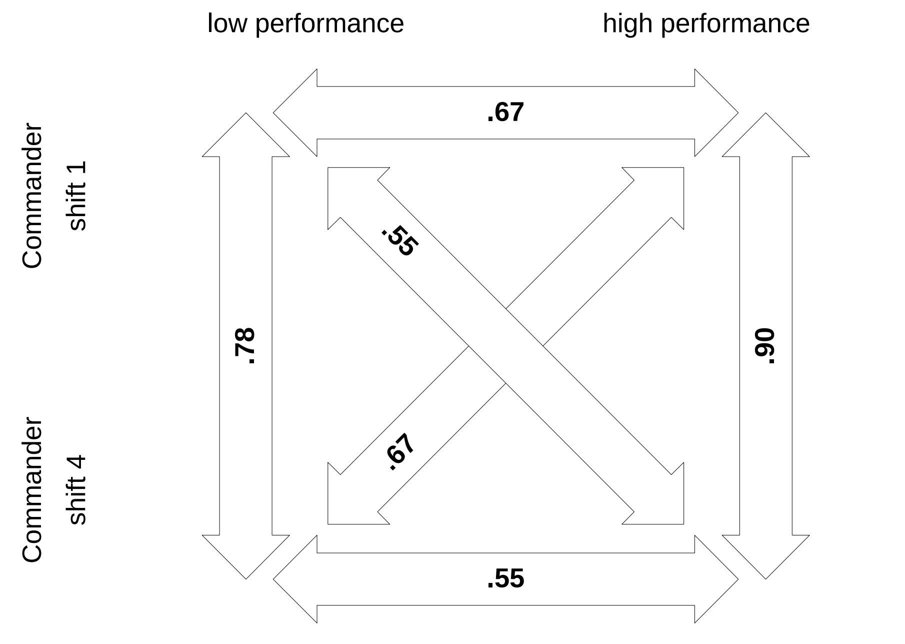


Figure 47 Pathfinder C: similarity of network representations for lag 1 sequences in shift 1 and 4 for commanders of low and high performing teams.

Specialists A and B, shift 1 and shift 4. Already the visual inspection of the Pathfinder network representations in Figure 45 and Figure 46 shows a huge similarity. So it is no surprise that the Pathfinder C values are all very high, showing a perfect similarity of C = 1.00 for the comparison of shift 1 and shift 4 for the specialists of each performance group.

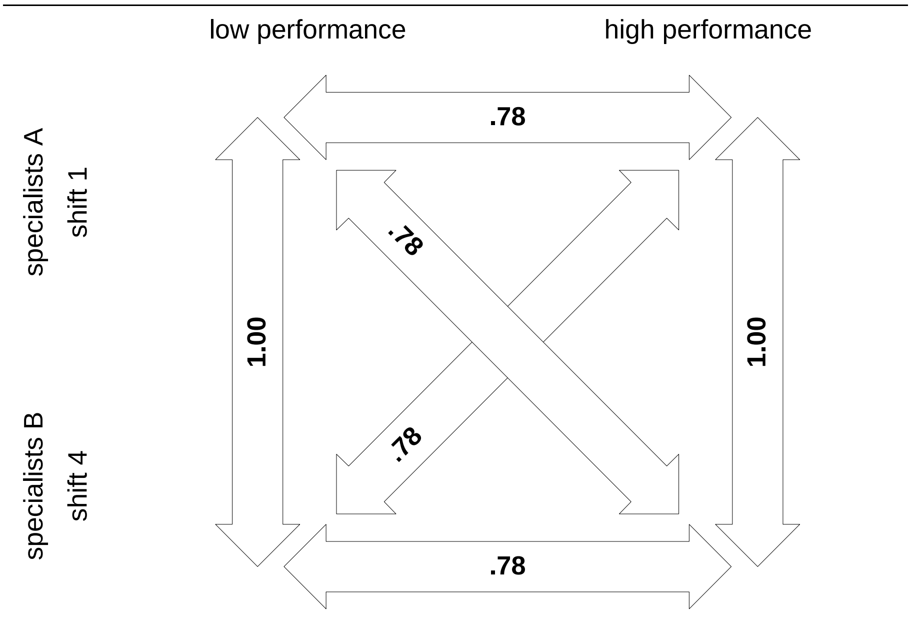


Figure 48 Pathfinder C: similarity of network representations for lag 1 sequences in shift 1 and 4 for specialists A of low and high performing teams.

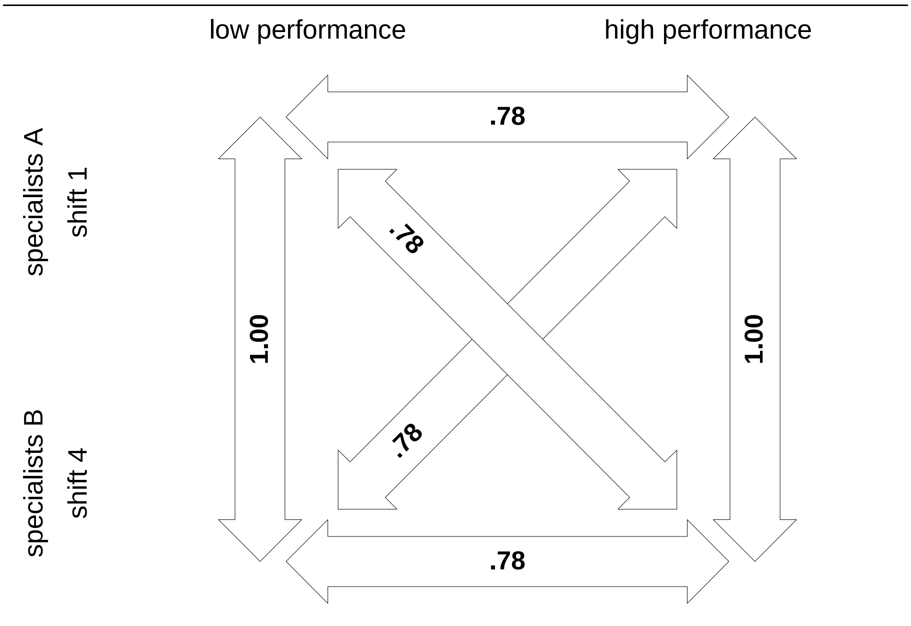


Figure 49 Pathfinder C: similarity of network representations for lag 1 sequences in shift 1 and 4 for specialists B of low and high performing teams

Conclusion. On an aggregated level, collapsing or summing up the events for low and high performing teams, the PRONET analyses does not help that much to discover how the teams did their work. The expectation is that collapsing data produces "more reliable estimations of transition frequencies because there are more observations for each event" (Cooke et al., 1996, p. 38). But the results of the PRONET analyses lead to very similar network representations in shift 1 and shift 4 for both performance groups, especially for specialists. This might of course be the reality: Commanders and specialists of low or high performing teams do not differ that much in their sequential organization (lag 1) of the task. But this is not very likely, because other analyses show differences. And there are other reasons why these results using PRONET could be misleading.

Collapsing the data for all teams with low respectively high performance is only reasonable if the variation within the collapsed groups is not too big. All teams of the two group should have similar sequential patterns each. If this is not the case the collapsed data does not represent a real team.

In the next chapter I present a closer look at the coherence of the data.

Coherence of the data

The *coherence* is a measure that reflects the consistency of the data (Schvaneveldt, n.d.). It is calculated in two steps: (i) for each pair of items a measure of relatedness is calculated by correlating the proximities between the items and all other items, then (ii) coherence is computed by correlating the original proximity data with the indirect measures. If there are many cells with the value 0 in the matrix or if there are nods that are not connected, it is more likely that coherence is low. The example in Table 71 suggests that it is to be expected that coherence should be lower for low performing teams and higher for high performing teams.

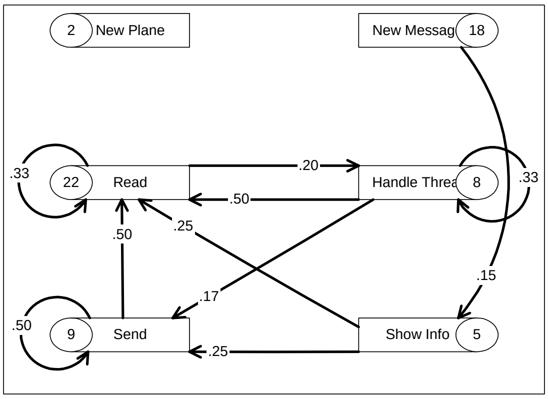
Looking at the coherence measure shows that the values are very low. The range is from .003 (specialists A, shift 4, high performing teams) to .206 (specialists A, shift 1, high performing teams). The coherence values should be above .200 (Schvaneveldt, n.d.). Lower values could (not must!) be an indicator of errors in the data. And probably the data is in this case really erroneous. The matrices representing the conditional probabilities (Table 165) must be symmetric. This results in a lot of empty cells (0). And there are extreme cases as the reaction to a New Plane which is most likely a Show Information with conditional probabilities above .80. The matrix is therefore very distorted. And it is well known that almost all algorithms based on MDS like techniques are sensible to outliers and extreme cases (Läge, 2003; Streule, Schlatter, Rüfenacht, & Läge, 2003). That pathfinder *C* shows almost no variation is due to the calculation of the *C* measure, which does not take into account the weight of the paths from one nod to another (Figure 43).

Table 71 PRONET: Coherence of proximity data, an example.

pathfinder net

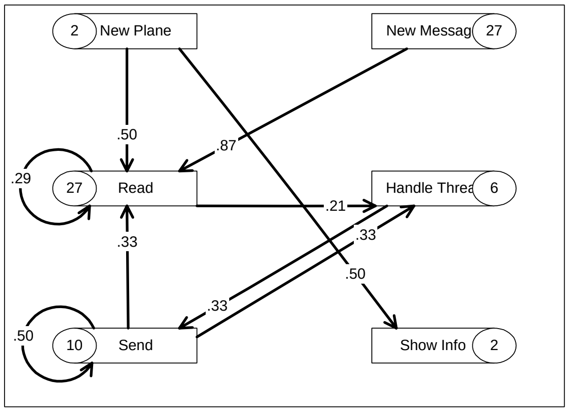
coherence = .002

commander, team 423, shift 1, lag 1



coherence = .435

commander, team 520, shift 1, lag 1



conditional probabilities

commander, team 423, shift 1, lag 1

	New Plane	New Message	Handle Threat	Read Message	Send Message	Show Information
New Plane	0.00	0.00	0.00	0.00	0.00	1.00
New Message	0.00	0.00	0.08	0.77	0.00	0.15
Handle Threat	0.00	0.00	0.33	0.50	0.17	0.00
Read Message	0.00	0.00	0.20	0.33	0.40	0.07
Send Message	0.00	0.00	0.00	0.50	0.50	0.00
Show Information	0.00	0.00	0.50	0.25	0.00	0.25

commander, team 520, shift 1, lag 1

	New Plane	New Message	Handle Threat	Read Message	Send Message	Show Information
New Plane	0.00	0.00	0.50	0.00	0.00	0.50
New Message	0.00	0.00	0.04	0.87	0.09	0.00
Handle Threat	0.00	0.00	0.00	0.67	0.33	0.00
Read Message	0.00	0.00	0.21	0.29	0.43	0.07
Send Message	0.00	0.00	0.33	0.33	0.33	0.00
Show Information	0.00	0.00	0.00	0.00	0.00	0.00

matrix (raw data)

```
DATA:  s1c423.prx
distances
6 nodes
0 decimals
1 min
99 max
matrix:
 0  0   0  0   0  100
 0  0   8 77   0  15
 0  0  33 50  17   0
 0  0  20 33  40   7
 0  0   0 50  50   0
 0  0  50 25   0  25
```

```
DATA:  s1c520.prx
distances
6 nodes
0 decimals
1 min
99 max
matrix:
 0  0  50  0   0  50
 0  0   4 87   9   0
 0  0   0 67  33   0
 0  0  21 29  43   7
 0  0  33 33  33   0
 0  0   0  0   0   0
```

results from the pathfinder analyses

LAYOUT
1 level
6 nodes
1.0 size factor
2 dimensions
-0.543 1.944 min max x
-0.866 1.462 min max y
1.944 1.462 New Plane
1.369 0.848 New Message
-0.100 -0.127 Handle Threat
-0.018 -0.658 Read Message
-0.543 -0.814 Send Message
0.500 -0.866 Show Information

LAYOUT
1 level
6 nodes
1.0 size factor
2 dimensions
-1.636 1.479 min max x
-2.291 1.120 min max y
1.479 -0.773 New Plane
0.720 1.120 New Message
-1.435 0.099 Handle Threat
-1.636 -0.529 Read Message
-1.015 -0.390 Send Message
0.119 -2.291 Show Information

PFNET S1L1T423.PRX
6 nodes
10 links
directed with loops
5 q (5 = n-1)
infinite r
15 minimum link weight
50 maximum link weight
links:

node1	node2	Weight	type
2	6	15	x
3	3	33	x
3	4	50	x
3	5	17	x
4	3	20	x
4	4	33	x
5	4	50	x
5	5	50	x
6	4	25	x
6	6	25	x

belongs to low performing group

PFNET S1L1T520.PRX
6 nodes
9 links
directed with loops
5 q (5 = n-1)
infinite r
21 minimum link weight
87 maximum link weight
links:

node1	node2	Weight	type
1	3	50	x
1	6	50	x
2	4	87	x
3	5	33	x
4	3	21	x
4	4	29	x
5	3	33	x
5	4	33	x
5	5	33	x

belongs to high performing group

The mean coherence (*coh*) in shift 1 for lag 1 sequences for low performing teams (median split) is $coh_{\text{low}} = 0.11$ (SD = .078), for high performing teams $coh_{\text{high}} = 0.14$ (SD = .105). The difference is not statistically significant (t (95.51) = -1.53, p = .13). Parting the teams in three equal groups (low, middle, high performance) and just comparing the lowest third with the highest third shows that coherence is higher for high performing teams: $coh_{\text{lowest third}} = 0.10$ (SD = .065), $coh_{\text{highest third}} = 0.15$ (SD = .096) (t (61.28) = -2.23, p = .03).

Conclusion. Although the coherence is rather low, it is not an indicator of erroneous data. There are mainly three reasons for the low values: (i) overall low frequencies of events, due to the person-oriented analyses, (ii) the distinction of system events and initiated events leads to a lot of cells with zeros, and (iii) commanders especially of low performing teams have nods that are not connected. Therefore I decided to continue the analyses and calculate pathfinder *C* for all commanders for shift 1, lag 1 sequences.

Similarity of Commander's Pathfinder Networks

This chapter extends the analyses presented in chapter 0. There the basis for all teams were collapsed data for low and high performing teams, now the analyses are done using pathfinder network representations calculated individually for each commander.

The computation of individual networks, comparing all networks and deriving the pathfinder *C* value is rather cumbersome. For every single person an own data matrix has to be generated (as shown in Table 71). This results in 109 matrixes per role, shift and lag. Given 109 resulting pathfinder networks 5886 *C* values can be calculated, comparing all networks. In shift 1 1540 *C* values compare the networks of the low performing teams, 1387 those of the high performing teams.

The mean *C* (calculation based on individually calculated *C* values) for commanders of the low performing teams is $C_{\text{low performing groups}} = 0.295$ (SD = .138), and for the high performing groups $C_{\text{low performing groups}} = 0.299$ (SD = .126). This difference is not at all statistically significant (t (2915.21) = -0.98, p = .33). Having the same mean *C* value expresses only that networks of commanders of low performing teams are among them as similar as the networks of the high performing teams. If there are any differences between the networks of those two performance groups the similarity comparing the network representations of low and high performing teams should be near to zero. But this value is $C_{\text{comparing low and high performing teams}} = .293$ (SD = .127). Comparing all three means shows no statistically significant differences (F (2, 5838) = 1.11, p = .33). This means that all network representations computed using the Pathfinder algorithm seem to be very similar.

Finally, I built three performance groups. Looking at the two extreme groups – the low^{-3-} group in which network representations of commanders are compared that belong to the lowest performance group and the high^{-3-} group where commanders belong to highest performance group – gives no huge difference of the *C* values: C_{low}^{-3-} = 0.291 (SD = 0.145), C_{high}^{-3-} = 0.310 (SD = 0.129). This mean difference is statistically significant (t (1238.32) = -2.48, p = .01). This means that commanders of the highest performance group have among them more similar Pathfinder network representations than commanders of the lowest performance group. Nevertheless, because the *C* values are rather low, the conclusion is that neither commanders of low performing teams nor commanders of high performing teams have network representations that are among them very similar.

A closer look at the link weights

There is no automated way to extract the link weights from the Pathfinder network representations. They are stored in the Pathfinder layout files, an example of such a file is given in the last part of Table 71. Based on the propositions of Kiekel et al. (n.d.) the minimal, maximal, mean and median link weight were calculated.

Comparing commanders of low and high performing teams. As shown in Table 72 there are no statistically significant differences between the means for commanders of low and high performing teams for the minimal link weight, the maximal link weight, the mean, nor the median link weight. Comparing just one third of the commanders with the lowest vs. the highest performance in shift 1 shows one almost statistically significant difference: commanders of high performing teams have a higher minimal link weight than commanders of low performing teams (mean $_{\text{commander low performing teams}}$ = 13.36 (SD = 3.68), mean $_{\text{commander high performing teams}}$ = 15.42 (SD = 5.20), $t(70) = -1.94$, $p = .06$).

Kiekel et al. (n.d.) report a study, in which the minimum link weight, the maximum length and the median length were good predictors of team performance. Something that does not hold for the ATC data, at least for commanders in shift 1. A hierarchical stepwise regression explains 6% of the variance in performance on day one ($F(3, 105) = 3.32$, $R^2_{adj.} = .06$, $p = .23$, with minimal chain length $\beta = .29$, $p = .01$, maximal chain length $\beta = .25$, $p = .09$, and mean chain length $\beta = -.36$, $p = .02$).

Table 72 Means, standard deviations, and t-test of minimal, maximal, mean, and median link weights of Pathfinder network representations.

	low performing		high performing			
	mean	SD	mean	SD		
minimal link weight	13.32	3.49	14.72	4.76	$t(107) = -1.75$, $p = .08$	n.s.
maximal link weight	69.41	14.72	69.60	17.29	$t(107) = -0.63$, $p = .95$	n.s.
mean link weight	39.28	6.64	38.09	7.29	$t(107) = 0.89$, $p = .37$	n.s.
median link weight	38.77	10.16	36.35	10.28	$t(107) = 1.24$, $p = .22$	n.s.

Note. N = 109 commanders, median split of performance in shift 1, N $_{\text{low performance}}$ = 56, N $_{\text{high performance}}$ = 53

Review of the Research Questions to Lag Sequential Analyses

SEQ I. The activities of commanders and specialist have a certain regularity. It is possible to identify meaningful patterns.

PRONET analysis identifies patterns.
And it is possible to meaningfully interpret the patterns.

SEQ II. Moreover, low and high performing teams show different patterns.

It is possible to show different patterns between low and high performing teams. Nevertheless, these differences are not that big that low and high performing teams show completely different patterns.

The values of Pathfinder *C* as measure of the similarity of network representations are high.

SEQ III. It is possible to predict performance if the identified patterns are entered as predictors in a regression model.

There are several measures calculated with PRONET/Pathfinder that can be used for further analysis: Pathfinder *C* as measure of the similarity of network representations or link weights (minimal, maximal, mean).

But none of these measures showed any difference between high and low performing teams. In a further analysis the coding scheme must be used with its sub-categories and not only with its main categories (definition of coding scheme in chapter 6.8). Then PRONET/Pathfinder should detect differences.

Consequently no regression analyses were run.

SEQ IV. Due to the nature of the ATC task and how it is implemented, patterns of directly adjacent events are better predictors of performance than either patterns combining events that follow one another after some other events happened or patterns of long sequences (six or more succeeding events).

As no regression analyses were run and as only conditional probabilities of lag 1 sequences were calculated this question can not be answered.

8.8.3 Evaluation of PRONET Applied to the ATC Data

The results of the analyses with PRONET/pathfinder are somehow disappointing: commanders and specialists of low and high performing teams do almost the same, the network representations look alike, which is reflected in high Pathfinder *C* values. The conclusion so far: much effort, no reasonable result!

But only lag 1 sequences were analyzed. It might well be that lag 2 or higher sequences would give better results. Additionally, one could collapse lags (adding all sequences of interest of lag 1, lag 2 to lag n).

Pathfinder *C* ignores the information on the weights of the links. It reduces the information in the data quite heavily. And if the good procedural structure is already developed in shift 1 no differences can be found comparing it to the structure in shift 4. Nevertheless commanders or specialists do not necessarily the same thing in the two shifts. A hypothetical example: Given a New Plane commanders react either with a Show Information or with a Read Message. In shift 1 the path weights are: weight $_{\text{New Plane – Show Information}}$ = .50, weight $_{\text{New Plane – Read Message}}$ = .50. Both weights are exactly of the same size. In shift 4 this may change to weight $_{\text{New Plane – Show Information}}$ = .80, weight $_{\text{New Plane – Read Message}}$ = .10, reflecting that the commander now reacts more likely with looking up plane information if there is a new plane in the airspace. The calculation of pathfinder *C* however ignores this information and treats both situations alike.

Kiekel et al. (n.d.) proposed a way how to use the qualitative data derived from PRONET analyses in quantitative analyses. They built typical chains for different lags. Then path weights were analyzed, using them as predictors in a regression analyses (a) the minimal path weight, b) the maximum path weight, and c) the median of the path weight). At least for commanders in shift 1 in the ATC data link weights have almost no predictive power (6% of explained variance in performance shift 1).

PRONET uses conditional (transitional) probabilities to run Pathfinder analyses. Cooke, Neville, and Rowe (1996) propose to use this measure without further discussing preconditions. This is somehow problematic. Conditional probabilities are in fact measures that show “the most likely ways of ‘moving‘ from one state to another” (Bakeman & Gottman, 1986, p. 149) and are therefore plausible measures for sequential associations. But conditional probabilities have their limitations if it comes to compare the values of two or more subjects. Conditional probabilities are calculated row by row, not taking into account the relation between the frequencies of the given events. *Example*. Given a Read Message the next events could be either a Read Message, a Send Message, or a Show Information with conditional probabilities of 0.67, 0.33, and 0.00. This means that after a Read Message the most probable reaction is to immediately read another message. The absolute frequencies for specialist I are 4, 2, and 0, for specialist II they are 8, 4, and 0. All in all specialist II has twice as much events following a Read Message than specialist I. If the overall frequency of all events of specialist I is 15, the given Read Message contributes with 40% to this number. For specialist II, who does exactly the same as specialist I – except for the Read Messages - the total number of events is 21 and the proportion of Read Message is 57%. Although the conditional probabilities are the same, in the context of all the other events the meaning of this information might well be different. In the literature on lag sequential analyses the use of adjusted residuals, which takes into account the frequencies of the events and their expected frequencies, is recommended.

As a consequence PRONET analyses should be run using adjusted residuals. They show how much a certain event sequence is hindered or fostered. To use this measures in PRONET/pathfinder analyses it is important that the high values can be interpreted as a stronger relation between tow events than lower values. The higher the (absolute) adjusted residuals the more “similar” are the two events.

But running PRONET/Pathfinder analyses using adjusted residuals instead of conditional probabilities implies to create new, single matrices for every shift, every shift member and for every lag of interest. Apart from being used in some limited experimental setting with a few groups the work to do is immense, because neither Pathfinder nor PRONET contain appropriate tools to build the matrices from log files.

8.9 Data Mining

In chapter 5.3.3 data mining techniques were introduced as part of a process called knowledge discovery in databases (KDD). The aim of all KDD and data mining techniques is to find interesting, “hidden” patterns in huge amounts of data. To my knowledge data mining techniques have never been applied in small group research, and seldom in psychology. It was therefore a great opportunity that we had a reasonable amount of data from the ATC simulation (the automatically recorded log-files) and the possibility to work together with Paul Cotofrei and Kilian Stoffel (Institut interfacultaire d'informatique, knowledge information and data processing, Université de Neuchâtel). This collaboration started with a simple question: Is it possible to apply data mining techniques to the ATC data? A first result of this collaboration is presented in this chapter.

In this chapter data mining techniques are applied to the ATC data. The aim is to test whether this methods can be used to analyze observational data from a psychological simulation study and to extract meaningful patterns from the data. The second question is, how this information can be used in regression analyses to predict performance.

8.9.1 Method Subsection: Data Mining Analyses

The data mining analyses are based on the process variables defined in chapter 6.8. The total N is 109 teams.

Data Selection

In lag sequential analyses (chapter 8.7) and in PRONET analyses (chapter 8.8) only the main categories of the coding scheme were used: New Plane, New Message, Handle Threat, Read Message, Send Message, and Show Information.

For data mining analyses the same coding scheme was used. However, the variables selected for the analyses were not exactly the same as for lag sequential analyses and PRONET analyses:

- Only initiated events were used in data mining analyses: Handle Threat, Read Message, Send Message, and Show Information.
  This reduction was necessary to omit parallel events. A new message can arrive at the inbox at any time, for example whilst a commander or specialist

is reading or sending a message. Excluding the system events (New Plane, New Message) reduces the complexity of the analyses.

- The content coding of the sent messages was included in the analyses: task, strategy or non-task/non-strategy related message content (see Table 21 for details).
  The content coding was skipped in lag sequential analyses to reduce the number of cells the contingency table. As data mining techniques are made to handle huge data sets this restriction was no longer necessary.

Data mining analyses were run for low and high performing teams, excluding teams with a medium performance from the analyses (trisection). The criteria to build the performance groups was the overall performance on day one, respectively day two. For every shift it was calculated whether the team belonged to the low, medium or high performance group. Shift 8 was excluded from the analyses.

The 109 teams worked on a total of 763 shifts (seven[17] shifts * 109 teams). Shift 8 was excluded (- 109 shifts): 654 shifts remained. Due to the trisection, 116 shifts from day one and 115 shifts from day two, from teams with a medium performance, were additionally excluded from data mining analyses.

The data mining algorithm was then applied to the remaining 211 shifts of low and high performing teams from day one, and separately to the remaining 212 shifts of low and high performing teams on day 2. The data was searched for regular patterns on day one and day two separately. As all shifts from day one were analyzed simultaneously, it is not possible to say in which shift a specific pattern was found.

Mining the Data

Often data mining algorithms search for the co-occurrence of events. A simple example is: Four persons go shopping and fill their baskets. The question is, which products are together in the same basket. The basket of person 1 is filled with A, B, C, D, the basket of person 2 with A, C, basket of person 3 with A, D, and basket of person 4 with B, E, F. One pattern (products bought together) is e.g., A and C. This combination of products can be found for person 1 and person 2, but not for person 3 and 4. A pattern or rule could be: A and C are bought together.

[17] Shift 1 to shift6, and shift 8. Shift 7 was not used in the analyses because no data was available for this shift in some experimental conditions. See chapter 6.5.

To decide on the quality of the found solution (rule) two criteria can be applied: confidence and support.

Confidence. The confidence is the number of instances that a rule (A and C are bought together) predicts correctly, expressed as a proportion of all instances it applies to. The confidence is calculated as: 2 (number of baskets with A and C) / 3 (number of baskets with A) = 0.66.

Support. In the basket example the support is the ratio between the number of baskets which contain the pattern (A and C are bought together) and the total number of baskets. The support is calculated as: 2 (number of baskets with A and C) / 4 (total number of baskets) = 0.50.

There are several types of data mining algorithms which aim to classify, cluster, find association rules or sequential patterns in the data that go beyond the simple example of the four baskets. In the ATC data – as well as in financial market data, currency exchange rates, network traffic data, sensor information from robots, signals from biomedical sources like electrocardiographs, etc. – multiple sequences evolve over time. This means that a sequence of A -> B -> C is not the same as a sequence C -> B -> A, or B -> C -> A, etc. The events are ordered in time. Consequently the ATC data was scanned for subsequences of events.

Algorithm Used to Detect Patterns in the ATC Data

In this chapter I will give a short introduction to the algorithm used to detect patterns in the ATC simulation. As there was no statistical tool, no software readily available to analyze the ATC data, the software was written by Paul Cotofrei.

The following example is fictive and serves as an illustration of the data mining algorithm used to detect patterns in the ATC data.

Given are the events A, B, C, D (A = working on email messages, B = making a phone call, C = reading a text, D = writing a text or some other events). Given these four coded events the following sequences of sixteen events could be observed:

Person I: A A B C D D C A A B B A A C C D

Person II: B C D D A B C A B C A B C D D A

Person X: …

Out of this sequence of sixteen events fifteen lag 1 pairs per person can be built:

	1		3		5		7		9		11		13		15	
Person I	A	A	B	C	D	D	C	A	A	B	B	A	A	C	C	D
		2		4		6		8		10		12		14		

	1		3		5		7		9		11		13		15	
Person II	B	C	D	D	A	B	C	A	B	C	A	B	C	D	D	A
		2		4		6		8		10		12		14		

All possible lag 1 sequences for the person I and II for the events A, B, C, and D are presented in Table 73. Person I has much more different sequences of two events than person II. Setting the support to 50% (= 0.50) means that all sequences are considered as relevant and taken as basis for further analysis that are found (in this example) at least for one person. The support is calculated as: (number of persons with a certain sequence) / (total number of persons). No support is found for the sequences A -> D, B -> D, C -> B, and D -> B.

Table 73 Tallies for lag 1 sequences given a sequence of sixteen events A, B, C D.

	Person I					Person II			
	A	B	C	D		A	B	C	D
A	YES	YES	YES		A	NO	YES	NO	
B	YES	YES	YES		B	NO	NO	YES	
C	YES		YES	YES	C	YES		NO	YES
D	NO		YES	YES	D	YES		NO	YES

Note: Green = support is at least 50%

Taking all the combinations of two events with a support of at least 50% and adding the third event gives the picture presented in Table 74. Again there are more sequences of three elements found for person I than for person II. Several sequences of three events get a support of at least 50%, e.g. [AA]B, [AA]C, [AB]B etc. All those triples are taken to the next step in the analyses.

Table 74 Sequences of three events, taking sequences of two events with a support of minimal 50% as base.

	Person I				Person II			
	A	B	C	D	A	B	C	D
[AA]		YES	YES			NO	NO	
[AB]		YES	YES			NO	YES	
[AC]			YES				NO	
[BA]	YES				NO			
[BB]	YES				NO			
[BC]				YES	YES			YES
[CA]	YES	NO			NO	YES		
[CC]				YES				NO
[CD]				YES				YES
[DA]		NO				YES		
[DC]	YES				NO			
[DD]	NO		YES		YES		NO	

Note: Green = support is at least 50%

Taking all the sequences of three events with a support of at least 50% and adding the fourth event gives the picture presented in Table 75. A sequence found for person I and person I is e.g., A -> B -> C -> D, this means that the support is 100%:

Person 1	A	A	B	C	D	D	C	A	A	B	B	A	A	C	C	D
Person 2	B	C	D	D	A	B	C	A	B	C	A	B	C	D	D	A

The sequence C -> A -> B -> C has a support of 50% and is only found for person II:

Person 1	A	A	B	C	D	D	C	A	A	B	B	A	A	C	C	D
Person 2	B	C	D	D	A	B	C	A	B	C	A	B	C	D	D	A

Table 75 Sequences of four events, taking sequences of three events with a support of minimal 50% as base.

	Person I					Person II			
	A	B	C	D		A	B	C	D
[AAB]		YES	YES		[AAB]		NO	NO	
[AAC]	YES				[AAC]	NO			
[ABB]	YES				[ABB]	NO			
[ABC]				YES	[ABC]				YES
[ACC]				YES	[ACC]				NO
[BAA]			YES		[BAA]		NO		
[BBA]	YES				[BBA]	NO			
[BCA]		NO			[BCA]		YES		
[BCD]				YES	[BCD]				YES
[CAA]		YES			[CAA]		NO		
[CAB]			NO		[CAB]			YES	
[CCD]					[CCD]				
[CDD]	NO		YES		[CDD]	YES		NO	
[DAB]			NO		[DAB]			YES	
[DCA]	YES				[DCA]	NO			
[DDA]		NO			[DDA]		YES		
[DDC]	YES				[DDC]	NO			

Note: Green = support is at least 50%

The algorithm is applied to the data until no more event can be added to a sequence, getting a support of at least 50%.

8.9.2 Results Data Mining Analyzes

The data mining algorithm was applied separately to the ATC data for low and high performing teams on day one (shift 1 to shift 3) and on day two (shift 4 to shift 6). Separate analyses were run for commanders, specialists A and specialists B.

The result of the analyses show all patterns with a support of at least 0.50[18]. The two values (for commanders, resp. specialists of low and high performing teams) were tested for statistical significance. A significant different result is marked in the table with “different”.

A support of less than 50% (or 0.50) is reported in the tables as zero. However, it would be wrong to conclude, that a value of zero stands for no support. The correct interpretation is: the support of the pattern is less than the minimal support value of

[18] The support value of 0.50 is set before the analyses are run. The way how the algorithm works and how the statistical test are run can lead to a final support value that can be below 0.50.

50%. If both support values (low and high performing) were below 0.50 a point (.) is written in the table.

Support values for commanders of low and high performing teams, day one and day two

The results for commanders are presented in Table 76. Several sequences with a support of at least 0.50 were found on day one and on day two, but not all sequences were found on both days. The sequence ieH-ieH (Handle Threat -> Handle Threat) got a support of less than 0.50 for low and high performing teams on day one. On day two the support for this sequence ieH-ieH is 0.40 for commanders of low performing teams and below 0.50 for commanders of high performing teams. The sequence ieH-ieR (Handle Threat -> Read Message) has a support of 0.89 for commanders of low performing teams and of 0.98 for commanders of high performing teams on day one. These two support values are different. The sequence ieH-ieS100 (Handle Threat -> Send message with task related content) has a support value of 0.42 for commanders of low performing teams and 0.51 for commanders of high performing teams. However, this difference is not statistically significant. This is just to give a few examples on how to read Table 76.

Day one, commanders of low and high performing teams. There is a total of 17 patterns with two events, six patterns (35%) are different for commanders of low and high performing teams, 65% are found with the same support value for commanders of low and high performing teams. The different patterns with two events are:

(1) IeR-ieS001 (reading a message and then sending a message with non-task and non-strategy related content, $support_{\text{low performing}} = 0.44$, $support_{\text{high performing}} < 0.50$),

(2) ieR-ieH (Read Message followed by a Handle Threat, $support_{\text{low performing}} = 0.93$, $support_{\text{high performing}} = 1.00$),

(3) ieR-ieSi1 (Read Message followed by looking up critical plane information, $support_{\text{low performing}} = 0.71$, $support_{\text{high performing}} = 0.83$),

(4) ieS100-ieS100 (sending a message with task related content followed by a sending a second message again with task related content, $support_{\text{low performing}} = 0.49$, $support_{\text{high performing}} < 0.50$),

(5) ieH-ieR (assigning the threat level followed by reading a message, $support_{\text{low performing}} = 0.89$, $support_{\text{high performing}} < 0.98$),

(6) ieSi1-ieH (looking up critical plane information followed by a threat assignment, $support_{\text{low performing}} < 0.50$, $support_{\text{high performing}} = 0.69$).

These are solely the differences in the sequences with two events on day 1 for commanders of low and high performing teams. The total number of sequences found in the data is: commanders day 1: 63, day 2: 65, specialists A day 1: 88, day 2:

112, specialists B day 1: 71, day 2: 81. This sums up to 480 identified sequences for both days with a support of at least 0.50 (an overview is presented Table 77).

Table 76 Support values of sequences found with data mining analyses, commanders of low and high performing teams on day one and day two.

			day 1			day 2		
	Sequence		low	high		low	high	
1	ieH-ieH	70-70	.	.	.	0.40	0.00	different
2	ieH-ieR	70-50	0.89	0.98	different	1.00	0.99	equal
3	ieH-ieS100	70-63	0.42	0.51	equal	0.55	0.60	equal
4	ieH-ieSi1	70-72	0.44	0.53	equal	0.63	0.46	different
5	ieR-ieH	50-70	0.93	1.00	different	0.99	1.00	equal
6	ieR-ieR	50-50	1.00	1.00	equal	1.00	1.00	equal
7	ieR-ieS001	50-66	0.44	0.00	different	0.56	0.59	equal
8	ieR-ieS010	50-67	0.45	0.55	equal	0.62	0.59	equal
9	ieR-ieS100	50-63	0.83	0.85	equal	0.67	0.70	equal
10	ieR-ieSi1	50-72	0.71	0.83	different	0.76	0.80	equal
11	ieS001-ieR	66-50	0.48	0.48	equal	0.60	0.64	equal
12	ieS010-ieR	67-50	0.49	0.56	equal	0.63	0.68	equal
13	ieS100-ieR	63-50	0.91	0.92	equal	0.85	0.82	equal
14	ieS100-ieS100	63-63	0.49	0.00	different	.	.	.
15	ieSi1-ieH	72-70	0.00	0.69	different	0.58	0.79	different
16	ieSi1-ieR	72-50	0.72	0.75	equal	0.63	0.57	equal
17	ieSi1-ieS100	72-63	0.57	0.51	equal	0.54	0.00	different
18	ieSi1-ieSi1	72-72	0.45	0.45	equal	0.00	0.41	different
1	ieH-ieR-ieH	70-50-70	0.48	0.64	different	0.72	0.66	equal
2	ieH-ieR-ieR	70-50-50	0.80	0.86	equal	0.93	0.95	equal
3	ieH-ieS100-ieR	70-63-50	0.00	0.43	different	0.47	0.52	equal
4	ieR-ieH-ieR	50-70-50	0.84	0.96	different	0.96	0.96	equal
5	ieR-ieH-ieS100	50-70-63	.	.	.	0.46	0.00	different
6	ieR-ieH-ieSi1	50-70-72	.	.	.	0.53	0.00	different
7	ieR-ieR-ieH	50-50-70	0.88	0.96	different	0.98	0.98	equal
8	ieR-ieR-ieR	50-50-50	0.97	0.92	equal	0.90	0.94	equal
9	ieR-ieR-ieS001	50-50-66	.	.	.	0.00	0.43	different
10	ieR-ieR-ieS100	50-50-63	0.67	0.69	equal	0.40	0.54	different
11	ieR-ieR-ieSi1	50-50-72	0.52	0.66	different	0.49	0.51	equal
12	ieR-ieS001-ieR	50-66-50	.	.	.	0.45	0.45	equal
13	ieR-ieS010-ieR	50-67-50	0.00	0.47	different	0.54	0.48	equal
14	ieR-ieS100-ieR	50-63-50	0.73	0.75	equal	0.60	0.63	equal
15	ieR-ieSi1-ieH	50-72-70	.	.	.	0.00	0.46	different
16	ieS001-ieR-ieR	66-50-50	.	.	.	0.00	0.44	different
17	ieS010-ieR-ieR	67-50-50	0.00	0.45	different	0.42	0.50	equal
18	ieS100-ieR-ieH	63-50-70	0.47	0.53	equal	0.48	0.45	equal
19	ieS100-ieR-ieR	63-50-50	0.80	0.76	equal	0.73	0.67	equal
20	ieS100-ieS100-ieR	63-63-50	0.44	0.00	different	.	.	.
21	ieSi1-ieH-ieR	72-70-50	0.00	0.45	different	0.00	0.42	different
22	ieSi1-ieR-ieR	72-50-50	0.53	0.46	equal	.	.	.
23	ieSi1-ieS100-ieR	72-63-50	.	.	.	0.43	0.00	different
1	ieH-ieR-ieH-ieR	70-50-70-50	0.00	0.54	different	0.60	0.58	equal
2	ieH-ieR-ieR-ieH	70-50-50-70	0.00	0.47	different	0.58	0.61	equal
3	ieH-ieR-ieR-ieR	70-50-50-50	0.63	0.76	different	0.68	0.73	equal
4	ieR-ieH-ieR-ieH	50-70-50-70	0.44	0.57	equal	0.64	0.59	equal
5	ieR-ieH-ieR-ieR	50-70-50-50	0.70	0.83	different	0.85	0.90	equal
6	ieR-ieR-ieH-ieR	50-50-70-50	0.74	0.85	different	0.88	0.90	equal
7	ieR-ieR-ieR-ieH	50-50-50-70	0.72	0.75	equal	0.77	0.84	equal
8	ieR-ieR-ieR-ieR	50-50-50-50	0.83	0.75	equal	0.66	0.74	equal
9	ieR-ieR-ieR-ieS100	50-50-50-63	0.47	0.48	equal	.	.	.
10	ieR-ieR-ieR-ieSi1	50-50-50-72	0.00	0.45	different	.	.	.
11	ieR-ieR-ieS100-ieR	50-50-63-50	0.53	0.58	equal	0.00	0.46	different
12	ieR-ieS100-ieR-ieR	50-63-50-50	0.56	0.58	equal	0.00	0.47	different
13	ieS100-ieR-ieH-ieR	63-50-70-50	0.00	0.48	different	.	.	.
14	ieS100-ieR-ieR-ieR	63-50-50-50	0.59	0.57	equal	0.42	0.50	equal
1	ieH-ieR-ieH-ieR-ieR	70-50-70-50-50	.	.	.	0.44	0.44	equal
2	ieH-ieR-ieR-ieH-ieR	70-50-50-70-50	.	.	.	0.46	0.54	equal
3	ieH-ieR-ieR-ieR-ieR	70-50-50-50-50	0.42	0.53	equal	0.41	0.53	equal
4	ieR-ieH-ieR-ieH-ieR	50-70-50-70-50	0.00	0.49	different	0.55	0.55	equal
5	ieR-ieH-ieR-ieR-ieH	50-70-50-50-70	0.00	0.43	different	0.50	0.56	equal
6	ieR-ieH-ieR-ieR-ieR	50-70-50-50-50	0.52	0.64	equal	0.61	0.66	equal
7	ieR-ieR-ieH-ieR-ieH	50-50-70-50-70	0.00	0.41	different	0.48	0.46	equal
8	ieR-ieR-ieH-ieR-ieR	50-50-70-50-50	0.50	0.70	different	0.59	0.68	equal
9	ieR-ieR-ieR-ieH-ieR	50-50-50-70-50	0.56	0.61	equal	0.63	0.72	equal
10	ieR-ieR-ieR-ieR-ieH	50-50-50-50-70	0.52	0.50	equal	0.49	0.56	equal
11	ieR-ieR-ieR-ieR-ieR	50-50-50-50-50	0.61	0.61	equal	0.50	0.45	equal
12	ieR-ieR-ieS100-ieR-ieR	50-50-63-50-50	0.00	0.41	different	.	.	.
13	ieS100-ieR-ieR-ieR-ieR	63-50-50-50-50	0.45	0.00	different	.	.	.
1	ieR-ieH-ieR-ieR-ieH-ieR	50-70-50-50-70-50	.	.	.	0.00	0.45	different
2	ieR-ieH-ieR-ieR-ieR-ieR	50-70-50-50-50-50	0.00	0.44	different	0.00	0.47	different
3	ieR-ieR-ieH-ieR-ieR-ieR	50-50-70-50-50-50	0.00	0.46	different	0.43	0.47	equal
4	ieR-ieR-ieR-ieH-ieR-ieR	50-50-50-70-50-50	0.41	0.47	equal	0.00	0.49	different
5	ieR-ieR-ieR-ieR-ieH-ieR	50-50-50-50-70-50	0.00	0.43	different	0.00	0.45	different
6	ieR-ieR-ieR-ieR-ieR-ieR	50-50-50-50-50-50	0.00	0.42	different	.	.	.

Note. The 109 teams were assigned to three groups of the same size according to their performance (low – medium – high). Results are presented for the two extreme groups. Sequence = pattern, succession of events, low = support values for commanders of low performing teams, high = support values for commanders of high performing teams; equal: found sequence has the same support for commanders of low and high performing teams, different = support value is statistically significant different.

Table 77 Summaries of number of sequences found with a specific number of events, using data mining analyses, low and high performing teams.

lenght of sequence		day1 number found	equal		different		day 2 number found	equal		different	
commander	2	17	11	65%	6	35%	17	12	71%	5	29%
	3	16	7	44%	9	56%	21	13	62%	8	38%
	4	14	7	50%	7	50%	11	9	82%	2	18%
	5	11	5	45%	6	55%	11	11	100%	0	0%
	6	5	1	20%	4	80%	5	1	20%	4	80%
	7	.	.	.	.	.	.	.	.	.	.
	8	.	.	.	.	.	.	.	.	.	.
	9	.	.	.	.	.	.	.	.	.	.
	Total	63	31	49%	32	51%	65	46	71%	19	29%
specialist A	2	18	13	72%	5	28%	21	14	67%	7	33%
	3	26	19	73%	7	27%	29	17	59%	12	41%
	4	20	14	70%	6	30%	24	15	63%	9	38%
	5	11	6	55%	5	45%	16	12	75%	4	25%
	6	7	6	86%	1	14%	9	8	89%	1	11%
	7	4	1	25%	3	75%	8	4	50%	4	50%
	8	1	1	100%	0	0%	4	2	50%	2	50%
	9	1	0	0%	1	100%	1	0	0%	1	100%
	Total	88	60	68%	28	32%	112	72	64%	40	36%
specialist B	2	20	16	80%	4	20%	19	15	79%	4	21%
	3	27	20	74%	7	26%	28	14	50%	14	50%
	4	16	10	63%	6	38%	20	10	50%	10	50%
	5	7	3	43%	4	57%	12	6	50%	6	50%
	6	1	0	0%	1	100%	2	0	0%	2	100%
	7	.	.	.	.	.	.	.	.	.	.
	8	.	.	.	.	.	.	.	.	.	.
	9	.	.	.	.	.	.	.	.	.	.
	Total	71	49	69%	22	31%	81	45	56%	36	44%

Note. Length of sequences found for commanders, specialists A, specialists B with low and high performance on day one and day two. The table contains no information for teams with a medium performance.

Summarizing Results: Support Values for Commanders and Specialists

The most interesting findings in Table 76 are as follows:

Commander

Commander. Generally, support is higher for sequences with 2 to 3 events than for longer sequences. This can be observed on day one and day two. One of the main tasks a commander has to do is reading messages. Consequently, a lot of sequences contain a combination of ReadMessage (ieR) – Read Message (ieR).

Commanders Sequences with 2 events (17 on day one, 17 on day two). Overall the support for sequences with two events is higher on day two than on day one. There is only one sequence with a statistically different support for commanders of low and high performing teams on day one and day two: looking up plane information (ieSi1) followed by a threat assignment (ieH). Commanders of low performing teams have on both days less support for this sequence. High support is found on both days for the following sequences: threat assignment followed by reading a message, reading a message followed by a threat assignment, reading a message followed by reading the next message. The biggest differences for low and high performing teams on day one are found for the sequences (i) reading a message followed by sending a message with non-task and non-strategy related content getting only support for commanders of low performing teams, (ii) sending a message with task-related content followed by doing the same again gets more support for commanders of low performing teams. On day two the picture changes a bit. The biggest differences can now be found for a sequence like (i) threat assignment followed by looking up plane information getting more support for commanders of low performing teams, (ii) looking up plane information, followed by sending a message with task-related content gets again more support for commanders of low performing teams, as well as (iii) looking up plane information followed by the same thing again, or (iv) a sequence of two threat assignments.

Commanders Sequences with 3 events (16 on day one, 21 on day two). Sequences with a high support for commanders of low and high performing teams are for example (i) threat assignment followed by reading messages, or (ii) reading a message then setting the threat level, then reading the next message, or (iii) reading messages followed by a threat assignment. There are sequences that can only be found for commanders of high performing teams, and only on day two: reading a message followed by looking up plane information followed by a threat assignment (ieR-ieSi1-ieH), or sending a message with non-task and non strategy related content followed by reading messages (ieS001-ieR-ieR). Other sequences not found on day one getting support on day two for commanders of low performing teams only are: (i) reading a message, followed by a threat assignment, followed by sending a message with task related content (ieR-ieH-ieS100), (ii) reading a message, followed by a threat assignment, and then followed by looking up plane information (ieR-ieH-ieSi1), and (iii) looking up plane information, followed by sending a message with task related content, and then reading a message (ieSi1-ieS100-ieR).

Commanders Sequences with 4 events (14 on day one, 11 on day two). There are two sequences that get support for commanders of low and high performing teams on day one, but only for commanders of high performing teams on day two. Both sequences include sending a message with task related content: ieR-ieS100-ieR-ieR, and ieR-ieR-ieS100-ieR. All other differences found on day one for the two groups vanish on day two. Most often the support values of commanders of low performing teams move toward the support values of commanders of high performing teams from day one to day two. Commanders of low performing teams obviously apply on day two some sequences that were already used by commanders of high performing teams on day one.

Commanders sequences with 5 events (11 on day one, 11 on day two). Commanders of high performing teams have higher support values for sequences with 5 events on day one – on day two there are no more differences in support values for commanders of low and high performing teams. On day one there is only one sequence (ieS100-ieR-ieR-ieR-ieR) getting a higher support for commanders of low performing teams than for commanders of high performing teams. Again as for sequences with 4 events support values for commanders of low performing teams on day two move towards the values of the commanders of the high performing teams.

Commanders sequences with 6 events (5 on day one, 5 on day two). On day one and day two more sequences with 6 events and high support can be found for commanders of high performing teams. But overall the support values are lower for sequences with 6 events than for all other lengths of sequences. All sequences of 6 events are some combinations of reading a message (ieR) and threat assignment (ieH).

Specialist A

Specialist A. The main task of specialists is looking up plane information. The longest sequences for specialists A contain 5 events, all of them contain at least one Show Information. Specialists A of low performing teams have a higher support for a sequence ieR-ieS001 (reading a message followed by sending a message with non-task and non-strategy related content) on day one. On day two no more differences can be observed between specialist A of low and high performing teams in the sequence ieR-ieS001. All specialists A have a high support for a sequence of ieR-ieSi1 or ieR-ieSi0 (Read Message followed by looking up plane information, either the critical parameter or some other parameter). The interesting point is, that specialists A of low performing teams have a higher support for the sequence ieR – ieSi0 than specialists A of high performing teams. For the sequence ieR – ieSi1 we find exactly the opposite. Specialists A of high performing teams get a higher support value for this sequence than specialists A of low performing teams. Specialists A of low performing teams get on day one higher support values for sequences of reading a message and then looking up plane information. This might be a cue that specialists A of low performing teams rely more on commanders' instructions and look up plane information only if they are asked to do it. Another finding is that specialists A have very long sequences of Show Information. On day one this behavior can be found for specialists A of low and high performing teams whereas on day two mainly commanders of low performing teams show this behavior.

Specialist B

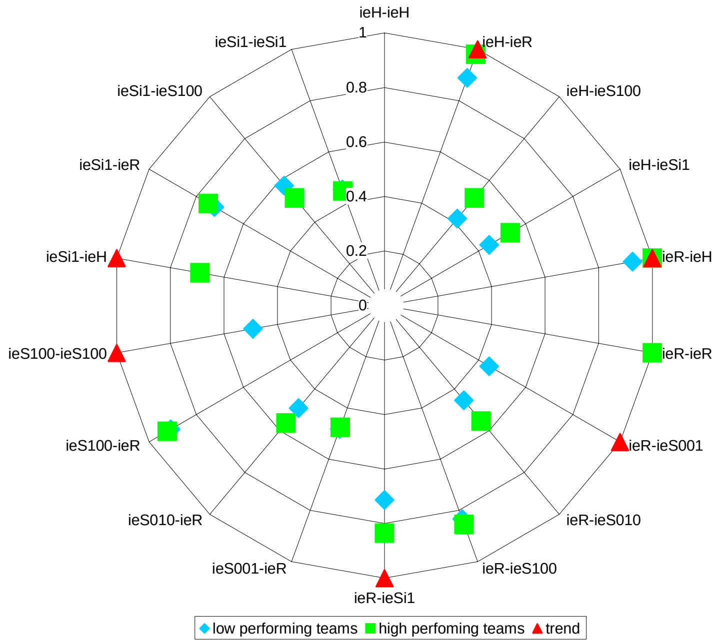
Specialist B. The sequences found for specialists B are shorter than those for specialists A. Again: sequences that contain looking up plane information followed by sending a message with non-task and non-strategy related content get more support for specialists B of low than for those of high performing teams. Looking at sequences of Show Information reveals some differences between specialists of low and high performing teams that show a differential handling of critical and non-critical information. Specialists B of high performing teams seam to weight critical information as more relevant insofar as they have a greater support for sequences with several times looking up critical plane information (ieSi1) or looking up this critical information in the beginning of the sequence.

Again: it is not at all easy to see the relevant differences and especially the changes and development from shift 1 to shift 8. Just to give a short reminder what all this analyses should be useful for: Data mining technologies should help us to detect patterns in the data that are relevant in describing low and high performing teams. The trouble with all the results up to this point is, that there is still too much information to get a clear picture of the situation.

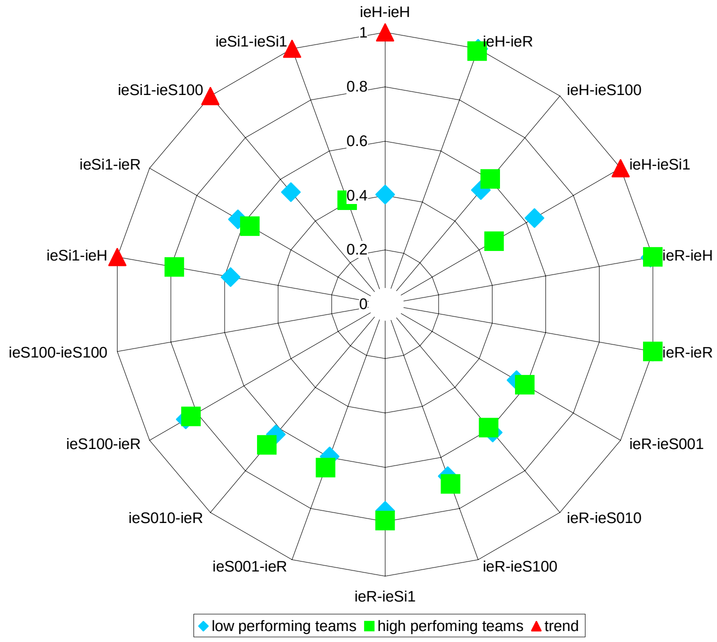
A graphical representation of the support values

All support values for commanders and specialists were transformed into diagrams to facilitate the overview of the results and the comparison of day one and day two. An example of such a diagram (commander, day one, sequences of two events):

day 1



day 2

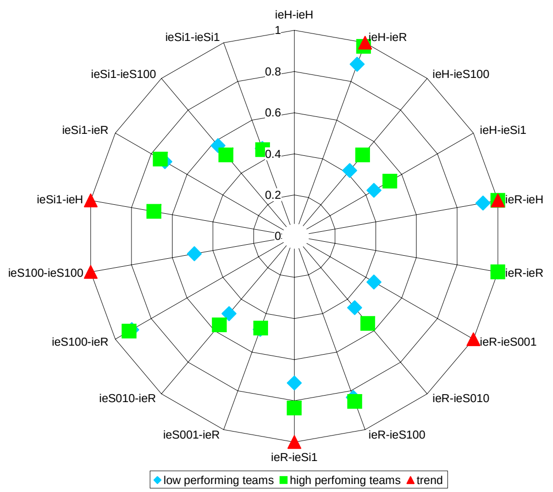


The labels outside of the circle describe the sequences: ieH-ieH (Handle Threat -> Handle Threat), ieH-ieR (Handle Threat -> Read Message) and so on. The blue diamonds (◆) are the support values for the commanders (resp. specialists) of the low performing teams. The green quadrates (■) are the support values for the commanders (resp. specialists) of the high performing teams. Statistically significant differences in the support values between commanders (resp. specialists) of low and high performing teams are marked with a traingle (▲) on the outer line. The support values for day one and day two are presented alongside allowing a direct comparison of the changes.

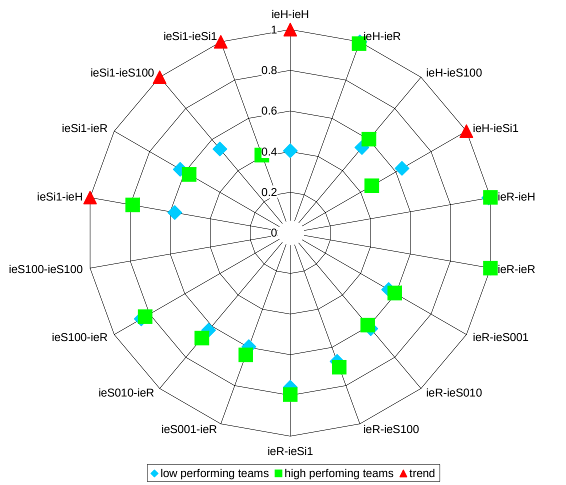
The upper diagram presents data from day one, the lower diagram data from day two. Now it can easily be seen, that the sequence ieH-ieH (Handle Treat followed by another Handle Threat) has on day one support values below 0.5, but that this sequence gets some support on day two – but only for commanders of low performing teams. The next sequence (turning clockwise) is ieH-ieR (Handle Threat followed by a Read Message) gets high support for commanders of low and high performing teams on day one and day two. But on day one the support values for commanders of high performing teams is significantly higher than the support value for low performing teams. On day two this difference disappears.

These diagrams can then easily be used to discuss the group process, allowing to identify possible interesting sequences. A direct application of this method could be that in a team intervention those diagrams are used as a input for a discussion on how to change some routines and how to improve cooperation. And there are of course useful to facilitate the definition of *Task Adaptive Behaviors* insofar as they represent empirically found sequences in the behavioral streams. Detailed analyses of single sequences give additional insight into the group process. An example will be given after presenting the diagrams for commanders in Figure 50. The diagrams for specialists A are in Figure 56 (appendix), for specialists B in Figure 57 (appendix).

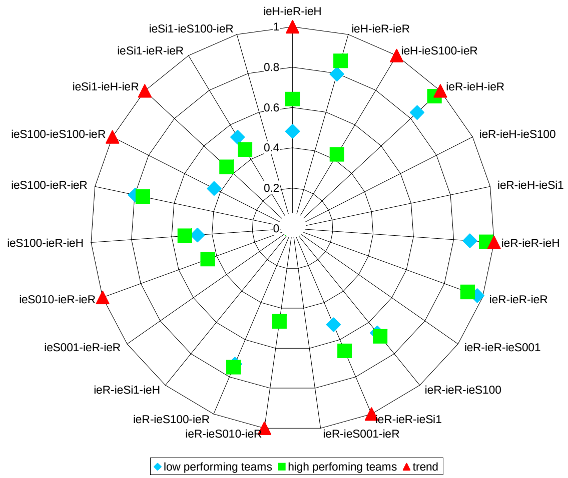
sequences of 2 events – day one



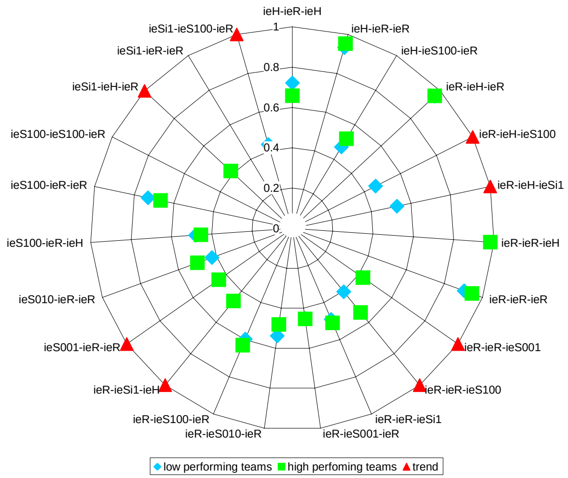
sequences of 2 events – day two



sequences of 3 events – day one



sequences of 3 events – day two



Almost all commanders of low and high performing teams assign the threat level of a plane after having read a message (ieR-ieH) on day one and day two at least once. The information from the experts was used to re-adjust the threat level of a plane.

Commanders of high performing teams show already on day one a sequence of ieSi1-ieH (looking up plane information and then doing a threat assignment). This is a pattern not often shown from commanders of low performing teams on day one (support below .50) and even on day two (support significantly lower for commanders of low performing teams).

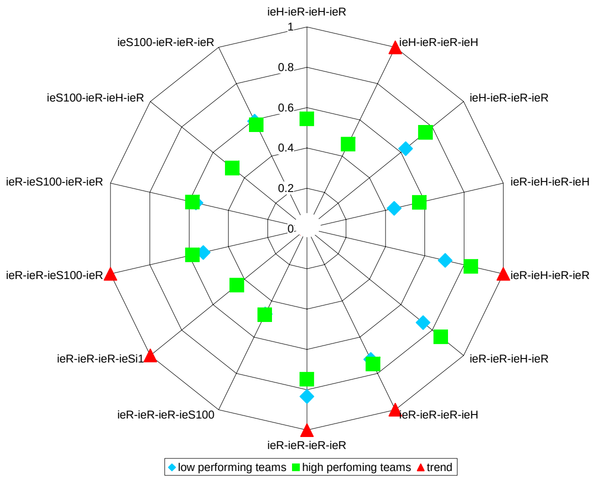
Only for commanders of low performing teams a sequence of ieSi1-ieS100 (looking up plane information and then sending a message with task related content) or ieSi1-ieSi (looking up plane information twice), or ieH-ieH (assign the threat level twice) gets some support.

On day one there is only one sequence of three events that gets a significantly higher support for commanders of low performing teams than for commanders of high performing teams: ieS100-ieR-ieR (sending a message wit task related content and then reading two messages). On day two it is also one sequence: ieSi1-ieS100-ieR (looking up plane information, then sending a message with task related content, then reading a message).

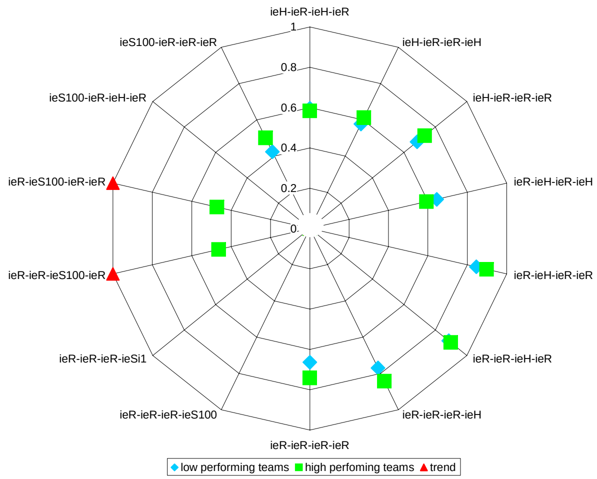
There are several sequences of three events with a higher support for commanders of high performing teams, on day one and day two. Quite a lot of these sequences contain a ieH, the threat assignment of a plane.

Commanders of low performing teams show less sequences of three events and they miss somehow to use the information they got from the specialist or by looking up the plane information to assign the threat level.

sequences of 4 events – day one



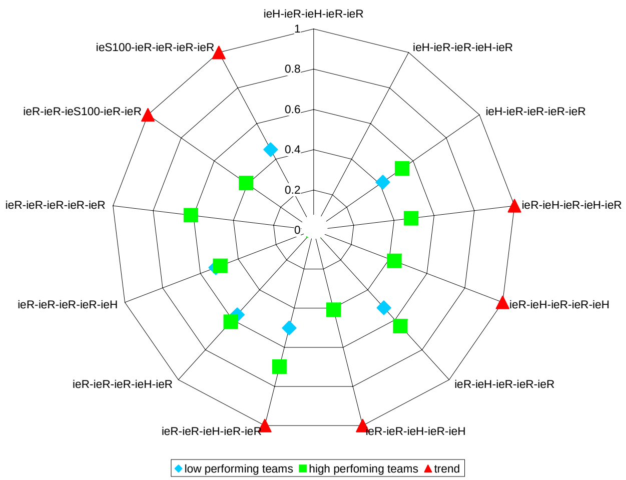
sequences of 4 events – day two



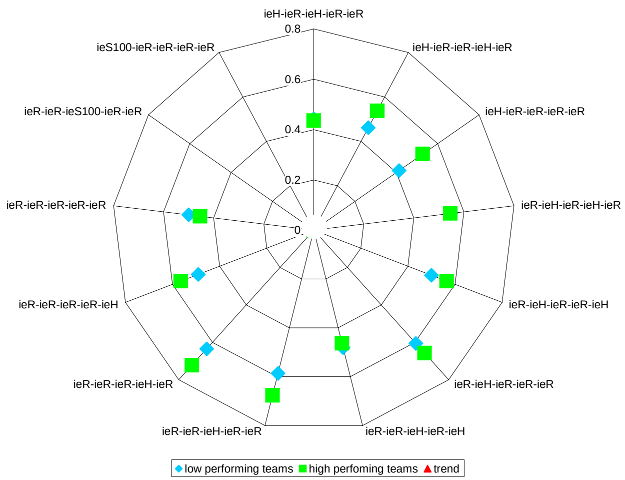
On day one there is one sequence of four events getting more support for commanders of low performing teams: ieR-ieR-ieR-ieR (reading four messages).

There are two sequences on day two getting more support for commanders of high performing teams than for commanders of low performing teams: ieR-ieS100-ieR-ieR (reading a message, then sending a message with task related content, then reading two messages), or the similar sequence ieR-ieR-ieS100-ieR. These two sequences are best seen as phases of an intense probably plane related discussion where the commander needs some additional information on a plane.

sequences of 5 events – day one



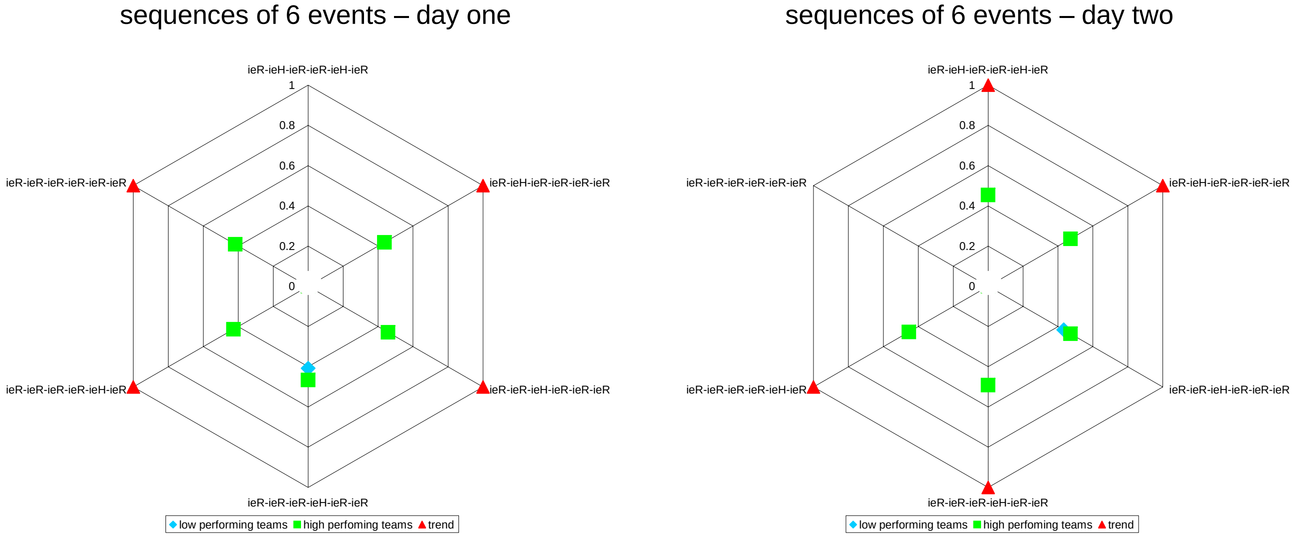
sequences of 5 events – day two



Again, there are more sequences of five events getting higher support for commanders of high performing teams than for commanders of low performing teams.

There is only one sequence of five events getting more support for commanders of low performing teams. It is a sequence on day one: ieS100-ieR-ieR-ieR-ieR. These commanders send a message with task related content and start then reading messages.

Again, commanders of high performing teams have more support for sequences in which a ieH is present. They already use the information they get from the specialists on day one to re-adjust the threat level of the planes. On day two no more differences in the sequences of five events between commanders of low and high performing teams can be observed.



Sequences of six events are the longest sequences found in the ATC data for commanders. And most sequences of six events are only found for commanders of high performing teams.

Commanders of low performing teams show a less consistent behavior over six succeeding events.

It is interesting to see that on day one commanders of high performing teams show a succession of six ieR (Read Message), something that gets a support of below .50 in day two. All other sequences of six events are some combinations of reading messages and a threat assignment.

Note. Results are presented for the two extreme groups: all the teams with the lowest performance and all the teams with the highest performance on day one and day two.

Figure 50 Data mining analyses: Sequences for commanders of low and high performing teams for day one and day two.

These diagrams of the support values condense and visualize the information from data mining analyses and help to find interesting patterns. These results are first of all descriptive. But they help to understand what the teams do on the micro-behavioral level. This is further illustrated in the following example.

Chatting Commanders

The support values for the commanders sequence ieR-ieS001 (Read Message followed by sending a message with non-task and non-strategy related content) are different on day one for commanders of low and high performing teams (Table 76). The support value for this sequence is rather low, indicating that the sequence can be found for some but certainly not all commanders of low performing teams. The support value of 0.00 for commanders of high performing teams signifies that the chance to find such a sequence on day one for commanders of high performing teams is below 0.50. The chance is not zero and there are probably also some commanders of high performing teams showing this sequences

For a more detailed analysis, I additionally calculated the absolute frequency of this sequence ieR-ieS001 for all commanders (all 109 teams, not only the low and high performing teams used in data mining analyses). Thus, the frequency of a sequential pattern found in the extreme group of the low performing commanders was calculated for all commanders.

The numbers in Table 78 show that the mean frequency of this sequence ieR-ieS001 is - not surprisingly - low. The highest mean can be found in shift 3 (mean = 1.18). It can also be seen that the standard deviation is huge, indicating that some commanders show this sequence in their behavior whilst others don't.

Table 78 Data mining analyses: Means and standard deviations of the sequence ieR-ieS001 for commanders, day one.

ieR-ieS001	mean	sd
shift 1	0.43	0.74
shift 2	0.85	1.08
shift 3	1.18	1.45

Note. N = 109 teams

The mean for the frequency of the sequence ieR-ieS001 is equal in shift 1 for all teams of all experimental conditions ($F(1,95) = 1.30$, $p = .27$) and also for low and high performing teams (median split of performance day one, $F(1,95) = 0.04$, $p = .84$). No interaction can be found ($F(6.95) = 0.05$, $p = 1.00$).

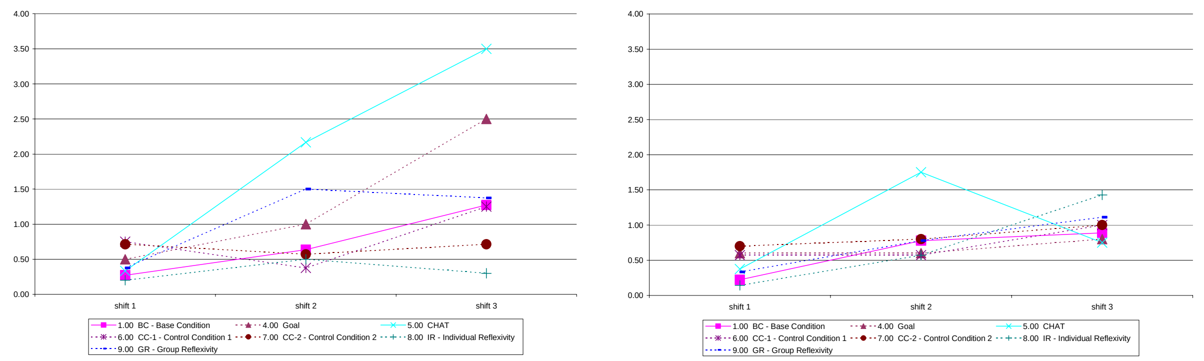
In shift 2 commanders of low and high performing teams (median split) belonging to the CHAT condition show more sequences ieR-ieS001 than any other commander. In shift 2 the teams of the CHAT condition had an additional five minutes time (twenty minutes instead of fifteen minutes) without the need to observe additional planes. The effect is obvious: commanders of the chat condition start talking about non-task and non-strategy related matters.

In shift 3 the frequency of ieR-ieS001 further goes up (Table 78). However, substantial differences can be observed for commanders of low and high performing teams (median split) and for commanders of the different experimental conditions.

A GLM repeated shows no within-subjects effects for performance ($F(2,190) = 1.94$, $p = .146$) and for the experimental conditions ($F(12.190) = 1.56$, $p = .108$) but for the three-way interaction ieR-ieS001 * performance * condition ($F(12,190) = 1.81$, $p = .049$). See Figure 51.

The sequence ieR-ieS001 stands for the exchange of non-task and non-strategy related information. The commander uses his time to chat, to communicate most probably task irrelevant contents. All commanders of the CHAT condition use this chat communication more often in shift 2. The difference between the commanders of the low performing and high performing teams can be seen in shift 3. Commanders of high performing teams of the chat condition show no increased frequency of the sequence ieR-ieS001 in shift 3, whereas commanders of the low performing teams continue to chat at a even higher rate.

commanders of low performing teams | commanders of high performing teams



Note. N = 109 teams, median split overall performance day one.

Figure 51 Sequence ieR – ieS001 for commanders of low and high performing teams (median split) on day one.

This example illustrates that data mining techniques detect relevant patterns that show differences in the group process. I do not think that such a pattern would attract some attention, if it would not be detected by data mining tools. However, it turned out that this sequence shows nicely some effects of the chat condition.

8.9.3 Predicting Performance per Shift: Sequences derived from Data Mining analyses

The support values presented as results of the data mining analyses in Table 76 can not be used in regression analyses to predict performance. Support values show the probability that a certain sequence can be found at least once for commanders (resp. specialists) of low or high performing teams.

Preparatory Steps

For all sequences with a support of at least 0.50 (numbers of commanders in Table 76, specialists A Table 174, appendix, specialists B Table 175, appendix) the frequency of occurrence of the specific sequence was calculated per shift for commanders and specialists of all 109 teams. If the support value was below 0.50 the frequency for this sequence was set to zero. This has the effect, that only relevant patterns are used in regression analyses.

The results of data mining analyses show interesting differences between low and high performing teams (like the example given in chapter 0: ieR – ieS001). But even if there is a difference between the two performance groups in the support value of a certain sequence this does not necessarily signify that this is really important to explain performance differences. Thus it might well be that it is not the presence or absence of a sequence which predicts performance, but their frequency. Data mining analyses are then just taken as a tool to identify interesting sequences.

There was a total of 480 detected patterns with data mining techniques for day one and day two (see Table 77). Most sequences could be observed on day one and day two. Nevertheless, there are still over two hundred interesting sequences. Running regression analyses to predict performance with over 200 sequences (variables) is something that should definitively not be done. A pre-selection of relevant variables is also not possible because data mining techniques are ment to be used to detect patterns also in situations where the task is not known. In the ATC-simulation it would be possible to use the knowledge gained in the definition of the *Task Adaptive Behavior* to make such a pre-selection. This would mean to give up the initial idea to give data mining techniques a chance to serve as a valuable tool in the definition of something like the *Task Adaptive Behavior*.

Therefore, I first ran separate regression analyses for commanders and specialists A and B, using the method forward with the probability level of .15 for entering a variable (Tabachnick & Fidell, 2001). This step aimed to reduce the variables entered in the final regression equation, combining sequences from commanders and specialists. Two separate regressions were run. The first regression equation predicts performance by just entering sequences identified by data mining techniques. A second equation controls for the effects of preceding performance, *input variables*, and *summary-level process variables* before entering the sequences. The same procedure already used in the chapter on the task adaptive behaviors (chapter 8.6.3) and in the chapter on lag sequential analysis (chapter 8.7.5) was applied.

Predicting Performance using the Frequency of Sequences identified with Data Mining Techniques

The sequences found with data mining techniques are presented in Table 76. Taking the frequency of these sequences to predict performance explains 46% of variance in shift 1 up to 69% of variance in shift 6. These amount of explained variance number is higher than the variance that was explained by summary-level variables, task adaptive behavior variables, or lag 1 adjusted residuals from lag sequential analyses. If the frequencies of the sequences are entered in the regression model after controlling for the preceding performance and after entering input variables and summary level process variables they still explain additional 16% of variance in performance in shift 1 up to 35% in shift 2. Sequences derived from data mining analyses are better predictors than the *summary level process* variables (Table 55) or the *task adaptive behavior* variables (Table 57).

Table 79 Explained variance (R2) using sequences found by data mining analyses (equation 1), and controlling for preceding performance, input variables and summary-level process variables (equation 2).

	Variance explained by equation 1		equation 2								
dependent variable: performance in…	*data mining sequences*		preceding performance		plus *Input* factors		plus *summary level process* variables		plus DATA MINING		change due to *DATA MINING*
	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	R^2	$R^2_{adj.}$	*diff.* R^2
shift 1	0.455	0.387	-	-	0.130	0.105	0.321	0.267	0.482	0.398	0.161
shift 2	0.670	0.604	0.212	0.205	0.236	0.222	0.337	0.305	0.687	0.625	0.350
shift 3	0.589	0.512	0.323	0.316	0.407	0.390	0.468	0.443	0.656	0.605	0.188
shift 4	0.674	0.59	0.235	0.228	0.353	0.314	0.470	0.410	0.650	0.585	0.180
shift 5	0.653	0.588	0.271	0.264	0.326	0.307	0.446	0.407	0.734	0.677	0.288
shift 6	0.694	0.597	0.405	0.400	0.464	0.443	0.515	0.476	0.773	0.705	0.258
shift 8	0.668	0.606	0.331	0.325	0.455	0.417	0.563	0.518	0.759	0.708	0.196

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Comparing these results with the results using *task adaptive behaviors* as predictors of performance is not completely legitimate. *Task adaptive behaviors* are built upon theoretical assumptions, data mining techniques just search for the co-occurrence of events in the data set. The value of the predictive power of the sequences depends heavily on the possibility to interpret them ex post meaningfully.

The sequences that were used in the regression models as predictors of performance are summarized in Table 80 (the details are in Table 176 to Table 189 in the appendix).

Table 80 summarizes the results of the regression analyses to predict performance per shift. The sign of the beta values (+ / -) of all variables in the final regression model per shift is reported. The name of the sequence is written in the first column (e.g., ieH-ieR = Handle Threat followed by a Read Message). Positive beta values are marked with a plus sign (+) and are green. Negative beta values are marked with a – sign (-) and are red. All beta values from the final regression model per shift are reported. The columns labeled day 1 and day 2 pool the information from the single shifts of day one and day two. If a certain sequence appears in one shift with a negative beta value and in another shift with a positive beta value this is marked wit a -+ in brown. For example the sequence ieR-ieS001-ieR (Read Message -> Send Message with non-task and non-strategy related content -> Read Message) has a negative beta value in shift 4 but a positive beta value in shift 8. Additionally, the information on the support values is drawn into Table 80. This is just to illustrate that not all sequences that were found for commanders or specialists of low or high performing teams with a different support value are relevant if it comes to predict performance. An example is the sequence ieR-ieS010-ieR (Read Message -> Send Message with strategy related content -> Read Message). This sequence had a higher support for commanders of high performing teams than for commanders of low performing teams (indicated by a dashed green line). However, this disparity seems to have no effect on the performance, if the frequency of these sequence is taken as predictor of performance.

Table 80 Summary Data mining: Sequences found with data mining techniques as predictors of performance.

sequence	shift 1	shift 2	shift 3	day one	shift 4	shift 5	shift 6	shift 8	day two
commander									
ieH-ieR, EC22							-		-
ieH-ieS100, EC23	+			+					
ieH-ieSi1, EC24		+		+		+			+
ieR-ieS001, EC27					+				+
ieR-ieS010, EC28							+	+	+
ieS100-ieS100, EC214			-	-					
ieSi1-ieR, EC216			+	+					
ieSi1-ieSi1, EC218	+			+					
ieR-ieH-ieSi1, EC36		-		-		-			-
ieR-ieS001-ieR, EC312					-			+	-+
ieR-ieS010-ieR, EC313					-	-			-
ieR-ieSi1-ieH, EC315								-	
ieS001-ieR-ieR, EC316								-	
ieS100-ieR-ieH, EC318	+			+					
ieH-ieR-ieR-ieR, EC43		-		-					
ieR-ieR-ieR-ieR, EC48							-		-
ieR-ieR-ieR-ieS100, EC49						-			-
ieR-ieR-ieR-ieSi1, EC410					-				-
ieR-ieS100-ieR-ieR, EC412						+			+
ieH-ieR-ieR-ieH-ieR, EC52		-		-	-				-
ieR-ieH-ieR-ieH-ieR, EC54							+		+
ieR-ieR-ieR-ieH-ieR, EC59		+		+					
ieH-ieR-ieH-ieR-ieR, EC512								-	
ieR-ieR-ieR-ieR-ieH-ieR, EC65					+				+
ieR-ieR-ieR-ieR-ieR-ieR, EC66		-		-					

(continued on next page)

sequence	shift 1	shift 2	shift 3	day one	shift 4	shift 5	shift 6	shift 8	day two
specialist A									
ieS001-ieSi1, EA28		+		+					
ieS100-ieR, EA29							-		-
ieS100-ieSi0, EA210						+			+
ieSi0-ieSi0. EA215							-		-
ieSi1-ieSi1, EA221		+		+	+				+
ieR-ieSi0-ieSi1, EA35							-		-
ieS100-ieR-ieR, EA39	-			-					
ieS100-ieR-ieSi0, EA310							+		+
ieSi0-ieS001-ieR, EA314							-	+	-+
ieSi0-ieS001-ieSi0, EA315						+			+
ieSi0-ieSi1-ieSi0, EA325							+		+
ieSi1-ieS100-ieSi0, EA328						-			-
ieSi1-ieSi0-ieSi1, EA332						+			+
ieSi1-ieSi1-ieS100, EA333							+	+	+
ieSi0-ieSi0-ieS001-ieSi0, EA47			-	-					
ieSi1-ieSi0-ieSi0-ieS100, EA422		-		-					
ieSi0-ieSi0-ieSi0-ieSi0-ieS001, EA53							+		+
ieSi0-ieSi0-ieSi0-ieSi1-ieSi0, EA57		-		-					
ieSi1-ieSi1-ieSi0-ieSi0-ieSi0, EA515							-		-
ieSi1-ieSi1-ieSi1-ieSi0-ieSi0, EA516	-			-					
ieSi0-ieSi0-ieSi0-ieSi1-ieSi0-ieSi0, EA65		+		+					
ieSi1-ieSi1-ieSi0-ieSi0-ieSi0-ieSi0, EA69							+		+
ieSi0-ieSi0-ieSi1-ieSi0-ieSi0-ieSi0-ieSi0, EA76		-		-					
specialist B									
ieR-ieR, EB21			+	+					
ieR-ieSi1, EB25			+	+		-			-
ieS100-ieR, EB28	+			+					
ieSi1-ieS001, EB217			-	-					
ieR-ieSi0-ieS100, EB32			-	-			-		-
ieSi0-ieSi0-ieR, EB313						+			+
ieSi0-ieSi1-ieR, EB317		-		-					
ieSi1-ieS100-ieSi1, EB325			+	+					
ieSi1-ieSi0-ieSi1, EB330	+			+					
ieSi0-ieS100-ieSi0-ieSi0, EB45							+		+
ieSi0-ieSi1-ieSi1-ieSi0, EB417								+	
ieSi1-ieS100-ieSi0-ieSi0, EB419							-	-	-
ieSi1-ieSi1-ieSi1-ieSi0, EB423			+	+					
ieSi1-ieSi1-ieSi0-ieSi0-ieSi0, EB512						+			+

Note. N = 109 teams, controlling for preceding performance, *input variables* and *summary-level process variables*., + / - direction of effect (beta value).

higher support value for team member of high performing teams

higher support value for team member of low performing teams

Day one, commanders. There are six strategies of commanders linked with high performance on day one: (i) sending task related information after a Handle Threat,

(ii) looking up critical plane information after a Handel Threat, (iii) reading a message after looking up critical plane information, (iv) a sequence of two adjacent Show Information, (v) sending a message with task related content followed by reading a message, followed by setting the threat level, and (vi) a sequence of reading a message three times, followed by a threat assignment then switching back to reading messages.

Five strategies are linked with low performance: (i) sending a message with task related content if that was just done before, (ii) reading a message, followed by setting the threat level, and then looking up critical plane information, (iii) reading messages (3 times) after setting the threat level, (iv) a succession of threat assignments and reading messages and (v) a series of six Read Message.

Commanders' strategies linked with good performance guarantee that specialists get informed (ieH-isS100), that the commander himself gets more confidence about what he knows (ieH-ieSi1 or ieSi1-ieSi1) or that he uses information from the specialists to adjust the threat level of the plane (ieR-ieR-ieR-ieH-ieR). Commanders' strategies linked with low performance are either inefficiently used message tools (ies100-ieS100), or verifying critical information to late (ieR-ieH-ieSi1), or just spending too much time reading (ieR-ieR-ieR-ieR-ieR-ieR).

Transforming this observations into a recommendation for commanders reads as follows: On day one commanders should give away task related information to the experts after critical events (assignment of the threat level), verify the information they ask on planes immediately, use the information they got from the experts to re-adjust the threat assignment. But they should not fall into a routine of just reading messages.

Day two, commanders. On day two also six strategies of commanders are linked with high performance, five of them are different: (i) looking up critical plane information after a Handel Threat, (ii) reading a message and then sending a message with non-task and non-strategy related content, (iii) reading a message and then sending a message with strategic content, (iv) reading a message, sending a task related message and then switching back to reading messages, (v) reading messages (3 times), assigning the threat level, then switching back to reading messages, and (vi) a sequence of Read Message followed by a threat assignment. Seven strategies of commanders are linked with low performance on day two: (i) threat assignment immediately followed by reading a message, (ii) looking up critical plane information after a threat assignment and reading a message, (iii) reading a message, sending a message with non-task and non-strategy related content and then reading the next message, or (iv) reading a message, sending a message with strategy related content and then reading the next message, (v) a sequence of four times Read Message, (vi) a sequence of three Read Message followed by sending a message with task related content, and (vii) a succession of threat assignments and reading messages.

Transforming these observations into a recommendation for commanders reads as follows: On day two commanders should send messages with strategy related content (ieR-ieS010) or a content that is not directly related to the task or strategies (ieR-ieS001). It is also good to send task-related information to the specialists, if this information is not too old (ieR-ieS100-ieR-ieR-ieR). On day two – other than on day one – longer sequences of just reading messages, but followed by a threat assignment are linked with high performance (ieR-ieR-ieR.ieR-ieH-ieR). Reading a message just after a threat assignment is linked to low performance. If messages contain a strategy related content they should not be followed by another Read Message (ieR-ieS001-ieR). Too long sequences of just reading messages have an negative impact on performance.

Review of the Research Questions to Data Mining Analyses

SEQ I. The activities of commanders and specialist have a certain regularity. It is possible to identify meaningful patterns.

Data mining analysis identifies patterns.
It is possible to meaningfully interpret the patterns.

SEQ II. Moreover, low and high performing teams show different patterns.

It is possible to show different patterns between low and high performing teams. Support values for specific sequences were calculated. Some support values differed statistically significant for commanders or specialists of low and high performing teams.

SEQ III. It is possible to predict performance if the identified patterns are entered as predictors in a regression model.

The calculated frequency of the sequences per shift can be used as predictors of performance. After controlling for the preceding per-

formance and after entering input variables and summary-level variables the frequencies of the patterns found explain still additional 16% of variance in performance in shift 1 to 35% in shift 2.

SEQ IV. Due to the nature of the ATC task and how it is implemented, patterns of directly adjacent events are better predictors of performance than either patterns combining events that follow one another after some other events happened or patterns of long sequences (six or more succeeding events).

No, there are also long sequences that predict performance. An example is the commander engaged in continuously reading messages, just inter-rupting this sequence by new threat assignments

8.9.4 Evaluation of Data Mining Techniques Applied to the ATC Data

In order to detect patterns discriminating between teams of low or high performance data mining techniques were applied to the ATC data. It was demonstrated that data mining works well with the ATC data. By taking the results of the data mining analyses, the frequencies of the patterns found were calculated. Entering these frequencies into a regression, performance could be predicted very well. There is a great amount of variance explained by the patterns. Thus, the first aim is clearly reached: the method works and sequences that predict performance are identified.

But it is not possible to find patterns that are constant over time or that show some traceable development. There is not one commanders' strategy that predicts performance in all shifts (cf. rows labeled shift 1 to shift 8 in Table 80). The task itself and the growing expertise of the team members bring about a dynamic that makes it difficult to find a set of easily recognizable strategies.

Thus it is hard to find a summarizing – or generalizing – statement integrating all the findings in a convincing and simple message. These mirrors maybe a reality of the group process: the circumstances change from shift to shift (the task itself and the expertise of the team), the groups react and change their strategies accordingly.

Generalizing statements must be made on a rather abstract level. It is good for commanders to …

- … validate information used in critical situations immediately after it has been used (as e.g., in ieH-ieSi1),

- … benefit from the information sent by the specialists to re-adjust the threat assignment,
- … send messages with task or strategy related content to the specialists – if this information is not too old,

Commanders should avoid to …

- … stay too long in a mode of just reading messages,
- … send old messages to specialists (as e.g., in ieR-ieR-ieR-ieS100)

Data mining techniques are a perfect tool to detect sequences in a behavioral stream. But Data mining has also its hurdles: the 'meanings' are not suggested by the data or the computers, they have to be imposed on data by human beings. To facilitate the interpretation of the data it is useful to transform them into diagrams (see e.g., Figure 50). However, these diagrams contain still a lot of information and are not easily read. Nevertheless, they map the process and can be used as a means to launch the debate about what happened in the group process. Although the method was applied to data gathered in an experimental setting, it is obvious that presenting the information on the group process might enrich many team intervention programs.

It is not to forget that the applied data mining algorithm only searched for the occurrence or non-occurrence of sequences (setting the support value to .50). This information must be combined with the frequency of the sequences. Doing this raises the question of what to do with such an amount of data. In a strictly exploratory procedure I proposed to first identify those sequences that predict performance for each role separately and then combining this reduced set of variables in one regression to determine what sequences have the power to best predict performance (summarized in Table 80). It was shown that the prediction of performance works perfectly – but that it is not at all easy to detect some constant or developing patterns from shift 1 to shift 8. But nevertheless it was possible to formulate some general statements describing poor and good strategies in the ATC simulation for commanders.

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9 Integration and Discussion

A process is a series of actions, a sequence of events or steps towards achieving a particular end. A process has a time-axis. (Oxford reference online).

Processes in small groups can be looked at from two directions. The first one is macro-perspective. It examines the development of the group and the changes occurring during its life cycle (McGrath & Tschan, 2004b). I went the other way around. I took the micro-perspective and had a closer look at single action units, at single communication acts to investigate how teams work together.

I observed the teams in a way behavioral researchers or developmental psychologist are used to observe e.g. small children's play. Every single act was coded such that its type and its meaning was captured together with its time stamp. This allowed me to run sequential analyses, gaining insight into the group process on a micro-behavioral level.

In small group research the group process is a hot topic. Almost in all perceptions on small groups, the process is implicitly or explicitly mentioned (Poole et al., 2004). But if one looks at how 'process' is defined and operationalized in empirical studies a great definitional diversity becomes apparent. I distinguished three types of research on group processes.

Evaluative measures on the group process. Typically evaluative measures are questionnaire based data, where team members are asked to evaluate the group process. Concepts used are cohesion, attraction to the group, mutual support, workload sharing, potency and others. These measures are often taken just once, after a session or after having worked together for some time. It is often criticized that such singular measures can hardly be seen as process measures. Process measures should be taken repeatedly. Another critic is that evaluative measures are often biased by the output of the group process – especially, if the measuring happens at the end of a process. The most important critic is, however, that all these measures do not really map what is going on in the groups and teams whilst they interact. Imagine two teams with the same task to solve, the same expertise and the same group composition. Both teams rate their climate, their cohesion, their joint effort. If the ratings of the two group is alike, do we then conclude that the way the team did its job, is the same for both groups? Not necessarily. The group process can be very different. Or the other way round: If the rating of the climate, cohesion or joint effort is different in both teams, the interaction process on a micro-behavioral level could be very similar.

A lot of conceptions and theories in small group research see the group interaction process as an important agent between the input and output. This should also be reflected in the way we analyze group processes. It is important to know the team members' evaluation of the group process. But additionally we should have a closer look at the micro-behavioral organization of the group process.

This is done in studies representing the group process as frequencies of behaviors (coding and counting approaches). The coding is most often done solely for communication acts without including other behavioral acts. Examples are Bales' IPA categories (Bales, 2002), the coding of irregular communications in pilot transcripts from Prinzo, Britton, and Hendrix (1995), or behavioral marker systems used in crew resource management as NOTECHS (Klampfer et al., 2001). A coding system that does not only focus on communication but also takes into account behavioral acts was used by Tschan et al. (2000) in the analyses of a simulated air traffic control scenario.

A common characteristic of these coding approaches is the way the data is analyzed. Analyses are run using summary level process variables. The frequencies of the acts are summed up for specific periods of time. However, this aggregation of the data wipes off any information on the sequence of the single acts. In a business meeting of 30 minutes it could happen that a employee gets a rebuke from his boss. A coding and counting approach tells us that there was one rebuke within the 30 minutes. But it is likely that the effect this rebuke has on the employee, the meeting and the group process depends also on the point of time the boss made his rebuke (in the first minutes of the meeting or in the last minutes). Furthermore, the employee's and his colleagues immediate reactions to the rebuke is very important.

We need to go a step further and analyze data collected in a coding and counting approach with respect to the temporal sequence of the acts. This is something which is rarely done in small group research. There are a few examples like the analysis of communication sequences in crew communication of Bowers et al. (1998), Brauners' (2002) work on the development of transactive memory systems and the work of Becker-Beck and colleagues (Becker-Beck, 1994, 1997, 2001), who run sequential analyses on SYMLOG coded discussions.

I used data from an air-traffic control (ATC) simulation. A hierarchical structured team of three persons (commander and two specialists) had to observe an airspace. The team members worked in different rooms with no face-to-face contact. All communication within the team was done through an e-mail system that allows sending and receiving typed text messages. The teams observed planes in an air space and had to determine the threat level of each plane at each moment during fifteen-minute work shifts. Up to four planes were moving in the air-space in a shift. Each of the two specialists observe each different parameters (like speed, height, distance, ...) of the plane. This parameter information needs to be transmitted to the commander. The commander only has the knowledge how to calculate the threat level of a plane out of this parameter information.

Three methods were selected to analyze the sequential patterns in the ATC data: knowledge discovery in databases / data mining, lag sequential analyses (Bakeman & Quera, 1995a), and procedural network representations (Cooke et al., 1996).

As it is described in the knowledge discovery in databases (KDD) procedure (Figure 6, p. 59), the first steps in all analyses are data cleaning, selection and preparation. On first sight, this is a rather trivial statement. But as there is no common standard on how sequential data is best organized in a database (Bakeman & Quera, 1995a) things get more complicated. This issue is raised in several chapters of my thesis. The automatically stored ATC log-files are described in chapter 6.5 (p. 78ff.). In chapter 6.8 (p. 84ff.) the coding of the process variables is explained and finally method specific transformations are presented in the chapters describing the application of the methods on the ATC data.

These preparatory steps turned out to be quite time-consuming and sometimes really tedious. It is not to forget that only for a short time desktop computers have had the capacity to handle bigger databases with an accurate speed. When we started our project in 1996 and I run first analyses it took hours just to calculate simple frequencies. Obviously, this was partly due to the fact, that we only used standard computer programs (as SPSS) and did not start to program own and probably faster software tools by ourselves.

Having the data ready for analyses with the three methods selected, the first question was: What can be detected in the data that we have not known before? Every method was used as exploratory tool.

In a further step the question was: Is it worth the effort? There are several ways to find an answer to this question. One possibility is to calculate the amount of additionally explained variance in an outcome variable when sequential variables are used – in addition to input variables like gender or team performance in an earlier shift and in addition to summary level process variables.

All analyses in my thesis are based on data gathered from 109 teams (of three persons) working together for at least seven shifts of at least 15 minutes duration. Compared to many studies citied in my thesis this is a big sample.

It could be shown that - although the data was gathered form 1996 to 2000 – there was no significant change in the age of the participants, nor in the gender composition of the teams. Also computer expertise was the same for all participants. However, there was a clear effect that men reported higher computer expertise than women (see chapter 6.4).

I defined four types of coded events (with the main categories: Read Message, Send Message, Show Information for commanders as well as specialists A and B, and Handle Threat for commanders, see chapter 6.8, p. 84ff.). Every event was coded alongside with a time stamp and information on the content of the act. Additionally task adaptive behaviors were coded as they are defined in Tschan et al. (2000). All coding were done on the level of the single fifteen-minute shift.

All in all, data from seven shits was available. Shift 1 to shift 3 were identical to shift 4 to shift 6, shift 8 was more demanding to teams. In this last shift, designed as a test shift, more dangerous planes had to be observed. Shift 7 was skipped because there was no data available for some teams (details in chapter 6, p. 65ff).

Based on an act by act coding, summary level process variables were calculated per shift. The same was done for task adaptive behavior variables. GLM repeated measures showed that eight of ten summary level process variables and all eleven task adaptive behavior variables showed variation over time (chapter 8.3).

Commanders have to send messages at least to instruct their specialists, to signal the identification of a plane and to motivate the specialists. For specialists the mail system is mainly a means to send plane related information to the commander. It was therefore expected that commanders use periods with a low workload (few and non-dangerous planes) to instruct their specialists. Consequently the commanders frequency of sending messages should be highest in shift 1 and especially in shift 4. However, the highest frequency of sending messages are found in shift 3 and shift 6. It seems as if commanders did not use the periods with a low workload to instruct their specialists properly. Instead, they asked for information and instructed their specialists in those shifts with many and/or dangerous planes. In these shifts specialists should know what information a commander needs and deliver it spontaneously.
Commanders read much more messages than specialists. The number of read messages is lowest in shifts with only two planes (shift 1 and shift 4) and highest in shift 8 with four planes. This shows that the team uses the email system mainly to transport plane related information, as the number of messages goes up if more planes have to be observed. Specialists read less messages than commanders, and this is constant over time. Reading a message has a completely different function for specialists than for commanders. Given the basic instruction at the beginning

of the simulation a specialist could even function without reading a single message.
Looking up plane information is the main task of the specialists (beside of sending this information to the commander). It was expected that the number of lookups varies with the number of planes in the airspace. This was not the case. The number of lookups increases for specialists steadily from shift 1 to shift 8. It is as if the specialists get more and more used to this task, they do it more or less automatically. The effect is that if there are only few planes they are better observed than in situations with more planes in the airspace.
The number of threat assignments and the accuracy of the threat assignment determines the final performance. It is the commanders duty to make this threat assignment. It was expected that the number of threat assignments is higher if the planes are more dangerous (which also means that they change the threat level more often). However, the highest number of threat assignments is found in shift 4 with only two moderately dangerous planes. On the other hand, the number of threat assignments is higher on day two (shifts 4 to 8) than on day 1 (shift 1 to shift 3). Obviously, the commanders realized the importance of the threat assignment.

In Tschan et al. (2000) task adaptive behaviors were calculated per day (day one = shift 1 to 3, day two = shift 4 to 6). The basic task masteries describe the capability to handle the task. For commanders it can be shown that the number of failures decreases steadily from shift 1 to shift 8. For specialists, the picture is less clear. Specialists have more trouble with the basic task mastery. This is probably due to the inclusion of the number of planes, for which specialists missed to look up information. This results in the worst basic task mastery in shift 8 for specialist A and B. It seems as if many specialists reached their limit in a situation with four planes in the airspace. They no longer managed to observe all parameters of the planes. The plane handling of commanders and specialists is better on day two than on day one. An increase in expertise is visible. But as the tension increases in shift 8 with four planes in the airspace plane handling gets impaired. Message handling gets better from shift to shift both for commanders and specialists. There are not many messages from the commander to the specialists with a strategic or instructional content. And if there is such a message it is most likely to be found in shift 4 or in shift 6. Shift 4 is the first shift on day two. I expected the commander to send a message to his team welcoming them back on the job and giving them some hints on how to proceed. It was not expected that the number of strategic comments goes up in shift 6. In shift 6 planes get more dangerous and I assume that many commanders realized only in this situation that their strategies were not good enough. They tried to correct whatever they still could. This indicates also that some strategies are probably not developed in advance but in the situation when they are needed.

These first results give some interesting insight in the development of the teams from shift 1 to shift 8. First of all, the results show that summary-level variables as well as task adaptive behavior variables vary over time, they show differences between commanders and specialists. It was also shown that teams get better on day two, especially with regards to task adaptive behaviors.

These input variables, summary-level process variables and task adaptive behavior variables were then used to predict performance.

Input variables (age, gender, computer expertise) variables explain 11% of the variance of the performance in shift 1. In shift 2 the percentage goes down to 4% and stays in the range of 12% to 20% for shifts 3 to shift 8. Adding the performance of preceding shifts to the regression model as a first step, raises the explained variance from 22% in shift 2 to 42% in shift 8. The range of additionally explained variance by input variables after controlling for preceding performance is 6% to 12%. It is mainly the computer expertise of the commander that accounts for this results, often together with him being male or being a university student. This results are not surprising and the variance explained in performance is in the expected range.

Summary-level process variables as frequency aggregates of events should have the power to predict performance even better than input variables. Summary-level process variables alone explain 5% (shift 3) to 25% (shift 8) of variance in performance. When the preceding performance and the input variables are added to the regression model the explained variance is in the range of 31% (shift 2) to 52% (shift 8). The range of additionally explained variance after controlling for the preceding performance is between 5% (shift 6) and 19% (shift 1). Summary level process variables have clearly the power to predict performance. The prediction is better than for input variables. It is often the number of the commanders' threat assignments, the fact that specialists A send his/her messages fast, and that specialists B have a high frequency in looking up the plane information on day 2.

Task adaptive behavior variables alone explain 16% of variance in performance in shift 4 up to 50% in shift 2. Just taking task adaptive behavior variables as single predictors of performance per shift gives much better results than using either only input variables or summary-level process variables. If task adaptive behavior variables are entered in the regression model after entering input variables and summary-level process variables they still explain additional 6% of the variance in performance in shift 8 up to 26% in shift 1. Task adaptive behavior variables add additional explanatory power to the regression model which is not included in the other models.

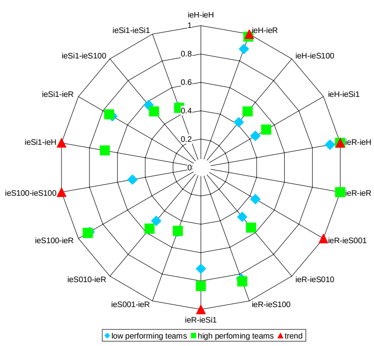
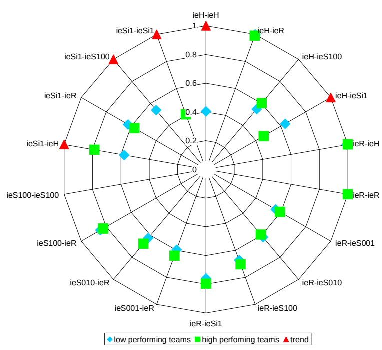
Results up to this point clearly highlight that the outcome variable (performance) can be predicted by input variables, by summary-level process variables and even better by task adaptive behavior variables. The amount of total variance explained varies from shift to shift, and reaches a maximum of 62% in shift 3, when taking into account the preceding performance, input factors, summary-level process variables and task adaptive behaviors. The amount of variance explained is high and the question is, if it is really possible to further augment this number.

The struggle to get a perfect prediction of the performance of a team covers just one question of my thesis. The more important questions is how data mining techniques, lag sequential analysis and procedural network representation have to be applied to the ATC data to obtain a deeper insight into the group process on a micro-behavioral level. It is also the question, how to visualize the results. And most important: what can be learnt from the exploratory data analysis, which all those methods offer?

Data mining analyses (chapter 5.3.3 and 8.9) were run for day one and day two separately for teams with low and high performance (tripartition). The algorithm used was programmed by Paul Cotofrei and Kilian Stoffel. It searched the data for directly adjacent sequences with a minimal support value of 0.50. The length of the sequences was only limited by the support value set. The sequential ordering of the data was respected such that A -> B is different from B -> A. The longest sequences found with a minimal support of 0.50 for commanders span over six succeeding events, for specialists A over nine events, and for specialists B over six events. For these analyses the coding of the variables contained information on the act (sending or reading a message, …), on the message content (task-related, strategy-related, non-task and non-strategy related), and the time of occurrence (time stamp).

The primary results of the analyses were tables with support values (Table 76, p. 215) and information on statistically significant differences between low and high performing teams. These numbers were then transformed into graphs. This allows a direct comparison of day one and day two sequences for low and high performing teams.

The graphical representation of the results shows differences between low (◆) and high (■) performing teams. Statistically significant differences in the support values are labeled as trend (▲). The following graphs show the example from commanders of low and high performing teams for sequences of a length of two events.

sequences of 2 events – day one	sequences of 2 events – day two
	

For example we find that the sequence threat assignment (ieH) followed by reading a message (ieR) has a support of 1 on day one for teams with a high performance, and lower support value for teams with a low performance. On day two both low and high performing teams have a support value of 1. This example shows several things. There are differences between low and high performing teams. This specific sequence can be found with a high support, this means that all commanders of the high performing team show this sequence at least once on day one and day two. It also shows that on day one some commanders of the low performing teams never show this sequences. Comparing day one and day two the development of the teams can be seen. In this case then all commanders use the specific sequence at least once.

All in all over two hundred sequences were detected on day one and also on day two for commanders and specialists. It is the challenge of exploratory methods to filter the information, i.e. in this case to extract the most relevant patterns. I took one example of a commanders sequence of two events: reading a message followed by sending a message with non-task and non-strategy related content. The support values differ for low and high performing teams. As the support value does not consider, how often the specific commanders showed this sequence, I additionally calculated this number per shift. The interesting finding is: In shift 1, the frequency of this sequence is the same for low and high performing teams of any experimental condition. In shift 2 all commanders of the CHAT condition show an increased frequency of this pattern. This is due to the additional five minutes they were given in the beginning of shift 2 without the need to observe planes. In shift 3 for the CHAT condition the frequency for this pattern reaches again the level of all other teams, but only for teams with a high performance. Low performing teams of the CHAT condition continue to show this pattern at a high rate also in shift 3 (Figure 51, p. 227).

Without the information we got from data mining analyses hardly anybody would have imagined that a sequence of reading a message followed by sending a message with non-task and non-strategy related content could be of interest. But the detailed analyses of this pattern reveals that commanders of low performing teams of the CHAT condition have another style to respond to messages – they continue to chat and neglect the task related communication.

In a next step I calculated the frequencies per shift of all sequences with a support of at least .5. This information was then entered in a statistical stepwise regression to find the optimally matching regression model to predict performance. My aim was to use best the information from data mining analyses to predict performance.

Results show that such patterns have at best the power to explain 61% of variance in performance (shift 8) and at least 39% (shift 1). Controlling for preceding performance, input variables, summary-level variables and task adaptive behaviors the sequences identified with data mining techniques still account for 16% (shift1) to 29% percent (shift 5) of additionally explained variance. Obviously, there is something in the sequential patterns that is important to perform well.

There were finally twenty-five sequences of commanders that stayed in the regression equation. Wich sequence stays in the equation changes however from shift to shift. The overall picture is rather fragmented. However, there are sequences which clearly have a negative effect on performance: e.g. a commander should not read a message, then assign the threat level and then look up plane information. He or she should not stay too long in a mode of just reading messages and assigning the threat level. I summarized the findings as follows: A commander should validate information used in critical situations immediately after it has been used, benefit from the information sent by the specialists to re-adjust the threat assignment, send messages with task or strategy related content to the specialists – if this information is not too old. Commanders should avoid to stay too long in a mode of just reading messages, or to send old messages to the specialists.

Data mining techniques can be applied to behavioral observation data and communication. Discussing the process of knowledge discovery in databases (KDD) I cited Klösgen's (1996) criteria to decide whether or not patterns detected are interesting. We have some *evidence* that the criteria are interesting as it is possible to identify statistically significant patterns for low and high performing teams and as the frequency of the patterns can predict performance in a regression model. *Redundancy* is a criteria that is hard to met with just one study. The results are *useful* as they show that in a setting like the ATC simulation commanders should switch modes (reading and threat assignment vs. sending messages) and be careful not to rely on old information. The *simplicity* is given in the graphical representation of the results. But the *generality* is then a criteria that can hardly be met by a single experimental simulation study.

According to my view data mining techniques are a valuable tool in the exploratory data analyses also of behavioral observation and communication data.

To run lag sequential analyses (chapter 5.3.1and 8.7), I followed the recommendations of Bakeman and Quera (1995a). The aim of lag sequential analyses is to detect patterns in behavior or in communication. Lag sequential analysis is always based on transition frequency or contingency tables. These tables map the frequency of how often a certain given behavior (also 'criterion' or 'initial behavior') is followed by a specific other target behavior (also 'matching behavior'). A lag 1 contingency table consists of all frequencies of directly adjacent behaviors. Lag 2 contingency tables map the frequencies of the second event after a given event. Different statistics can be computed. A chi-Square table statistics indicates that there are contingencies in the data and that a lag sequential analysis can be applied. Based on lag frequencies conditional probabilities and adjusted residuals (*z*-score) were calculated for all shifts from lag 1 to lag 5. The group process is represented in the adjusted residuals which show the inhibition or activation of sequences of given and target events. The *z*-score expresses the extent to which an observed value for a conditional probability differs from its expected value.

I had a closer look at shift 1, the first shift on day one and shift 4, the first shift on day 2. Both shifts are alike.

Results show that there are mainly lag 1 to lag 3 contingencies. Higher contingencies are less frequent. The adjusted residuals differ for low and high performing teams. But all in all there are not that many striking differences between the commanders of low and high performing teams. Just to name an example: If there is a New Message in shift 1 or shift 4 the probability that the next act is a Read Message is enhanced for commanders of low and high performing teams. The probability that the next act after a New Message is a Show Information or a Send Message is inhibited for commanders of high performing teams. However, in shift 4 this inhibition is highest for commanders of high performing teams. It can be observed that there is a high probability for commanders of low and high performing teams to read a message if there is a New Message. The difference between the two performance groups is to be found in the strength of the inhibition or enhancement of certain sequences. Commanders of high performing teams seem to have a stronger focus on reading a message than commanders of low performing teams. They are much more in danger of doing other things than reading massages than commanders of high performing teams.

Entering the *z*-scores (adjusted residuals) derived from lag sequential analyses in regression models is discussed controversially. If the results are interpreted with appropriate caution it can be shown that these z-scores explain additional variance in performance even if it is controlled for input factors and summary-level process variables.

To sum up: In shift 1 it is especially the commanders who have to get information on planes, exchange information and assign the threat level. Further it is important for commanders to react immediately to a new plane in the airspace and to take notice of the information they receive from the specialists. Specialists seem to be engaged in a strong routine of looking at the parameter information of the planes. They act according to their instruction. But it is important to interrupt this routine from time to time. Specialists do not have to react immediately to new planes coming into the airspace. But they have to react to messages from the commander, they have to read and respond to them.

Lag sequential analyses are limited to one lag at a time; one looks either at lag 1 or at lag 2 or at lag n contingencies. An analysis of long contiguous sequences is not possible. A lag 2 analysis may reveal that there is an enhanced probability that after

A follows C. But it is not known what happens at lag 1. Lag sequential analyses can be applied to a data set that contains only a few hundred observations (for data mining analyses much more observations are needed). The method is therefore suitable for the analyses of group interaction data for at least three reasons. First, the method can be used with relatively few observations. Second, it is a good tool to visualize the sequential dependencies in the observational data and therefore to map the group process. Third, indices capturing the conditional aspects of the data can be analyzed with standard parametric techniques.

Procedural network representation (PRONET) is a method proposed by Cooke and Neville (1996) to represent sequential data. The method uses the Pathfinder algorithm (Schvaneveldt, 1990) to calculate and map the temporal proximity of events. Conditional probabilities are used in PRONET analyses as indicator of the proximity of two events. Conditional probabilities express the probability that a certain event follows a specific given event. Thus PRONET uses the same contingency tables as were used in lag sequential analyses. But instead of calculating the adjusted residuals (*z*-score) PRONET submits the conditional probabilities directly to the Pathfinder algorithm. Conditional probabilities are calculated taking into account only the row frequencies. Adjusted residuals make a correction for the overall frequencies (Table 62).

The result of a PRONET/Pathfinder analysis is always a graphical representation of the relation of the variables (i.e. single acts) (Figure 44 to Figure 46). Differences between low and high performing teams are visible.

Results show for example, that commanders of low and high performing teams react differently to a New Plane in shift 1. If there is a New Plane commanders of low performing teams start sending a new message. For commanders of high performing teams the same path can be found as well, but additionally there is a path to a Read Message or to a threat assignment (Handle Threat). Commanders of high performing teams have a more differentiated reaction to a new plane.

Pathfinder *C* offers a measure to compare network representation. I compared the representations for low and high performing teams for shift 1 and shift 4 data. The network representations were quite similar. Hardly any difference between low and high performing teams could be found.

The difference between low and high performing teams is often due to minor differences in the patterning of the group process. But all Pathfinder *C* analyses I run were based on the main categories (Read Message, Send Message, …) not taking into account the content coding of the messages. It might well be that the network representations would differ if more categories were used.

PRONET can be used to map sequential relations in data. The graphs are easy to read. Any link can be read as “if – then” relation. PRONET uses the same contingency tables as lag sequential analyses. Accordingly, it has the same shortcomings in detecting longer, continuous sequences. A strength of PRONET is, however, the possibility to run a detailed link analyses (comparing link weights) or to compare different network representations (Pathfinder *C*).

I started my work on the analyses of the micro-behavioral organization by questioning the use of group “process” variables in research and consulting: Variables that evaluate the group process solely from the team members viewpoint.

If our aim is to optimize group interaction, if we want to foster performance in co-acting teams, if we want to give concrete advice how to ameliorate the joint effort of teams to perform effectively, we need to have more knowledge on the team process on a micro-behavioral level.

I selected three methods – knowledge discovery in databases (KDD) / data mining, lag sequential analyses and procedural network representations (PRONET). All three methods were discussed extensively. If the data base is big enough, data mining techniques are recommended to use. If the data base is limited, lag sequential analyses and PRONET are a better choice. Lag sequential analyses have been used in behavioral observation and developmental psychology for a long time. Thus the method is not unknown. PRONET and the Pathfinder algorithm are seldom used.

In the ATC simulation teams of three person had to work together to observe planes in a virtual airspace and to assign a threat level of the planes determined by nine parameters. I could show, that there is some development within the two sessions and within the seven work shifts. There is a gain in expertise from day one to day two, which is well reflected in the changes in task adaptive behaviors.

Comparing low and high performing teams showed some differences in the sequential patterning of the actions (regardless of the method used). However, the sequential patterning of actions between low and high performing teams often shows more similarities than dissimilarities. The differences between those two performance groups are often found in small differences in the sequential patterning of their actions. Nevertheless, these differences are relevant. Entering the information on the sequential pattering in regression models to predict performance always adds a significant amount of additionally explained variance (regardless of the method used).

Using data mining techniques, lag sequential analyses or PRONET helps to better understand significant aspects of the group process, that is how the group process evolves over time on the micro-behavioral level.

The application of data mining techniques, lag sequential analyses and procedural network representations (PRONET) to data gathered observing a group process was successful. Although the three methods stem from different areas they all aim to discover significant sequential patterns in the data. Data mining techniques are best suited for very large data sets (e.g., all transactions of a credit card company). It is then possible to detect contiguous sequences in the data. The data gathered from the 109 teams working on the air traffic control task during seven shifts of fifteen minutes is large enough to use data mining techniques. However, if the data base is smaller, lag sequential analyses and procedural network representations are better suited to analyze the data.

There are new insights into the group process due to the calculation of measures reflecting the temporal sequence of acts and their visualization. Just to name two example: (i) We never thought that it could be useful to look up plane information (Show Information) just after having set the threat level (Handel Threat). However, the analyses of the sequential patterns shows, that this is done by commanders of high performing teams in the early shifts. (ii) A detailed analyses of the sequence Read Message -> Send Message with non-task and non-strategy related content revealed interesting differences between commanders of low and high performing teams in different experimental conditions. Data mining analyses pointed to this difference. Results show that the extra time given to discuss in shift 2 to all teams of one experimental condition (CHAT-condition, see Table 13) had the desired effect: there was more communication in shift 2. This style of sending messages with non-task and non-strategy related content should be omitted if there are planes in the airspace. It is then observed that in shift 3 commanders of high performing teams of the CHAT-condition do not use this type of message more often than all other commanders. In contrast commanders of low performing teams continue to chat. They send even more messages with non-task and non-strategy related content in shift 3 than they did in shift 2.

Measures reflecting temporal associations in the data can be used to calculate *t*-tests, ANOVAS or regression models. It was shown, that this information on the temporal sequences in the group process helps to ameliorate the prediction of the teams performance. Regression models were analyzed for shift 1 to shift 8 performance. Adding the information on the sequential organization of the group process to the regression model explains up to 35% of the variance in performance, after the preceding performance, input factors, and the frequency of the acts were entered in the equation. All in all the explained variance is between 50% and 76%.

I think that it is really worth the effort to use sequential methods also in small group research. The temporal structure of the group process may not be very different for low and high performing teams. But there are differences that can be uncovered with sequential methods. And it turned out that these differences are very powerful predictors of the groups performances.

Furthermore, these small differences can never be detected by using either questionnaire data or by calculating overall frequencies (coding and counting approach). To improve the group process in co-acting teams a detailed analyses of the temporal sequences on a micro-behavioral level is indispensable. The information from these analyses can be used to describe the group process and to predict performance. The next step to go would be to formulate a team intervention program. These information on what the team really does can then be used for an optimal coaching.

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UNIVERSITÉ DE NEUCHÂTEL
FACULTÉ DES SCIENCES ÉCONOMIQUES ET SOCIALES

REGULAR PATTERNS IN THE GROUP PROCESS: HOW THEY ARE DETECTED, WHAT THEY TELL US, AND HOW THEY ARE RELATED TO PERFORMANCE

THÈSE

PRÉSENTÉE A LA FACULTÉ DES SCIENCES ÉCONOMIQUES ET SOCIALES
POUR OBTENIR LE GRADE DE DOCTEUR EN PSYCHOLOGIE DU TRAVAIL

PAR

NÄGELE STALDER CHRISTOF

Monsieur Christof NAEGELE STALDER est autorisé a imprimer sa thèse de doctorat en Psychologie du travail intitulée :

“Regular Patterns in the Group Process: How They Are Detected, What They Tell Us, and How They Are Related to Performance”

Il assume seul la responsabilité des opinions énoncées.

Neuchâtel, le 14 décembre 2004

Le Doyen
de la Faculté des sciences
économiques et sociales

Michel Dubois

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1 Additional Friendly Plane in Shift 5 of the CHAT Condition

In shift 5 of the CHAT condition an additional friendly plane entered the airspace to mask the additional five minutes time. The plane entered the airspace shortly after the shift began and remained in the air-space for the rest of the time. It was assumed that any team would be capable to identify this plane quickly and therefore assigning the appropriate threat level within a few seconds. And this is exactly what 13 of 14 teams did. They scored 97 to 100 points on this plane. Only one team got a performance of just 87 for this plane. The team with the lowest performance for the first plane in shift 5 had also the lowest overall performance for this shift. It can be shown that especially low performing teams could profit from the additional plane. They gained 8 to 10 points. Good performing teams on the other hand benefited only slightly from this plane, their gain is 3 to 4 points. Nevertheless, the effects of the additional plane can be neglected. The rank order within the CHAT condition stays the same with and without the additional friendly plane. To make the performance measure of shift 5 of the CHAT-condition comparable to the other experimental conditions, shift 5 performance is calculated without taking into account the performance of the first (friendly) plane.

Table 81 Effects of the additional plane on performance in shift 5, CHAT-condition.

Group Number	L_F54	L_F51	L_F52	L_F53	mean	**mean without plane F54**
441	99	88	81	90	89.5	**86.3**
423	100	76	86	92	88.5	**84.7**
435	100	86	76	87	87.3	**83.0**
436	97	84	70	91	85.5	**81.7**
429	99	79	72	91	85.3	**80.7**
421	99	82	69	85	83.8	**78.7**
430	100	82	70	78	82.5	**76.7**
426	99	85	52	88	81.0	**75.0**
427	100	73	70	77	80.0	**73.3**
425	100	80	61	76	79.3	**72.3**
437	100	64	67	86	79.3	**72.3**
428	98	82	43	91	78.5	**72.0**
431	99	74	76	45	73.5	**65.0**
424	**87**	**53**	**45**	**40**	**56.3**	**46.0**

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2 Abbreviations of the Coding

A time code is always added to the categories (start and end time of event).

ieR – Read Message – reading a message
Sub categories:

ieR111	reading a message with task, strategy and non-task/non-strategy related content
ieR110	reading a message with task and strategy related content
ieR100	reading a message with task related content
ieR101	reading a message with task, and non-task/non-strategy related content
ieR011	reading a message with strategy and non-task/non-strategy related content
ieR001	reading a message with non-task/non-strategy related content
ieR010	reading a message with strategy related content

ieS – Send Message – sending a message
Sub categories:

ieS111	sending a message with task, strategy and non-task/non-strategy related content
ieS110	sending a message with task and strategy related content
ieS100	sending a message with task related content
ieS101	sending a message with task, and non-task/non-strategy related content
ieS011	sending a message with strategy and non-task/non-strategy related content
ieS001	sending a message with non-task/non-strategy related content
ieS010	sending a message with strategy related content
ieS110	sending a message with task and strategy related content

ieSi – Show Information – look up plane information
Sub categories:

ieSi1	look up plane information on critical parameter (IFF, corridor, direction)
ieSi0	look up plane information on “non”-critical parameter

ieH – Handle Threat – threat assignment of a plane
Sub categories:

IeHYX	Y is number of plane in shift, X is the threat level set

seNewMsg – seNewMs – New Message – a new message is in the inbox
Sub categories:
-

seNP – New Plane – a new plane is in the airspace
Sub categories:
-

3 Predicting Performance: Input variables

Table 82 Results of multiple regression, predicting performance shift 1, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
	.130	.105						5.225	3	105	.002

Predictors in trimmed model	Beta	t	Sig.
education specialist A	.282	3.090	.003
education commander	-.160	-1.717	.089
computer expertise commander	.138	1.484	.141

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	-0.046	-0.501	0.617
CHAT condition (dummy coded)	0.006	0.064	0.949
Control Condition 1 (dummy coded)	-0.010	-0.104	0.917
Control Condition 2 (dummy coded)	0.122	1.329	0.187
Individual Reflexivity (dummy coded)	0.002	0.019	0.985
Group Reflexivity (dummy coded)	0.050	0.533	0.595
age commander	-0.098	-1.072	0.286
gender commander	-0.070	-0.702	0.484
education commander			
computer expertise commander			
age specialist A	0.042	0.447	0.656
gender specialist A	0.015	0.163	0.871
education specialist A			
computer expertise specialist A	0.117	1.292	0.199
age specialist B	0.014	0.151	0.880
gender specialist B	-0.001	-0.013	0.989
education specialist B	-0.041	-0.436	0.664
computer expertise specialist B	-0.009	-0.099	0.922

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 83 Results of multiple regression, predicting performance shift 2, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
	.053	.035						2.972	2	106	.055

Predictors in trimmed model	Beta	t	Sig.
education commander	-.160	-1.686	.095
gender commander	.159	1.678	.096

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.075	0.790	0.432
CHAT condition (dummy coded)	0.119	1.244	0.216
Control Condition 1 (dummy coded)	-0.001	-0.010	0.992
Control Condition 2 (dummy coded)	0.034	0.355	0.723
Individual Reflexivity (dummy coded)	-0.066	-0.691	0.491
Group Reflexivity (dummy coded)	-0.004	-0.037	0.971
age commander	-0.063	-0.650	0.517
gender commander			
education commander			
computer expertise commander	0.076	0.731	0.466
age specialist A	-0.113	-1.178	0.241
gender specialist A	0.100	1.049	0.297
education specialist A	0.084	0.889	0.376
computer expertise specialist A	0.116	1.229	0.222
age specialist B	-0.062	-0.656	0.513
gender specialist B	-0.050	-0.511	0.610
education specialist B	0.056	0.583	0.561
computer expertise specialist B	-0.072	-0.754	0.453

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 84 Results of multiple regression, predicting performance shift 2 controlling for precedent performance, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.212	.205						28.81	1	107	.000
2	.236	.222	.024	3.303	1	106	.072	16.37	2	106	.000

Predictors in trimmed model	Beta	t	Sig.
(1) performance shift 1	.456	5.375	.000
(2) gender commander	.154	1.817	.072

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.099	1.162	0.248
CHAT condition (dummy coded)	0.079	0.923	0.358
Control Condition 1 (dummy coded)	0.031	0.357	0.721
Control Condition 2 (dummy coded)	-0.038	-0.435	0.665
Individual Reflexivity (dummy coded)	-0.024	-0.280	0.780
Group Reflexivity (dummy coded)	-0.041	-0.481	0.631
age commander	-0.029	-0.341	0.734
gender commander			
education commander	-0.077	-0.888	0.377
computer expertise commander	0.029	0.311	0.756
age specialist A	-0.112	-1.318	0.190
gender specialist A	0.089	1.046	0.298
education specialist A	-0.046	-0.517	0.606
computer expertise specialist A	0.059	0.689	0.492
age specialist B	-0.059	-0.696	0.488
gender specialist B	-0.031	-0.362	0.718
education specialist B	0.042	0.493	0.623
computer expertise specialist B	-0.040	-0.472	0.638

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 85 Results of multiple regression, predicting performance shift 3, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
	.181	.150						5.794	4	104	.000

Predictors in trimmed model	Beta	t	Sig.
gender commander	.277	3.102	.002
education specialist A	.187	2.096	.039
age specialist A	-.209	-2.310	.023
education commander	-.164	-1.819	.072

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.028	0.314	0.754
CHAT condition (dummy coded)	0.126	1.387	0.168
Control Condition 1 (dummy coded)	0.056	0.617	0.539
Control Condition 2 (dummy coded)	0.019	0.209	0.835
Individual Reflexivity (dummy coded)	-0.121	-1.265	0.209
Group Reflexivity (dummy coded)	-0.074	-0.815	0.417
age commander	-0.070	-0.768	0.444
gender commander			
education commander			
computer expertise commander	0.140	1.428	0.156
age specialist A			
gender specialist A	0.072	0.800	0.426
education specialist A			
computer expertise specialist A	0.125	1.418	0.159
age specialist B	-0.089	-0.943	0.348
gender specialist B	-0.029	-0.318	0.751
education specialist B	0.033	0.358	0.721
computer expertise specialist B	0.030	0.319	0.750

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 86 Results of multiple regression, predicting performance shift 3 controlling for precedent performance, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.323	.316						50.94	1	107	.000
2	.380	.368	.057	9.768	1	106	.002	32.44	2	106	.000
3	.407	.390	.028	4.882	1	105	.029	24.05	3	105	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 2	.538	7.117	.000
(2) gender commander	.240	3.167	.002
(3) age commander	-.166	-2.209	.029

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.006	0.078	0.938
CHAT condition (dummy coded)	0.089	1.171	0.244
Control Condition 1 (dummy coded)	0.049	0.640	0.524
Control Condition 2 (dummy coded)	-0.017	-0.228	0.820
Individual Reflexivity (dummy coded)	-0.105	-1.362	0.176
Group Reflexivity (dummy coded)	-0.068	-0.889	0.376
age commander	-0.032	-0.416	0.678
gender commander			
education commander	-0.050	-0.640	0.524
computer expertise commander	0.070	0.844	0.401
age specialist A			
gender specialist A	0.031	0.413	0.680
education specialist A	0.077	0.997	0.321
computer expertise specialist A	0.054	0.713	0.477
age specialist B	-0.101	-1.289	0.200
gender specialist B	-0.013	-0.174	0.863
education specialist B	0.031	0.405	0.686
computer expertise specialist B	0.023	0.300	0.764

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 87 Results of multiple regression, predicting performance shift 4, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
	.133	.117						8.160	2	106	.001

Predictors in trimmed model	Beta	t	Sig.
computer expertise commander	.334	3.682	.000
age commander	-.172	-1.903	.060

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	-0.050	-0.548	0.585
CHAT condition (dummy coded)	-0.070	-0.770	0.443
Control Condition 1 (dummy coded)	-0.122	-1.313	0.192
Control Condition 2 (dummy coded)	0.128	1.420	0.159
Individual Reflexivity (dummy coded)	-0.073	-0.808	0.421
Group Reflexivity (dummy coded)	0.032	0.344	0.731
age commander			
gender commander	0.076	0.772	0.442
education commander	0.041	0.441	0.660
computer expertise commander			
age specialist A	-0.001	-0.014	0.989
gender specialist A	-0.112	-1.230	0.221
education specialist A	0.064	0.702	0.484
computer expertise specialist A	0.093	1.028	0.306
age specialist B	-0.046	-0.506	0.614
gender specialist B	0.043	0.475	0.636
education specialist B	0.013	0.147	0.884
computer expertise specialist B	0.031	0.338	0.736

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 88 Results of multiple regression, predicting performance shift 4 controlling for precedent performance, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.235	.228						32.93	1	107	.000
2	.281	.268	.046	6.791	1	106	.010	20.75	2	106	.000
3	.299	.279	.018	2.674	1	105	.105	14.95	3	105	.000
4	.319	.293	.020	3.072	1	104	.083	12.20	4	104	.000
5	.337	.304	.017	2.694	1	103	.104	10.46	5	103	.000
6	.353	.314	.016	2.505	1	102	.117	9.26	6	102	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 3	.473	5.588	.000
(2) computer expertise commander	.277	3.289	.001
(3) gender specialist A	-.160	-1.975	.051
(4) CHAT condition	-.157	-1.908	.059
(5) age commander	-.143	-1.766	.080
(6) education commander	.133	1.583	.117

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	-0.077	-0.943	0.348
CHAT condition (dummy coded)			
Control Condition 1 (dummy coded)	-0.118	-1.424	0.158
Control Condition 2 (dummy coded)	0.073	0.891	0.375
Individual Reflexivity (dummy coded)	-0.052	-0.643	0.522
Group Reflexivity (dummy coded)	-0.015	-0.178	0.859
age commander			
gender commander	0.028	0.320	0.750
education commander			
computer expertise commander			
age specialist A	0.050	0.602	0.549
gender specialist A			
education specialist A	-0.025	-0.301	0.764
computer expertise specialist A	0.124	1.374	0.172
age specialist B	-0.008	-0.094	0.926
gender specialist B	0.077	0.928	0.356
education specialist B	-0.039	-0.472	0.638
computer expertise specialist B	-0.077	-0.943	0.348

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 89 Results of multiple regression, predicting performance shift 5, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
	.204	.166						5.293	5	103	.000

Predictors in trimmed model	Beta	t	Sig.
computer expertise commander	.284	2.955	.004
gender commander	.218	2.273	.025
Control Condition 2	.148	1.685	.095
age specialist B	-.137	-1.541	.126
age commander	-.132	-1.481	.142

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.093	1.032	0.305
CHAT condition (dummy coded)	0.061	0.676	0.501
Control Condition 1 (dummy coded)	0.021	0.221	0.826
Control Condition 2 (dummy coded)			
Individual Reflexivity (dummy coded)	0.016	0.175	0.862
Group Reflexivity (dummy coded)	-0.053	-0.575	0.567
age commander			
gender commander			
education commander	-0.037	-0.404	0.687
computer expertise commander			
age specialist A	-0.011	-0.116	0.908
gender specialist A	-0.119	-1.339	0.183
education specialist A	0.029	0.319	0.750
computer expertise specialist A	0.042	0.475	0.636
age specialist B			
gender specialist B	-0.079	-0.884	0.379
education specialist B	0.030	0.337	0.737
computer expertise specialist B	0.073	0.814	0.417

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 90 Results of multiple regression, predicting performance shift 5 controlling for precedent performance, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.271	.264						39.75	1	107	.000
2	.308	.295	.037	5.655	1	106	.019	23.57	2	106	.000
3	.326	.307	.018	2.844	1	105	.095	16.93	3	105	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 4	.447	5.307	.000
(2) computer expertise commander	.150	1.691	.094
(3) gender commander	.147	1.687	.095

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	-0.077	-0.943	0.348
CHAT condition (dummy coded)			
Control Condition 1 (dummy coded)	-0.118	-1.424	0.158
Control Condition 2 (dummy coded)	0.073	0.891	0.375
Individual Reflexivity (dummy coded)	-0.052	-0.643	0.522
Group Reflexivity (dummy coded)	-0.015	-0.178	0.859
age commander			
gender commander	0.028	0.320	0.750
education commander			
computer expertise commander			
age specialist A	0.050	0.602	0.549
gender specialist A			
education specialist A	-0.025	-0.301	0.764
computer expertise specialist A	0.124	1.374	0.172
age specialist B	-0.008	-0.094	0.926
gender specialist B	0.077	0.928	0.356
education specialist B	-0.039	-0.472	0.638
computer expertise specialist B	-0.077	-0.943	0.348

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 91 Results of multiple regression, predicting performance shift 6, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
	.188	.165						8.096	3	105	.000

Predictors in trimmed model	Beta	t	Sig.
computer expertise commander	.273	2.873	.005
age commander	-.249	-2.808	.006
gender commander	.187	1.959	.053

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.041	0.457	0.648
CHAT condition (dummy coded)	-0.037	-0.418	0.677
Control Condition 1 (dummy coded)	-0.034	-0.368	0.713
Control Condition 2 (dummy coded)	0.041	0.469	0.640
Individual Reflexivity (dummy coded)	0.019	0.219	0.827
Group Reflexivity (dummy coded)	0.038	0.426	0.671
age commander			
gender commander			
education commander	0.080	0.885	0.378
computer expertise commander			
age specialist A	-0.108	-1.216	0.227
gender specialist A	-0.050	-0.564	0.574
education specialist A	0.040	0.450	0.654
computer expertise specialist A	0.102	1.164	0.247
age specialist B	-0.127	-1.431	0.155
gender specialist B	-0.121	-1.367	0.174
education specialist B	0.102	1.155	0.251
computer expertise specialist B	0.033	0.370	0.712

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 92 Results of multiple regression, predicting performance shift 6 controlling for precedent performance, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.405	.400						72.89	1	107	.000
2	.423	.412	.017	3.196	1	106	.077	38.79	2	106	.000
3	.443	.427	.021	3.917	1	105	.050	27.88	3	105	.000
4	.464	.443	.020	3.968	1	104	.049	22.49	4	104	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 5	.587	7.616	.000
(2) age commander	-.161	-2.203	.030
(3) computer expertise commander	.179	2.314	.023
(4) education commander	.148	1.992	.049

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.038	0.519	0.605
CHAT condition (dummy coded)	-0.097	-1.325	0.188
Control Condition 1 (dummy coded)	0.000	-0.001	1.000
Control Condition 2 (dummy coded)	-0.041	-0.563	0.575
Individual Reflexivity (dummy coded)	0.090	1.241	0.218
Group Reflexivity (dummy coded)	0.019	0.258	0.797
age commander			
gender commander	0.084	1.064	0.290
education commander			
computer expertise commander			
age specialist A	-0.052	-0.694	0.489
gender specialist A	-0.040	-0.552	0.582
education specialist A	-0.068	-0.917	0.361
computer expertise specialist A	0.018	0.241	0.810
age specialist B	-0.058	-0.793	0.430
gender specialist B	-0.073	-0.998	0.321
education specialist B	0.056	0.769	0.444
computer expertise specialist B	0.062	0.863	0.390

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 93 Results of multiple regression, predicting performance shift 8, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
	.251	.207						5.691	6	102	.000

Predictors in trimmed model	Beta	t	Sig.
computer expertise commander	.274	2.882	.005
computer expertise specialist A	.228	2.634	.010
gender commander	.222	2.368	.020
age commander	-.204	-2.345	.021
education commander	.138	1.542	.126
education specialist B	.128	1.456	.149

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.042	0.471	0.639
CHAT condition (dummy coded)	0.020	0.225	0.822
Control Condition 1 (dummy coded)	-0.078	-0.870	0.387
Control Condition 2 (dummy coded)	-0.110	-1.270	0.207
Individual Reflexivity (dummy coded)	0.027	0.306	0.760
Group Reflexivity (dummy coded)	-0.007	-0.083	0.934
age commander			
gender commander			
education commander			
computer expertise commander			
age specialist A	0.070	0.784	0.435
gender specialist A	-0.073	-0.744	0.459
education specialist A	0.056	0.644	0.521
computer expertise specialist A			
age specialist B	-0.077	-0.886	0.378
gender specialist B	0.038	0.429	0.669
education specialist B			
computer expertise specialist B	0.100	1.152	0.252

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 94 Results of multiple regression, predicting performance shift 8 controlling for precedent performance, with *input variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.331	.325						52.89	1	107	.000
2	.359	.347	.028	4.655	1	106	.033	29.68	2	106	.000
3	.388	.370	.029	4.902	1	105	.029	22.15	3	105	.000
4	.412	.390	.025	4.345	1	104	.040	18.23	4	104	.000
5	.429	.402	.017	3.111	1	103	.081	15.50	5	103	.000
6	.442	.409	.013	2.350	1	102	.128	13.48	6	102	.000
7	.455	.417	.013	2.344	1	101	.129	12.04	7	101	.000

Predictors in trimmed model	Beta	t	Sig.
mean performance shift 1 to shift 6	.541	6.760	.000
(2) Control Condition 2	-.177	-2.372	.020
(3) education commander	.175	2.278	.025
(4) computer expertise commander	.162	2.037	.044
(5) computer expertise specialist A	.150	2.002	.048
(6) computer expertise specialist B	.128	1.731	.087
(7) education specialist B	.117	1.531	.129

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.038	0.519	0.605
CHAT condition (dummy coded)	-0.097	-1.325	0.188
Control Condition 1 (dummy coded)	0.000	-0.001	1.000
Control Condition 2 (dummy coded)	-0.041	-0.563	0.575
Individual Reflexivity (dummy coded)	0.090	1.241	0.218
Group Reflexivity (dummy coded)	0.019	0.258	0.797
age commander			
gender commander	0.084	1.064	0.290
education commander			
computer expertise commander			
age specialist A	-0.052	-0.694	0.489
gender specialist A	-0.040	-0.552	0.582
education specialist A	-0.068	-0.917	0.361
computer expertise specialist A	0.018	0.241	0.810
age specialist B	-0.058	-0.793	0.430
gender specialist B	-0.073	-0.998	0.321
education specialist B	0.056	0.769	0.444
computer expertise specialist B	0.062	0.863	0.390

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

4 Predicting Performance: Summary Level Process Variables

Table 95 Results of multiple regression, predicting performance shift 1, with *summary level process* variables, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.096	.088	.096	11.37	1	107	.001	11.37	1	107	.001
2	.158	.142	.062	7.75	1	106	.006	9.92	2	106	.000
3	.185	.161	.027	3.48	1	105	.065	7.93	3	105	.000
4	.205	.174	.020	2.66	1	104	.106	6.70	4	104	.000
5	.229	.191	.024	3.18	1	103	.078	6.11	5	103	.000

Predictors in trimmed model	Beta	t	Sig.
(1) duration Send Message, specialist A	-.330	-3.775	.000
(2) number Handle Threat, commander	.218	2.432	.017
(3) duration Send Message, commander	-.120	-1.280	.203
(4) number Read Message, specialist B	.185	2.058	.042
(5) duration Read Message, specialist B	-.169	-1.783	.078

Excluded Predictors	Beta-In	t	Sig.
number Handle Threat, commander			
number Read Message, commander	-0.128	-1.216	0.227
number Send Message, commander	0.023	0.217	0.829
number Show Info, commander	0.100	1.140	0.257
duration Read Message, commander	0.043	0.411	0.682
duration Send Message, commander			
number Read Message, specialist A	-0.030	-0.211	0.833
number Send Message, specialist A	0.066	0.717	0.475
number Show Info, specialist A	0.029	0.311	0.756
duration Read Message, specialist A			
duration Send Message, specialist A			
number Read Message, specialist B			
number Send Message, specialist B	-0.065	-0.717	0.475
number Show Info, specialist B	0.016	0.186	0.853
duration Read Message, specialist B	0.078	0.640	0.524
duration Send Message, specialist B	-0.058	-0.621	0.536

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 96 Results of multiple regression, predicting performance shift 1, with *input* and *summary level process* variables, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.076	.067	.076	8.812	1	107	.004	8.812	1	107	.004
2	.112	.095	.036	4.242	1	106	.042	6.660	2	106	.002
3	.130	.105	.018	2.204	1	105	.141	5.225	3	105	.002
4	.201	.170	.071	9.285	1	104	.003	6.549	4	104	.000
5	.259	.223	.058	7.993	1	103	.006	7.190	5	103	.000
6	.289	.248	.031	4.411	1	102	.038	6.926	6	102	.000
7	.304	.256	.015	2.115	1	101	.149	6.303	7	101	.000
8	.321	.267	.017	2.509	1	100	.116	5.912	8	100	.000

Predictors in trimmed model	Beta	t	Sig.
(1) education specialist A	.244	2.929	.004
(2) education commander	-.088	-1.016	.312
(3) computer expertise commander	.157	1.810	.073
(4) duration Send Message, specialist A	-.293	-3.473	.001
(5) number Handle Threat, commander	.199	2.297	.024
(6) duration Send Message, commander	-.147	-1.630	.106
(7) number Read Message, specialist B	.161	1.854	.067
(8) duration Read Message, specialist A	-.146	-1.584	.116

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	-0.106	-1.218	0.226
CHAT condition (dummy coded)	-0.008	-0.088	0.930
Control Condition 1 (dummy coded)	0.039	0.461	0.646
Control Condition 2 (dummy coded)	0.112	1.355	0.178
Individual Reflexivity (dummy coded)	-0.051	-0.562	0.575
Group Reflexivity (dummy coded)	0.037	0.430	0.668
age commander	-0.044	-0.510	0.611
gender commander	-0.087	-0.942	0.348
education commander			
computer expertise commander			
age specialist A	0.035	0.404	0.687
gender specialist A	-0.062	-0.724	0.471
education specialist A			
computer expertise specialist A	0.085	0.983	0.328
age specialist B	0.003	0.036	0.971
gender specialist B	-0.075	-0.856	0.394
education specialist B	-0.060	-0.690	0.492
computer expertise specialist B	-0.003	-0.039	0.969
number Handle Threat, commander			
number Read Message, commander	-0.097	-0.938	0.350
number Send Message, commander	0.083	0.785	0.434
number Show Info, commander	0.060	0.713	0.478
duration Read Message, commander	-0.008	-0.078	0.938
duration Send Message, commander			
number Read Message, specialist A	-0.047	-0.348	0.729
number Send Message, specialist A	0.052	0.591	0.556
number Show Info, specialist A	0.010	0.109	0.913
duration Read Message, specialist A			
duration Send Message, specialist A			
number Read Message, specialist B			
number Send Message, specialist B	-0.074	-0.837	0.404
number Show Info, specialist B	0.064	0.745	0.458
duration Read Message, specialist B	-0.004	-0.033	0.974
duration Send Message, specialist B	-0.090	-0.998	0.321

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 97 Results of multiple regression, predicting performance shift 2, with *summary level process* variables, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.124	.116	.124	15.19	1	107	.000	15.19	1	107	.000
2	.150	.134	.025	3.16	1	106	.078	9.33	2	106	.000

Predictors in trimmed model	Beta	t	Sig.
(1) number Handle Threat, commander	.349	3.895	.000
(2) number Read Message, specialist B	-.159	-1.779	.078

Excluded Predictors	Beta-In	t	Sig.
number Handle Threat, commander			
number Read Message, commander	0.043	0.422	0.674
number Send Message, commander	-0.036	-0.352	0.725
number Show Info, commander	0.107	1.186	0.238
duration Read Message, commander	0.012	0.133	0.895
duration Send Message, commander	-0.064	-0.675	0.501
number Read Message, specialist A	0.140	1.188	0.237
number Send Message, specialist A	0.015	0.149	0.882
number Show Info, specialist A	0.071	0.781	0.437
duration Read Message, specialist A	0.086	0.828	0.409
duration Send Message, specialist A	-0.016	-0.175	0.861
number Read Message, specialist B			
number Send Message, specialist B	0.026	0.291	0.771
number Show Info, specialist B	0.068	0.735	0.464
duration Read Message, specialist B	0.038	0.294	0.770
duration Send Message, specialist B	0.031	0.342	0.733

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 98 Results of multiple regression, predicting performance shift 2, with *input* and *summary level process* variables, controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.212	.205	.212	28.81	1	107	.000	28.81	1	107	.000
2	.236	.222	.024	3.303	1	106	.072	16.37	2	106	.000
3	.299	.279	.063	9.499	1	105	.003	14.95	3	105	.000
4	.320	.294	.021	3.178	1	104	.078	12.24	4	104	.000
5	.337	.305	.017	2.664	1	103	.106	10.48	5	103	.000

Predictors in trimmed model	Beta	t	Sig.
(1) performance shift 1	.422	5.150	.000
(2) gender commander	.075	.897	.372
(3) number Handle Threat, commander	.249	3.003	.003
(4) number Read Message, specialist B	-.158	-1.924	.057
(5) number Show Info, commander	.132	1.632	.106

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.089	1.099	0.274
CHAT condition (dummy coded)	0.049	0.585	0.560
Control Condition 1 (dummy coded)	0.079	0.957	0.341
Control Condition 2 (dummy coded)	-0.063	-0.753	0.453
Individual Reflexivity (dummy coded)	-0.063	-0.738	0.462
Group Reflexivity (dummy coded)	-0.028	-0.341	0.734
age commander	-0.026	-0.321	0.749
gender commander			
education commander	-0.072	-0.849	0.398
computer expertise commander	0.013	0.144	0.886
age specialist A	-0.044	-0.520	0.604
gender specialist A	0.079	0.964	0.337
education specialist A	-0.003	-0.039	0.969
computer expertise specialist A	0.034	0.417	0.677
age specialist B	-0.028	-0.341	0.734
gender specialist B	-0.061	-0.729	0.468
education specialist B	0.064	0.788	0.433
computer expertise specialist B	-0.022	-0.270	0.787
number Handle Threat, commander			
number Read Message, commander	0.010	0.101	0.920
number Send Message, commander	-0.058	-0.624	0.534
number Show Info, commander			
duration Read Message, commander	-0.064	-0.743	0.459
duration Send Message, commander	0.015	0.168	0.867
number Read Message, specialist A	0.150	1.411	0.161
number Send Message, specialist A	-0.045	-0.500	0.618
number Show Info, specialist A	0.008	0.094	0.925
duration Read Message, specialist A	0.104	1.129	0.262
duration Send Message, specialist A	0.094	1.110	0.269
number Read Message, specialist B			
number Send Message, specialist B	0.030	0.357	0.722
number Show Info, specialist B	0.043	0.513	0.609
duration Read Message, specialist B	-0.012	-0.097	0.923
duration Send Message, specialist B	0.031	0.375	0.709

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 99 Results of multiple regression, predicting performance shift 3, with *summary level process* variables, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.043	.034	.043	4.817	1	107	.030	4.82	1	107	.030
2	.068	.050	.024	2.778	1	106	.098	3.84	2	106	.025

Predictors in trimmed model	Beta	t	Sig.
(1) number Send Message, specialist A	.216	2.296	.024
(2) duration Send Message, commander	-.157	-1.667	.098

Excluded Predictors	Beta-In	t	Sig.
number Handle Threat, commander	-0.026	-0.267	0.790
number Read Message, commander	-0.095	-0.802	0.424
number Send Message, commander	-0.069	-0.554	0.581
number Show Info, commander	0.094	0.982	0.329
duration Read Message, commander	-0.155	-1.418	0.159
duration Send Message, commander			
number Read Message, specialist A	0.031	0.296	0.768
number Send Message, specialist A			
number Show Info, specialist A	0.081	0.856	0.394
duration Read Message, specialist A	0.018	0.160	0.874
duration Send Message, specialist A	0.100	1.062	0.291
number Read Message, specialist B	0.037	0.363	0.717
number Send Message, specialist B	-0.051	-0.526	0.600
number Show Info, specialist B	0.079	0.810	0.419
duration Read Message, specialist B	0.068	0.630	0.530
duration Send Message, specialist B	-0.079	-0.835	0.405

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 100 Results of multiple regression, predicting performance shift 3, with *input* and *summary level process* variables, controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.323	.316	.323	50.94	1	107	.000	50.94	1	107	.000
2	.380	.368	.057	9.77	1	106	.002	32.44	2	106	.000
3	.407	.390	.028	4.88	1	105	.029	24.05	3	105	.000
4	.435	.413	.027	5.03	1	104	.027	19.99	4	104	.000
5	.468	.443	.034	6.56	1	103	.012	18.16	5	103	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 2	.583	7.932	.000
(2) gender commander	.285	3.855	.000
(3) age, specialist A	-.131	-1.801	.075
(4) number Send Message, commander	-.282	-3.306	.001
(5) number Read Message, specialist B	.220	2.561	.012

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.066	0.882	0.380
CHAT condition (dummy coded)	0.096	1.321	0.189
Control Condition 1 (dummy coded)	0.008	0.105	0.917
Control Condition 2 (dummy coded)	0.002	0.031	0.975
Individual Reflexivity (dummy coded)	-0.134	-1.787	0.077
Group Reflexivity (dummy coded)	-0.034	-0.456	0.649
age commander	-0.005	-0.072	0.943
gender commander			
education commander	0.011	0.140	0.889
computer expertise commander	0.108	1.366	0.175
age specialist A			
gender specialist A	0.008	0.111	0.912
education specialist A	0.063	0.844	0.401
computer expertise specialist A	0.017	0.229	0.819
age specialist B	-0.078	-1.037	0.302
gender specialist B	-0.042	-0.577	0.565
education specialist B	0.054	0.745	0.458
computer expertise specialist B	0.007	0.099	0.922
number Handle Threat, commander	-0.063	-0.842	0.402
number Read Message, commander	-0.054	-0.723	0.471
number Send Message, commander			
number Show Info, commander	0.027	0.358	0.721
duration Read Message, commander	-0.073	-0.869	0.387
duration Send Message, commander	-0.035	-0.365	0.716
number Read Message, specialist A	-0.006	-0.052	0.958
number Send Message, specialist A	-0.007	-0.092	0.927
number Show Info, specialist A	-0.001	-0.012	0.991
duration Read Message, specialist A	-0.049	-0.531	0.596
duration Send Message, specialist A	0.070	0.950	0.344
number Read Message, specialist B			
number Send Message, specialist B	-0.017	-0.237	0.813
number Show Info, specialist B	-0.006	-0.076	0.940
duration Read Message, specialist B	-0.004	-0.034	0.973
duration Send Message, specialist B	0.028	0.365	0.716

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of F is smaller than 0.15.

Table 101 Results of multiple regression, predicting performance shift 4, with *summary level process* variables, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.065	.056	.065	7.416	1	107	.008	7.416	1	107	.008
2	.118	.101	.053	6.329	1	106	.013	7.057	2	106	.001
3	.150	.126	.033	4.052	1	105	.047	6.191	3	105	.001

Predictors in trimmed model	Beta	t	Sig.
(1) duration Send Message, specialist A	-.276	-3.038	.003
(2) duration Read Message, commander	.220	2.425	.017
(3) number Show Info, specialist B	.182	2.013	.047

Excluded Predictors	Beta-In	t	Sig.
number Handle Threat, commander	-0.072	-0.786	0.434
number Read Message, commander	0.106	1.161	0.248
number Send Message, commander	0.096	0.978	0.330
number Show Info, commander	0.011	0.113	0.910
duration Read Message, commander			
duration Send Message, commander	-0.103	-0.981	0.329
number Read Message, specialist A	0.039	0.414	0.679
number Send Message, specialist A	0.118	1.295	0.198
number Show Info, specialist A	-0.016	-0.171	0.864
duration Read Message, specialist A	-0.069	-0.683	0.496
duration Send Message, specialist A			
number Read Message, specialist B	0.016	0.166	0.869
number Send Message, specialist B	0.076	0.827	0.410
number Show Info, specialist B			
duration Read Message, specialist B	-0.072	-0.694	0.489
duration Send Message, specialist B	-0.042	-0.425	0.672

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 102 Results of multiple regression, predicting performance shift 4, with *input* and *summary level process* variables, controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.235	.228	.235	32.93	1	107	.000	32.93	1	107	.000
2	.281	.268	.046	6.791	1	106	.010	20.75	2	106	.000
3	.299	.279	.018	2.674	1	105	.105	14.95	3	105	.000
4	.319	.293	.020	3.072	1	104	.083	12.20	4	104	.000
5	.337	.304	.017	2.694	1	103	.104	10.46	5	103	.000
6	.353	.314	.016	2.505	1	102	.117	9.26	6	102	.000
7	.400	.358	.047	7.922	1	101	.006	9.61	7	103	.000
8	.419	.372	.019	3.317	1	100	.072	9.01	8	104	.000
9	.438	.387	.019	3.346	1	99	.070	8.57	9	105	.000
10	.457	.401	.019	3.413	1	98	.068	8.24	10	106	.000
11	.470	.410	.013	2.442	1	97	.121	7.83	11	107	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 3	.439	5.421	.000
(2) computer expertise, commander	.286	3.652	.000
(3) gender, specialist A	-.158	-2.069	.041
(4) CHAT condition	-.146	-1.913	.059
(5) age, commander	-.119	-1.532	.129
(6) education, commander	.168	2.091	.039
(7) duration Read Message, specialist B	-.119	-1.370	.174
(8) duration Send Message, specialist A	-.186	-2.258	.026
(9) number Handle Threat, commander	-.130	-1.675	.097
(10) number Show Info, specialist B	.148	1.881	.063
(11) duration Read Message, command.	.132	1.563	.121

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	-0.040	-0.495	0.622
CHAT condition (dummy coded)			
Control Condition 1 (dummy coded)	-0.100	-1.268	0.208
Control Condition 2 (dummy coded)	0.032	0.405	0.686
Individual Reflexivity (dummy coded)	0.067	0.810	0.420
Group Reflexivity (dummy coded)	-0.041	-0.519	0.605
age commander			
gender commander	0.064	0.757	0.451
education commander			
computer expertise commander			
age specialist A	-0.015	-0.181	0.856
gender specialist A			
education specialist A	-0.024	-0.291	0.772
computer expertise specialist A	0.132	1.525	0.131
age specialist B	-0.008	-0.106	0.916
gender specialist B	0.030	0.362	0.718
education specialist B	0.003	0.044	0.965
computer expertise specialist B	0.012	0.152	0.879
number Handle Threat, commander			
number Read Message, commander	0.049	0.570	0.570
number Send Message, commander	0.021	0.242	0.809
number Show Info, commander	0.043	0.484	0.629
duration Read Message, commander			
duration Send Message, commander	-0.086	-0.795	0.428
number Read Message, specialist A	0.045	0.555	0.580
number Send Message, specialist A	0.072	0.815	0.417
number Show Info, specialist A	-0.040	-0.487	0.627
duration Read Message, specialist A	-0.069	-0.707	0.481
duration Send Message, specialist A			
number Read Message, specialist B	0.066	0.651	0.516
number Send Message, specialist B	-0.005	-0.062	0.951
number Show Info, specialist B			
duration Read Message, specialist B			
duration Send Message, specialist B	0.027	0.308	0.759

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of F is smaller than 0.15.

Table 103 Results of multiple regression, predicting performance shift 5, with *summary level process* variables, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.071	.062	.071	8.124	1	107	.005	8.124	1	107	.005
2	.122	.106	.052	6.259	1	106	.014	7.391	2	106	.001
3	.149	.125	.027	3.302	1	105	.072	6.135	3	105	.001

Predictors in trimmed model	Beta	t	Sig.
(1) duration Read Message, specialist B	-.250	-2.765	.007
(2) number Show Info, specialist B	.212	2.330	.022
(3) number Show Info, commander	.165	1.817	.072

Excluded Predictors	Beta-In	t	Sig.
number Handle Threat, commander	0.128	1.394	0.166
number Read Message, commander	0.042	0.452	0.652
number Send Message, commander	0.141	1.409	0.162
number Show Info, commander	0.030	0.314	0.755
duration Read Message, commander	-0.104	-0.907	0.367
duration Send Message, commander			
number Read Message, specialist A	0.060	0.548	0.585
number Send Message, specialist A	0.109	1.201	0.232
number Show Info, specialist A	-0.087	-0.964	0.337
duration Read Message, specialist A	0.035	0.315	0.753
duration Send Message, specialist A	-0.005	-0.055	0.957
number Read Message, specialist B	0.092	0.798	0.427
number Send Message, specialist B	0.040	0.431	0.668
number Show Info, specialist B			
duration Read Message, specialist B			
duration Send Message, specialist B	-0.020	-0.201	0.841

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 104 Results of multiple regression, predicting performance shift 5, with *input* and *summary level process* variables, controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.271	.264	.271	39.75	1	107	.000	39.75	1	107	.000
2	.308	.295	.037	5.655	1	106	.019	23.57	2	106	.000
3	.326	.307	.018	2.844	1	105	.095	16.93	3	105	.000
4	.370	.345	.044	7.181	1	104	.009	15.24	4	104	.000
5	.411	.383	.042	7.317	1	103	.008	14.34	5	103	.000
6	.431	.397	.019	3.469	1	102	.065	12.87	6	102	.000
7	.446	.407	.015	2.705	1	101	.103	11.60	7	101	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 4	.434	5.267	.000
(2) computer expertise, commander	.174	2.085	.040
(3) gender, commander	.136	1.637	.105
(4) number Show Info, specialist B	.207	2.709	.008
(5) number Show Info, specialist A	-.245	-3.138	.002
(6) duration Send Message, commander	-.142	-1.864	.065
(7) number Handle Threat, commander	.128	1.645	.103

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.045	0.586	0.559
CHAT condition (dummy coded)	0.094	1.083	0.281
Control Condition 1 (dummy coded)	0.004	0.056	0.955
Control Condition 2 (dummy coded)	0.039	0.505	0.614
Individual Reflexivity (dummy coded)	0.062	0.818	0.415
Group Reflexivity (dummy coded)	-0.042	-0.556	0.580
age commander	-0.029	-0.370	0.712
gender commander			
education commander	0.134	1.665	0.099
computer expertise commander			
age specialist A	-0.069	-0.892	0.375
gender specialist A	-0.109	-1.420	0.159
education specialist A	0.050	0.617	0.539
computer expertise specialist A	-0.004	-0.058	0.953
age specialist B	-0.093	-1.199	0.233
gender specialist B	-0.177	-2.349	0.021
education specialist B	0.067	0.894	0.374
computer expertise specialist B	0.039	0.506	0.614
number Handle Threat, commander			
number Read Message, commander	-0.090	-1.065	0.289
number Send Message, commander	0.097	1.011	0.314
number Show Info, commander	0.071	0.877	0.383
duration Read Message, commander	0.039	0.435	0.665
duration Send Message, commander			
number Read Message, specialist A	0.053	0.619	0.537
number Send Message, specialist A	0.035	0.424	0.672
number Show Info, specialist A			
duration Read Message, specialist A	0.100	1.010	0.315
duration Send Message, specialist A	0.004	0.055	0.956
number Read Message, specialist B	0.020	0.248	0.805
number Send Message, specialist B	-0.072	-0.906	0.367
number Show Info, specialist B			
duration Read Message, specialist B	-0.063	-0.653	0.515
duration Send Message, specialist B	-0.025	-0.312	0.755

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 105 Results of multiple regression, predicting performance shift 6, with *summary level process* variables, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.244	.059	.059	6.755	1	107	.011	6.755	1	107	.011
2	.345	.119	.060	7.171	1	106	.009	7.185	2	106	.001
3	.420	.176	.057	7.278	1	105	.008	7.481	3	105	.000
4	.444	.197	.021	2.723	1	104	.102	6.383	4	104	.000
5	.463	.215	.017	2.294	1	103	.133	5.629	5	103	.000

Predictors in trimmed model	Beta	t	Sig.
(1) duration Read Message, specialist B	-.474	-3.834	.000
(2) number Read Message, specialist B	.584	3.618	.000
(3) number Read Message, specialist A	-.374	-2.878	.005
(4) number Send Message, specialist A	.267	2.242	.027
(5) number Read Message, commander	-.190	-1.515	.133

Excluded Predictors	Beta-In	t	Sig.
number Handle Threat, commander	0.099	1.075	0.285
number Read Message, commander			
number Send Message, commander	0.056	0.507	0.613
number Show Info, commander	0.016	0.173	0.863
duration Read Message, commander	-0.094	-0.943	0.348
duration Send Message, commander	0.032	0.294	0.769
number Read Message, specialist A			
number Send Message, specialist A			
number Show Info, specialist A	0.028	0.301	0.764
duration Read Message, specialist A	0.155	1.161	0.248
duration Send Message, specialist A	-0.069	-0.731	0.467
number Read Message, specialist B			
number Send Message, specialist B	-0.066	-0.363	0.717
number Show Info, specialist B	0.129	1.424	0.158
duration Read Message, specialist B			
duration Send Message, specialist B	-0.072	-0.809	0.420

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 106 Results of multiple regression, predicting performance shift 6, with *input* and *summary level process* variables, controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.405	.400	.405	72.89	1	107	.000	72.89	1	107	.000
2	.423	.412	.017	3.196	1	106	.077	38.79	2	106	.000
3	.443	.427	.021	3.917	1	105	.050	27.88	3	105	.000
4	.464	.443	.020	3.968	1	104	.049	22.49	4	104	.000
5	.478	.453	.015	2.889	1	103	.092	18.90	5	103	.000
6	.489	.459	.011	2.186	1	102	.142	16.29	6	102	.000
7	.502	.467	.013	2.557	1	101	.113	14.55	7	101	.000
8	.515	.476	.013	2.601	1	100	.110	13.25	8	100	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 5	.537	6.893	.000
(2) age, commander	-.099	-1.332	.186
(3) computer expertise, commander	.203	2.665	.009
(4) education, commander	.136	1.844	.068
(5) duration Read Message, specialist B	-.283	-2.645	.009
(6) number Send Message, specialist A	.136	1.700	.092
(7) number Send Message, specialist B	-.172	-2.087	.039
(8) number Read Message, specialist B	.173	1.613	.110

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.006	0.083	0.934
CHAT condition (dummy coded)	-0.074	-1.024	0.308
Control Condition 1 (dummy coded)	0.024	0.325	0.746
Control Condition 2 (dummy coded)	-0.032	-0.446	0.656
Individual Reflexivity (dummy coded)	0.107	1.496	0.138
Group Reflexivity (dummy coded)	0.018	0.246	0.806
age commander			
gender commander	0.062	0.788	0.433
education commander			
computer expertise commander			
age specialist A	-0.077	-1.034	0.304
gender specialist A	-0.072	-0.989	0.325
education specialist A	-0.092	-1.272	0.206
computer expertise specialist A	0.024	0.333	0.740
age specialist B	-0.035	-0.478	0.634
gender specialist B	-0.052	-0.711	0.479
education specialist B	0.050	0.683	0.496
computer expertise specialist B	0.063	0.872	0.385
number Handle Threat, commander	-0.033	-0.443	0.659
number Read Message, commander	-0.090	-0.514	0.608
number Send Message, commander	-0.107	-1.316	0.191
number Show Info, commander	0.060	0.806	0.422
duration Read Message, commander	0.033	0.407	0.685
duration Send Message, commander	-0.055	-0.650	0.517
number Read Message, specialist A	-0.131	-1.222	0.225
number Send Message, specialist A			
number Show Info, specialist A	-0.042	-0.567	0.572
duration Read Message, specialist A	-0.028	-0.332	0.741
duration Send Message, specialist A	0.012	0.163	0.871
number Read Message, specialist B			
number Send Message, specialist B			
number Show Info, specialist B	0.095	1.248	0.215
duration Read Message, specialist B			
duration Send Message, specialist B	-0.001	-0.012	0.990

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 107 Results of multiple regression, predicting performance shift 8, with *summary level process* variables, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.145	.137	.145	18.16	1	107	.000	18.16	1	107	.011
2	.225	.210	.080	10.92	1	106	.001	15.38	2	106	.001
3	.256	.235	.031	4.43	1	105	.038	12.06	3	105	.000
4	.273	.245	.017	2.44	1	104	.122	9.78	4	104	.000

Predictors in trimmed model	Beta	t	Sig.
(1) duration Send Message, specialist A	-.359	-4.177	.000
(2) number Read Message, specialist A	-.235	-2.707	.008
(3) number Send Message, specialist A	.183	2.129	.036
(4) number Show Info, specialist B	.132	1.561	.122

Excluded Predictors	Beta-In	t	Sig.
number Handle Threat, commander	0.068	0.777	0.439
number Read Message, commander	-0.102	-0.779	0.438
number Send Message, commander	0.004	0.039	0.969
number Show Info, commander	-0.039	-0.456	0.650
duration Read Message, commander	-0.043	-0.471	0.638
duration Send Message, commander	0.018	0.161	0.873
number Read Message, specialist A	-0.111	-0.886	0.378
number Send Message, specialist A			
number Show Info, specialist A	0.051	0.582	0.562
duration Read Message, specialist A			
duration Send Message, specialist A			
number Read Message, specialist B	0.065	0.658	0.512
number Send Message, specialist B	-0.018	-0.190	0.849
number Show Info, specialist B			
duration Read Message, specialist B	-0.044	-0.450	0.653
duration Send Message, specialist B	0.030	0.305	0.761

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 108 Results of multiple regression, predicting performance shift 6, with *input* and *summary level process* variables, controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.331	.325	.331	52.89	1	107	.000	52.89	1	107	.000
2	.359	.347	.028	4.66	1	106	.033	26.68	2	106	.000
3	.388	.370	.029	4.90	1	105	.029	22.15	3	105	.000
4	.412	.390	.025	4.35	1	104	.040	18.23	4	104	.000
5	.429	.402	.017	3.11	1	103	.081	15.50	5	103	.000
6	.442	.409	.013	2.35	1	102	.128	13.48	6	102	.000
7	.455	.417	.013	2.34	1	101	.129	12.04	7	101	.000
8	.508	.468	.053	10.75	1	100	.001	12.89	8	100	.000
9	.549	.508	.041	9.00	1	99	.003	13.38	9	99	.000
10	.563	.518	.014	3.14	1	98	.080	12.62	10	98	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 6	.446	5.900	.000
(2) Control Condition 2	-.164	-2.405	.018
(3) education, commander	.191	2.624	.010
(4) computer expertise, commander	.168	2.271	.025
(5) computer expertise, specialist A	.136	1.986	.050
(6) computer expertise, specialist B	.028	.388	.699
(7) education, specialist B	.129	1.855	.067
(8) duration Read Message, specialist A	-.202	-2.917	.004
(9) duration Send Message, specialist A	-.214	-3.027	.003
(10) number Show Info, specialist B	.131	1.771	.080

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.042	0.594	0.554
CHAT condition (dummy coded)	-0.027	-0.381	0.704
Control Condition 1 (dummy coded)	-0.038	-0.551	0.583
Control Condition 2 (dummy coded)			
Individual Reflexivity (dummy coded)	0.071	1.007	0.317
Group Reflexivity (dummy coded)	-0.128	-1.830	0.070
age commander	-0.044	-0.630	0.530
gender commander	0.042	0.556	0.580
education commander			
computer expertise commander			
age specialist A	0.055	0.760	0.449
gender specialist A	-0.004	-0.054	0.957
education specialist A			
computer expertise specialist A			
age specialist B	0.007	0.097	0.923
gender specialist B	-0.053	-0.695	0.489
education specialist B	0.006	0.086	0.932
computer expertise specialist B			
number Handle Threat, commander	0.009	0.130	0.897
number Read Message, commander	-0.017	-0.234	0.816
number Send Message, commander	-0.027	-0.325	0.746
number Show Info, commander	-0.053	-0.744	0.458
duration Read Message, commander	0.032	0.441	0.660
duration Send Message, commander	0.012	0.130	0.897
number Read Message, specialist A	-0.077	-0.791	0.431
number Send Message, specialist A	0.056	0.750	0.455
number Show Info, specialist A	0.013	0.185	0.854
duration Read Message, specialist A			
duration Send Message, specialist A			
number Read Message, specialist B	0.007	0.089	0.929
number Send Message, specialist B	-0.012	-0.170	0.866
number Show Info, specialist B			
duration Read Message, specialist B	-0.097	-1.202	0.232
duration Send Message, specialist B	0.000	0.002	0.999

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

5 Predicting Performance: Task Adaptive Behavior Variables

Table 109 Results of multiple regression, predicting performance shift 1, with *task adaptive behavior variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.183	.176	.183	23.99	1	107	.000	23.99	1	107	.000
2	.226	.212	.043	5.882	1	106	.017	15.49	2	106	.000
3	.245	.223	.019	2.587	1	105	.111	11.34	3	105	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Plane Handling, commander	.397	4.646	.000
(2) Motivational and Corrective Leadership, commander	-.215	-2.520	.013
(3) Basic Task Mastery Specialist A	.137	1.609	.111

Excluded Predictors	Beta-In	t	Sig.
Basis Task Mastery, commander	-.152	-1.260	.211
Basic Task Mastery, specialist A			
Basic Task Mastery, specialist B	.015	.169	.866
Plane Handling, commander			
Plane Handling, specialist A	.056	.641	.523
Plane Handling, specialist B	.036	.415	.679
Message Handling, commander	.017	.170	.865
Message Handling, specialist A	.113	1.236	.219
Message Handling, specialist B	.033	.373	.710
Strategic Leadership, commander	.076	.870	.386
Motivational and Corrective Leadership, commander			

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 110 Results of multiple regression, predicting performance shift 1, with *input*, *summary level process* variables, and *task adaptive behavior variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.076	.067	.076	8.812	1	107	.004	8.812	1	107	.004
2	.112	.095	.036	4.242	1	106	.042	6.660	2	106	.002
3	.130	.105	.018	2.204	1	105	.141	5.225	3	105	.002
4	.201	.170	.071	9.285	1	104	.003	6.549	4	104	.000
5	.259	.223	.058	7.993	1	103	.006	7.190	5	103	.000
6	.289	.248	.031	4.411	1	102	.038	6.926	6	102	.000
7	.304	.256	.015	2.115	1	101	.149	6.303	7	101	.000
8	.321	.267	.017	2.509	1	100	.116	5.912	8	100	.000
9	.604	.365	.044	6.825	1	99	.010	6.319	9	99	.000
10	.618	.382	.018	2.778	1	98	.099	6.067	10	98	.000
11	.629	.396	.013	2.112	1	97	.149	5.770	11	97	.000

Predictors in trimmed model	Beta	t	Sig.
(1) education specialist A	.232	2.893	.005
(2) education commander	-.058	-.692	.491
(3) computer expertise commander	.232	1.158	.250
(4) duration Send Message, specialist A	-.058	-2.585	.011
(5) number Handle Threat, commander	.098	.014	.989
(6) duration Send Message, commander	-.220	-1.109	.270
(7) number Read Message, specialist B	.002	1.390	.168
(8) duration Read Message, specialist A	-.100	-1.658	.101
(9) Plane Handling, commander	.117	2.378	.019
(10) Motivational and Corrective Leadership, commander	-.149	-1.686	.095
(11) Basic Task Mastery, specialist A	.302	1.453	.149

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	-.133	-1.566	.121
CHAT condition (dummy coded)	.003	.031	.976
Control Condition 1 (dummy coded)	.042	.513	.609
Control Condition 2 (dummy coded)	.120	1.502	.137
Individual Reflexivity (dummy coded)	-.086	-.984	.328
Group Reflexivity (dummy coded)	.037	.451	.653
age commander	-.046	-.542	.589
gender commander	-.071	-.775	.440
education commander			
computer expertise commander	.172	1.866	.065
age specialist A	.080	.917	.362
gender specialist A	-.043	-.508	.613
education specialist A			
computer expertise specialist A	.122	1.436	.154
age specialist B	.015	.178	.859
gender specialist B	-.055	-.643	.522
education specialist B	-.045	-.536	.593
computer expertise specialist B	-.010	-.119	.906
number Handle Threat, commander			
number Read Message, commander	-.046	-.455	.650
number Send Message, commander	.031	.293	.770
number Show Info, commander	.048	.577	.566
duration Read Message, commander	.027	.269	.788
duration Send Message, commander			
number Read Message, specialist A	-.032	-.241	.810
number Send Message, specialist A	.100	1.146	.255
number Show Info, specialist A	-.021	-.245	.807
duration Read Message, specialist A			
duration Send Message, specialist A			
number Read Message, specialist B			
number Send Message, specialist B	-.093	-1.080	.283
number Show Info, specialist B	-.011	-.127	.899
duration Read Message, specialist B	.031	.267	.790
duration Send Message, specialist B	-.043	-.485	.629
Basis Task Mastery, commander	-.087	-.734	.465
Basic Task Mastery, specialist A			
Basic Task Mastery, specialist B	.006	.064	.949
Plane Handling, commander			
Plane Handling, specialist A	-.035	-.407	.685
Plane Handling, specialist B	.050	.596	.552
Message Handling, commander	.076	.760	.449
Message Handling, specialist A	.017	.190	.850
Message Handling, specialist B	.039	.454	.651
Strategic Leadership, commander	.124	1.413	.161
Motivational and Corrective Leadership, commander			

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 111 Results of multiple regression, predicting performance shift 2, with *task adaptive behavior variables* variables, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.361	.355	.361	60.44	1	107	.000	60.45	1	107	.000
2	.418	.407	.057	10.38	1	106	.002	38.06	2	106	.000
3	.458	.442	.040	7.722	1	105	.006	29.56	3	105	.000
4	.476	.456	.019	3.698	1	104	.057	23.66	4	104	.000
5	.501	.477	.025	5.120	1	103	.026	20.70	5	103	.000
6	.520	.492	.019	4.029	1	102	.047	18.43	6	102	.000
7	.530	.498	.010	2.181	1	101	.143	16.29	7	101	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Plane Handling, commander	.479	5.032	.000
(2) Basic Task Mastery, commander	-.355	-4.037	.000
(3) Plane Handling, specialist A	.209	2.995	.003
(4) Basic Task Mastery, specialist B	.190	2.517	.013
(5) Message Handling, commander	-.211	-2.572	.012
(6) Message Handling, specialist B	.153	2.140	.035
(7) Basic Task Mastery, specialist A	-.102	-1.477	.143

Excluded Predictors	Beta-In	t	Sig.
Basis Task Mastery, commander			
Basic Task Mastery, specialist A			
Basic Task Mastery, specialist B			
Plane Handling, commander			
Plane Handling, specialist A			
Plane Handling, specialist B	.079	1.094	.276
Message Handling, commander			
Message Handling, specialist A	.021	.294	.769
Message Handling, specialist B			
Strategic Leadership, commander	.032	.452	.652
Motivational and Corrective Leadership, commander	.087	1.260	.210

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 112 Results of multiple regression, predicting performance shift 2, with *input* and *summary level process* variables, and *task adaptive behavior variables* controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.212	.205	.212	28.81	1	107	.000	28.81	1	107	.000
2	.236	.222	.024	3.303	1	106	.072	16.37	2	106	.000
3	.299	.279	.063	9.499	1	105	.003	14.95	3	105	.000
4	.320	.294	.021	3.178	1	104	.078	12.24	4	104	.000
5	.337	.305	.017	2.664	1	103	.106	10.48	5	103	.000
6	.540	.513	.203	45.11	1	102	.000	19.99	6	102	.000
7	.574	.544	.033	7.929	1	101	.006	19.43	7	101	.000
8	.601	.569	.027	6.867	1	100	.010	18.85	8	100	.000

Predictors in trimmed model	Beta	t	Sig.
(1) performance shift 1	.265	3.941	.000
(2) gender commander	.015	.223	.824
(3) number Handle Threat, commander	-.203	-2.144	.034
(4) number Read Message, specialist B	-.292	-4.326	.000
(5) number Show Info, commander	.014	.213	.832
(6) Plane Handling, commander	.581	5.135	.000
(7) Basic Task Mastery, commander	-.293	-3.531	.001
(8) Basic Task Mastery, specialist B	.181	2.620	.010

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.003	0.047	0.963
CHAT condition (dummy coded)	0.025	0.368	0.714
Control Condition 1 (dummy coded)	0.070	1.085	0.281
Control Condition 2 (dummy coded)	-0.089	-1.345	0.182
Individual Reflexivity (dummy coded)	-0.111	-1.659	0.100
Group Reflexivity (dummy coded)	0.037	0.555	0.580
age commander	-0.052	-0.786	0.434
gender commander			
education commander	-0.041	-0.607	0.545
computer expertise commander	0.022	0.310	0.757
age specialist A	-0.029	-0.425	0.672
gender specialist A	0.063	0.978	0.331
education specialist A	-0.054	-0.794	0.429
computer expertise specialist A	0.015	0.238	0.813
age specialist B	0.002	0.033	0.973
gender specialist B	-0.009	-0.137	0.891
education specialist B	-0.128	-1.886	0.062
computer expertise specialist B	0.024	0.361	0.719
number Handle Threat, commander			
number Read Message, commander	-0.011	-0.145	0.885
number Send Message, commander	0.018	0.228	0.820
number Show Info, commander			
duration Read Message, commander	-0.005	-0.075	0.940
duration Send Message, commander	0.051	0.740	0.461
number Read Message, specialist A	0.095	1.113	0.268
number Send Message, specialist A	-0.032	-0.446	0.657
number Show Info, specialist A	0.019	0.285	0.776
duration Read Message, specialist A	0.033	0.451	0.653
duration Send Message, specialist A	0.007	0.098	0.922
number Read Message, specialist B			
number Send Message, specialist B	0.023	0.347	0.729
number Show Info, specialist B	0.062	0.911	0.365
duration Read Message, specialist B	-0.050	-0.530	0.597
duration Send Message, specialist B	-0.018	-0.279	0.781
Basis Task Mastery, commander			
Basic Task Mastery, specialist A	-0.058	-0.902	0.369
Basic Task Mastery, specialist B			
Plane Handling, commander			
Plane Handling, specialist A	0.094	1.422	0.158
Plane Handling, specialist B	0.062	0.944	0.347
Message Handling, commander	-0.041	-0.514	0.608
Message Handling, specialist A	0.006	0.085	0.932
Message Handling, specialist B	0.072	1.101	0.274
Strategic Leadership, commander	0.036	0.536	0.593
Motivational and Corrective Leadership, commander	0.053	0.816	0.416

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 113 Results of multiple regression, predicting performance shift 3, with *task adaptive behavior variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.403	.397	.403	72.10	1	107	.000	72.10	1	107	.000
2	.444	.434	.042	7.933	1	106	.006	42.35	2	106	.000
3	.470	.455	.026	5.199	1	105	.025	31.09	3	105	.000
4	.484	.464	.014	2.744	1	104	.101	24.39	4	104	.000
5	.499	.475	.015	3.080	1	103	.082	20.52	5	103	.000
6	.510	.481	.011	2.305	1	102	.132	17.70	6	102	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Plane Handling, commander	.513	6.549	.000
(2) Message Handling, specialist B	.130	1.683	.095
(3) Plane Handling, specialist B	.143	1.954	.053
(4) Plane Handling, specialist A	.127	1.785	.077
(5) Basic Task Mastery, commander	-.148	-1.897	.061
(6) Message Handling, specialist A	.114	1.518	.132

Excluded Predictors	Beta-In	t	Sig.
Basis Task Mastery, commander			
Basic Task Mastery, specialist A	-.035	-.482	.631
Basic Task Mastery, specialist B	-.052	-.707	.481
Plane Handling, commander			
Plane Handling, specialist A			
Plane Handling, specialist B			
Message Handling, commander	-.057	-.770	.443
Message Handling, specialist A			
Message Handling, specialist B			
Strategic Leadership, commander	.050	.658	.512
Motivational and Corrective Leadership, commander	-.056	-.791	.431

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 114 Results of multiple regression, predicting performance shift 3, with *input* and *summary level process* variables, and *task adaptive behavior variables* controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.323	.316	.323	50.94	1	107	.000	50.94	1	107	.000
2	.380	.368	.057	9.768	1	106	.002	32.44	2	106	.000
3	.407	.390	.028	4.882	1	105	.029	24.05	3	105	.000
4	.435	.413	.027	5.034	1	104	.027	19.99	4	104	.000
5	.468	.443	.034	6.557	1	103	.012	18.16	5	103	.000
6	.619	.596	.150	40.26	1	102	.000	27.61	6	102	.000
7	.637	.612	.018	5.050	1	101	.027	25.33	7	101	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 2	.397	5.856	.000
(2) gender commander	.227	3.650	.000
(3) age, specialist A	-.003	-.049	.961
(4) number Send Message, commander	-.246	-3.186	.002
(5) number Read Message, specialist B	.146	1.953	.054
(6) Plane Handling, commander	.432	6.315	.000
(7) Message Handling, specialist B	.153	2.247	.027

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	-0.008	-0.131	0.896
CHAT condition (dummy coded)	0.101	1.667	0.099
Control Condition 1 (dummy coded)	0.006	0.101	0.920
Control Condition 2 (dummy coded)	-0.019	-0.303	0.762
Individual Reflexivity (dummy coded)	-0.138	-2.211	0.029
Group Reflexivity (dummy coded)	0.000	-0.008	0.994
age commander	-0.034	-0.545	0.587
gender commander			
education commander	-0.072	-1.097	0.275
computer expertise commander	0.057	0.849	0.398
age specialist A			
gender specialist A	-0.004	-0.065	0.948
education specialist A	0.062	1.001	0.319
computer expertise specialist A	0.000	0.004	0.997
age specialist B	-0.069	-1.101	0.274
gender specialist B	-0.018	-0.286	0.775
education specialist B	-0.008	-0.126	0.900
computer expertise specialist B	-0.009	-0.139	0.890
number Handle Threat, commander	-0.291	-4.616	0.000
number Read Message, commander	-0.118	-1.880	0.063
number Send Message, commander			
number Show Info, commander	0.026	0.415	0.679
duration Read Message, commander	0.021	0.287	0.774
duration Send Message, commander	-0.027	-0.329	0.743
number Read Message, specialist A	-0.021	-0.222	0.825
number Send Message, specialist A	-0.013	-0.197	0.844
number Show Info, specialist A	0.014	0.213	0.832
duration Read Message, specialist A	-0.041	-0.528	0.599
duration Send Message, specialist A	0.121	1.979	0.051
number Read Message, specialist B			
number Send Message, specialist B	-0.040	-0.646	0.520
number Show Info, specialist B	-0.061	-0.944	0.348
duration Read Message, specialist B	0.068	0.735	0.464
duration Send Message, specialist B	0.092	1.447	0.151
Basis Task Mastery, commander	-0.058	-0.839	0.404
Basic Task Mastery, specialist A	0.000	0.004	0.997
Basic Task Mastery, specialist B	-0.015	-0.236	0.814
Plane Handling, commander			
Plane Handling, specialist A	0.012	0.183	0.856
Plane Handling, specialist B	0.080	1.272	0.206
Message Handling, commander	-0.057	-0.834	0.407
Message Handling, specialist A	0.027	0.406	0.686
Message Handling, specialist B			
Strategic Leadership, commander	0.038	0.589	0.557
Motivational and Corrective Leadership, commander	-0.039	-0.632	0.529

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 115 Results of multiple regression, predicting performance shift 4, with *task adaptive behavior variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.096	.088	.096	11.37	1	107	.001	11.37	1	107	.001
2	.149	.133	.053	6.572	1	106	.012	9.27	2	106	.000
3	.171	.147	.022	2.773	1	105	.099	7.21	3	105	.000
4	.188	.157	.018	2.248	1	104	.137	6.03	4	104	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Plane Handling, specialist A	.195	2.036	.044
(2) Message Handling, specialist A	.259	2.711	.008
(3) Plane Handling, specialist B	.150	1.682	.096
(4) Strategic Leadership, commander	.141	1.499	.137

Excluded Predictors	Beta-In	t	Sig.
Basis Task Mastery, commander	-.129	-1.382	.170
Basic Task Mastery, specialist A	-.031	-.352	.725
Basic Task Mastery, specialist B	-.011	-.124	.902
Plane Handling, commander	.135	1.407	.162
Plane Handling, specialist A			
Plane Handling, specialist B			
Message Handling, commander	-.054	-.583	.561
Message Handling, specialist A			
Message Handling, specialist B	.021	.205	.838
Strategic Leadership, commander			
Motivational and Corrective Leadership, commander	-.049	-.541	.590

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 116 Results of multiple regression, predicting performance shift 4, with *input* and *summary level process* variables, and *task adaptive behavior variables* controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.235	.228	.235	32.93	1	107	.000	32.93	1	107	.000
2	.281	.268	.046	6.791	1	106	.010	20.75	2	106	.000
3	.299	.279	.018	2.674	1	105	.105	14.95	3	105	.000
4	.319	.293	.020	3.072	1	104	.083	12.20	4	104	.000
5	.337	.304	.017	2.694	1	103	.104	10.46	5	103	.000
6	.353	.314	.016	2.505	1	102	.117	9.26	6	102	.000
7	.400	.358	.047	7.922	1	101	.006	9.61	7	101	.000
8	.419	.372	.019	3.317	1	100	.072	9.01	8	100	.000
9	.438	.387	.019	3.346	1	99	.070	8.57	9	99	.000
10	.457	.401	.019	3.413	1	98	.068	8.24	10	98	.000
11	.470	.410	.013	2.442	1	97	.121	7.83	11	97	.000
12	.523	.463	.052	10.56	1	96	.002	8.76	12	96	.000
13	.543	.480	.020	4.142	1	95	.045	8.70	13	95	.000
14	.560	.495	.018	3.780	1	94	.055	8.56	14	94	.000
15	.580	.513	.020	4.419	1	93	.038	8.57	15	93	.000
16	.599	.529	.019	4.290	1	92	.041	8.59	16	92	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 3	.377	4.866	.000
(2) computer expertise, commander	.222	3.103	.003
(3) gender, specialist A	-.091	-1.292	.199
(4) CHAT condition	-.137	-1.950	.054
(5) age, commander	-.123	-1.758	.082
(6) education, commander	.168	2.319	.023
(7) duration Read Message, specialist B	-.137	-1.695	.093
(8) duration Send Message, specialist A	-.198	-2.555	.012
(9) number Handle Threat, commander	-.521	-4.252	.000
(10) number Show Info, specialist B	.115	1.610	.111
(11) duration Read Message, command.	.101	1.334	.185
(12) Plane Handling, commander	.453	3.482	.001
(13) Plane Handling, specialist A	.167	2.262	.026
(14) Basic Task Mastery, commander	-.210	-2.801	.006
(15) Message Handling, specialist B	-.179	-2.174	.032
(16) Basic Task Mastery, specialist B	.142	2.071	.041

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.002	0.031	0.975
CHAT condition (dummy coded)			
Control Condition 1 (dummy coded)	-0.114	-1.609	0.111
Control Condition 2 (dummy coded)	0.033	0.450	0.654
Individual Reflexivity (dummy coded)	0.060	0.776	0.440
Group Reflexivity (dummy coded)	-0.051	-0.703	0.484
age commander			
gender commander	0.048	0.620	0.537
education commander			
computer expertise commander			
age specialist A	-0.002	-0.030	0.976
gender specialist A	-.043	-.508	.613
education specialist A	-0.062	-0.833	0.407
computer expertise specialist A	0.095	1.199	0.233
age specialist B	0.037	0.515	0.608
gender specialist B	0.104	1.402	0.164
education specialist B	0.056	0.801	0.425
computer expertise specialist B	0.076	1.059	0.293
number Handle Threat, commander			
number Read Message, commander	0.001	0.018	0.986
number Send Message, commander	-0.005	-0.059	0.953
number Show Info, commander	-0.027	-0.331	0.741
duration Read Message, commander			
duration Send Message, commander	0.118	1.082	0.282
number Read Message, specialist A	0.012	0.155	0.877
number Send Message, specialist A	0.010	0.117	0.907
number Show Info, specialist A	-0.119	-1.483	0.142
duration Read Message, specialist A	-0.005	-0.054	0.957
duration Send Message, specialist A			
number Read Message, specialist B	0.026	0.245	0.807
number Send Message, specialist B	-0.010	-0.130	0.896
number Show Info, specialist B	-.011	-.127	.899
duration Read Message, specialist B			
duration Send Message, specialist B	-0.001	-0.016	0.987
Basis Task Mastery, commander			
Basic Task Mastery, specialist A	-0.082	-1.173	0.244
Basic Task Mastery, specialist B			
Plane Handling, commander			
Plane Handling, specialist A			
Plane Handling, specialist B	-0.025	-0.154	0.878
Message Handling, commander	-0.136	-1.355	0.179
Message Handling, specialist A	-0.007	-0.072	0.943
Message Handling, specialist B			
Strategic Leadership, commander	0.021	0.266	0.790
Motivational and Corrective Leadership, commander	0.029	0.417	0.677

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of F is smaller than 0.15.

Table 117 Results of multiple regression, predicting performance shift 5, with *task adaptive behavior variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.244	.237	.244	34.51	1	107	.000	34.51	1	107	.000
2	.328	.315	.084	13.29	1	106	.000	25.88	2	106	.000
3	.394	.377	.066	11.39	1	105	.001	22.74	3	105	.000
4	.436	.414	.042	7.758	1	104	.006	20.09	4	104	.000
5	.455	.428	.019	3.544	1	103	.063	17.18	5	103	.000
6	.469	.437	.014	2.676	1	102	.105	14.99	6	102	.000
7	.480	.444	.011	2.186	1	101	.142	13.31	7	101	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Plane Handling, commander	.490	5.489	.000
(2) Message Handling, specialist B	.302	3.700	.000
(3) Basic Task Mastery, commander	-.264	-3.448	.001
(4) Message Handling, commander	-.244	-2.867	.005
(5) Strategic Leadership, commander	.142	1.856	.066
(6) Message Handling, specialist A	.129	1.604	.112
(7) Motivational and Corrective leadership, commander	-.109	-1.479	.142

Excluded Predictors	Beta-In	t	Sig.
Basis Task Mastery, commander			
Basic Task Mastery, specialist A	-.001	-.020	.984
Basic Task Mastery, specialist B	.077	1.035	.303
Plane Handling, commander			
Plane Handling, specialist A	-.066	-.823	.412
Plane Handling, specialist B	.071	.936	.351
Message Handling, commander			
Message Handling, specialist A			
Message Handling, specialist B			
Strategic Leadership, commander			
Motivational and Corrective Leadership, commander			

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 118 Results of multiple regression, predicting performance shift 5, with *input* and *summary level process* variables, and *task adaptive behavior variables* controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.271	.264	.271	39.75	1	107	.000	39.75	1	107	.000
2	.308	.295	.037	5.655	1	106	.019	23.57	2	106	.000
3	.326	.307	.018	2.844	1	105	.095	16.93	3	105	.000
4	.370	.345	.044	7.181	1	104	.009	15.24	4	104	.000
5	.411	.383	.042	7.317	1	103	.008	14.34	5	103	.000
6	.431	.397	.019	3.469	1	102	.065	12.87	6	102	.000
7	.446	.407	.015	2.705	1	101	.103	11.60	7	101	.000
8	.602	.570	.156	39.32	1	100	.000	18.91	8	100	.000
9	.630	.596	.028	7.431	1	99	.008	18.72	9	99	.000
10	.644	.608	.014	3.871	1	98	.052	17.72	10	98	.000
11	.660	.621	.016	4.451	1	97	.037	17.08	11	97	.000
12	.672	.631	.013	3.717	1	96	.057	16.41	12	96	.000
13	.686	.643	.013	4.076	1	95	.046	15.94	13	95	.000
14	.695	.649	.009	2.733	1	94	.102	15.27	14	94	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 4	.204	2.815	.006
(2) computer expertise, commander	.102	1.480	.142
(3) gender, commander	.138	2.128	.036
(4) number Show Info, specialist B	.348	3.176	.002
(5) number Show Info, specialist A	-.126	-1.990	.050
(6) duration Send Message, commander	.030	.426	.671
(7) number Handle Threat, commander	-.512	-3.835	.000
(8) Plane Handling, commander	.832	5.927	.000
(9) Basic Task Mastery, commander	-.158	-2.511	.014
(10) Message Handling, specialist A	.096	1.367	.175
(11) Message Handling, commander	-.173	-2.414	.018
(12) Message Handling, specialist B	.203	2.678	.009
(13) Plane Handling, specialist B	-.259	-2.345	.021
(14) Basic Task Mastery, specialist B	.102	1.653	.102

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.032	0.525	0.601
CHAT condition (dummy coded)	0.088	1.272	0.207
Control Condition 1 (dummy coded)	-0.033	-0.563	0.575
Control Condition 2 (dummy coded)	-0.009	-0.143	0.886
Individual Reflexivity (dummy coded)	0.065	1.094	0.277
Group Reflexivity (dummy coded)	-0.025	-0.428	0.669
age commander	-0.001	-0.021	0.983
gender commander			
education commander	0.091	1.434	0.155
computer expertise commander			
age specialist A	-0.046	-0.760	0.449
gender specialist A	-0.026	-0.428	0.670
education specialist A	-0.042	-0.623	0.535
computer expertise specialist A	-0.015	-0.254	0.800
age specialist B	-0.015	-0.235	0.815
gender specialist B	-0.105	-1.724	0.088
education specialist B	0.018	0.310	0.758
computer expertise specialist B	0.041	0.682	0.497
number Handle Threat, commander			
number Read Message, commander	-0.043	-0.571	0.569
number Send Message, commander	-0.122	-1.353	0.179
number Show Info, commander	-0.011	-0.174	0.862
duration Read Message, commander	0.000	0.003	0.998
duration Send Message, commander			
number Read Message, specialist A	-0.107	-1.493	0.139
number Send Message, specialist A	0.038	0.543	0.588
number Show Info, specialist A			
duration Read Message, specialist A	-0.034	-0.391	0.697
duration Send Message, specialist A	0.032	0.530	0.598
number Read Message, specialist B	-0.063	-0.923	0.359
number Send Message, specialist B	-0.038	-0.528	0.599
number Show Info, specialist B			
duration Read Message, specialist B	-0.092	-1.135	0.259
duration Send Message, specialist B	-0.003	-0.047	0.962
Basis Task Mastery, commander			
Basic Task Mastery, specialist A	-0.027	-0.461	0.646
Basic Task Mastery, specialist B			
Plane Handling, commander			
Plane Handling, specialist A	-0.030	-0.430	0.668
Plane Handling, specialist B			
Message Handling, commander			
Message Handling, specialist A	0.098	1.375	0.172
Message Handling, specialist B	0.037	0.558	0.578
Strategic Leadership, commander			
Motivational and Corrective Leadership, commander			

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 119 Results of multiple regression, predicting performance shift 6, with *task adaptive behavior variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.276	.269	.276	40.76	1	107	.000	40.76	1	107	.011
2	.370	.358	.094	15.79	1	106	.000	31.09	2	106	.001
3	.399	.382	.030	5.198	1	105	.025	23.28	3	105	.000
4	.416	.394	.017	2.975	1	104	.088	18.53	4	104	.000
5	.429	.401	.013	2.306	1	103	.132	15.47	5	103	.000
6	.442	.409	.013	2.300	1	102	.132	13.44	6	102	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Plane Handling, commander	.389	4.514	.000
(2) Message handling, specialist A	.194	2.234	.028
(3) Strategic Leadership, commander	.168	2.175	.032
(4) Message Handling, specialist B	.155	1.841	.069
(5) Plane Handling, specialist A	.157	1.848	.068
(6) Message Handling, commander	-.126	-1.517	.132

Excluded Predictors	Beta-In	t	Sig.
Basis Task Mastery, commander	-0.029	-0.368	0.713
Basic Task Mastery, specialist A	-0.015	-0.201	0.841
Basic Task Mastery, specialist B	-0.018	-0.235	0.815
Plane Handling, commander			
Plane Handling, specialist A			
Plane Handling, specialist B	0.006	0.072	0.942
Message Handling, commander			
Message Handling, specialist A			
Message Handling, specialist B			
Strategic Leadership, commander			
Motivational and Corrective Leadership, commander	0.027	0.362	0.718

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 120 Results of multiple regression, predicting performance shift 6, with *input* and *summary level process* variables, and *task adaptive behavior variables* controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.405	.400	.405	72.89	1	107	.000	72.89	1	107	.000
2	.423	.412	.017	3.196	1	106	.077	38.79	2	106	.000
3	.443	.427	.021	3.917	1	105	.050	27.88	3	105	.000
4	.464	.443	.020	3.968	1	104	.049	22.49	4	104	.000
5	.478	.453	.015	2.889	1	103	.092	18.90	5	103	.000
6	.489	.459	.011	2.186	1	102	.142	16.29	6	102	.000
7	.502	.467	.013	2.557	1	101	.113	14.55	7	101	.000
8	.515	.476	.013	2.601	1	100	.110	13.25	8	100	.000
9	.556	.516	.042	9.303	1	99	.003	13.79	9	99	.000
10	.570	.527	.014	3.198	1	98	.077	13.01	10	98	.000
11	.581	.534	.011	2.474	1	97	.119	12.23	11	97	.000
12	.591	.540	.010	2.400	1	96	.125	11.57	12	96	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 5	.445	5.372	.000
(2) age, commander	-.107	-1.503	.136
(3) computer expertise, commander	.124	1.664	.099
(4) education, commander	.120	1.727	.087
(5) duration Read Message, specialist B	-.224	-2.137	.035
(6) number Send Message, specialist A	.075	.956	.341
(7) number Send Message, specialist B	-.141	-1.805	.074
(8) number Read Message, specialist B	.127	1.249	.215
(9) Strategic Leadership, commander	.177	2.586	.011
(10) Motivational and Corrective leadership, commander	.110	1.586	.116
(11) Plane Handling, commander	.137	1.661	.100
(12) Message Handling, specialist A	.120	1.549	.125

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	-0.026	-0.376	0.708
CHAT condition (dummy coded)	-0.011	-0.153	0.879
Control Condition 1 (dummy coded)	0.022	0.317	0.752
Control Condition 2 (dummy coded)	-0.062	-0.899	0.371
Individual Reflexivity (dummy coded)	0.046	0.632	0.529
Group Reflexivity (dummy coded)	-0.003	-0.041	0.967
age commander			
gender commander	0.021	0.279	0.781
education commander			
computer expertise commander	0.005	0.079	0.937
age specialist A	-0.060	-0.855	0.395
gender specialist A	-0.123	-1.756	0.082
education specialist A	-0.058	-0.832	0.408
computer expertise specialist A	.122	1.436	.154
age specialist B	-0.044	-0.640	0.523
gender specialist B	-0.020	-0.293	0.770
education specialist B	0.038	0.559	0.578
computer expertise specialist B	0.061	0.896	0.372
number Handle Threat, commander	-0.096	-1.195	0.235
number Read Message, commander	-0.083	-0.490	0.625
number Send Message, commander	-0.158	-2.029	0.045
number Show Info, commander	0.051	0.716	0.476
duration Read Message, commander	0.066	0.855	0.395
duration Send Message, commander	-0.155	-1.758	0.082
number Read Message, specialist A	-0.137	-1.288	0.201
number Send Message, specialist A			
number Show Info, specialist A	-0.037	-0.534	0.594
duration Read Message, specialist A	-0.039	-0.382	0.703
duration Send Message, specialist A	0.055	0.745	0.458
number Read Message, specialist B			
number Send Message, specialist B			
number Show Info, specialist B	0.088	1.227	0.223
duration Read Message, specialist B			
duration Send Message, specialist B	0.065	0.907	0.366
Basis Task Mastery, commander	0.017	0.242	0.809
Basic Task Mastery, specialist A	-0.033	-0.472	0.638
Basic Task Mastery, specialist B	0.035	0.500	0.618
Plane Handling, commander			
Plane Handling, specialist A	0.076	0.963	0.338
Plane Handling, specialist B	0.067	0.940	0.349
Message Handling, commander	-0.100	-1.127	0.262
Message Handling, specialist A			
Message Handling, specialist B	-0.061	-0.662	0.509
Strategic Leadership, commander			
Motivational and Corrective Leadership, commander			

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 121 Results of multiple regression, predicting performance shift 8, with *task adaptive behavior variables*, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.187	.179	.187	24.57	1	107	.000	24.57	1	107	.000
2	.282	.269	.096	14.14	1	106	.000	20.87	2	106	.000
3	.332	.313	.050	7.793	1	105	.006	17.40	3	105	.000
4	.346	.321	.014	2.250	1	104	.137	13.77	4	104	.000
5	.360	.329	.013	2.170	1	103	.144	11.57	5	103	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Message Handling, specialist A	.234	2.440	.016
(2) Strategic Leadership, commander	.249	3.041	.003
(3) Plane Handling, specialist A	.206	2.325	.022
(4) Message Handling, specialist B	.140	1.521	.131
(5) Plane Handling, commander	.123	1.473	.144

Excluded Predictors	Beta-In	t	Sig.
Basis Task Mastery, commander	constant, excluded from analyses		
Basic Task Mastery, specialist A	-.054	-.637	.525
Basic Task Mastery, specialist B	.080	.972	.333
Plane Handling, commander			
Plane Handling, specialist A			
Plane Handling, specialist B	.071	.883	.380
Message Handling, commander	.075	.915	.362
Message Handling, specialist A			
Message Handling, specialist B			
Strategic Leadership, commander			
Motivational and Corrective Leadership, commander	-.070	-.872	.385

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

Table 122 Results of multiple regression, predicting performance shift 6, with *input* and *summary level process* variables, and *task adaptive behavior variables* controlling for performance of preceding shifts, trimmed model.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.331	.325	.331	52.89	1	107	.000	52.89	1	107	.000
2	.359	.347	.028	4.655	1	106	.033	26.68	2	106	.000
3	.388	.370	.029	4.902	1	105	.029	22.15	3	105	.000
4	.412	.390	.025	4.345	1	104	.040	18.23	4	104	.000
5	.429	.402	.017	3.111	1	103	.081	15.50	5	103	.000
6	.442	.409	.013	2.350	1	102	.128	13.48	6	102	.000
7	.455	.417	.013	2.344	1	101	.129	12.04	7	101	.000
8	.508	.468	.053	10.75	1	100	.001	12.89	8	100	.000
9	.549	.508	.041	9.002	1	99	.003	13.38	9	99	.000
10	.563	.518	.014	3.137	1	98	.080	12.62	10	98	.000
11	.610	.566	.047	11.75	1	97	.001	13.79	11	97	.000
12	.630	.583	.020	5.069	1	96	.027	13.60	12	96	.000
13	.642	.593	.013	3.387	1	95	.069	13.12	13	95	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 6	.354	4.866	.000
(2) Control Condition 2	-.108	-1.676	.097
(3) education, commander	.153	2.247	.027
(4) computer expertise, commander	.097	1.370	.174
(5) computer expertise, specialist A	.136	2.022	.046
(6) computer expertise, specialist B	.051	.761	.449
(7) education, specialist B	.164	2.531	.013
(8) duration Read Message, specialist A	-.179	-2.770	.007
(9) duration Send Message, specialist A	-.219	-3.285	.001
(10) number Show Info, specialist B	.163	2.382	.019
(11) Strategic Leadership, commander	.218	3.184	.002
(12) Message Handling, specialist B	.147	2.138	.035
(13) Basic Task Mastery, specialist B	.123	1.840	.069

Excluded Predictors	Beta-In	t	Sig.
Base Condition (reference category)	-	-	-
Goal condition (dummy coded)	0.014	0.205	0.838
CHAT condition (dummy coded)	0.036	0.537	0.593
Control Condition 1 (dummy coded)	-0.026	-0.417	0.678
Control Condition 2 (dummy coded)			
Individual Reflexivity (dummy coded)	0.004	0.053	0.958
Group Reflexivity (dummy coded)	-0.118	-1.786	0.077
age commander	-0.088	-1.366	0.175
gender commander	0.002	0.034	0.973
education commander			
computer expertise commander			
age specialist A	0.040	0.586	0.559
gender specialist A	-0.012	-0.170	0.865
education specialist A	0.000	0.001	1.000
computer expertise specialist A	.122	1.436	.154
age specialist B	-0.031	-0.470	0.639
gender specialist B	-0.013	-0.172	0.864
education specialist B			
computer expertise specialist B			
number Handle Threat, commander	-0.046	-0.699	0.486
number Read Message, commander	-0.050	-0.744	0.458
number Send Message, commander	-0.092	-1.195	0.235
number Show Info, commander	-0.095	-1.443	0.152
duration Read Message, commander	0.026	0.370	0.712
duration Send Message, commander	-0.097	-1.081	0.283
number Read Message, specialist A	-0.120	-1.322	0.189
number Send Message, specialist A	0.018	0.259	0.796
number Show Info, specialist A	0.044	0.664	0.509
duration Read Message, specialist A			
duration Send Message, specialist A			
number Read Message, specialist B	0.022	0.291	0.771
number Send Message, specialist B	-0.063	-0.925	0.357
number Show Info, specialist B			
duration Read Message, specialist B	-0.052	-0.669	0.505
duration Send Message, specialist B	-0.001	-0.014	0.988
Basis Task Mastery, commander	constant, excluded from analyses		
Basic Task Mastery, specialist A	0.010	0.143	0.887
Basic Task Mastery, specialist B			
Plane Handling, commander	0.028	0.382	0.703
Plane Handling, specialist A	0.027	0.346	0.730
Plane Handling, specialist B	-0.113	-1.170	0.245
Message Handling, commander	-0.011	-0.170	0.866
Message Handling, specialist A	0.080	0.933	0.353
Message Handling, specialist B			
Strategic Leadership, commander			
Motivational and Corrective Leadership, commander	-0.003	-0.049	0.961

Note. N = 109 teams. Performance of the preceding shifts was entered in to the regression equation first, all other variables were entered using the method forward. Independent variables are entered into the equation if the smallest probability of *F* is smaller than 0.15.

6 Lag Sequential Analysis

6.1 Descriptive Statistics Shift 1 and Shift 4

In shift 1 specialists have a higher activity than commanders. Just counting the events shows that specialist A have 10’311, specialist B 8’129 and the commanders only 4’698 initiated events. The main activity of the specialists is to look up plane information (Show Information) with relative frequency of 71%, specialists A and 63%, specialists B. The main activity for commanders in shift 1 - with a relative frequency of 56% - is Read Message. In shift 4 (first shift on day two), whose task structure is exactly like shift 1, – commanders have 4’941 events, specialists A 13’513, and specialists B 10’225 (details in Table 123).

Comparing the frequencies for low and high performing teams, again no great differences are observed. In shift 1 commanders of low performing teams show less Handle Threat and slightly more Read Message and Send Message than commanders of high performing teams. Specialists A of high performing teams have less Read Message and less Send Message, but more Show Information than specialists A of low performing teams. For specialists B there are no differences. Right form the start (shift 1) high performing teams seem to concentrate on the role specific task, whereas low performing teams have not only a lower frequency of activities but also spend more time exchanging, especially between the commander and specialist A. In shift 4 there are no differences for commanders and specialists A of low and high performing teams. But now specialists B of low performing teams have a slightly higher relative frequency of Send Message and Read Message than specialists B of high performing teams. See Table 123.

Table 123 Lag sequential analysis: Descriptive statistics, shift 1 and shift 4, lag 0.

shift 1

		frequency			relative frequency		
		all	low	high	all	low	high
commander	New Plane	218	112	106			
	New Message	2'533	1'292	1'241			
	Handle Threat	547	237	310	0.12	0.10	0.13
	Read Message	2'637	1'341	1'296	0.56	0.57	0.55
	Send Message	931	484	447	0.20	0.21	0.19
	Show Information	473	214	259	0.10	0.09	0.11
	Other Activities	110	66	44	0.02	0.03	0.02
	Totals	4'698	2'342	2'356	1.00	1.00	1.00
specialist A	New Plane	218	112	106			
	New Message	1'044	586	458			
	Handle Threat	547	237	296			
	Read Message	1'108	613	476	0.11	0.14	0.09
	Send Message	1'320	649	641	0.13	0.15	0.13
	Show Information	7'713	3'100	3'836	0.75	0.70	0.76
	Other Activities	170	75	94	0.02	0.02	0.02
	Totals	10'311	4'437	5'047	1.00	1.00	1.00
specialist B	New Plane	218	112	106			
	New Message	937	489	448			
	Handle Threat	547	234	310			
	Read Message	1'049	522	525	0.13	0.13	0.13
	Send Message	1'370	714	651	0.17	0.17	0.16
	Show Information	5'470	2'709	2'721	0.67	0.66	0.68
	Other Activities	240	159	81	0.03	0.04	0.02
	Totals	8'129	4'104	3'978	1.00	1.00	1.00

shift 4

		frequency			relative frequency		
		all	low	high	all	low	high
commander	New Plane	218	110	108			
	New Message	2'587	1'235	1'352			
	Handle Threa	854	438	416	0.17	0.18	0.16
	Read Messag	2'683	1'275	1'408	0.54	0.54	0.55
	Send Messag	889	436	453	0.18	0.18	0.18
	Show Informa	483	215	268	0.10	0.09	0.10
	Other Activitie	32	9	23	0.01	0.00	0.01
	Totals	4'941	2'373	2'568	1.00	1.00	1.00
specialist A	New Plane	218	110	108			
	New Message	1'134	570	564			
	Handle Threa	854	413	382			
	Read Messag	1'153	555	512	0.09	0.10	0.09
	Send Messag	1'343	598	647	0.10	0.11	0.11
	Show Informa	10'963	4'386	4'513	0.81	0.79	0.79
	Other Activitie	54	18	36	0.00	0.00	0.01
	Totals	13'513	5'557	5'708	1.00	1.00	1.00
specialist B	New Plane	218	110	108			
	New Message	1'126	587	539			
	Handle Threa	854	431	405			
	Read Messag	1'144	583	519	0.11	0.13	0.11
	Send Messag	1'389	669	688	0.14	0.15	0.14
	Show Informa	7'656	3'159	3'591	0.75	0.71	0.75
	Other Activitie	36	15	20	0.00	0.00	0.00
	Totals	10'225	4'426	4'818	1.00	1.00	1.00

Note. N = 109 teams; low = low performing teams, high = high performing teams, median split (shift 1 median = 68, shift 4 median = 79).

6.2 Technical Details SPSS Data File: Data Structure

Example (group 106, shift 1, commander):

ieS010,11.00-211.00 ieSi1,238.00-238.10 ieR100,269.00-314.00 …

The commander sends a message with strategy related content. He needs 200 seconds to write the message, from second 11 to 211. Then he looks up the plane information, 27 seconds after he has finished writing the message; 31 seconds later the commanders reads a message, which will have some information on planes in it.

<u>Data structure</u>

<group number>
IEvent(1, shift 1), start time – end time IEvent(2, shift 1), start time – end time …
&
SEvent(1, shift 1), start time – end time SEvent(2, shift 1), start time – end time …
;
IEvent(1, shift 2), start time – end time IEvent(2, shift 2), start time – end time …
&
SEvent(1, shift 2), start time – end time SEvent(2, shift 2), start time – end time …
;

… shifts 3 to 8

(experimental condition) /

…next group…

<u>Additional Information in Data File</u>

<106>	group number
&	sign to separate the different streams
;	sign to separate shifts
(1) /	(1) = experimental condition (1 to 9)
/	/ = sign to separate groups

Table 124 Example of data file for lag sequential analysis.

<106>
ieS010,11.00-211.00 ieSi1,238.00-238.10 ieR100,269.00-314.00 ieR100,329.00-342.00 ieR100,351.00-382.00 ieSi1,392.00-392.10 ieR100,404.00-416.00 ieR100,424.00-433.00 ieR100,437.00-464.00 ieR100,469.00-481.00 ieR100,485.00-503.00 ieS010,509.00-601.00 ieOTHER,617.00-617.10 ieR001,633.00-670.00 ieR100,675.00-699.00 ieR100,708.00-739.00 ieOTHER,740.00-740.10 ieR100,746.00-781.00 ieR100,785.00-806.00 ieS010,820.00-1271.00
&
seNP1,17.00-17.10 seNewMsg,78.00-78.10 seNewMsg,126.00-126.10 seNewMsg,227.00-227.10 seNewMsg,261.00-261.10 seNewMsg,320.00-320.10 seNP2,333.00-333.10 seNewMsg,357.00-357.10 seNewMsg,393.00-393.10 seNewMsg,425.00-425.10 seNewMsg,515.00-515.10 seNewMsg,609.00-609.10 seNewMsg,660.00-660.10 seNewMsg,683.00-683.10 seNewMsg,723.00-723.10
&
dthr-2.0,17.00-265.00 dthr-1.0,266.00-315.00 dthr-3.0,316.00-447.00 dthr-2.0,448.00-900.00
;
ieS001,9.00-87.00 ieR100,107.00-127.00 ieR100,140.00-157.00 ieR010,161.00-167.00 ieR100,185.00-199.00 ieR100,205.00-214.00 ieR010,218.00-229.00 ieR100,232.00-242.00 ieR100,249.00-271.00 ieSi1,282.00-282.10 ieSi1,297.00-297.10 ieSi1,339.00-339.10 ieR100,351.00-388.00 ieR100,401.00-419.00 ieR100,425.00-438.00 ieR100,443.00-453.00 ieR100,456.00-465.00 ieR100,470.00-492.00 ieR100,496.00-518.00 ieH23,529.00-529.10 ieR100,563.00-575.00

ieR100,578.00-596.00 ieR100,599.00-608.00 ieR100,612.00-629.00 ieH24,637.00-637.10 ieR001,643.00-661.00 ieR100,666.00-686.00 ieR100,689.00-706.00 ieR100,709.00-724.00 ieH25,733.00-733.10 ieR100,737.00-758.00 ieR100,761.00-775.00 ieS100,780.00-810.00 ieS100,818.00-833.00 ieR001,876.00-898.00
&
seNP1,32.00-32.10 seNewMsg,69.00-69.10 seNewMsg,102.00-102.10 seNewMsg,128.00-128.10 seNewMsg,164.00-164.10 seNewMsg,171.00-171.10 seNewMsg,195.00-195.10 seNewMsg,197.00-197.10 seNP2,213.00-213.10 seNewMsg,237.00-237.10 seNewMsg,276.00-276.10 seNP3,304.00-304.10 seNewMsg,330.00-330.10 seNewMsg,341.00-341.10 seNewMsg,360.00-360.10 seNewMsg,378.00-378.10 seNewMsg,413.00-413.10 seNewMsg,423.00-423.10 seNewMsg,437.00-437.10 seNewMsg,473.00-473.10 seNewMsg,474.00-474.10 seNewMsg,507.00-507.10 seNewMsg,570.00-570.10 seNewMsg,600.00-600.10 seNewMsg,660.00-660.10 seNewMsg,674.00-674.10 seNewMsg,690.00-690.10 seNewMsg,737.00-737.10 seNewMsg,852.00-852.10
&
dthr-2.0,32.00-212.00 dthr-4.0,213.00-303.00 dthr-3.0,304.00-528.00 dthr-2.0,529.00-821.00 dthr-1.0,822.00-900.00
;
ieSi1,13.00-13.10 ieS010,50.00-133.00 ieR001,142.00-175.00 ieR100,179.00-228.00 ieH14,241.00-241.10 ieS001,245.00-278.00 ieR100,284.00-308.00 ieS001,312.00-337.00 ieSi1,352.00-352.10 ieH21,379.00-379.10 ieSi1,395.00-395.10 ieSi1,413.00-413.10 ieSi1,419.00-419.10 ieR001,429.00-444.00 ieR100,447.00-452.00 ieS010,457.00-506.00 ieR001,511.00-558.00 ieR001,560.00-614.00 ieH33,628.00-628.10 ieR001,630.00-638.00 ieSi1,656.00-656.10 ieSi1,657.00-657.10 ieSi1,662.00-662.10 ieSi1,666.00-666.10 ieSi1,684.00-684.10 ieSi1,689.00-689.10 ieSi1,694.00-694.10 ieR100,707.00-761.00 ieR100,764.00-791.00 ieH34,802.00-802.10 ieR100,802.00-836.00 ieH35,847.00-847.10 ieR100,849.00-866.00 ieR100,871.00-882.00 ieR100,884.00-903.00
&

etc.

6.3 GSEQ-SDIS Command Files

A sample GSEQ-SDIS command file to calculate simple and lag sequential statistics for commanders and specialists, for all shifts.

I think that it is a big advantage that GESEQ-SDIS can be run using syntax files (like in SPSS). They are easy to understand and facilitate the work.

```
File "X:\projekt nac-d\Data\SequentialDataAnalyses\seq.mds";
VARS beding = 1 (BC=1 TIK=2  Comp=3 Goal=4 CHAT=5 CC1=6 CC2=7 IR=8 GR=9)
     rolle = 2 (commander = 1 specA = 2 specB = 3);
recode seNP = seNP1 seNP2 seNP3 seNP4;
recode seNM = seNewMsg;
recode ieH = ieH10 ieH11 ieH12 ieH13 ieH14 ieH15 ieH20 ieH21 ieH22 ieH23 ieH24 ieH25
ieH30 ieH31 ieH32 ieH33 ieH34 ieH35 ieH40 ieH41 ieH42 ieH43 ieH44 ieH45;
recode ieR = ieR001 ieR010 ieR011 ieR100 ieR101 ieR110;
recode ieS = ieS001 ieS010 ieS011 ieS100 ieS101 ieS110;
recode ieSi = ieSi0 ieSi1;
recode ieOt = ieOTHER;
event;
Pool no+ no* ;
Simple freq relf rate dura reld prob avgd  (seNP seNM ieH ieR  ieS ieSi  ieOt);
Stats jntf expf conp rsdl adjr pval xsq gsq yulq kappa phi odds;
target ieR ieS ieSi ieH ;
lags 1 ;
given seNP seNM ieH ieR ieS ieSi;
Export "X:\projekt nac-d\Data\SequentialDataAnalyses\seq cab (4) lag 1.tab"  jntf  adjr adjr$ xsq
xsq$ gsq gsq$  tabs label overwrite;
```

Table 125 Codes used to name the lag sequential variables (lag frequencies, adjusted residuals, and recoded adjusted residuals) in the SPSS data file.

day 1	role	given/target	Read Message	Send Message	Show Information	Handle Threat	day 2	role	given/target	Read Message	Send Message	Show Information	Handle Threat
shift 1	C	New Plane	1	2	3	4	shift 4	C	New Plane	181	182	183	184
		New Message	5	6	7	8			New Message	185	186	187	188
		Handle Threat	9	10	11	12			Handle Threat	189	190	191	192
		Read Message	13	14	15	16			Read Message	193	194	195	196
		Send Message	17	18	19	20			Send Message	197	198	199	200
		Show Info	21	22	23	24			Show Info	201	202	203	204
	A	New Plane	25	26	27			A	New Plane	205	206	207	
		New Message	28	29	30				New Message	208	209	210	
		Handle Threat	31	32	33				Handle Threat	211	212	213	
		Read Message	34	35	36				Read Message	214	215	216	
		Send Message	37	38	39				Send Message	217	218	219	
		Show Info	40	41	42				Show Info	220	221	222	
	B	New Plane	43	44	45			B	New Plane	223	224	225	
		New Message	46	47	48				New Message	226	227	228	
		Handle Threat	49	50	51				Handle Threat	229	230	231	
		Read Message	52	53	54				Read Message	232	233	234	
		Send Message	55	56	57				Send Message	235	236	237	
		Show Info	58	59	60				Show Info	238	239	240	
shift 2	C	New Plane	61	62	63	64	shift 5	C	New Plane	241	242	243	244
		New Message	65	66	67	68			New Message	245	246	247	248
		Handle Threat	69	70	71	72			Handle Threat	249	250	251	252
		Read Message	73	74	75	76			Read Message	253	254	255	256
		Send Message	77	78	79	80			Send Message	257	258	259	260
		Show Info	81	82	83	84			Show Info	261	262	263	264
	A	New Plane	85	86	87			A	New Plane	265	266	267	
		New Message	88	89	90				New Message	268	269	270	
		Handle Threat	91	92	93				Handle Threat	271	272	273	
		Read Message	94	95	96				Read Message	274	275	276	
		Send Message	97	98	99				Send Message	277	278	279	
		Show Info	100	101	102				Show Info	280	281	282	
	B	New Plane	103	104	105			B	New Plane	283	284	285	
		New Message	106	107	108				New Message	286	287	288	
		Handle Threat	109	110	111				Handle Threat	289	290	291	
		Read Message	112	113	114				Read Message	292	293	294	
		Send Message	115	116	117				Send Message	295	296	297	
		Show Info	118	119	120				Show Info	298	299	300	
shift 3	C	New Plane	121	122	123	124	shift 6	C	New Plane	301	302	303	304
		New Message	125	126	127	128			New Message	305	306	307	308
		Handle Threat	129	130	131	132			Handle Threat	309	310	311	312
		Read Message	133	134	135	136			Read Message	313	314	315	316
		Send Message	137	138	139	140			Send Message	317	318	319	320
		Show Info	141	142	143	144			Show Info	321	322	323	324
	A	New Plane	145	146	147			A	New Plane	325	326	327	
		New Message	148	149	150				New Message	328	329	330	
		Handle Threat	151	152	153				Handle Threat	331	332	333	
		Read Message	154	155	156				Read Message	334	335	336	
		Send Message	157	158	159				Send Message	337	338	339	
		Show Info	160	161	162				Show Info	340	341	342	
	B	New Plane	163	164	165			B	New Plane	343	344	345	
		New Message	166	167	168				New Message	346	347	348	
		Handle Threat	169	170	171				Handle Threat	349	350	351	
		Read Message	172	173	174				Read Message	352	353	354	
		Send Message	175	176	177				Send Message	355	356	357	
		Show Info	178	179	180				Show Info	358	359	360	
							shift 8	C	New Plane	361	362	363	364
									New Message	365	366	367	368
									Handle Threat	369	370	371	372
									Read Message	373	374	375	376
									Send Message	377	378	379	380
									Show Info	381	382	383	384
								A	New Plane	385	386	387	
									New Message	388	389	390	
									Handle Threat	391	392	393	
									Read Message	394	395	396	
									Send Message	397	398	399	
									Show Info	400	401	402	
								B	New Plane	403	404	405	
									New Message	406	407	408	
									Handle Threat	409	410	411	
									Read Message	412	413	414	
									Send Message	415	416	417	
									Show Info	418	419	420	

6.4 Adjusted Residuals, all Roles, lag 2 to lag 5, shift 1

Table 126 Adjusted residuals, lag 2, shift 1.

Commander

all

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-9.62 -**	**5.50 +**	**7.71 +**	0.96
New Message	**4.29 +**	-1.79	**-5.65 -**	0.71
Handle Threat	-2.24	**3.74 +**	-0.15	-1.05
Read Message	1.85	-1.65	**-5.32 -**	**3.92 +**
Send Message	**4.65 +**	-2.08	1.18	**-5.50 -**
Show Information	**-8.72 -**	1.68	**14.05 +**	-1.30

low

	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-6.06 -**	**4.63 +**	**3.55 +**	0.37
New Message	2.27	-2.05	-2.48	1.28
Handle Threat	-0.72	1.68	-0.70	-0.45
Read Message	1.66	-0.81	**-3.82 -**	1.80
Send Message	2.42	-0.09	-0.03	**-3.67 -**
Show Information	**-6.13 -**	0.95	**10.80 +**	-1.03

high

	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-7.47 -**	**3.21 +**	**7.02 +**	0.90
New Message	**3.77 +**	-0.46	**-5.36 -**	-0.18
Handle Threat	-2.26	**3.65 +**	0.25	-1.11
Read Message	0.87	-1.64	**-3.62 -**	**3.81 +**
Send Message	**4.15 +**	-2.90	1.61	**-4.10 -**
Show Information	**-6.15 -**	1.50	**9.17 +**	-0.94

Specialist A

all

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.66	2.23	-0.55	
New Message	**18.31 +**	1.84	**-14.82 -**	
Handle Threat	0.26	2.30	-2.00	
Read Message	**7.39 +**	**7.38 +**	**-11.22 -**	
Send Message	**14.36 +**	-1.92	**-8.96 -**	
Show Information	**-24.03 -**	**-5.89 -**	**22.19 +**	

low

	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.05	1.61	-0.46	.
New Message	**10.50 +**	0.67	**-8.57 -**	.
Handle Threat	-0.37	2.26	-1.49	.
Read Message	**4.24 +**	**4.11 +**	**-6.48 -**	.
Send Message	**10.50 +**	-1.76	**-6.66 -**	.
Show Information	**-15.67 -**	**-3.31 -**	**14.61 +**	.

high

	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.94	0.88	0.66	.
New Message	**13.28 +**	1.00	**-10.14 -**	.
Handle Threat	0.58	0.81	-1.06	.
Read Message	**4.91 +**	**5.03 +**	**-7.50 -**	.
Send Message	**8.13 +**	-1.77	**-4.29 -**	.
Show Information	**-15.34 -**	-2.94	**13.14 +**	.

Specialist B

all

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-3.65 -**	**3.13 +**	0.09	
New Message	**14.66 +**	-0.51	**-10.33 -**	
Handle Threat	1.02	0.29	-0.99	
Read Message	**4.61 +**	**6.08 +**	**-8.39 -**	
Send Message	**12.55 +**	-2.41	**-7.22 -**	
Show Information	**-19.74 -**	-2.93	**16.89 +**	

low

	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-3.33 -**	**3.38 +**	-0.39	.
New Message	**9.55 +**	-0.21	**-6.78 -**	.
Handle Threat	1.57	-0.22	-0.96	.
Read Message	2.80	**4.33 +**	**-5.65 -**	.
Send Message	**8.98 +**	-1.47	**-5.32 -**	.
Show Information	**-13.55 -**	-2.51	**11.96 +**	.

high

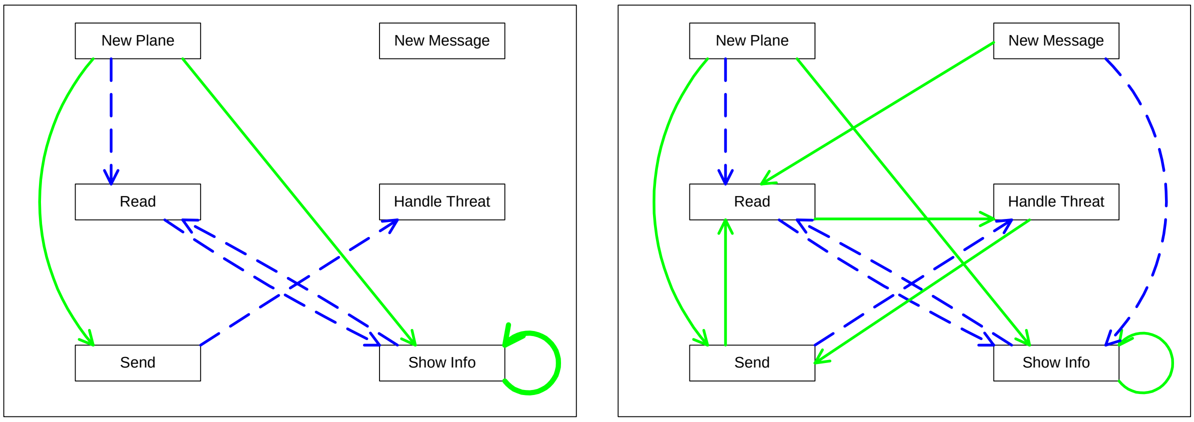
	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.81	0.89	0.61	.
New Message	**11.21 +**	-0.56	**-7.83 -**	.
Handle Threat	-0.16	0.73	-0.48	.
Read Message	**3.65 +**	**4.26 +**	**-6.18 -**	.
Send Message	**8.77 +**	-2.10	**-4.77 -**	.
Show Information	**-14.24 -**	-1.58	**11.82 +**	.

Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53).

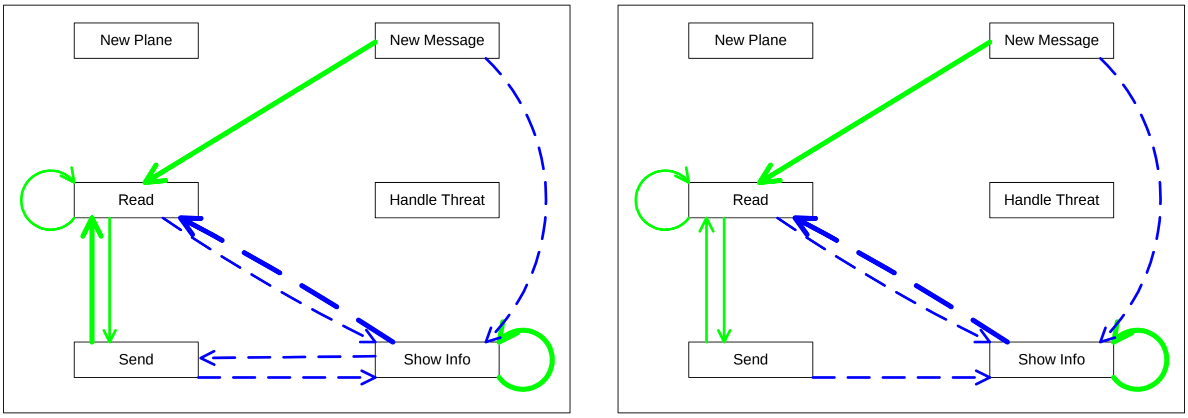
Figure 52 Adjusted residuals, all roles, lag 2, shift 1.

low performance high performance

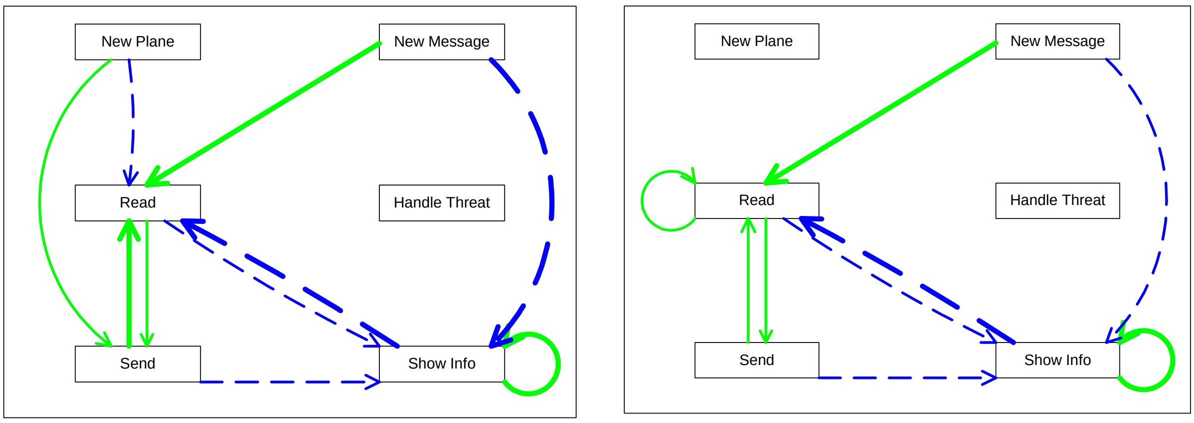
Commander



Specialist A



Specialists B



Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53); **green, bold lines** = enhancing, adj. residual > +10; green, thin lines = enhancing, adj. residual between +3.07 (commanders), respectively +2.98 (specialists) and +10; **blue, bold dashed lines** = inhibiting, adj. residual < -10; blue, thin dashed lines = inhibiting, adj. residual between -10 and -3.07 (commanders), respectively -2.98 (specialists).

Table 127 Adjusted residuals, all roles, lag 3, shift 1.

Commander

	commander	Read Message	Send Message	Show Information	Handle Threat
all	New Plane	**-7.83 -**	**5.80 +**	**6.20 +**	-0.61
	New Message	2.78	-2.91	**-3.87 -**	2.68
	Handle Threat	0.97	-0.03	-0.86	-0.67
	Read Message	2.28	-1.14	-2.12	-0.22
	Send Message	-0.70	**3.29 +**	-0.92	-2.12
	Show Information	**-4.22 -**	-0.68	**9.18 +**	-0.80
		Read Message	Send Message	Show Information	Handle Threat
low	New Plane	**-4.94 -**	**4.32 +**	2.83	-0.28
	New Message	2.42	-2.52	-2.37	1.52
	Handle Threat	0.26	-0.06	0.26	-0.57
	Read Message	1.24	-0.32	-1.98	0.19
	Send Message	-0.66	2.47	-1.28	-1.06
	Show Information	**-3.11 -**	-0.89	**8.40 +**	-1.26
		Read Message	Send Message	Show Information	Handle Threat
high	New Plane	**-6.15 -**	**3.87 +**	**5.85 +**	-0.56
	New Message	1.40	-1.67	-2.98	2.42
	Handle Threat	1.16	0.10	-1.40	-0.57
	Read Message	2.00	-1.28	-1.09	-0.50
	Send Message	-0.35	2.16	-0.05	-1.87
	Show Information	-2.80	-0.03	**4.90 +**	-0.17

Specialist A

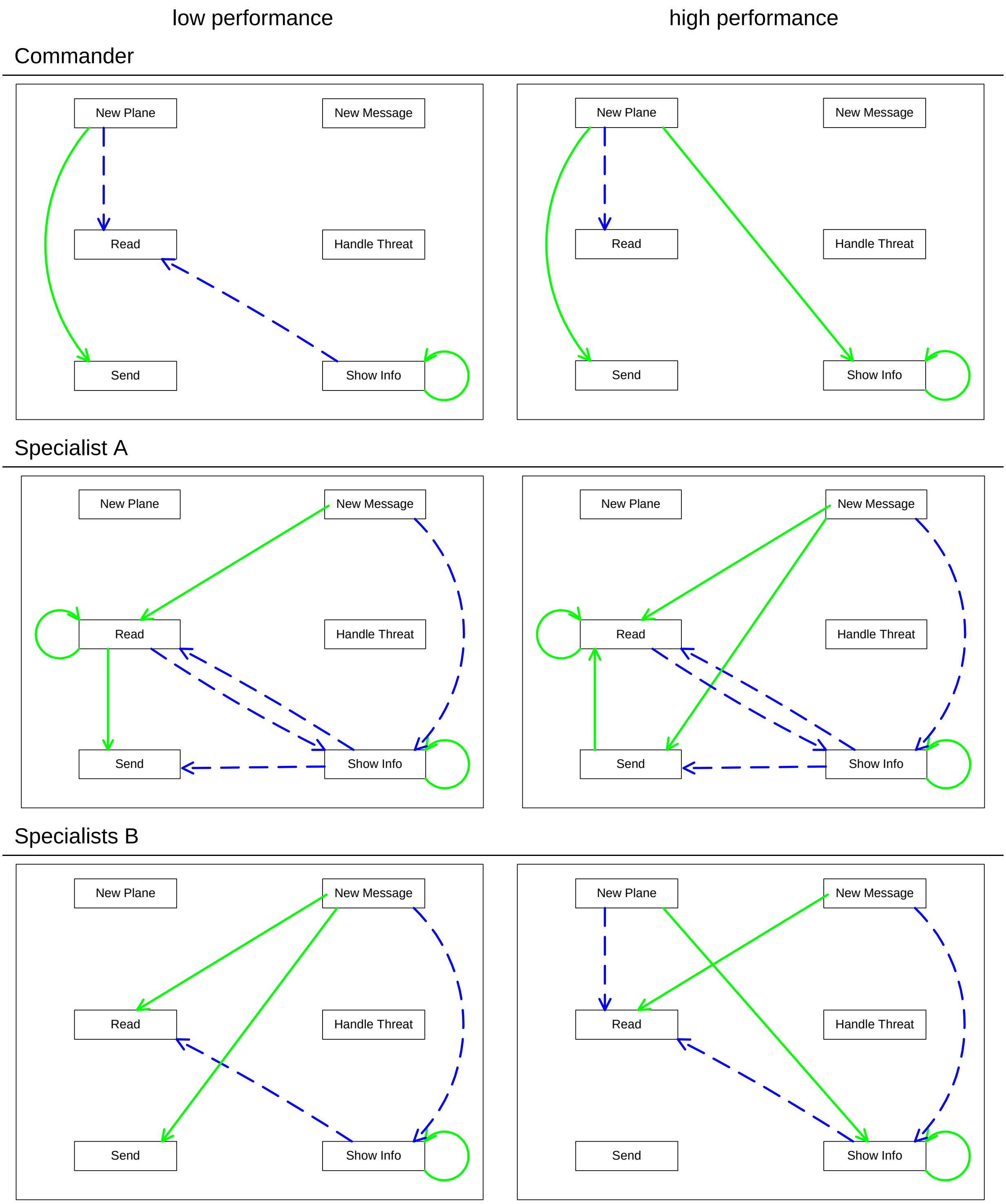
	specialist	Read Message	Send Message	Show Information	Handle Threat
all	New Plane	**-3.62 -**	0.02	2.64	
	New Message	**11.15 +**	**5.38 +**	**-12.41 -**	
	Handle Threat	2.66	-1.26	-0.96	
	Read Message	**6.13 +**	**6.17 +**	**-9.35 -**	
	Send Message	**3.94 +**	0.39	**-3.20 -**	
	Show Information	**-12.90 -**	**-6.51 -**	**14.59 +**	
		Read Message	Send Message	Show Information	Handle Threat
low	New Plane	-2.90	0.67	1.71	.
	New Message	**6.55 +**	2.01	**-6.62 -**	.
	Handle Threat	0.86	-1.54	0.54	.
	Read Message	**3.64 +**	**4.33 +**	**-6.20 -**	.
	Send Message	1.02	-0.17	-0.65	.
	Show Information	**-6.64 -**	**-3.48 -**	**7.84 +**	.
		Read Message	Send Message	Show Information	Handle Threat
high	New Plane	-2.62	-1.22	2.83	.
	New Message	**7.66 +**	**4.79 +**	**-9.26 -**	.
	Handle Threat	2.74	-0.55	-1.49	.
	Read Message	**3.56 +**	2.61	**-4.61 -**	.
	Send Message	**3.29 +**	-0.08	-2.26	.
	Show Information	**-9.06 -**	**-3.50 -**	**9.21 +**	.

Specialist B

	specialist	Read Message	Send Message	Show Information	Handle Threat
all	New Plane	**-3.46 -**	-1.23	**3.57 +**	
	New Message	**7.26 +**	2.70	**-7.58 -**	
	Handle Threat	0.41	-0.07	-0.24	
	Read Message	1.82	2.50	**-3.40 -**	
	Send Message	**3.92 +**	-0.31	-2.64	
	Show Information	**-7.33 -**	-2.51	**7.48 +**	
		Read Message	Send Message	Show Information	Handle Threat
low	New Plane	-1.65	-1.05	2.08	.
	New Message	**5.68 +**	**3.96 +**	**-7.45 -**	.
	Handle Threat	0.23	-1.14	0.78	.
	Read Message	1.55	1.97	-2.77	.
	Send Message	2.61	-0.35	-1.62	.
	Show Information	**-5.86 -**	-2.54	**6.41 +**	.
		Read Message	Send Message	Show Information	Handle Threat
high	New Plane	**-3.26 -**	-0.71	**3.00 +**	.
	New Message	**4.56 +**	-0.47	**-3.02 -**	.
	Handle Threat	0.31	0.99	-1.04	.
	Read Message	1.00	1.44	-1.92	.
	Send Message	2.81	-0.10	-2.02	.
	Show Information	**-4.37 -**	-0.83	**3.93 +**	.

Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53).

Figure 53 Adjusted residuals, all roles, lag 3, shift 1.



Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53); **green, bold lines** = enhancing, adj. residual > +10; green, thin lines = enhancing, adj. residual between +3.07 (commanders), respectively +2.98 (specialists) and +10; **blue, bold dashed lines** = inhibiting, adj. residual < -10; blue, thin dashed lines = inhibiting, adj. residual between -10 and -3.07 (commanders), respectively -2.98 (specialists).

Table 128 Adjusted residuals, all roles, lag 4, shift 1.

Commander

	commander	Read Message	Send Message	Show Information	Handle Threat
all	New Plane	**-5.50 -**	**3.44 +**	**4.89 +**	-0.07
	New Message	2.52	-2.86	-1.62	1.03
	Handle Threat	1.21	-0.10	-1.73	-0.21
	Read Message	-0.48	1.54	-1.93	0.54
	Send Message	0.60	0.86	-1.47	-0.66
	Show Information	-2.10	-0.90	**7.05 +**	-1.83
		Read Message	Send Message	Show Information	Handle Threat
low	New Plane	**-3.84 -**	2.38	**3.37 +**	0.07
	New Message	2.06	-1.74	-2.51	1.18
	Handle Threat	0.14	0.97	-0.71	-0.87
	Read Message	-1.07	1.23	-0.29	0.35
	Send Message	1.93	-1.14	-1.50	-0.28
	Show Information	-2.04	-0.07	**5.92 +**	-1.82
		Read Message	Send Message	Show Information	Handle Threat
high	New Plane	**-3.93 -**	2.51	**3.53 +**	-0.17
	New Message	1.51	-2.33	0.10	0.34
	Handle Threat	1.57	-0.94	-1.74	0.28
	Read Message	0.32	0.88	-2.29	0.52
	Send Message	-1.09	2.42	-0.60	-0.62
	Show Information	-0.93	-1.13	**4.15 +**	-0.95

Specialist A

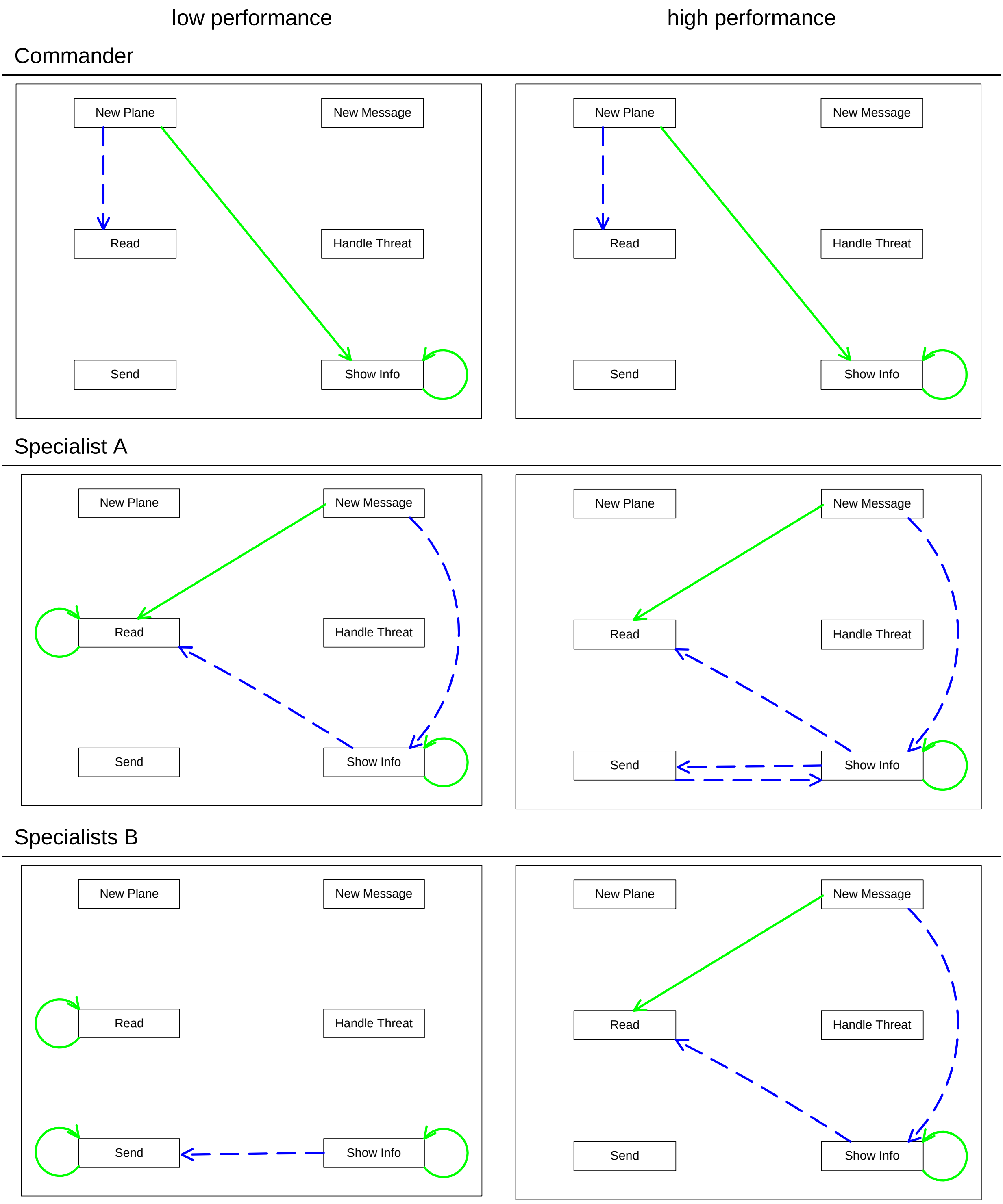
	specialist	Read Message	Send Message	Show Information	Handle Threat
all	New Plane	-1.09	0.65	0.29	
	New Message	**7.94 +**	1.39	**-6.94 -**	
	Handle Threat	0.38	-0.06	-0.23	
	Read Message	**4.96 +**	1.88	**-5.12 -**	
	Send Message	**3.03 +**	**4.27 +**	**-5.59 -**	
	Show Information	**-9.36 -**	**-4.87 -**	**10.72 +**	
		Read Message	Send Message	Show Information	Handle Threat
low	New Plane	-0.28	-0.99	0.99	.
	New Message	**4.10 +**	0.75	**-3.75 -**	.
	Handle Threat	-0.28	-1.11	1.09	.
	Read Message	**3.00 +**	0.44	-2.67	.
	Send Message	0.85	2.25	-2.42	.
	Show Information	**-4.86 -**	-1.48	**4.91 +**	.
		Read Message	Send Message	Show Information	Handle Threat
high	New Plane	-2.05	1.46	0.29	.
	New Message	**5.96 +**	-0.05	**-4.19 -**	.
	Handle Threat	0.65	0.51	-0.87	.
	Read Message	2.45	1.05	-2.58	.
	Send Message	2.37	2.78	**-3.91 -**	.
	Show Information	**-5.92 -**	**-3.08 -**	**6.68 +**	.

Specialist B

	specialist	Read Message	Send Message	Show Information	Handle Threat
all	New Plane	-1.87	0.61	0.89	
	New Message	**4.70 +**	1.49	**-4.72 -**	
	Handle Threat	0.21	0.96	-0.95	
	Read Message	**3.17 +**	0.04	-2.39	
	Send Message	0.26	2.91	-2.57	
	Show Information	**-4.44 -**	**-3.60 -**	**6.25 +**	
		Read Message	Send Message	Show Information	Handle Threat
low	New Plane	-0.90	0.24	0.46	.
	New Message	2.47	0.42	-2.17	.
	Handle Threat	-0.27	1.91	-1.37	.
	Read Message	**3.02 +**	0.35	-2.52	.
	Send Message	-0.56	**3.23 +**	-2.26	.
	Show Information	-2.53	**-3.68 -**	**4.91 +**	.
		Read Message	Send Message	Show Information	Handle Threat
high	New Plane	-1.79	0.59	0.87	.
	New Message	**4.14 +**	1.72	**-4.51 -**	.
	Handle Threat	0.53	-0.36	-0.10	.
	Read Message	1.44	-0.28	-0.85	.
	Send Message	0.90	0.83	-1.35	.
	Show Information	**-3.69 -**	-1.42	**3.92 +**	.

Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53).

Figure 54 Adjusted residuals, all roles, lag 4, shift 1.



Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53); **green, bold lines** = enhancing, adj. residual > +10; green, thin lines = enhancing, adj. residual between +3.07 (commanders), respectively +2.98 (specialists) and +10; **blue, bold dashed lines** = inhibiting, adj. residual < -10; blue, thin dashed lines = inhibiting, adj. residual between -10 and -3.07 (commanders), respectively -2.98 (specialists).

Table 129 Adjusted residuals, all roles lag 5, shift 1.

Commander

	commander	Read Message	Send Message	Show Information	Handle Threat
all	New Plane	-1.66	1.09	1.29	0.09
	New Message	-0.15	0.62	-0.45	-0.12
	Handle Threat	1.60	-0.15	-1.61	-0.82
	Read Message	1.09	-0.97	-1.49	0.80
	Send Message	-1.50	0.63	-0.35	1.79
	Show Information	-0.35	-0.74	**4.90 +**	-2.79
		Read Message	Send Message	Show Information	Handle Threat
low	New Plane	0.20	1.22	-1.34	-0.72
	New Message	0.73	-0.32	-0.47	-0.34
	Handle Threat	-0.43	-0.58	0.54	0.96
	Read Message	-0.83	0.95	-0.87	0.82
	Send Message	0.75	-0.72	-1.19	0.76
	Show Information	-0.57	-0.50	**4.62 +**	-2.43
		Read Message	Send Message	Show Information	Handle Threat
high	New Plane	-2.51	0.31	2.91	0.75
	New Message	-1.01	1.17	-0.10	0.25
	Handle Threat	2.57	0.44	-2.57	-1.95
	Read Message	2.34	-2.38	-1.24	0.33
	Send Message	-2.97	1.66	0.69	1.83
	Show Information	0.10	-0.49	2.44	-1.68

Specialist A

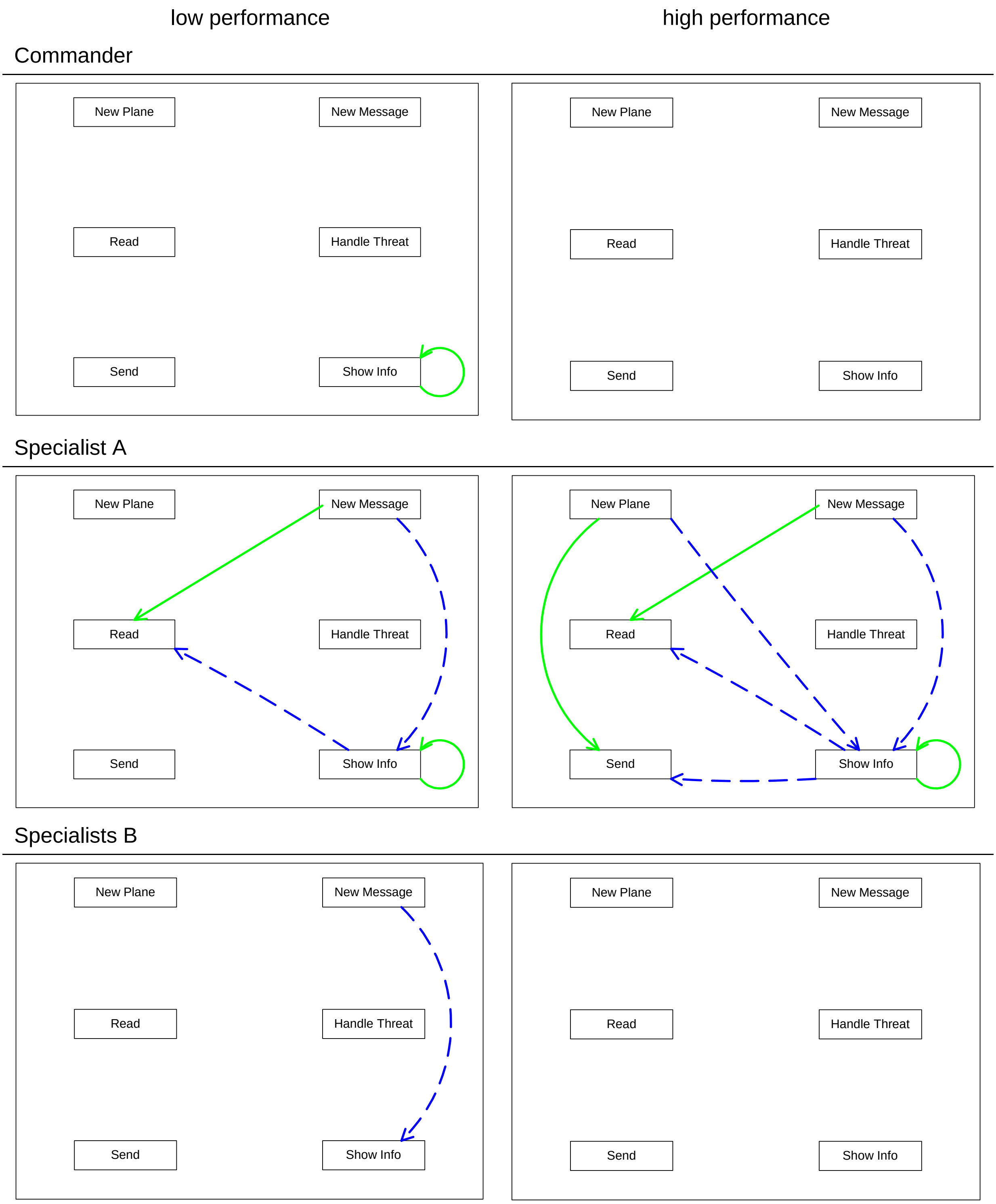
	specialist	Read Message	Send Message	Show Information	Handle Threat
all	New Plane	-1.49	**3.66 +**	-1.77	
	New Message	**8.02 +**	**3.23 +**	**-8.45 -**	
	Handle Threat	1.08	2.54	-2.79	
	Read Message	2.83	0.71	-2.65	
	Send Message	1.20	1.62	-2.16	
	Show Information	**-7.23 -**	**-5.48 -**	**9.63 +**	
		Read Message	Send Message	Show Information	Handle Threat
low	New Plane	-1.88	0.07	1.40	.
	New Message	**5.47 +**	1.13	**-5.11 -**	.
	Handle Threat	-1.10	1.48	-0.31	.
	Read Message	1.10	-0.08	-0.79	.
	Send Message	0.74	0.78	-1.18	.
	Show Information	**-3.63 -**	-1.81	**4.22 +**	.
		Read Message	Send Message	Show Information	Handle Threat
high	New Plane	-0.69	**4.72 +**	**-3.28 -**	.
	New Message	**3.98 +**	2.19	**-4.59 -**	.
	Handle Threat	2.42	1.19	-2.68	.
	Read Message	1.39	-0.08	-0.93	.
	Send Message	-0.14	0.09	0.03	.
	Show Information	**-3.87 -**	**-3.08 -**	**5.22 +**	.

Specialist B

	specialist	Read Message	Send Message	Show Information	Handle Threat
all	New Plane	-1.64	-0.75	1.83	
	New Message	**3.63 +**	1.95	**-4.30 -**	
	Handle Threat	0.78	-0.40	-0.26	
	Read Message	2.45	-0.98	-1.02	
	Send Message	-0.02	1.75	-1.41	
	Show Information	**-3.52 -**	-1.36	**3.74 +**	
		Read Message	Send Message	Show Information	Handle Threat
low	New Plane	-1.58	-1.72	2.59	.
	New Message	2.70	1.52	**-3.25 -**	.
	Handle Threat	0.20	-0.21	0.03	.
	Read Message	2.40	-0.44	-1.42	.
	Send Message	-0.23	1.57	-1.13	.
	Show Information	-2.53	-1.11	2.79	.
		Read Message	Send Message	Show Information	Handle Threat
high	New Plane	-0.72	0.76	-0.07	.
	New Message	2.43	1.10	-2.72	.
	Handle Threat	0.82	-0.26	-0.40	.
	Read Message	1.04	-1.07	0.09	.
	Send Message	0.07	0.92	-0.80	.
	Show Information	-2.32	-0.70	2.31	.

Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53).

Figure 55 Adjusted residuals, all roles, lag 5, shift 1.



Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53); **green, bold lines** = enhancing, adj. residual > +10; green, thin lines = enhancing, adj. residual between +3.07 (commanders), respectively +2.98 (specialists) and +10; **blue, bold dashed lines** = inhibiting, adj. residual < -10; blue, thin dashed lines = inhibiting, adj. residual between -10 and -3.07 (commanders), respectively -2.98 (specialists).

6.5 Adjusted Residuals, all Roles, lag 1 to lag 5, shift 2

Table 130 Adjusted residuals, shift 2, commander, N = 109 teams.

lag 1

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-8.70 -**	-2.37	**18.11 +**	-1.05
New Message	**20.05 +**	**-17.72 -**	**-10.64 -**	-0.64
Handle Threat	**5.05 +**	1.87	0.75	**-9.00 -**
Read Message	**-11.81 -**	**10.97 +**	**-6.37 -**	**10.13 +**
Send Message	**-5.68 -**	**11.78 +**	0.99	**-4.64 -**
Show Information	**-13.75 -**	**5.33 +**	**15.39 +**	0.40

lag 2

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-8.50 -**	**3.17 +**	**9.73 +**	0.35
New Message	2.89	-2.34	**-6.36 -**	**3.50 +**
Handle Threat	-1.42	2.82	-0.16	-0.73
Read Message	1.78	0.31	**-4.80 -**	1.17
Send Message	**5.98 +**	-2.90	**3.11 +**	**-7.49 -**
Show Information	**-7.76 -**	1.65	**10.12 +**	0.55

lag 3

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-5.82 -**	2.06	**6.32 +**	0.72
New Message	**3.31 +**	-1.21	**-3.66 -**	-0.32
Handle Threat	-0.57	-1.46	0.57	1.67
Read Message	2.82	-2.57	-2.90	1.02
Send Message	**-3.60 -**	**5.22 +**	2.67	-2.33
Show Information	-2.30	1.23	**3.84 +**	-1.15

lag 4

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-4.31 -**	2.90	**4.58 +**	-0.65
New Message	2.84	**-4.70 -**	-2.30	2.49
Handle Threat	1.42	-1.53	-1.03	0.39
Read Message	-0.06	1.54	-0.96	-0.63
Send Message	-0.81	2.67	-0.08	-1.40
Show Information	-2.63	2.37	**3.94 +**	-1.84

lag 5

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.43	-0.30	**4.87 +**	-1.58
New Message	1.83	-0.55	-2.68	0.18
Handle Threat	0.84	-0.02	-1.61	0.16
Read Message	-1.11	-0.95	0.27	2.12
Send Message	0.03	1.71	-0.59	-1.18
Show Information	-1.33	1.08	**3.43 +**	-1.90

Table 131 Adjusted residuals, shift 2, specialist A, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	**3.54 +**	**-3.55 -**	0.50	
New Message	**44.30 +**	**-4.29 -**	**-26.71 -**	
Handle Threat	**4.38 +**	1.72	**-4.41 -**	
Read Message	**14.69 +**	**4.90 +**	**-14.07 -**	
Send Message	**7.40 +**	**-8.67 -**	2.09	
Show Information	**-41.44 -**	**4.80 +**	**24.35 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	**3.92 +**	2.21	**-4.49 -**	
New Message	**21.13 +**	2.34	**-16.32 -**	
Handle Threat	1.34	1.42	-2.09	
Read Message	**7.31 +**	**5.16 +**	**-9.24 -**	
Send Message	**15.42 +**	-2.07	**-8.79 -**	
Show Information	**-27.74 -**	**-4.15 -**	**22.31 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.07	0.76	-0.58	
New Message	**13.81 +**	**4.96 +**	**-13.49 -**	
Handle Threat	1.25	-0.98	-0.04	
Read Message	**6.55 +**	**3.30 +**	**-7.18 -**	
Send Message	**5.03 +**	-0.80	-2.76	
Show Information	**-15.14 -**	**-3.71 -**	**13.38 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.37	0.31	-0.50	
New Message	**11.49 +**	**3.84 +**	**-10.99 -**	
Handle Threat	-0.38	2.36	-1.69	
Read Message	**4.32 +**	1.52	**-4.20 -**	
Send Message	0.81	2.37	-2.51	
Show Information	**-9.15 -**	**-5.86 -**	**11.07 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.77	**3.48 +**	**-3.40 -**	
New Message	**9.74 +**	**3.00 +**	**-9.10 -**	
Handle Threat	0.14	2.57	-2.22	
Read Message	**3.99 +**	2.77	**-5.00 -**	
Send Message	2.12	**3.33 +**	**-4.19 -**	
Show Information	**-9.23 -**	**-7.80 -**	**12.72 +**	

Table 132 Adjusted residuals, shift 2, specialist B, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.55	**-3.62 -**	2.57	
New Message	**37.35 +**	**-4.83 -**	**-23.11 -**	
Handle Threat	**3.32 +**	-1.61	-1.09	
Read Message	**12.91 +**	1.52	**-10.61 -**	
Send Message	**6.67 +**	**-8.74 -**	2.34	
Show Information	**-36.34 -**	**9.07 +**	**18.90 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.18	1.92	-1.70	
New Message	**21.31 +**	0.29	**-15.72 -**	
Handle Threat	-2.03	2.43	-0.52	
Read Message	**6.23 +**	2.87	**-6.89 -**	
Send Message	**11.77 +**	1.15	**-9.50 -**	
Show Information	**-23.13 -**	**-4.63 -**	**20.61 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.22	0.26	0.67	
New Message	**13.70 +**	-1.30	**-8.93 -**	
Handle Threat	-0.35	-0.11	0.34	
Read Message	1.47	1.44	-2.25	
Send Message	2.83	1.46	**-3.26 -**	
Show Information	**-10.26 -**	-1.12	**8.40 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.19	-1.28	1.19	
New Message	**5.88 +**	2.41	**-6.27 -**	
Handle Threat	0.21	-0.56	0.31	
Read Message	2.88	-1.32	-1.03	
Send Message	0.38	**4.20 +**	**-3.71 -**	
Show Information	**-5.50 -**	-2.78	**6.29 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.57	1.43	-0.02	
New Message	**8.49 +**	2.00	**-7.84 -**	
Handle Threat	-1.07	0.26	0.57	
Read Message	1.25	0.39	-1.23	
Send Message	-0.44	1.97	-1.29	
Show Information	**-4.31 -**	**-3.41 -**	**5.94 +**	

6.6 Adjusted Residuals, lag 1 to lag 5, shift 3

Table 133 Adjusted residuals, shift 3, commander, N = 109 teams.

lag1

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-12.73 -**	-2.50	**28.78 +**	**-3.32 -**
New Message	**22.25 +**	**-19.07 -**	**-8.83 -**	**-3.29 -**
Handle Threat	**6.40 +**	**4.17 +**	-1.20	**-11.13 -**
Read Message	**-13.44 -**	**11.73 +**	**-8.08 -**	**11.94 +**
Send Message	**-3.33 -**	**7.01 +**	1.01	**-3.22 -**
Show Information	**-15.55 -**	**7.02 +**	**9.31 +**	**5.92 +**

lag 2

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-12.22 -**	**5.16 +**	**8.49 +**	**4.38 +**
New Message	1.47	-2.95	**-5.59 -**	**4.94 +**
Handle Threat	1.18	1.73	0.91	**-3.76 -**
Read Message	-1.02	1.52	-1.35	0.80
Send Message	**10.98 +**	**-5.24 -**	-0.35	**-8.56 -**
Show Information	**-6.05 -**	3.05	**5.82 +**	0.55

lag 3

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-9.35 -**	**3.70 +**	**7.05 +**	**3.24 +**
New Message	2.49	-2.11	-1.71	0.08
Handle Threat	0.09	0.70	-0.98	-0.08
Read Message	**3.77 +**	-2.02	-2.34	-1.18
Send Message	-2.84	2.67	1.07	0.29
Show Information	-1.47	0.90	2.36	-0.69

lag 4

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-5.27 -**	**4.85 +**	**3.18 +**	-0.18
New Message	2.05	-2.86	-0.52	0.47
Handle Threat	-0.15	-1.09	-0.95	1.89
Read Message	0.64	0.39	-2.42	0.56
Send Message	-0.73	2.10	1.10	-1.84
Show Information	0.18	-0.38	2.98	-2.00

lag 5

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.13	-1.50	2.85	-0.45
New Message	0.60	-0.15	-0.42	-0.31
Handle Threat	1.88	-0.54	-2.06	-0.40
Read Message	-0.30	0.81	-1.62	0.76
Send Message	0.11	-1.42	1.29	0.26
Show Information	**-3.11 -**	2.35	2.88	-0.32

Table 134 Adjusted residuals, shift 3, specialist A, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.31	-2.64	2.33	
New Message	**51.86 +**	**-3.43 -**	**-33.41 -**	
Handle Threat	**4.13 +**	0.55	**-3.32 -**	
Read Message	**18.64 +**	1.89	**-14.51 -**	
Send Message	**6.43 +**	**-7.51 -**	1.54	
Show Information	**-45.75 -**	**5.14 +**	**27.78 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.08	**4.06 +**	**-3.32 -**	
New Message	**27.69 +**	-0.23	**-19.11 -**	
Handle Threat	1.53	0.33	-1.33	
Read Message	**6.29 +**	**4.59 +**	**-8.07 -**	
Send Message	**17.39 +**	-1.62	**-10.82 -**	
Show Information	**-30.33 -**	-2.78	**23.37 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.53	0.08	-0.44	
New Message	**17.40 +**	**5.11 +**	**-16.26 -**	
Handle Threat	-0.18	1.92	-1.41	
Read Message	1.65	1.38	-2.26	
Send Message	**7.90 +**	-2.96	**-3.16 -**	
Show Information	**-15.56 -**	-2.76	**13.09 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.63	1.13	-1.34	
New Message	**12.98 +**	2.35	**-10.97 -**	
Handle Threat	-0.16	0.81	-0.53	
Read Message	2.59	0.62	-2.31	
Send Message	**4.73 +**	2.24	**-5.10 -**	
Show Information	**-11.73 -**	**-3.83 -**	**11.27 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.03	**4.79 +**	**-3.10 -**	
New Message	**9.39 +**	**3.03 +**	**-9.00 -**	
Handle Threat	1.12	**3.20 +**	**-3.34 -**	
Read Message	-0.12	**3.55 +**	-2.75	
Send Message	**3.50 +**	0.80	**-3.09 -**	
Show Information	**-7.65 -**	**-7.27 -**	**11.16 +**	

Table 135 Adjusted residuals, shift 3, specialist B, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.73	**-3.93 -**	**3.71 +**	
New Message	**44.25 +**	**-5.71 -**	**-27.17 -**	
Handle Threat	**4.01 +**	0.94	**-3.65 -**	
Read Message	**11.33 +**	2.57	**-10.23 -**	
Send Message	**5.23 +**	**-7.44 -**	2.27	
Show Information	**-38.24 -**	**6.53 +**	**22.18 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-2.23	1.84	0.11	
New Message	**20.77 +**	-1.26	**-13.93 -**	
Handle Threat	0.94	1.07	-1.54	
Read Message	**3.38 +**	2.38	**-4.36 -**	
Send Message	**15.02 +**	-1.49	**-9.61 -**	
Show Information	**-23.49 -**	-0.91	**17.65 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-2.43	-2.80	**4.02 +**	
New Message	**12.70 +**	1.38	**-10.31 -**	
Handle Threat	0.04	-2.11	1.67	
Read Message	0.63	-1.46	0.73	
Send Message	**6.74 +**	0.67	**-5.42 -**	
Show Information	**-11.50 -**	1.67	**6.97 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.10	-1.73	2.20	
New Message	**7.43 +**	2.44	**-7.36 -**	
Handle Threat	0.70	0.29	-0.74	
Read Message	-0.63	0.06	0.40	
Send Message	2.06	-0.84	-0.81	
Show Information	**-5.37 -**	-0.51	**4.30 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.37	**4.07 +**	-2.31	
New Message	**6.65 +**	0.32	**-5.08 -**	
Handle Threat	-0.09	1.90	-1.48	
Read Message	-1.40	1.42	-0.14	
Send Message	-0.06	2.58	-2.04	
Show Information	-2.52	**-5.13 -**	**5.98 +**	

6.7 Adjusted Residuals, lag 1 to lag 5, shift 4

Table 136 Adjusted residuals, shift 4, commander, N = 109 teams.

lag 1

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-10.78 -**	**-3.26 -**	**24.74 +**	-2.09
New Message	**28.20 +**	**-20.53 -**	**-12.92 -**	**-6.31 -**
Handle Threat	2.40	**6.60 +**	-1.92	**-8.18 -**
Read Message	**-16.07 -**	**13.52 +**	**-9.28 -**	**14.84 +**
Send Message	**-4.56 -**	**5.10 +**	2.68	-1.20
Show Information	**-16.88 -**	**4.94 +**	**23.42 +**	-1.22

lag 2

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-11.34 -**	**4.86 +**	**10.87 +**	1.79
New Message	-0.65	-1.21	**-7.82 -**	**7.89 +**
Handle Threat	0.93	0.58	2.06	**-3.33 -**
Read Message	**3.64 +**	-0.43	**-6.30 -**	0.41
Send Message	**9.61 +**	**-6.26 -**	1.91	**-7.72 -**
Show Information	**-9.92 -**	**6.32 +**	**13.71 +**	**-3.62 -**

lag 3

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-8.29 -**	**6.09 +**	**8.61 +**	-1.52
New Message	**5.77 +**	-1.96	**-5.95 -**	-1.21
Handle Threat	-0.06	1.99	-1.77	-0.59
Read Message	0.65	-1.95	-2.48	2.87
Send Message	-2.51	1.28	1.45	0.93
Show Information	**-3.44 -**	-0.88	**10.90 +**	-2.63

lag 4

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-4.86 -**	2.52	**5.13 +**	0.12
New Message	0.47	-0.29	**-3.21 -**	2.00
Handle Threat	1.94	-1.27	-1.63	-0.10
Read Message	0.80	-0.98	-1.06	0.69
Send Message	0.00	2.42	-0.19	-2.22
Show Information	-1.50	-0.85	**6.89 +**	-2.22

lag 5

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.69	0.41	**3.14 +**	-0.47
New Message	-0.69	1.29	-1.08	0.43
Handle Threat	0.00	0.50	-0.53	-0.10
Read Message	2.85	-2.51	-1.75	0.01
Send Message	-1.71	2.67	-1.25	0.52
Show Information	-0.88	-1.80	**5.40 +**	-1.00

Table 137 Adjusted residuals, shift 4, specialist A, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.44	-2.40	2.88	
New Message	**57.87 +**	**-3.92 -**	**-38.86 -**	
Handle Threat	**4.44 +**	1.40	**-4.29 -**	
Read Message	**15.45 +**	**8.26 +**	**-17.51 -**	
Send Message	**5.51 +**	**-5.95 -**	0.58	
Show Information	**-47.89 -**	0.32	**34.40 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	1.18	1.30	-1.85	
New Message	**28.42 +**	**3.24 +**	**-23.04 -**	
Handle Threat	2.12	0.58	-1.98	
Read Message	**6.88 +**	**6.33 +**	**-9.84 -**	
Send Message	**19.39 +**	**-3.49 -**	**-11.34 -**	
Show Information	**-32.57 -**	**-3.96 -**	**26.59 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.34	1.69	-1.05	
New Message	**15.98 +**	**3.89 +**	**-14.56 -**	
Handle Threat	0.12	0.79	-0.70	
Read Message	**3.14 +**	**3.10 +**	**-4.65 -**	
Send Message	**9.82 +**	-0.89	**-6.43 -**	
Show Information	**-16.59 -**	**-4.20 -**	**15.23 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	1.48	0.38	-1.36	
New Message	**9.77 +**	**3.54 +**	**-9.79 -**	
Handle Threat	-0.71	0.36	0.23	
Read Message	2.80	2.13	**-3.67 -**	
Send Message	**5.86 +**	2.09	**-5.84 -**	
Show Information	**-10.63 -**	**-4.72 -**	**11.32 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	2.03	**5.62 +**	**-5.77 -**	
New Message	**6.21 +**	1.71	**-5.81 -**	
Handle Threat	-0.42	2.07	-1.28	
Read Message	2.47	**3.59 +**	**-4.53 -**	
Send Message	0.30	0.64	-0.71	
Show Information	**-5.37 -**	**-5.87 -**	**8.39 +**	

Table 138 Adjusted residuals, shift 4, specialist B, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.11	**-3.90 -**	**3.17 +**	
New Message	**47.57 +**	**-3.85 -**	**-31.75 -**	
Handle Threat	2.98	1.05	**-3.01 -**	
Read Message	**10.51 +**	**8.11 +**	**-14.11 -**	
Send Message	**6.35 +**	**-6.85 -**	0.77	
Show Information	**-40.46 -**	1.57	**28.35 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.57	1.23	-0.56	
New Message	**24.17 +**	1.03	**-18.53 -**	
Handle Threat	2.49	0.53	-2.24	
Read Message	**4.69 +**	**3.46 +**	**-6.18 -**	
Send Message	**17.39 +**	-1.55	**-11.52 -**	
Show Information	**-29.07 -**	-2.29	**23.12 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.09	-1.84	2.26	
New Message	**13.39 +**	**3.56 +**	**-12.64 -**	
Handle Threat	1.65	-1.51	-0.02	
Read Message	1.17	**3.79 +**	**-3.86 -**	
Send Message	**6.77 +**	-2.49	**-3.00 -**	
Show Information	**-13.43 -**	-1.44	**10.99 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.35	-0.96	1.01	
New Message	**9.06 +**	2.43	**-8.58 -**	
Handle Threat	-1.22	1.76	-0.50	
Read Message	2.17	2.22	**-3.35 -**	
Send Message	2.08	2.28	**-3.33 -**	
Show Information	**-7.22 -**	**-4.86 -**	**9.14 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.69	**3.03 +**	-1.89	
New Message	**6.50 +**	**4.05 +**	**-7.98 -**	
Handle Threat	0.44	0.63	-0.82	
Read Message	1.27	2.29	-2.75	
Send Message	-0.41	**4.43 +**	**-3.21 -**	
Show Information	**-4.30 -**	**-7.73 -**	**9.27 +**	

6.8 Adjusted Residuals, all Roles, lag 1 to lag 5, shift 5

Table 139 Adjusted residuals, shift 5, commander, N = 109 teams.

lag 1

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-12.31 -**	-2.86	**26.62 +**	-2.73
New Message	**25.33 +**	**-18.15 -**	**-13.72 -**	**-5.39 -**
Handle Threat	**3.19 +**	**6.96 +**	1.34	**-10.79 -**
Read Message	**-14.06 -**	**9.15 +**	**-6.08 -**	**14.19 +**
Send Message	-2.39	**6.47 +**	0.93	**-3.22 -**
Show Information	**-17.16 -**	**7.17 +**	**12.47 +**	**5.55 +**

lag 2

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-11.30 -**	2.63	**8.96 +**	**5.00 +**
New Message	1.10	-2.91	**-7.34 -**	**6.50 +**
Handle Threat	2.11	1.43	0.76	**-4.34 -**
Read Message	2.47	-1.02	-2.37	-0.42
Send Message	**7.80 +**	-2.99	2.31	**-8.72 -**
Show Information	**-8.78 -**	**6.79 +**	**7.27 +**	-0.33

lag 3

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-10.97 -**	**8.07 +**	**7.87 +**	0.93
New Message	**3.85 +**	**-3.87 -**	-2.88	0.62
Handle Threat	1.24	2.23	-3.07	-1.15
Read Message	2.32	**-3.46 -**	-0.19	0.20
Send Message	-2.49	1.23	0.81	1.43
Show Information	-1.83	**3.19 +**	2.63	-2.34

lag 4

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-3.58 -**	**3.74 +**	0.85	0.66
New Message	1.78	-2.02	-1.78	0.78
Handle Threat	0.73	-0.42	-0.56	-0.15
Read Message	-1.13	-0.66	0.48	1.59
Send Message	0.14	1.08	1.80	-2.36
Show Information	0.50	1.44	0.47	-2.14

lag 5

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	-2.88	**4.42 +**	1.03	-0.87
New Message	0.34	-1.98	0.23	1.05
Handle Threat	2.88	-1.00	-2.52	-0.89
Read Message	0.24	-0.50	-0.63	0.57
Send Message	-1.15	0.94	0.34	0.39
Show Information	-1.41	1.48	3.04	-1.67

Table 140 Adjusted residuals, shift 5, specialist A, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	2.52	**-3.89 -**	1.31	
New Message	**62.20 +**	-2.55	**-41.10 -**	
Handle Threat	**4.84 +**	0.83	**-4.01 -**	
Read Message	**16.19 +**	**9.05 +**	**-18.33 -**	
Send Message	**5.41 +**	**-5.85 -**	0.85	
Show Information	**-49.26 -**	0.12	**34.03 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	2.58	2.31	**-3.60 -**	
New Message	**31.55 +**	2.03	**-23.37 -**	
Handle Threat	2.97	2.49	**-4.02 -**	
Read Message	**10.31 +**	**3.34 +**	**-9.75 -**	
Send Message	**18.19 +**	**-4.00 -**	**-9.40 -**	
Show Information	**-35.04 -**	-2.52	**26.18 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.88	2.33	-2.44	
New Message	**20.10 +**	**3.03 +**	**-16.26 -**	
Handle Threat	1.27	2.27	-2.66	
Read Message	**4.93 +**	2.81	**-5.61 -**	
Send Message	**10.47 +**	-1.68	**-5.90 -**	
Show Information	**-20.48 -**	**-3.95 -**	**17.25 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	1.03	-0.08	-0.64	
New Message	**15.44 +**	**5.26 +**	**-14.79 -**	
Handle Threat	1.84	1.80	-2.68	
Read Message	**4.81 +**	0.94	**-4.06 -**	
Send Message	**3.48 +**	-0.55	-1.97	
Show Information	**-14.06 -**	**-3.87 -**	**12.74 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	1.80	**5.40 +**	**-5.50 -**	
New Message	**11.75 +**	2.64	**-10.19 -**	
Handle Threat	2.07	**3.02 +**	**-3.80 -**	
Read Message	1.89	**4.16 +**	**-4.58 -**	
Send Message	1.43	**3.28 +**	**-3.57 -**	
Show Information	**-9.69 -**	**-8.76 -**	**13.58 +**	

Table 141 Adjusted residuals, shift 5, specialist B, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.93	**-4.25 -**	2.80	
New Message	**46.89 +**	**-5.34 -**	**-28.37 -**	
Handle Threat	1.83	1.80	-2.74	
Read Message	**18.34 +**	**3.42 +**	**-15.57 -**	
Send Message	**4.62 +**	**-6.59 -**	2.13	
Show Information	**-41.00 -**	**4.86 +**	**24.66 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	1.86	-0.01	-1.29	
New Message	**23.35 +**	1.08	**-17.16 -**	
Handle Threat	0.73	0.78	-1.14	
Read Message	**7.03 +**	2.21	**-6.70 -**	
Send Message	**14.81 +**	-1.58	**-9.04 -**	
Show Information	**-27.16 -**	-1.24	**19.95 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.22	-1.58	2.14	
New Message	**16.59 +**	2.42	**-13.52 -**	
Handle Threat	-0.73	0.81	-0.15	
Read Message	2.86	0.53	-2.42	
Send Message	**5.02 +**	0.26	**-3.70 -**	
Show Information	**-13.21 -**	-1.75	**10.63 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.11	-1.01	1.59	
New Message	**10.22 +**	2.31	**-8.99 -**	
Handle Threat	1.10	**3.07 +**	**-3.26 -**	
Read Message	1.57	0.02	-1.11	
Send Message	2.37	2.21	**-3.45 -**	
Show Information	**-8.27 -**	**-4.13 -**	**9.12 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.78	**3.26 +**	-2.11	
New Message	**7.98 +**	2.65	**-7.71 -**	
Handle Threat	0.45	1.97	-1.91	
Read Message	**4.15 +**	2.33	**-4.79 -**	
Send Message	1.31	**5.35 +**	**-5.27 -**	
Show Information	**-7.49 -**	**-8.35 -**	**12.01 +**	

6.9 Adjusted Residuals, all Roles, lag 1 to lag 5, shift 6

Table 142 Adjusted residuals, shift 6, commander, N = 109 teams.

lag 1

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-12.70 -**	**-5.32 -**	**32.11 +**	**-3.59 -**
New Message	**29.11 +**	**-22.19 -**	**-12.84 -**	**-5.64 -**
Handle Threat	**3.16 +**	**11.19 +**	**-3.25 -**	**-11.91 -**
Read Message	**-15.51 -**	**10.74 +**	**-6.59 -**	**14.19 +**
Send Message	**-5.62 -**	**8.64 +**	1.29	-2.08
Show Information	**-18.51 -**	**5.44 +**	**14.32 +**	**7.04 +**

lag 2

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-11.94 -**	1.09	**9.38 +**	**6.98 +**
New Message	0.27	-2.63	**-6.33 -**	**6.68 +**
Handle Threat	1.04	3.01	-0.94	**-3.43 -**
Read Message	2.49	-0.28	-3.07	-0.60
Send Message	**11.98 +**	**-5.95 -**	1.25	**-10.15 -**
Show Information	**-10.96 -**	**7.81 +**	**9.23 +**	-0.41

lag 3

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-11.45 -**	**10.11 +**	**4.37 +**	1.61
New Message	2.02	-2.70	**-3.42 -**	2.46
Handle Threat	1.40	0.87	-0.57	-2.13
Read Message	**4.60 +**	**-4.29 -**	-3.06	0.50
Send Message	-2.26	1.37	1.07	0.77
Show Information	-2.52	2.33	**8.37 +**	**-5.03 -**

lag 4

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-5.29 -**	**3.43 +**	2.28	1.77
New Message	2.23	-1.86	-2.64	0.84
Handle Threat	1.98	-0.41	0.29	-2.29
Read Message	-0.35	0.99	-2.97	1.64
Send Message	-1.30	0.08	1.24	0.66
Show Information	-0.56	-0.48	**7.06 +**	**-3.90 -**

lag 5

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.17	2.62	-0.83	-0.36
New Message	0.86	0.12	-1.99	0.24
Handle Threat	1.83	-0.58	-1.24	-0.85
Read Message	1.11	-0.86	-1.35	0.38
Send Message	-1.98	1.19	0.79	0.80
Show Information	-2.77	-1.31	**7.58 +**	-0.76

Table 143 Adjusted residuals, shift 6, specialist A, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	1.30	-1.59	0.32	
New Message	**63.17 +**	-1.16	**-43.41 -**	
Handle Threat	**6.46 +**	1.90	**-6.00 -**	
Read Message	**20.94 +**	**7.81 +**	**-20.72 -**	
Send Message	**7.63 +**	**-4.20 -**	-2.11	
Show Information	**-54.13 -**	-2.36	**39.79 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.84	**3.40 +**	**-3.22 -**	
New Message	**36.59 +**	**3.70 +**	**-28.50 -**	
Handle Threat	2.51	2.16	**-3.43 -**	
Read Message	**7.15 +**	**7.81 +**	**-11.05 -**	
Send Message	**21.88 +**	-2.53	**-13.37 -**	
Show Information	**-37.34 -**	**-6.76 -**	**31.39 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.97	2.40	-2.54	
New Message	**20.62 +**	**6.35 +**	**-19.38 -**	
Handle Threat	0.67	2.83	-2.65	
Read Message	**4.12 +**	0.13	**-2.99 -**	
Send Message	**14.52 +**	-0.38	**-9.90 -**	
Show Information	**-22.15 -**	**-5.37 -**	**19.69 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	1.55	0.52	-1.49	
New Message	**12.24 +**	**3.40 +**	**-11.22 -**	
Handle Threat	0.90	2.22	-2.34	
Read Message	1.64	1.76	-2.51	
Send Message	**6.64 +**	**4.53 +**	**-8.16 -**	
Show Information	**-12.11 -**	**-6.71 -**	**13.68 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	1.29	**7.07 +**	**-6.36 -**	
New Message	**9.13 +**	2.31	**-8.20 -**	
Handle Threat	1.37	**4.29 +**	**-4.27 -**	
Read Message	0.88	**4.21 +**	**-3.86 -**	
Send Message	2.47	**3.61 +**	**-4.52 -**	
Show Information	**-7.84 -**	**-9.80 -**	**13.07 +**	

Table 144 Adjusted residuals, shift 6, specialist B, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.22	-2.69	1.97	
New Message	**46.20 +**	**-3.71 -**	**-30.37 -**	
Handle Threat	**3.58 +**	1.85	**-4.04 -**	
Read Message	**16.20 +**	**6.71 +**	**-16.98 -**	
Send Message	**6.26 +**	**-7.80 -**	1.65	
Show Information	**-41.77 -**	1.90	**28.60 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.53	2.14	-1.31	
New Message	**25.14 +**	**3.59 +**	**-20.98 -**	
Handle Threat	0.05	0.54	-0.46	
Read Message	**7.58 +**	**5.12 +**	**-9.52 -**	
Send Message	**14.88 +**	**-3.70 -**	**-7.82 -**	
Show Information	**-27.61 -**	**-3.63 -**	**22.80 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.26	-0.96	0.95	
New Message	**16.29 +**	**4.23 +**	**-15.13 -**	
Handle Threat	0.66	-1.12	0.40	
Read Message	**4.53 +**	-0.18	**-3.13 -**	
Send Message	**5.70 +**	-0.40	**-3.81 -**	
Show Information	**-15.62 -**	-1.12	**12.18 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-2.24	-1.56	2.85	
New Message	**11.95 +**	2.65	**-10.75 -**	
Handle Threat	-0.62	1.36	-0.62	
Read Message	2.92	-0.50	-1.72	
Send Message	**3.50 +**	2.75	**-4.71 -**	
Show Information	**-9.59 -**	**-3.25 -**	**9.51 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.15	**4.11 +**	**-3.35 -**	
New Message	**9.59 +**	1.66	**-8.26 -**	
Handle Threat	0.66	2.43	-2.39	
Read Message	1.39	**3.18 +**	**-3.52 -**	
Send Message	1.38	2.94	**-3.32 -**	
Show Information	**-7.46 -**	**-7.21 -**	**11.09 +**	

6.10 Adjusted Residuals, all Roles, lag 1 to lag 5, shift 8

Table 145 Adjusted residuals, shift 8, commander, N = 109 teams.

lag 1

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-14.52 -**	**-5.40 -**	**28.90 +**	-1.05
New Message	**25.53 +**	**-16.78 -**	**-14.33 -**	**-5.78 -**
Handle Threat	**5.52 +**	**9.03 +**	1.88	**-14.94 -**
Read Message	**-12.51 -**	**5.58 +**	**-6.70 -**	**15.45 +**
Send Message	**-3.18 -**	**8.08 +**	-0.24	-2.38
Show Information	**-18.92 -**	**7.87 +**	**9.65 +**	**8.58 +**

lag 2

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-15.99 -**	2.56	**11.99 +**	**7.78 +**
New Message	**3.70 +**	**-4.55 -**	**-8.94 -**	**5.86 +**
Handle Threat	2.59	1.40	0.67	**-4.61 -**
Read Message	1.97	-1.14	-2.99	0.81
Send Message	**10.28 +**	**-5.39 -**	1.55	**-8.95 -**
Show Information	**-10.02 -**	**11.28 +**	**8.29 +**	**-3.24 -**

lag 3

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-12.67 -**	**11.90 +**	**5.11 +**	1.81
New Message	**3.60 +**	-2.94	**-4.26 -**	1.23
Handle Threat	-0.24	0.95	-0.61	-0.01
Read Message	**4.78 +**	**-4.26 -**	-1.63	-1.08
Send Message	-0.65	-0.17	0.94	0.20
Show Information	**-3.88 -**	2.25	**6.33 +**	-1.89

lag 4

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-6.46 -**	**7.16 +**	**3.61 +**	-0.58
New Message	**4.22 +**	**-3.66 -**	**-3.75 -**	0.63
Handle Threat	0.98	-1.39	0.21	-0.24
Read Message	-1.57	0.89	-0.09	1.23
Send Message	-0.06	1.81	1.04	-2.09
Show Information	-0.94	-0.66	2.57	-0.30

lag 5

commander	Read Message	Send Message	Show Information	Handle Threat
New Plane	**-3.31 -**	1.04	**3.34 +**	0.62
New Message	0.07	0.83	**-3.23 -**	1.68
Handle Threat	-0.28	1.28	1.04	-1.41
Read Message	1.56	-2.27	0.02	-0.12
Send Message	-0.14	0.59	-0.11	-0.20
Show Information	0.20	-0.58	1.77	-1.11

Table 146 Adjusted residuals, shift 8, specialist A, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.34	-1.33	0.84	
New Message	**58.05 +**	-2.61	**-36.66 -**	
Handle Threat	**5.02 +**	0.57	**-3.81 -**	
Read Message	**21.31 +**	**5.57 +**	**-18.71 -**	
Send Message	**5.63 +**	**-6.13 -**	1.18	
Show Information	**-47.38 -**	1.46	**30.45 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	**4.13 +**	**5.42 +**	**-7.12 -**	
New Message	**32.22 +**	1.05	**-22.32 -**	
Handle Threat	0.71	2.53	-2.51	
Read Message	**8.29 +**	2.80	**-7.78 -**	
Send Message	**22.43 +**	**-4.72 -**	**-11.14 -**	
Show Information	**-35.07 -**	-2.34	**25.25 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	2.36	2.33	**-3.45 -**	
New Message	**17.95 +**	**4.01 +**	**-15.21 -**	
Handle Threat	-0.38	0.30	0.01	
Read Message	**3.61 +**	2.44	**-4.37 -**	
Send Message	**12.97 +**	-0.94	**-7.90 -**	
Show Information	**-19.14 -**	**-3.54 -**	**15.62 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	0.62	1.09	-1.29	
New Message	**11.13 +**	**5.50 +**	**-11.85 -**	
Handle Threat	-0.53	**3.10 +**	-2.15	
Read Message	**2.99 +**	0.33	-2.25	
Send Message	**5.46 +**	**3.09 +**	**-6.14 -**	
Show Information	**-10.23 -**	**-6.93 -**	**12.41 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	1.13	2.27	-2.58	
New Message	**8.20 +**	**4.12 +**	**-8.79 -**	
Handle Threat	0.51	**3.27 +**	-2.98	
Read Message	-0.38	**3.08 +**	-2.23	
Send Message	0.65	2.41	-2.38	
Show Information	**-4.92 -**	**-7.66 -**	**9.45 +**	

Table 147 Adjusted residuals, shift 8, specialist B, N = 109 teams.

lag 1

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.07	**-4.05 -**	**4.05 +**	
New Message	**46.95 +**	**-4.50 -**	**-28.67 -**	
Handle Threat	0.82	-1.62	0.76	
Read Message	**17.93 +**	**3.26 +**	**-15.02 -**	
Send Message	**4.97 +**	**-7.50 -**	2.70	
Show Information	**-38.85 -**	**6.95 +**	**21.09 +**	

lag 2

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-2.15	2.76	-0.77	
New Message	**21.60 +**	-1.42	**-13.75 -**	
Handle Threat	-0.03	-0.74	0.62	
Read Message	**10.01 +**	2.27	**-8.77 -**	
Send Message	**14.46 +**	-2.62	**-7.84 -**	
Show Information	**-25.21 -**	0.76	**16.79 +**	

lag 3

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.72	0.92	0.44	
New Message	**16.25 +**	2.80	**-13.53 -**	
Handle Threat	-1.20	-2.59	2.94	
Read Message	**6.82 +**	-2.43	-2.74	
Send Message	**3.78 +**	-1.45	-1.43	
Show Information	**-13.54 -**	2.01	**7.74 +**	

lag 4

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-1.30	-1.82	2.39	
New Message	**9.90 +**	1.76	**-8.30 -**	
Handle Threat	0.05	1.45	-1.21	
Read Message	2.66	-2.79	0.43	
Send Message	1.33	0.38	-1.23	
Show Information	**-7.20 -**		**4.99 +**	

lag 5

specialist	Read Message	Send Message	Show Information	Handle Threat
New Plane	-0.13	2.40	-1.87	
New Message	**9.77 +**	1.17	**-7.74 -**	
Handle Threat	-0.23	**4.04 +**	**-3.13 -**	
Read Message	**3.96 +**	-0.03	-2.72	
Send Message	-1.25	2.23	-0.95	
Show Information	**-6.37 -**	**-5.33 -**	**8.77 +**	

6.11 Predicting Performance: Lag Sequential Analyses

Table 148 Results of multiple regression, predicting performance shift 1 with *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.062	.054	.062	7.117	1	107	.009	7.117	1	107	.009
2	.100	.083	.038	4.431	1	106	.038	5.888	2	106	.004
3	.145	.120	.045	5.508	1	105	.021	5.928	3	105	. 001
4	.175	.143	.030	3.740	1	104	.056	5.497	4	104	. 000
5	.208	.169	.033	4.289	1	103	.041	5.395	5	103	. 000
6	.240	.195	.032	4.356	1	102	.039	5.368	6	102	. 000
7	.266	.216	.026	3.632	1	101	.060	5.239	7	101	.000
8	.288	.231	.022	3.033	1	100	.085	5.055	8	100	.000
9	.315	.252	.027	3.838	1	99	.053	5.048	9	99	.000
10	.344	.277	.029	4.325	1	98	.040	5.128	10	98	.000
11	.363	.291	.020	3.043	1	97	.084	5.036	11	97	.000
12	.384	.306	.020	3.125	1	96	.080	4.978	12	96	.000
13	.401	.319	.017	2.723	1	95	.102	4.887	13	95	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Read Message -> Show Information, C 14	.346	4.138	.000
(2) Send Message -> Show Information, spec B 57	-.188	-2.229	.028
(3)New Message -> Read Message, spec B 28	-.343	-3.805	.000
(4) Show Information -> Read Message, spec A 40	-.262	-2.968	.004
(5) New Message -> Show Information, spec A 48	-.174	-2.006	.048
(6) Send Message -> Send Message, C 18	.220	2.266	.026
(7) Send Message -> Read Message, C 17	.192	2.094	.039
(8) New Message -> Show Information, C 7	-.235	-2.731	.008
(9) Read Message -> Show Information, C 15	.256	2.621	.010
(10) Handle Threat -> Handle Threat, C 12	.234	2.368	.020
(11) New Plane -> Read Message, spec B 43	.188	2.229	.028
(12) New Plane -> Show Information, C 3	.173	1.921	.058
(13) New Plane -> Read Message, spec A 25	.136	1.650	.102

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 149 Results of multiple regression, predicting performance shift 1 with preceding performance, *input*, *summary level process* variables, and *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.076	.067	.076	8.812	1	107	.004	8.812	1	107	.004
2	.112	.095	.036	4.242	1	106	.042	6.660	2	106	.002
3	.130	.105	.018	2.204	1	105	.141	5.225	3	105	. 002
4	.201	.170	.071	9.285	1	104	.003	6.549	4	104	. 000
5	.259	.223	.058	7.993	1	103	.006	7.190	5	103	. 000
6	.289	.248	.031	4.411	1	102	.038	6.926	6	102	. 000
7	.304	.256	.015	2.115	1	101	.149	6.303	7	101	.000
8	.321	.267	.017	2.509	1	100	.116	5.921	8	100	.000
9	.364	.306	.043	6.683	1	99	.011	6.296	9	99	.000
10	.398	.337	.034	5.596	1	98	.020	6.489	10	98	.000
11	.427	.362	.029	4.844	1	97	.030	6.571	11	97	.000
12	.456	.388	.029	5.092	1	96	.026	6.702	12	96	.000
13	.479	.408	.023	4.234	1	95	.042	6.720	13	95	.000
14	.495	.420	.016	3.004	1	94	.086	6.586	14	94	.000
15	.509	.430	.014	2.588	1	93	.111	6.424	15	93	.000
16	.522	.439	.013	2.530	1	92	.115	6.279	16	92	.000
17	.533	.446	.011	2.164	1	91	.145	6.112	17	91	.000
18	.546	.456	.013	2.656	1	90	.107	6.025	18	90	.000

Predictors in trimmed model	Beta	t	Sig.
(1) education, specialist A	.228	2.945	.004
(2) education, commander	-.151	-1.847	.068
(3) computer expertise, commander	.149	1.821	.072
(4) duration Send Message, specialist A	-.298	-3.776	.000
(5) number of Handle Threat, commander	.247	3.102	.003
(6) duration of Send Message, commander	-.170	-2.085	.040
(7) number of Read Message, specialist B	.073	.872	.385
(8) duration or Read Message, specialist A	-.083	-.974	.333
(9) New Message -> Read message, spec A 28	-.301	-3.763	.000
(10) Read Message -> Send Message, spec C 14	.229	2.959	.004
(11) New Plane -> Read Message, spec A 25	.173	2.336	.022
(12) Read Message -> Send Message, spec B 53	.149	1.895	.061
(13) Send Message -> Show Info, spec B 57	-.160	-2.087	.040
(14) New Message -> Handle Threat, C 8	-.091	-1.207	.230
(15) Send Message -> Handle Threat, C 20	-.152	-1.983	.050
(16) Read Message -> Read Message, spec A 34	-.166	-1.994	.049
(17) Show Info -> Read Message, spec A 40	-.150	-1.769	.080
(18) Read Message -> Read Message, spec B 52	.143	1.630	.107

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 150 Results of multiple regression, predicting performance shift 2 with *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.090	.081	.090	10.531	1	107	.002	10.531	1	107	.002
2	.134	.118	.045	5.493	1	106	.021	8.233	2	106	.000
3	.167	.143	.033	4.133	1	105	.045	7.029	3	105	. 000
4	.202	.171	.035	4.507	1	104	.036	6.547	4	104	. 000
5	.221	.183	.019	2.533	1	103	.115	5.844	5	103	. 000
6	.243	.199	.022	3.023	1	102	.085	5.469	6	102	. 000
7	.264	.213	.020	2.774	1	101	.099	5.166	7	101	.000
8	.284	.227	.020	2.848	1	100	.095	4.959	8	100	.000
9	.304	.241	.020	2.902	1	99	.092	4.814	9	99	.000
10	.320	.251	.016	2.311	1	98	.132	4.621	10	98	.000
11	.338	.263	.017	2.518	1	97	.116	4.495	11	97	.000
12	.353	.273	.016	2.338	1	96	.130	4.372	12	96	.000
13	.372	.286	.019	2.856	1	95	.094	4.333	13	95	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Show Information -> Read Message, C 81	-.263	-3.078	.003
(2) Handle Threat – Read Message, spec A 91	-.273	-3.211	.002
(3) Send Message -> Read Message, spec B 115	-.112	-1.140	.257
(4) Send Message -> Send Message, spec A 98	-.094	-1.042	.300
(5) New Message -> Show Information, spec B 108	-.178	-2.039	.044
(6) New Plane -> Show Information, C 63	.254	2.953	.004
(7) Handle Threat -> Handle Threat, C 72	-.133	-1.557	.123
(8) Show Information -> Send Message, C 82	-.155	-1.771	.080
(9) Show Info -> Send Message, spec B 119	-.237	-2.395	.019
(10) Read Message -> Read Message, spec A 94	.151	1.818	.072
(11) New Plane -> Handle Threat, C 64	.134	1.506	.136
(12) Send Message -> Show Information, C 79	.161	1.860	.066
(13) Send Message -> Show Info, spec B 117	.181	1.690	.094

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 151 Results of multiple regression, predicting performance shift 2 with preceding performance, *input*, *summary-level process* variables, and *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.212	.205	.212	28.807	1	107	.000	28.807	1	107	.004
2	.236	.222	.024	3.303	1	106	.072	16.368	2	106	.002
3	.299	.279	.063	9.499	1	105	.003	14.951	3	105	. 002
4	.320	.294	.021	3.178	1	104	.078	12.240	4	104	. 000
5	.337	.305	.017	2.664	1	103	.106	10.482	5	103	. 000
6	.368	.331	.031	5.045	1	102	.027	9.919	6	102	. 000
7	.404	.363	.036	6.099	1	101	.015	9.788	7	101	.000
8	.436	.391	.031	5.548	1	100	.020	9.653	8	100	.000
9	.455	.406	.020	3.574	1	99	.062	9.198	9	99	.000
10	.473	.419	.017	3.244	1	98	.075	8.790	10	98	.000
11	.494	.436	.021	3.957	1	97	.050	8.592	11	97	.000
12	.519	.459	.026	5.158	1	96	.025	8.644	12	96	.000
13	.545	.483	.026	5.449	1	95	.022	8.768	13	95	.000
14	.563	.498	.018	3.833	1	94	.053	8.658	14	94	.000
15	.576	.507	.012	2.733	1	93	.102	8.412	15	93	.000

Predictors in trimmed model	Beta	t	Sig.
(1) performance shift 1	.369	5.216	.000
(2) gender, commander	.064	.864	.390
(3) number of Handle Threat, commander	.338	4.025	.000
(4) number of Read Message, specialist B	-.216	-2.897	.005
(5) number of Show Information, commander	.064	.752	.454
(6) New Message -> Read Message, C 65	.301	2.836	.006
(7) New Message -> Send Message, C 66	.241	2.478	.015
(8) Read Message -> Handle Threat, C 76	-.193	-2.411	.018
(9) Handle Threat -> Read Message, spec A 91	-.149	-2.132	.036
(10) Read Message -> Read Message, spec A 94	.186	2.558	.012
(11) New Plane -> Show Information, C 63	.212	2.786	.006
(12) New Message -> Show Info, spec B 108	-.202	-2.722	.008
(13) Send Message -> Show Information, C 79	.194	2.679	.009
(14) New Plane -> Handle Threat, C 64	.145	2.088	.040
(15) Show Info -> Read Message, C 81	-.129	-1.653	.102

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 152 Results of multiple regression, predicting performance shift 3 with *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.044	.035	.044	4.961	1	107	.028	4.961	1	107	.028
2	.101	.084	.057	6.726	1	106	.011	5.976	2	106	.003
3	.148	.123	.046	5.698	1	105	.019	6.060	3	105	. 001
4	.188	.157	.040	5.178	1	104	.025	6.020	4	104	. 000
5	.230	.192	.042	5.554	1	103	.020	6.138	5	103	. 000
6	.260	.216	.030	4.156	1	102	.044	5.964	6	102	. 000
7	.288	.239	.029	4.068	1	101	.046	5.847	7	101	.000
8	.310	.255	.022	3.184	1	100	.077	5.625	8	100	.000
9	.328	.267	.018	2.596	1	99	.110	5.368	9	99	.000
10	.346	.280	.018	2.757	1	98	.100	5.193	10	98	.000
11	.365	.293	.019	2.899	1	97	.092	5.076	11	97	.000
12	.388	.311	.022	3.513	1	96	.064	5.066	12	96	.000
13	.414	.334	.026	4.271	1	95	.041	5.164	13	95	.000
14	.434	.349	.020	3.280	1	94	.073	5.145	14	94	.000
15	.449	.360	.015	2.590	1	93	.111	5.055	15	93	.000
16	.463	.370	.014	2.459	1	92	.120	4.967	16	92	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Read Message -> Handle Threat, C 136	-.290	-3.045	.003
(2) Read Message -> Read Message, C 133	-.176	-1.734	.086
(3) New Message -> Show information, C 127	-.225	-2.721	.008
(4) Handle Threat -> Show Information, spec B 171	-.280	-3.056	.003
(5) Handle Threat -> Read Message, spec B 169	-.214	-2.440	.017
(6) Send Message -> Read Message, spec B 175	-.128	-1.614	.110
(7) Read Message -> Read Message, spec B 172	.206	2.463	.016
(8) Handle Threat -> Handle Threat, C 132	.098	1.151	.253
(9) New Message -> Send Message, spec A 149	.207	2.519	.014
(10) Show Info -> Handle Threat, C 144	.164	2.000	.048
(11) Send Message -> Send Message, C 138	-.251	-2.765	.007
(12) New Message -> Send Message, C 126	-.332	-3.206	.002
(13) Show Info -> Read Message, spec B 178	.181	2.213	.029
(14) Read Message -> Send Message, spec A 155	-.156	-1.911	.059
(15) Send Message -> Send Message, spec A 158	-.124	-1.588	.116
(16) New Message -> Read Message, C 125	-.154	-1.568	.120

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 153 Results of multiple regression, predicting performance shift 3 with preceding performance, *input*, *summary-level process* variables, and *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.323	.316	.323	50.944	1	107	.000	50.944	1	107	.000
2	.380	.368	.057	9.768	1	106	.002	32.443	2	106	.000
3	.407	.390	.028	4.882	1	105	.029	24.048	3	105	. 000
4	.435	.413	.027	5.034	1	104	.027	19.988	4	104	. 000
5	.468	.443	.034	6.557	1	103	.012	18.156	5	103	. 000
6	.518	.489	.049	10.440	1	102	.002	18.257	6	102	. 000
7	.539	.508	.022	4.746	1	101	.032	16.901	7	101	.000
8	.556	.521	.017	3.774	1	100	.055	15.667	8	100	.000
9	.574	.536	.018	4.204	1	99	.043	14.839	9	99	.000
10	.590	.548	.016	3.779	1	98	.055	14.108	10	98	.000
11	.605	.560	.015	3.598	1	97	.061	13.493	11	97	.000
12	.619	.571	.014	3.540	1	96	.063	12.987	12	96	.000
13	.631	.581	.012	3.162	1	95	.079	12.501	13	95	.000
14	.640	.587	.009	2.417	1	94	.123	11.954	14	94	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 2	.590	8.876	.000
(2) gender, commander	.287	4.114	.000
(3) age, specialist A	-.095	-1.403	.164
(4) number of Send Message, commander	-.309	-3.853	.000
(5) number of Read Message, specialist B	.223	2.766	.007
(6) Send Message -> Read Message, spec B 175	-.212	-3.215	.002
(7) Show Info -> Send Message, spec A 161	-.140	-2.151	.034
(8) Read Message -> Handle Threat, C 136	-.293	-3.597	.001
(9) New Plane -> Send Message, C 122	-.158	-2.311	.023
(10) Read Message -> Read Message, C 133	-.264	-2.834	.006
(11) Send Message -> Send Message, spec B 176	-.162	-2.315	.023
(12) Read Message -> Send Message, C 134	-.143	-1.901	.060
(13) Handle Threat -> Show Info, spec B 171	-.113	-1.696	.093
(14) Handle Threat -> Handle Threat, C 132	.106	1.555	.123

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 154 Results of multiple regression, predicting performance shift 4 with *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.043	.034	.043	4.802	1	107	.031	4.802	1	107	.028
2	.074	.056	.031	3.512	1	106	.064	4.213	2	106	.003
3	.108	.082	.034	3.998	1	105	.048	4.221	3	105	. 001
4	.140	.107	.032	3.870	1	104	.052	4.220	4	104	. 000
5	.166	.125	.026	3.216	1	103	.076	4.019	5	103	. 000
6	.201	.154	.035	4.490	1	102	.037	4.273	6	102	. 000

Predictors in trimmed model	Beta	t	Sig.
(1) Send Message -> Read Message, spec B 235	.241	2.658	.009
(2) New Plane -> Send Message, C 182	-.197	-2.167	.033
(3) Read Message -> Handle Threat, C 196	-.211	-2.340	.021
(4) Show Info -> Show Info, spec B 240	-.208	-2.282	.025
(5) New Plane -> Show Info, C 183	.222	2.339	.021
(6) Show Info -> Red Message, C 201	-.197	-2.119	.037

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 155 Results of multiple regression, predicting performance shift 4 with preceding performance, *input*, *summary-level process* variables, and *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.235	.228	.235	32.932	1	107	.000	32.932	1	107	.028
2	.281	.268	.046	6.791	1	106	.010	20.753	2	106	.003
3	.299	.279	.018	2.674	1	105	.105	14.945	3	105	. 001
4	.319	.293	.020	3.072	1	104	.083	12.198	4	104	. 000
5	.337	.304	.017	2.694	1	103	.104	10.456	5	103	. 000
6	.353	.314	.016	2.505	1	102	.117	9.258	6	102	. 000
7	.400	.358	.047	7.922	1	101	.006	9.606	7	101	.000
8	.419	.372	.019	3.317	1	100	.072	9.012	8	100	.000
9	.438	.387	.019	3.346	1	99	.070	8.571	9	99	.000
10	.457	.401	.019	3.413	1	98	.068	8.243	10	98	.000
11	.470	.410	.013	2.442	1	97	.121	7.826	11	97	.000
12	.492	.428	.022	4.069	1	96	.046	7.740	12	96	.000
13	.505	.438	.014	2.628	1	95	.108	7.468	13	95	.000
14	.524	.454	.019	3.769	1	94	.055	7.406	14	94	.000
15	.538	.464	.014	2.798	1	93	.098	7.231	15	93	.000
16	.555	.477	.016	3.347	1	92	.071	7.159	16	92	.000
17	.566	.485	.011	2.334	1	91	.130	6.973	17	91	.000
18	.576	.491	.010	2.187	1	90	.143	6.793	18	90	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 3	.360	4.394	.000
(2) computer expertise, commander	.360	4.588	.000
(3) gender, specialist A	-.187	-2.467	.016
(4) CHAT condition	-.080	-1.090	.278
(5) age, commander	-.093	-1.259	.211
(6) education, commander	.206	2.614	.010
(7) duration Read Message, specialist B	-.159	-1.897	.061
(8) duration Send Message, specialist A	-.276	-3.441	.001
(9) number of Handle Threat, commander	-.253	-2.897	.005
(10) number of Show Information, specialist B	.270	2.981	.004
(11) duration of Read Message, commander	.217	2.524	.013
(12) Read Message -> Send Message, C 194	-.255	-2.782	.007
(13) Show Info -> Send message, C 202	-.170	-2.135	.035
(14) Read Message -> Read Message, C 193	-.177	-1.997	.049
(15) New Message, Send Message, spec B 227	-.198	-2.375	.020
(16) New Plane -> Send Message, C 182	-.162	-2.073	.041
(17) Read Message -> Show Info, spec A 216	.112	1.559	.123
(18) Send Message -> Read Message, spec B 235	.120	1.479	.143

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 156 Results of multiple regression, predicting performance shift 5 with *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.108	.100	.108	12.956	1	107	.000	12.956	1	107	.028
2	.170	.155	.062	7.946	1	106	.006	10.872	2	106	.003
3	.222	.200	.052	7.037	1	105	.009	10.006	3	105	. 001
4	.252	.223	.029	4.068	1	104	.046	8.741	4	104	. 000
5	.277	.241	.025	3.546	1	103	.063	7.873	5	103	. 000
6	.303	.262	.027	3.885	1	102	.051	7.392	6	102	. 000
7	.319	.271	.015	2.295	1	101	.133	6.744	7	101	.000
8	.333	.280	.015	2.186	1	100	.142	6.244	8	100	.000
9	.361	.302	.027	4.248	1	99	.042	6.202	9	99	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Show Info -> Handle Threat, C 264	.272	3.129	.002
(2) New Message -> Show Info, C 247	-.275	-3.338	.001
(3) New Plane -> Show Info, C 243	.231	2.662	.009
(4) Handle Threat -> Send Message, C 250	.158	1.850	.067
(5) Send Message -> Send Message, spec A 278	-.147	-1.799	.075
(6) Read Message -> Send Message, spec A 275	-.156	-1.869	.065
(7) Send Message -> Show Info, C 259	.135	1.634	.105
(8) Show Info -> Show Info, spec A 282	-.177	-2.066	.041
(9) New Message -> Show Info, spec B 288	-.180	-2.061	.042

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 157 Results of multiple regression, predicting performance shift 5 with preceding performance, *input*, *summary-level process* variables, and *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.271	.264	.271	39.753	1	107	.000	39.753	1	107	.028
2	.308	.295	.037	5.655	1	106	.019	23.569	2	106	.003
3	.326	.307	.018	2.844	1	105	.095	16.934	3	105	. 001
4	.370	.345	.044	7.181	1	104	.009	15.243	4	104	. 000
5	.411	.383	.042	7.317	1	103	.008	14.399	5	103	. 000
6	.431	.397	.019	3.469	1	102	.065	12.865	6	102	. 000
7	.446	.407	.015	2.705	1	101	.103	11.598	7	101	.000
8	.473	.431	.027	5.203	1	100	.025	11.221	8	100	.000
9	.498	.452	.025	4.862	1	99	.030	10.899	9	99	.000
10	.519	.470	.022	4.389	1	98	.039	10.584	10	98	.000
11	.534	.481	.015	3.056	1	97	.084	10.102	11	97	.000
12	.546	.489	.012	2.460	1	96	.120	9.604	12	96	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 4	.375	4.664	.000
(2) computer expertise, commander	.210	2.583	.011
(3) gender, commander	.147	1.884	.063
(4) number of Show Information, specialist B	.154	2.100	.038
(5) number of Show Information, specialist A	-.262	-3.470	.001
(6) duration Send Message, commander	-.202	-2.568	.012
(7) number of Handel Threat, commander	.159	2.103	.038
(8) Show Info -> Handle Threat, C 264	.156	2.032	.045
(9) Send Message -> Send Message, spec A 278	-.138	-1.888	.062
(10) Show Info -> Read Message, spec A 280	-.160	-2.055	.043
(11) New Message -> Read Message, spec B 286	.126	1.779	.078
(12) Handle Threat -> Send Message, C 250	.120	1.568	.120

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 158 Results of multiple regression, predicting performance shift 6 with *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.053	.044	.053	5.950	1	107	.016	5.950	1	107	.016
2	.097	.080	.044	5.196	1	106	.025	5.690	2	106	.004
3	.141	.116	.044	5.335	1	105	.023	5.727	3	105	. 001
4	.181	.149	.040	5.100	1	104	.026	5.738	4	104	. 000
5	.207	.169	.026	3.413	1	103	.068	5.379	5	103	. 000
6	.232	.187	.025	3.275	1	102	.073	5.128	6	102	. 000
7	.254	.202	.022	3.011	1	101	.086	4.912	7	101	.000
8	.275	.216	.021	2.832	1	100	.096	4.730	8	100	.000
9	.291	.227	.017	2.371	1	99	.127	4.525	9	99	.000

Predictors in trimmed model	Beta	t	Sig.
(1) Read Message -> Send Message, C 314	.231	2.662	.009
(2) Read Message -> Read Message, spec B 352	.228	2.588	.011
(3) Show Info -> Show Info, spec A 342	-.219	-2.446	.016
(4) New Plane -> Send message, C 302	-.341	-3.357	.001
(5) New Plane -> Read Message, spec B 343	.176	1.982	.050
(6) New Message -> Handle Threat, C 308	-.208	-2.289	.024
(7) Read Message -> Send Message, spec A 335	-.149	-1.650	.102
(8) Send Message -> Show Info, C 319	.180	1.791	.076
(9) Send Message -> Send Message, C 318	.135	1.540	.127

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 159 Results of multiple regression, predicting performance shift 6 with preceding performance, *input*, *summary-level process* variables, and *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.405	.400	.405	72.890	1	107	.000	72.890	1	107	.000
2	.423	.412	.017	3.196	1	106	.077	38.791	2	106	.000
3	.443	.427	.021	3.917	1	105	.050	27.878	3	105	. 000
4	.464	.443	.020	3.968	1	104	.049	22.492	4	104	. 000
5	.478	.453	.015	2.889	1	103	.092	18.898	5	103	. 000
6	.489	.459	.011	2.186	1	102	.142	16.294	6	102	. 000
7	.502	.467	.013	2.557	1	101	.113	14.545	7	101	.000
8	.515	.476	.013	2.601	1	100	.110	13.254	8	100	.000
9	.543	.502	.029	6.190	1	99	.015	13.080	9	99	.000
10	.562	.518	.019	4.310	1	98	.041	12.597	10	98	.000
11	.576	.528	.013	3.076	1	97	.083	11.974	11	97	.000
12	.587	.536	.011	2.620	1	96	.109	11.378	12	96	.000
13	.598	.543	.011	2.542	1	95	.114	10.867	13	95	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 5	.545	7.423	.000
(2) age, commander	-.118	-1.650	.102
(3) computer expertise, commander	.201	2.691	.008
(4) education, commander	.124	1.789	.077
(5) duration Read Message, specialist B	-.185	-1.770	.080
(6) number of Send Message, specialist A	.147	1.948	.054
(7) number of Send Message, specialist B	-.162	-1.993	.049
(8) number of Read Message, specialist B	.055	.513	.609
(9) Read Message -> Send Message, C 314	.138	1.950	.054
(10) New Plane -> Send Message, C 302	-.143	-2.118	.037
(11) Handle Threat -> Read Message, spec A 331	-.139	-2.014	.047
(12) Read Message -> Handle Threat, C 316	-.114	-1.685	.095
(13) Read Message -> Show Info, spec B 354	-.114	-1.594	.114

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 160 Results of multiple regression, predicting performance shift 8 with *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.061	.052	.061	6.916	1	107	.010	6.916	1	107	.010
2	.128	.112	.068	8.224	1	106	.005	7.804	2	106	.001
3	.173	.149	.045	5.683	1	105	.019	7.326	3	105	. 000
4	.223	.193	.050	6.688	1	104	.011	7.465	4	104	. 000
5	.250	.214	.027	3.724	1	103	.056	6.873	5	103	. 000
6	.273	.230	.023	3.201	1	102	.077	6.383	6	102	. 000
7	.296	.247	.023	3.243	1	101	.075	6.055	7	101	.000
8	.317	.262	.021	3.094	1	100	.082	5.795	8	100	.000
9	.341	.282	.025	3.711	1	99	.057	5.703	9	99	.000
10	.356	.291	.015	2.277	1	98	.135	5.426	10	98	.000
11	.374	.303	.017	2.677	1	97	.105	5.261	11	97	.000

Predictors in trimmed model	Beta	t	Sig.
(1) New Plane -> Handle Threat, C 364	.386	4.530	.000
(2) Show Info -> Show Info, spec A 402	-.271	-2.999	.003
(3) Handle Threat -> Send Message, spec B 410	.195	2.325	.022
(4) Send Message -> Read Message, spec A 397	-.213	-2.501	.014
(5) New Plane -> Show Info, C 363	.106	1.249	.215
(6) New Plane -> Show Info, spec B 405	-.123	-1.484	.141
(7) Read Message -> Show Info 414	.157	1.798	.075
(8) Handle Threat -> Send Message, spec A 392	.203	2.323	.022
(9) Handle Threat -> Read Message, spec B 409	.213	2.365	.020
(10) New Message -> Send Message, spec B 407	-.158	-1.787	.077
(11) Send Message -> Send Message, spec B 416	.145	1.636	.105

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15 C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

Table 161 Results of multiple regression, predicting performance shift 8 with preceding performance, *input*, *summary-level process* variables, and *adjusted residuals*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.331	.325	.331	52.894	1	107	.000	52.894	1	107	.028
2	.359	.347	.028	4.655	1	106	.033	29.678	2	106	.003
3	.388	.370	.029	4.902	1	105	.029	22.148	3	105	. 001
4	.412	.390	.025	4.345	1	104	.040	18.226	4	104	. 000
5	.429	.402	.017	3.111	1	103	.081	15.499	5	103	. 000
6	.442	.409	.013	2.350	1	102	.128	13.477	6	102	. 000
7	.455	.417	.013	2.344	1	101	.129	12.039	7	101	.000
8	.508	.468	.053	10.749	1	100	.001	12.894	8	100	.000
9	.549	.508	.041	9.002	1	99	.003	13.379	9	99	.000
10	.563	.518	.014	3.137	1	98	.080	12.615	10	98	.000
11	.594	.547	.031	7.344	1	97	.008	12.878	11	97	.000
12	.609	.560	.015	3.680	1	96	.058	12.437	12	96	.000
13	.624	.572	.015	3.789	1	95	.055	12.106	13	95	.000
14	.640	.586	.016	4.249	1	94	.042	11.929	14	94	.000
15	.651	.594	.011	2.857	1	93	.094	11.544	15	93	.000
16	.663	.604	.012	3.341	1	92	.071	11.304	16	92	.000
17	.675	.614	.012	3.421	1	91	.068	11.120	17	91	.000
18	.688	.626	.013	3.812	1	90	.054	11.039	18	90	.000
19	.700	.636	.012	3.623	1	89	.060	10.953	19	89	.000
20	.713	.648	.013	3.844	1	88	.053	10.930	20	88	.000

Predictors in trimmed model	Beta	t	Sig.
(1) mean performance shift 1 to shift 6	.435	6.361	.000
(2) Control Condition 2 (bed7)	-.133	-2.218	.029
(3) education, commander	.118	1.770	.080
(4) computer expertise, commander	.158	2.429	.017
(5) computer expertise, specialist A	.113	1.881	.063
(6) computer expertise, specialist B	.100	1.470	.145
(7) education, specialist B	.145	2.328	.022
(8) duration Read Message, specialist A	-.275	-4.436	.000
(9) duration Send Message, specialist A	-.224	-3.570	.001
(10) number of Show Information, specialist B	.007	.098	.922
(11) New Plane -> Show Info, spec A 387	.198	3.256	.002
(12) Read Message -> Read Message, C 373	-.248	-3.375	.001
(13) Handle Threat -> Read Message, spec B 409	.250	3.795	.000
(14) New Message -> Send Message, spec A 389	-.113	-1.804	.075
(15) New Plane -> Handle Threat, C 364	.119	1.939	.056
(16) Read Message -> Show Info, spec A 396	.171	2.679	.009
(17) New Message -> Send Message, spec B 407	-.122	-1.938	.056
(18) Show Info -> Read Message, C 381	.136	2.236	.028
(19) New message -> Handle Threat, C 368	.163	2.131	.036
(20) Read Message -> Read Message, spec B 412	.126	1.961	.053

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15. C = commander, spec A = specialist A, spec B = specialist B, Show Info = Show Information.

7 PROcedural NETwork Representations (PRONET)

PRONET uses the KNOT and the Pathfinder algorithm to run the sequential analyses. The input file for Pathfinder is a distance, similarity or correlation matrix. Pathfinder uses a handy tool to collect similarity data. But this works only if similarity ratings of concepts are gathered (the input file is a list of concepts which is than presented to the subject pair by pair). That conditional probabilities can be used as input for Pathfinder/PRONET analyses they must be transformed into matrices adding a head with all the necessary definitions. I used an Excel sheet to construct all the matrices. An example is given in Table 162.

Table 162 Example of an input for pathfinder analyses (shift 1, commanders of high performing teams, median split).

```
DATA:  s1ch.prx
distances
6 nodes
2 decimals
0.01 min
0.99 max
matrix:
0.00 0.00   0.11   0.12   0.13   0.65
0.00 0.00   0.15   0.74   0.07   0.04
0.00 0.00   0.03   0.67   0.20   0.10
0.00 0.00   0.18   0.46   0.31   0.06
0.00 0.00   0.07   0.41   0.41   0.11
0.00 0.00   0.11   0.16   0.26   0.46
```

Pathfinder is a MS-DOS based program. Most results are written into ASCII files that can be read in MS-Excel or transferred to SPSS. An example of a Pathfinder layout file is given in Table 163, an output file comparing network representations in Table 164.

Table 163 Example of a pathfinder layout output file.

```
LAYOUT
1 level
6 nodes
1.0 size factor
2 dimensions
 -1.208   1.828 min max x
 -0.285   2.722 min max y
  1.828   0.701 New Plane
  0.649   2.722 New Message
 -0.677   0.223 Handle Threat
 -1.208   1.418 Read Message
 -0.262  -0.285 Send Message
 -1.011   0.789 Show Information
PFNET C:\KNOT\S1CH.PRX
6 nodes
12 links
directed with loops
5 q (5 = n-1)
infinite r
0.03 minimum link weight
0.20 maximum link weight
links:
 node1 node2 Weight type
    1     3   0.11    x
    1     4   0.12    x
    1     5   0.13    x
    2     5   0.07    x
    2     6   0.04    x
    3     3   0.03    x
    3     5   0.20    x
    3     6   0.10    x
    4     6   0.06    x
    5     3   0.07    x
    6     3   0.11    x
    6     4   0.16    x
```

Table 164 Example of a pathfinder output file comparing four network representations.

```
KNOT Setup Summary:
Batch file: btchcmds.lst
Output file: KNOT.OUT
q = n-1
r = infinity

Coherence  File#  File Name
  -0.206     1  S1CH.PRX
  -0.046     2  S1CL.PRX
  -0.287     3  S4CH.PRX
  -0.286     4  S4CL.PRX

Similarities of pfnets:
 fl1 fl2 ln1 ln2 Cmn   E[C]   O-EC   Sim  E[S]   O-ES   PtPrb   TlPrb   Info

  2   1  12  12  11   4.00   7.00 0.846 0.206  0.641 0.00000 0.00000  22.05
  3   1  13  12  11   4.33   6.67 0.786 0.215  0.571 0.00000 0.00000  19.40
  3   2  13  12  10   4.33   5.67 0.667 0.215  0.452 0.00006 0.00006  14.04
  4   1  13  12  12   4.33   7.67 0.923 0.215  0.708 0.00000 0.00000  26.52
  4   2  13  12  12   4.33   7.67 0.923 0.215  0.708 0.00000 0.00000  26.52
  4   3  13  13  11   4.69   6.31 0.733 0.226  0.508 0.00001 0.00001  16.82

Correlations between data files:

 0.987
 0.967  0.931
 0.978  0.961  0.974
```

7.1 Conditional Probabilities Used in PRONET Analyses

The conditional probabilities were calculated with SDIS-GSEQ (Bakeman & Quera, 1995a), according to the instructions given by Cooke et al. (1996, p. 38). The values are not different from the values presented in the chapter on lag sequential analyses (shift 1 Table 61, page 165; shift 4 Table 165, page 111).

Table 165 Conditional probabilities, all roles, lag 1, shift 4.

Commander

		New Plane	New Message	Handle Threat	Read Message	Send Message	Show Information
low	New Plane	0.00	0.00	0.05	0.19	0.19	0.57
low	New Message	0.00	0.00	0.11	0.74	0.10	0.05
low	Handle Threat	0.00	0.00	0.03	0.67	0.22	0.08
low	Read Message	0.00	0.00	0.15	0.52	0.30	0.03
low	Send Message	0.00	0.00	0.03	0.39	0.47	0.11
low	Show Information	0.00	0.00	0.07	0.20	0.28	0.45
high	New Plane	0.00	0.00	0.11	0.15	0.09	0.64
high	New Message	0.00	0.00	0.14	0.75	0.08	0.04
high	Handle Threat	0.00	0.00	0.04	0.66	0.18	0.11
high	Read Message	0.00	0.00	0.18	0.48	0.29	0.05
high	Send Message	0.00	0.00	0.05	0.46	0.39	0.10
high	Show Information	0.00	0.00	0.12	0.16	0.26	0.47

Specialist A

		New Plane	New Message	Handle Threat	Read Message	Send Message	Show Information
low	New Plane	0.00	0.00	0.00	0.07	0.05	0.88
low	New Message	0.00	0.00	0.00	0.48	0.09	0.43
low	Handle Threat	0.00	0.00	0.00	0.13	0.16	0.71
low	Read Message	0.00	0.00	0.00	0.29	0.19	0.53
low	Send Message	0.00	0.00	0.00	0.24	0.05	0.71
low	Show Information	0.00	0.00	0.00	0.03	0.15	0.82
high	New Plane	0.00	0.00	0.00	0.07	0.06	0.88
high	New Message	0.00	0.00	0.00	0.49	0.12	0.39
high	Handle Threat	0.00	0.00	0.00	0.12	0.17	0.71
high	Read Message	0.00	0.00	0.00	0.29	0.12	0.59
high	Send Message	0.00	0.00	0.00	0.21	0.04	0.74
high	Show Information	0.00	0.00	0.00	0.03	0.15	0.82

Specialist B

		New Plane	New Message	Handle Threat	Read Message	Send Message	Show Information
low	New Plane	0.00	0.00	0.00	0.05	0.06	0.89
low	New Message	0.00	0.00	0.00	0.50	0.13	0.37
low	Handle Threat	0.00	0.00	0.00	0.18	0.19	0.63
low	Read Message	0.00	0.00	0.00	0.29	0.12	0.60
low	Send Message	0.00	0.00	0.00	0.25	0.04	0.71
low	Show Information	0.00	0.00	0.00	0.03	0.20	0.78
high	New Plane	0.00	0.00	0.00	0.13	0.08	0.79
high	New Message	0.00	0.00	0.00	0.51	0.12	0.37
high	Handle Threat	0.00	0.00	0.00	0.14	0.21	0.64
high	Read Message	0.00	0.00	0.00	0.26	0.19	0.55
high	Send Message	0.00	0.00	0.00	0.17	0.05	0.77
high	Show Information	0.00	0.00	0.00	0.04	0.21	0.75

Note. N = 109 teams, low = commanders, specialist of low performing teams (median split performance shift 1, N = 56), high = high performing teams (N = 53).

7.2 PRONET Results

The following tables show the results of the PRONET analyses in the raw form. Table 166 shows the results for shift 1, Table 167 for shift 4. Table 168 shows the result of the Pathfinder C calculation, comparing different network representations.

Table 166 Pathfinder analyses results for shift 1.

commander, low	sepc A, low	spec B, low
LAYOUT	LAYOUT	LAYOUT
1 level	1 level	1 level
6 nodes	6 nodes	6 nodes
1.0 size factor	1.0 size factor	1.0 size factor
2 dimensions	2 dimensions	2 dimensions
-1.368 1.891 min max x	-0.540 2.376 min max x	-0.540 2.376 min max x
-1.064 0.459 min max y	-2.555 0.788 min max y	-2.555 0.788 min max y
1.031 0.245 New Plane	2.376 -0.747 New Plane	2.376 -0.747 New Plane
1.891 0.459 New Message	1.630 -2.555 New Message	1.630 -2.555 New Message
-0.825 0.421 Handle Threat	1.185 0.788 Handle Threat	1.185 0.788 Handle Threat
-0.893 -0.099 Read Message	-0.540 -0.496 Read Message	-0.540 -0.496 Read Message
-0.378 -1.064 Send Message	-0.488 -1.139 Send Message	-0.488 -1.139 Send Message
-1.368 -0.276 Show Information	-0.348 -1.769 Show Information	-0.348 -1.769 Show Information
PFNET S1CL.PRX	PFNET S1AL.PRX	PFNET S1BL.PRX
6 nodes	6 nodes	6 nodes
8 links	8 links	8 links
directed with loops	directed with loops	directed with loops
5 q (5 = n-1)	5 q (5 = n-1)	5 q (5 = n-1)
infinite r	infinite r	infinite r
10 minimum link weight	16 minimum link weight	11 minimum link weight
19 maximum link weight	85 maximum link weight	88 maximum link weight
links:	links:	links:
node1 node2 Weight type	node1 node2 Weight type	node1 node2 Weight type
1 5 16 x	1 6 85 x	1 6 88 x
2 3 10 x	2 6 40 x	2 5 11 x
2 5 11 x	3 4 16 x	2 6 39 x
3 5 19 x	3 5 18 x	3 4 17 x
3 6 11 x	4 5 18 x	4 5 17 x
4 3 15 x	4 6 53 x	4 6 59 x
5 6 10 x	5 4 26 x	5 4 23 x
6 4 19 x	6 5 16 x	6 5 21 x

(continued on next page)

commander, high	spec A, high	spec B, high
LAYOUT	LAYOUT	LAYOUT
1 level	1 level	1 level
6 nodes	6 nodes	6 nodes
1.0 size factor	1.0 size factor	1.0 size factor
2 dimensions	2 dimensions	2 dimensions
-0.980 1.912 min max x	-0.540 2.376 min max x	-0.540 2.376 min max x
-0.549 2.648 min max y	-2.555 0.788 min max y	-2.555 0.788 min max y
1.912 1.102 New Plane	2.376 -0.747 New Plane	2.376 -0.747 New Plane
-0.009 2.648 New Message	1.630 -2.555 New Message	1.630 -2.555 New Message
-0.980 0.469 Handle Threat	1.185 0.788 Handle Threat	1.185 0.788 Handle Threat
-0.820 -0.127 Read Message	-0.540 -0.496 Read Message	-0.540 -0.496 Read Message
0.263 -0.549 Send Message	-0.488 -1.139 Send Message	-0.488 -1.139 Send Message
-0.372 0.378 Show Information	-0.348 -1.769 Show Information	-0.348 -1.769 Show Information
PFNET S1CH.PRX	PFNET S1AH.PRX	PFNET S1BH.PRX
6 nodes	6 nodes	6 nodes
10 links	8 links	8 links
directed with loops	directed with loops	directed with loops
5 q (5 = n-1)	5 q (5 = n-1)	5 q (5 = n-1)
infinite r	infinite r	infinite r
10 minimum link weight	10 minimum link weight	13 minimum link weight
20 maximum link weight	90 maximum link weight	56 maximum link weight
links:	links:	links:
node1 node2 Weight type	node1 node2 Weight type	node1 node2 Weight type
1 3 11 x	1 6 90 x	1 4 13 x
1 4 12 x	2 5 13 x	2 5 14 x
1 5 13 x	2 6 43 x	2 6 35 x
2 3 15 x	3 4 10 x	3 4 15 x
3 5 20 x	4 5 13 x	4 5 14 x
3 6 10 x	4 6 59 x	4 6 56 x
4 3 18 x	5 4 19 x	5 4 18 x
5 6 11 x	6 5 14 x	6 5 19 x
6 3 11 x		
6 4 16 x		

Table 167 Pathfinder analyses results for shift 4.

commander, low	sepc A, low	spec B, low
LAYOUT	LAYOUT	LAYOUT
1 level	1 level	1 level
6 nodes	6 nodes	6 nodes
1.0 size factor	1.0 size factor	1.0 size factor
2 dimensions	2 dimensions	2 dimensions
-1.368 1.891 min max x	-0.540 2.376 min max x	-0.540 2.376 min max x
-1.064 0.459 min max y	-2.555 0.788 min max y	-2.555 0.788 min max y
1.031 0.245 New Plane	2.376 -0.747 New Plane	2.376 -0.747 New Plane
1.891 0.459 New Message	1.630 -2.555 New Message	1.630 -2.555 New Message
-0.825 0.421 Handle Threat	1.185 0.788 Handle Threat	1.185 0.788 Handle Threat
-0.893 -0.099 Read Message	-0.540 -0.496 Read Message	-0.540 -0.496 Read Message
-0.378 -1.064 Send Message	-0.488 -1.139 Send Message	-0.488 -1.139 Send Message
-1.368 -0.276 Show Information	-0.348 -1.769 Show Information	-0.348 -1.769 Show Information
PFNET S4CL.PRX	PFNET S4AL.PRX	PFNET S4BL.PRX
6 nodes	6 nodes	6 nodes
8 links	8 links	8 links
directed with loops	directed with loops	directed with loops
5 q (5 = n-1)	5 q (5 = n-1)	5 q (5 = n-1)
infinite r	infinite r	infinite r
10 minimum link weight	13 minimum link weight	12 minimum link weight
22 maximum link weight	88 maximum link weight	89 maximum link weight
links:	links:	links:
node1 node2 Weight type	node1 node2 Weight type	node1 node2 Weight type
1 4 19 x	1 6 88 x	1 6 89 x
1 5 19 x	2 6 43 x	2 5 13 x
2 3 11 x	3 4 13 x	2 6 37 x
2 5 10 x	3 5 16 x	3 4 18 x
3 5 22 x	4 5 19 x	4 5 12 x
4 3 15 x	4 6 53 x	4 6 60 x
5 6 11 x	5 4 24 x	5 4 25 x
6 4 20 x	6 5 15 x	6 5 20 x

(continued on next page)

commander, high	spec A, high	spec B, high
LAYOUT	LAYOUT	LAYOUT
1 level	1 level	1 level
6 nodes	6 nodes	6 nodes
1.0 size factor	1.0 size factor	1.0 size factor
2 dimensions	2 dimensions	2 dimensions
-0.980 1.912 min max x	-0.540 2.376 min max x	-0.540 2.376 min max x
-0.549 2.648 min max y	-2.555 0.788 min max y	-2.555 0.788 min max y
1.912 1.102 New Plane	2.376 -0.747 New Plane	2.376 -0.747 New Plane
-0.009 2.648 New Message	1.630 -2.555 New Message	1.630 -2.555 New Message
-0.980 0.469 Handle Threat	1.185 0.788 Handle Threat	1.185 0.788 Handle Threat
-0.820 -0.127 Read Message	-0.540 -0.496 Read Message	-0.540 -0.496 Read Message
0.263 -0.549 Send Message	-0.488 -1.139 Send Message	-0.488 -1.139 Send Message
-0.372 0.378 Show Information	-0.348 -1.769 Show Information	-0.348 -1.769 Show Information
PFNET S4CH.PRX	PFNET S4AH.PRX	PFNET S4BH.PRX
6 nodes	6 nodes	6 nodes
9 links	8 links	8 links
directed with loops	directed with loops	directed with loops
5 q (5 = n-1)	5 q (5 = n-1)	5 q (5 = n-1)
infinite r	infinite r	infinite r
10 minimum link weight	12 minimum link weight	12 minimum link weight
18 maximum link weight	88 maximum link weight	55 maximum link weight
links:	links:	links:
node1 node2 Weight type	node1 node2 Weight type	node1 node2 Weight type
1 3 11 x	1 6 88 x	1 4 13 x
1 4 15 x	2 5 12 x	2 5 12 x
2 3 14 x	2 6 39 x	2 6 37 x
3 5 18 x	3 4 12 x	3 4 14 x
3 6 11 x	4 5 12 x	4 5 19 x
4 3 18 x	4 6 59 x	4 6 55 x
5 6 10 x	5 4 21 x	5 4 17 x
6 3 12 x	6 5 15 x	6 5 21 x
6 4 16 x		

Table 168 Pathfinder C results (similarities), shift 1 and shift 4, all teams.

```
KNOT Setup Summary:
File specification:  *.prx
Output file: S14CAB.OUT
q = 5
r = infinity

Coherence  File#  File Name
    0.083      1  S1AH.PRX
   -0.012      2  S1AL.PRX
    0.022      3  S1BH.PRX
   -0.061      4  S1BL.PRX
   -0.206      5  S1CH.PRX
   -0.046      6  S1CL.PRX
    0.003      7  S4AH.PRX
    0.052      8  S4AL.PRX
   -0.025      9  S4BH.PRX
   -0.029     10  S4BL.PRX
   -0.157     11  S4CH.PRX
   -0.102     12  S4CL.PRX
```

Similarities of pfnets:

fl1	fl2	ln1	ln2	Cmn	E[C]	O-EC	Sim	E[S]	O-ES	PtPrb	TlPrb	Info
2	1	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
3	1	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
3	2	8	8	6	2.13	3.87	0.600	0.161	0.439	0.00111	0.00114	9.78
4	1	8	8	8	2.13	5.87	1.000	0.161	0.839	0.00000	0.00000	22.48
4	2	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
4	3	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
5	1	10	8	0	2.67	-2.67	0.000	0.181	-0.181	0.02152	1.00000	-0.00
5	2	10	8	1	2.67	-1.67	0.059	0.181	-0.122	0.13245	0.97848	0.03
5	3	10	8	1	2.67	-1.67	0.059	0.181	-0.122	0.13245	0.97848	0.03
5	4	10	8	0	2.67	-2.67	0.000	0.181	-0.181	0.02152	1.00000	-0.00
6	1	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
6	2	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
6	3	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
6	4	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
6	5	8	10	7	2.67	4.33	0.636	0.181	0.456	0.00041	0.00042	11.23
7	1	8	8	8	2.13	5.87	1.000	0.161	0.839	0.00000	0.00000	22.48
7	2	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
7	3	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
7	4	8	8	8	2.13	5.87	1.000	0.161	0.839	0.00000	0.00000	22.48
7	5	8	10	0	2.67	-2.67	0.000	0.181	-0.181	0.02152	1.00000	-0.00
7	6	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
8	1	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
8	2	8	8	8	2.13	5.87	1.000	0.161	0.839	0.00000	0.00000	22.48
8	3	8	8	6	2.13	3.87	0.600	0.161	0.439	0.00111	0.00114	9.78
8	4	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
8	5	8	10	1	2.67	-1.67	0.059	0.181	-0.122	0.13245	0.97848	0.03
8	6	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
8	7	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
9	1	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
9	2	8	8	6	2.13	3.87	0.600	0.161	0.439	0.00111	0.00114	9.78
9	3	8	8	8	2.13	5.87	1.000	0.161	0.839	0.00000	0.00000	22.48
9	4	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
9	5	8	10	1	2.67	-1.67	0.059	0.181	-0.122	0.13245	0.97848	0.03
9	6	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
9	7	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
9	8	8	8	6	2.13	3.87	0.600	0.161	0.439	0.00111	0.00114	9.78
10	1	8	8	8	2.13	5.87	1.000	0.161	0.839	0.00000	0.00000	22.48
10	2	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
10	3	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
10	4	8	8	8	2.13	5.87	1.000	0.161	0.839	0.00000	0.00000	22.48
10	5	8	10	0	2.67	-2.67	0.000	0.181	-0.181	0.02152	1.00000	-0.00
10	6	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
10	7	8	8	8	2.13	5.87	1.000	0.161	0.839	0.00000	0.00000	22.48
10	8	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
10	9	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
11	1	9	8	0	2.40	-2.40	0.000	0.172	-0.172	0.03477	1.00000	0.00
11	2	9	8	1	2.40	-1.40	0.063	0.172	-0.109	0.17880	0.96523	0.05
11	3	9	8	1	2.40	-1.40	0.063	0.172	-0.109	0.17880	0.96523	0.05
11	4	9	8	0	2.40	-2.40	0.000	0.172	-0.172	0.03477	1.00000	0.00
11	5	9	10	9	3.00	6.00	0.900	0.194	0.706	0.00000	0.00000	20.45
11	6	9	8	6	2.40	3.60	0.545	0.172	0.374	0.00301	0.00314	8.31
11	7	9	8	0	2.40	-2.40	0.000	0.172	-0.172	0.03477	1.00000	0.00
11	8	9	8	1	2.40	-1.40	0.063	0.172	-0.109	0.17880	0.96523	0.05
11	9	9	8	1	2.40	-1.40	0.063	0.172	-0.109	0.17880	0.96523	0.05
11	10	9	8	0	2.40	-2.40	0.000	0.172	-0.172	0.03477	1.00000	0.00
12	1	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
12	2	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
12	3	8	8	2	2.13	-0.13	0.143	0.161	-0.018	0.35694	0.71226	0.49
12	4	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
12	5	8	10	7	2.67	4.33	0.636	0.181	0.456	0.00041	0.00042	11.23
12	6	8	8	7	2.13	4.87	0.778	0.161	0.617	0.00003	0.00003	15.01
12	7	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
12	8	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
12	9	8	8	2	2.13	-0.13	0.143	0.161	-0.018	0.35694	0.71226	0.49
12	10	8	8	1	2.13	-1.13	0.067	0.161	-0.095	0.23311	0.94537	0.08
12	11	8	9	6	2.40	3.60	0.545	0.172	0.374	0.00301	0.00314	8.31

```
Correlations between data files:

  0.993
  0.993  0.994
  0.989  0.995  0.993
  0.464  0.543  0.510  0.530
  0.433  0.513  0.486  0.495  0.987
  0.998  0.997  0.997  0.994  0.495  0.465
  0.997  0.999  0.993  0.993  0.514  0.484  0.997
  0.990  0.993  0.998  0.994  0.508  0.482  0.994  0.992
  0.992  0.996  0.994  0.998  0.537  0.505  0.997  0.994  0.992
  0.464  0.544  0.511  0.527  0.997  0.990  0.495  0.515  0.506  0.537
  0.423  0.505  0.477  0.489  0.988  0.997  0.456  0.474  0.476  0.496  0.986
```

Note. N = 109 teams.

8 Data Mining applied to the ATC Data

Data coding. The data for data mining analyses can be represented in log-files reporting each event on a single line. An example is given in Table 169. The commander of team 106 starts writing a message (67) in second 11, which lasts until second 211. Meanwhile a new plane comes into the airspace (81, at second 17). This changes immediately the threat level, and because the commander is still writing his message and he does not set the appropriate threat level a -102 is the results. This means that plane number 1 is underestimated (the minus sign) by 2 points (stars). Of course this changes also the overall threat assignment, which is now 502, which indicates that overall the threat assignment is two points too low. Those two numbers correspond, because only one plane is present in the airspace for the moment. As soon as there are more planes in the airspace those two numbers start to diverge. In second 78 a new message (80) comes into the inbox, another messages arrives at second 126, and again at second 227. Because the commander writes a new message from second 11 to 211 all events, except the last new message happened without him noticing that something happened. How the variables were built and named is described en detail in the appendix, chapter 3.

Table 169 Data structure for data-mining analyses.

Team	Role	Shift	DAEVE	EV_S	EV_E
106	1	1	67	11	211
106	1	1	81	17	17
106	1	1	-102	17	17
106	1	1	502	17	17
106	1	1	80	78	78
106	1	1	80	126	126
106	1	1	80	227	227
106	1	1	72	238	238
(…)					

Note. Group = number of team, Role = role of participant (1 = commander, 2 = specialist A, 3 = specialist B), DAEVE = number of event, EV_S = event start time, EV_E = event end time

8.1 Technical Details of the Data Sets used in Data Mining Analyses

The events are either represented as plain text variables like ieR100 = reading a message with task related content or with a numeric value, which is for ieR100 = 53. Details in Table 170.

To run data mining analyses two files are stored: (i) data file V-A follows the rule that there is no temporal overlap within one single stream. Therefore stream 1 to stream 7 are represented in seven distinct variables (Table 171), whereas (ii) data file V-B combines all information in one single variable (structure in Table 172, the necessary transformation are documented in Table 173).

Table 170 Correspondence of plain text and numeric variable representations, initiated events and system events.

ieR111	ieR110	ieR100	ieR101	ieR011	ieR001	ieR010	
51	52	53	54	55	56	57	
ieS111	ieS110	ieS100	ieS101	ieS011	ieS001	ieS010	
61	62	63	64	65	66	67	
ieSi0	ieSi1						
71	72						
ieH10[*]	*ieH11*	*ieH12*	*ieH13*	*ieH14*	*ieH15*	*ieH16*	*ieH17*
10	*11*	*12*	*13*	*14*	*15*	*16*	*17*
ieH20[*]	*ieH21*	*ieH22*	*ieH23*	*ieH24*	*ieH25*	*ieH26*	*ieH27*
20	*21*	*22*	*23*	*24*	*25*	*26*	*27*
ieH30[*]	*ieH31*	*ieH32*	*ieH33*	*ieH34*	*ieH35*	*ieH36*	*ieH37*
30	*31*	*32*	*33*	*34*	*35*	*36*	*37*
ieH40[*]	*ieH41*	*ieH42*	*ieH43*	*ieH44*	*ieH45*	*ieH46*	*ieH47*
40	*41*	*42*	*43*	*44*	*45*	*46*	*47*
ieH[**]							
70							
ieOTHER							
90							
seNewMsg	seNP1	seNP2	seNP3	seNP4			
80	81	82	83	84			

Note. [*]ieH10, ieH20, ieH30, ieH40 = The commander started to assign a new threat level to a plane but something went wrong. This could be that the commander cancelled the operation or that there was an error in the ATC log-file. The information in this variable has to be interpreted with caution. The 0 at the end signifies not setting the threat level to 0, but that we have no information on the threat level! The information on the plane (the first number) is ok. All in all this happens very rarely. For all teams, in all shifts 99’834 events are recoded for the commander. ieh10, ieH20, ieH30, and ieH40 together sum up to 32 events, this is 0.003% of all events.
[*]ieH70 = Handle Threat of commander = any event ieH10 to ieH47

Table 171 Structure data file V-A, no temporal overlap within one stream of events.

row position	row label	description
1	gruppe	group number
2	rolle	role, 1 = commander, 2 = specialist A, 3 = specialist B
3	beding	experimental condition (see Table 13)
4	schicht	number of shift (1 to 8)
5	daeve1	stream 1: events of commanders or specialists
6	ev1_s	onset time
7	ev1_e	offset time
8	daeve2	stream 2: system events
9	ev2_s	onset time
10	ev2_e	offset time
11	daeve3	stream 3: accuracy of threat assignment, plane 1
12	ev3_s	onset time
13	ev3_e	offset time
14	daeve4	stream 4: accuracy of threat assignment, plane 2
15	ev4_s	onset time
16	ev4_e	offset time
17	daeve5	stream 5: accuracy of threat assignment, plane 3
18	ev5_s	onset time
19	ev5_e	offset time
20	daeve6	stream 6: accuracy of threat assignment, plane 4
21	ev6_s	onset time
22	ev6_e	offset time
23	daeve7	overall accuracy of threat assignment (0 = perfect fit, the higher the value the less accurate is the threat assignment)
24	ev7_s	onset time
24	ev7_e	offset time

Table 172 Structure of data file V-B, all streams combined in one variable

row position	row label	description
1	gruppe	group number
2	rolle	role, 1 = commander, 2 = specialist A, 3 = specialist B
3	beding	experimental condition (see Table 13)
4	schicht	number of shift (1 to 8)
5	daeve	stream 1 to 7
6	ev_s	onset time
7	ev_e	offset time

Table 173 Necessary transformations to represent all information in one single variable (type A to type B transformations).

The data in the file V-A is e.g., presented as follows:

GRUPPE	(…)	DAEVE2	EV2_S	EV2_E	DAEVE3	EV3_S	EV3_E	(…)	DAEVE7	EV7_S	EV7_E
(…)											
106	(…)	21	17	17	-2	17	17	(…)	-3	17	17
(…)											

In file V-B this looks like:

GRUPPE	ROLLE	BEDING	SCHICHT	DAEVE	EV_S	EV_E
(…)						
106	1	1	1		11	211
106	1	1	1	81	17	17.1
106	1	1	1	-1.2	17	17
106	1	1	1	2	17	17
(…)						

Data stream 3 to stream 6 are recoded as follows:

stream 3: if (daeve3 < 0) daeve3 = -1* (100 + abs(daeve3)).
if (daeve3 >= 0) daeve3 = 100 + abs(daeve3).

stream 4: if (daeve4 < 0) daeve4 = -1* (200 + abs(daeve4)).
if (daeve4 >= 0) daeve4 = 200 + abs(daeve4).

stream 5: if (daeve5 < 0) daeve5 = -1* (300 + abs(daeve5)).
if (daeve5 >= 0) daeve5 = 300 + abs(daeve5).

stream 6: if (daeve6 < 0) daeve6 = -1* (400 + abs(daeve6)).
if (daeve6 >= 0) daeve6 = 400 + abs(daeve6).

stream 7: if (daeve7 < 0) daeve7 = -1* (500 + abs(daeve7).
if (daeve7 >= 0) daeve7 = 500 + abs(daeve7).

Format: [-]XYZ
[-] - = underestimation, no - = overestimation
X = plane number
Y = always 0
Z = the difference real threat level minus threat assignment of the team.
-103 = threat level is assigned 3 stars too low for plane 1
102 = threat level is assigned 2 stars too high for plane 1.

8.2 Support Values for Specialists of Low and High Performing Teams

Table 174 Support values for patterns of specialists A of low and high performing teams, day one and day two.

	Sequence		day 1 low	day 1 high		day 2 low	day 2 high	
1	ieR-ieR	50-50	0.72	0.75	equal	0.77	0.74	equal
2	**ieR-ieS001**	50-66	**0.52**	**0.00**	**different**	0.46	0.41	equal
3	**ieR-ieS100**	50-63	.	.	.	**0.46**	**0.00**	**different**
4	**ieR-ieSi0**	50-71	**0.99**	**0.93**	**different**	**0.94**	**0.84**	**different**
5	**ieR-ieSi1**	50-72	0.64	0.75	equal	**0.63**	**0.80**	**different**
6	**ieS001-ieR**	66-50	**0.72**	**0.57**	**different**	0.63	0.55	equal
7	ieS001-ieSi0	66-71	0.66	0.58	equal	0.64	0.55	equal
8	**ieS001-ieSi1**	66-72	.	.	.	**0.00**	**0.41**	**different**
9	ieS100-ieR	63-50	0.78	0.75	equal	0.70	0.80	equal
10	ieS100-ieSi0	63-71	0.81	0.80	equal	0.72	0.78	equal
11	**ieS100-ieSi1**	63-72	0.48	0.59	equal	**0.00**	**0.59**	**different**
12	ieSi0-ieR	71-50	0.77	0.80	equal	0.86	0.86	equal
13	ieSi0-ieS001	71-66	0.80	0.79	equal	0.82	0.72	equal
14	ieSi0-ieS100	71-63	0.90	0.92	equal	0.88	0.93	equal
15	ieSi0-ieSi0	71-71	1.00	1.00	equal	0.99	1.00	equal
16	ieSi0-ieSi1	71-72	0.96	0.96	equal	0.99	0.99	equal
17	**ieSi1-ieR**	72-50	**0.00**	**0.45**	**different**	0.44	0.48	equal
18	**ieSi1-ieS001**	72-66	.	.	.	**0.44**	**0.00**	**different**
19	**ieSi1-ieS100**	72-63	**0.67**	**0.79**	**different**	**0.65**	**0.81**	**different**
20	ieSi1-ieSi0	72-71	0.98	0.97	equal	0.99	0.99	equal
21	ieSi1-ieSi1	72-72	0.64	0.76	equal	0.77	0.81	equal
1	**ieR-ieR-ieR**	50-50-50	**0.42**	**0.00**	**different**	.	.	.
2	**ieR-ieR-ieSi0**	50-50-71	0.47	0.47	equal	**0.58**	**0.43**	**different**
3	**ieR-ieSi0-ieS100**	50-71-63	**0.42**	**0.00**	**different**	.	.	.
4	ieR-ieSi0-ieSi0	50-71-71	0.76	0.71	equal	0.75	0.67	equal
5	**ieR-ieSi0-ieSi1**	50-71-72	**0.56**	**0.00**	**different**	0.58	0.50	equal
6	**ieR-ieSi1-ieSi0**	50-72-71	.	.	.	**0.00**	**0.45**	**different**
7	**ieS001-ieR-ieSi0**	66-50-71	**0.45**	**0.00**	**different**	.	.	.
8	**ieS001-ieSi0-ieSi0**	66-71-71	**0.47**	**0.00**	**different**	**0.45**	**0.00**	**different**
9	**ieS100-ieR-ieR**	63-50-50	.	.	.	**0.00**	**0.45**	**different**
10	ieS100-ieR-ieSi0	63-50-71	0.50	0.43	equal	.	.	.
11	ieS100-ieR-ieSi0	63-50-71	.	.	.	0.40	0.47	equal
12	ieS100-ieSi0-ieSi0	63-71-71	0.61	0.60	equal	0.54	0.56	equal
13	ieSi0-ieR-ieSi0	71-50-71	0.44	0.44	equal	0.45	0.44	equal
14	ieSi0-ieS001-ieR	71-66-50	0.56	0.45	equal	0.48	0.46	equal
15	**ieSi0-ieS001-ieSi0**	71-66-71	0.49	0.47	equal	**0.51**	**0.00**	**different**
16	ieSi0-ieS100-ieR	71-63-50	0.64	0.53	equal	0.54	0.64	equal
17	ieSi0-ieS100-ieSi0	71-63-71	0.67	0.70	equal	0.57	0.65	equal
18	**ieSi0-ieS100-ieSi1**	71-63-72	**0.00**	**0.45**	**different**	.	.	.
19	ieSi0-ieSi0-ieR	71-71-50	0.69	0.64	equal	0.73	0.70	equal
20	**ieSi0-ieSi0-ieS001**	71-71-66	0.76	0.69	equal	**0.78**	**0.61**	**different**
21	**ieSi0-ieSi0-ieS100**	71-71-63	0.81	0.83	equal	**0.71**	**0.84**	**different**
22	ieSi0-ieSi0-ieSi0	71-71-71	0.94	0.96	equal	0.96	0.97	equal
23	ieSi0-ieSi0-ieSi1	71-71-72	0.92	0.90	equal	0.96	0.98	equal
24	**ieSi0-ieSi1-ieS100**	71-72-63	.	.	.	**0.00**	**0.51**	**different**
25	ieSi0-ieSi1-ieSi0	71-72-71	0.94	0.86	equal	0.96	0.93	equal
26	ieSi0-ieSi1-ieSi1	71-72-72	0.46	0.50	equal	0.67	0.69	equal
27	**ieSi1-ieS100-ieR**	72-63-50	.	.	.	**0.00**	**0.41**	**different**
28	ieSi1-ieS100-ieSi0	72-63-71	0.41	0.50	equal	.	.	.
29	**ieSi1-ieS100-ieSi1**	72-63-72	.	.	.	**0.00**	**0.44**	**different**
30	**ieSi1-ieSi0-ieS100**	72-71-63	.	.	.	**0.00**	**0.46**	**different**
31	ieSi1-ieSi0-ieSi0	72-71-71	0.95	0.95	equal	0.97	0.97	equal
32	ieSi1-ieSi0-ieSi1	72-71-72	.	.	.	0.45	0.55	equal
33	**ieSi1-ieSi1-ieS100**	72-72-63	.	.	.	**0.00**	**0.46**	**different**
34	ieSi1-ieSi1-ieSi0	72-72-71	0.51	0.63	equal	0.71	0.72	equal
35	**ieSi1-ieSi1-ieSi1**	72-72-72	**0.00**	**0.50**	**different**	0.53	0.58	equal
1	**ieR-ieR-ieSi0-ieSi0**	50-50-71-71	.	.	.	**0.40**	**0.00**	**different**
2	**ieR-ieSi0-ieSi0-ieSi0**	50-71-71-71	0.44	0.50	equal	**0.54**	**0.00**	**different**
3	**ieR-ieSi0-ieSi1-ieSi0**	50-71-72-71	**0.43**	**0.00**	**different**	0.48	0.41	equal
4	ieS100-ieSi0-ieSi0-ieSi0	63-71-71-71	0.43	0.48	equal	0.45	0.44	equal
5	ieSi0-ieS100-ieSi0-ieSi0	71-63-71-71	0.47	0.53	equal	.	.	.
6	**ieSi0-ieSi0-ieS001-ieR**	71-71-66-50	**0.44**	**0.00**	**different**	**0.40**	**0.00**	**different**
7	**ieSi0-ieSi0-ieS001-ieSi0**	71-71-66-71	**0.44**	**0.00**	**different**	.	.	.
8	**ieSi0-ieSi0-ieS100-ieR**	71-71-63-50	**0.43**	**0.00**	**different**	**0.00**	**0.43**	**different**
9	**ieSi0-ieSi0-ieS100-ieSi0**	71-71-63-71	0.50	0.52	equal	**0.00**	**0.42**	**different**
10	ieSi0-ieSi0-ieSi0-ieR	71-71-71-50	0.44	0.52	equal	0.57	0.44	equal
11	**ieSi0-ieSi0-ieSi0-ieS001**	71-71-71-66	0.61	0.54	equal	**0.62**	**0.44**	**different**
12	ieSi0-ieSi0-ieSi0-ieS100	71-71-71-63	0.55	0.61	equal	0.56	0.53	equal
13	ieSi0-ieSi0-ieSi0-ieSi0	71-71-71-71	0.84	0.85	equal	0.89	0.83	equal
14	ieSi0-ieSi0-ieSi0-ieSi1	71-71-71-72	0.79	0.81	equal	0.91	0.85	equal
15	ieSi0-ieSi0-ieSi1-ieSi0	71-71-72-71	0.81	0.77	equal	0.88	0.87	equal
16	**ieSi0-ieSi0-ieSi1-ieSi1**	71-71-72-72	**0.00**	**0.46**	**different**	0.58	0.64	equal
17	ieSi0-ieSi1-ieSi0-ieSi0	71-72-71-71	0.84	0.83	equal	0.88	0.85	equal
18	ieSi0-ieSi1-ieSi1-ieSi0	71-72-72-71	.	.	.	0.50	0.53	equal
19	ieSi0-ieSi1-ieSi1-ieSi1	71-72-72-72	.	.	.	0.40	0.41	equal
20	**ieSi1-ieSi0-ieSi0-ieR**	72-71-71-50	.	.	.	**0.42**	**0.00**	**different**
21	**ieSi1-ieSi0-ieSi0-ieS001**	72-71-71-66	**0.43**	**0.00**	**different**	**0.40**	**0.00**	**different**
22	**ieSi1-ieSi0-ieSi0-ieS100**	72-71-71-63	0.43	0.42	equal	**0.00**	**0.56**	**different**
23	ieSi1-ieSi0-ieSi0-ieSi0	72-71-71-71	0.83	0.89	equal	0.89	0.88	equal
24	ieSi1-ieSi0-ieSi0-ieSi1	72-71-71-72	.	.	.	0.45	0.56	equal
25	ieSi1-ieSi1-ieSi0-ieSi0	72-72-71-71	0.45	0.53	equal	0.61	0.65	equal
26	ieSi1-ieSi1-ieSi1-ieSi0	72-72-72-71	.	.	.	0.46	0.47	equal

(continued on next page)

			day 1			day 2		
	Sequence		low	high		low	high	
1	**ieR-ieSi0-ieSi0-ieSi0-ieSi0**	50-71-71-71-71	**0.00**	**0.41**	**different**	**0.41**	**0.00**	**different**
2	**ieSi0-ieSi0-ieSi0-ieSi0-ieR**	71-71-71-71-50	**0.00**	**0.43**	**different**	**0.42**	**0.00**	**different**
3	**ieSi0-ieSi0-ieSi0-ieSi0-ieS001**	71-71-71-71-66	**0.46**	**0.00**	**different**	**0.44**	**0.00**	**different**
4	**ieSi0-ieSi0-ieSi0-ieSi0-ieS100**	71-71-71-71-63	**0.00**	**0.44**	**different**	**0.40**	**0.00**	**different**
5	ieSi0-ieSi0-ieSi0-ieSi0-ieSi0	71-71-71-71-71	0.69	0.71	equal	0.80	0.71	equal
6	ieSi0-ieSi0-ieSi0-ieSi0-ieSi1	71-71-71-71-72	0.64	0.59	equal	0.76	0.73	equal
7	ieSi0-ieSi0-ieSi0-ieSi1-ieSi0	71-71-71-72-71	0.62	0.59	equal	0.76	0.68	equal
8	ieSi0-ieSi0-ieSi0-ieSi1-ieSi1	71-71-71-72-72	.	.	.	0.52	0.46	equal
9	ieSi0-ieSi0-ieSi1-ieSi0-ieSi0	71-71-72-71-71	0.70	0.63	equal	0.78	0.69	equal
10	ieSi0-ieSi0-ieSi1-ieSi1-ieSi0	71-71-72-72-71	.	.	.	0.42	0.43	equal
11	ieSi0-ieSi1-ieSi0-ieSi0-ieSi0	71-72-71-71-71	0.67	0.68	equal	0.72	0.67	equal
12	ieSi0-ieSi1-ieSi1-ieSi0-ieSi0	71-72-72-71-71	.	.	.	0.42	0.44	equal
13	ieSi1-ieSi0-ieSi0-ieSi0-ieSi0	72-71-71-71-71	0.67	0.67	equal	0.77	0.75	equal
14	ieSi1-ieSi0-ieSi0-ieSi0-ieSi1	72-71-71-71-72	.	.	.	0.42	0.42	equal
15	**ieSi1-ieSi1-ieSi0-ieSi0-ieSi0**	72-72-71-71-71	**0.00**	**0.49**	**different**	0.53	0.53	equal
16	ieSi1-ieSi1-ieSi1-ieSi0-ieSi0	72-72-72-71-71	.	.	.	0.40	0.43	equal
1	ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0	71-71-71-71-71-71	0.57	0.62	equal	0.71	0.64	equal
2	ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi1	71-71-71-71-71-72	0.47	0.49	equal	0.63	0.55	equal
3	**ieSi0-ieSi0-ieSi0-ieSi0-ieSi1-ieSi0**	71-71-71-71-72-71	**0.50**	**0.00**	**different**	0.58	0.52	equal
4	ieSi0-ieSi0-ieSi0-ieSi0-ieSi1-ieSi1	71-71-71-71-72-72	.	.	.	0.41	0.42	equal
5	**ieSi0-ieSi0-ieSi0-ieSi1-ieSi0-ieSi0**	71-71-71-72-71-71	0.54	0.50	equal	**0.65**	**0.49**	**different**
6	ieSi0-ieSi0-ieSi1-ieSi0-ieSi0-ieSi0	71-71-72-71-71-71	0.53	0.49	equal	0.63	0.55	equal
7	ieSi0-ieSi1-ieSi0-ieSi0-ieSi0-ieSi0	71-72-71-71-71-71	0.47	0.45	equal	0.61	0.55	equal
8	ieSi1-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0	72-71-71-71-71-71	0.50	0.52	equal	0.64	0.63	equal
9	ieSi1-ieSi1-ieSi0-ieSi0-ieSi0-ieSi0	72-72-71-71-71-71	.	.	.	0.41	0.44	equal
1	ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0	71-71-71-71-71-71-71	0.50	0.55	equal	0.58	0.54	equal
2	**ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi1**	71-71-71-71-71-71-72	**0.00**	**0.41**	**different**	0.55	0.46	equal
3	**ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi1-ieSi0**	71-71-71-71-71-72-71	.	.	.	**0.42**	**0.00**	**different**
4	**ieSi0-ieSi0-ieSi0-ieSi0-ieSi1-ieSi0-ieSi0**	71-71-71-71-72-71-71	**0.44**	**0.00**	**different**	**0.47**	**0.00**	**different**
5	**ieSi0-ieSi0-ieSi0-ieSi1-ieSi0-ieSi0-ieSi0**	71-71-71-72-71-71-71	.	.	.	**0.48**	**0.00**	**different**
6	ieSi0-ieSi0-ieSi1-ieSi0-ieSi0-ieSi0-ieSi0	71-71-72-71-71-71-71	.	.	.	0.48	0.43	equal
7	**ieSi0-ieSi1-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0**	71-72-71-71-71-71-71	.	.	.	**0.48**	**0.00**	**different**
8	**ieSi1-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0**	72-71-71-71-71-71-71	**0.00**	**0.44**	**different**	0.57	0.52	equal
1	ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0	71-71-71-71-71-71-71-71	0.43	0.50	equal	0.49	0.46	equal
2	**ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi1**	71-71-71-71-71-71-71-72	.	.	.	**0.43**	**0.00**	**different**
3	**ieSi0-ieSi1-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0**	71-72-71-71-71-71-71-71	.	.	.	**0.43**	**0.00**	**different**
4	ieSi1-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0	72-71-71-71-71-71-71-71	.	.	.	0.46	0.44	equal
1	**ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0**	71-71-71-71-71-71-71-71-71	**0.00**	**0.44**	**different**	**0.45**	**0.00**	**different**

Note. The 109 teams were parted into three groups of the same size according to their performance (low – medium – high). Results are presented for the two extreme groups: all the teams with the lowest performance and all the teams with the highest performance on day one, respectively on day two.

Table 175 Support values for patterns of specialists B of low and high performing teams, day one and day two.

	Sequence		day 1 low	day 1 high		day 2 low	day 2 high	
1	ieR-ieR	50-50	0.75	0.79	equal	0.78	0.77	equal
2	ieR-ieS001	50-66	0.42	0.41	equal	0.51	0.45	equal
3	**ieR-ieS100**	50-63	**0.00**	**0.44**	**different**	.	.	.
4	ieR-ieSi0	50-71	0.90	0.88	equal	0.91	0.93	equal
5	ieR-ieSi1	50-72	0.69	0.74	equal	0.67	0.69	equal
6	**ieS001-ieR**	66-50	**0.66**	**0.00**	**different**	**0.72**	**0.50**	**different**
7	**ieS001-ieSi0**	66-71	**0.59**	**0.44**	**different**	0.59	0.46	equal
8	ieS100-ieR	63-50	0.78	0.80	equal	0.70	0.79	equal
9	ieS100-ieSi0	63-71	0.84	0.80	equal	0.68	0.69	equal
10	ieS100-ieSi1	63-72	0.56	0.58	equal	0.47	0.54	equal
11	ieSi0-ieR	71-50	0.69	0.75	equal	0.74	0.74	equal
12	**ieSi0-ieS001**	71-66	0.67	0.61	equal	**0.73**	**0.55**	**different**
13	ieSi0-ieS100	71-63	0.89	0.91	equal	0.78	0.86	equal
14	ieSi0-ieSi0	71-71	0.98	1.00	equal	0.99	1.00	equal
15	ieSi0-ieSi1	71-72	0.94	0.97	equal	0.98	1.00	equal
16	ieSi1-ieR	72-50	0.54	0.65	equal	0.57	0.64	equal
17	**ieSi1-ieS001**	72-66	**0.62**	**0.49**	**different**	0.72	0.71	equal
18	**ieSi1-ieS100**	72-63	0.77	0.83	equal	**0.68**	**0.81**	**different**
19	**ieSi1-ieSi0**	72-71	0.92	0.94	equal	**0.95**	**1.00**	**different**
20	ieSi1-ieSi1	72-72	0.74	0.79	equal	0.75	0.81	equal
1	ieR-ieR-ieSi0	50-50-71	0.54	0.50	equal	0.50	0.52	equal
2	ieR-ieSi0-ieS100	50-71-63	0.45	0.50	equal	.	.	.
3	ieR-ieSi0-ieSi0	50-71-71	0.71	0.71	equal	0.80	0.84	equal
4	**ieS001-ieSi0-ieSi0**	66-71-71	**0.45**	**0.00**	**different**	**0.47**	**0.00**	**different**
5	**ieS100-ieR-ieR**	63-50-50	**0.00**	**0.41**	**different**	.	.	.
6	**ieS100-ieR-ieSi0**	63-50-71	0.50	0.52	equal	**0.00**	**0.51**	**different**
7	**ieS100-ieSi0-ieS100**	63-71-63	**0.00**	**0.46**	**different**	.	.	.
8	ieS100-ieSi0-ieSi0	63-71-71	0.70	0.69	equal	0.48	0.60	equal
9	**ieSi0-ieS001-ieR**	71-66-50	.	.	.	**0.42**	**0.00**	**different**
10	**ieSi0-ieS100-ieR**	71-63-50	0.62	0.53	equal	**0.42**	**0.65**	**different**
11	ieSi0-ieS100-ieSi0	71-63-71	0.69	0.67	equal	0.45	0.47	equal
12	**ieSi0-ieS100-ieSi1**	71-63-72	**0.00**	**0.42**	**different**	.	.	.
13	**ieSi0-ieSi0-ieR**	71-71-50	0.43	0.50	equal	**0.42**	**0.00**	**different**
14	ieSi0-ieSi0-ieS100	71-71-63	0.69	0.65	equal	0.43	0.50	equal
15	ieSi0-ieSi0-ieSi0	71-71-71	0.89	0.89	equal	0.88	0.87	equal
16	ieSi0-ieSi0-ieSi1	71-71-72	0.92	0.95	equal	0.96	0.99	equal
17	**ieSi0-ieSi1-ieR**	71-72-50	.	.	.	**0.00**	**0.41**	**different**
18	**ieSi0-ieSi1-ieS001**	71-72-66	**0.44**	**0.00**	**different**	0.52	0.51	equal
19	ieSi0-ieSi1-ieS100	71-72-63	0.54	0.52	equal	0.42	0.56	equal
20	ieSi0-ieSi1-ieSi0	71-72-71	0.75	0.84	equal	0.88	0.94	equal
21	**ieSi0-ieSi1-ieSi1**	71-72-72	0.59	0.67	equal	**0.58**	**0.73**	**different**
22	**ieSi1-ieS001-ieR**	72-66-50	.	.	.	**0.40**	**0.00**	**different**
23	**ieSi1-ieS100-ieR**	72-63-50	0.44	0.45	equal	**0.00**	**0.46**	**different**
24	**ieSi1-ieS100-ieSi0**	72-63-71	0.47	0.51	equal	**0.00**	**0.51**	**different**
25	**ieSi1-ieS100-ieSi1**	72-63-72	.	.	.	**0.00**	**0.44**	**different**
26	ieSi1-ieSi0-ieR	72-71-50	.	.	.	0.46	0.51	equal
27	**ieSi1-ieSi0-ieS001**	72-71-66	**0.42**	**0.00**	**different**	**0.47**	**0.00**	**different**
28	ieSi1-ieSi0-ieS100	72-71-63	0.41	0.43	equal	0.44	0.57	equal
29	ieSi1-ieSi0-ieSi0	72-71-71	0.82	0.85	equal	0.89	0.94	equal
30	**ieSi1-ieSi0-ieSi1**	72-71-72	**0.00**	**0.46**	**different**	**0.00**	**0.54**	**different**
31	ieSi1-ieSi1-ieSi0	72-72-71	0.59	0.57	equal	0.59	0.69	equal
32	**ieSi1-ieSi1-ieSi1**	72-72-72	0.48	0.57	equal	**0.45**	**0.59**	**different**
1	**ieR-ieSi0-ieSi0-ieSi0**	50-71-71-71	**0.45**	**0.00**	**different**	.	.	.
2	ieR-ieSi0-ieSi0-ieSi1	50-71-71-72	0.41	0.44	equal	0.64	0.62	equal
3	ieS100-ieSi0-ieSi0-ieSi0	63-71-71-71	0.44	0.47	equal	.	.	.
4	**ieS100-ieSi0-ieSi0-ieSi1**	63-71-71-72	.	.	.	**0.00**	**0.44**	**different**
5	ieSi0-ieS100-ieSi0-ieSi0	71-63-71-71	0.52	0.54	equal	.	.	.
6	**ieSi0-ieSi0-ieSi0-ieS100**	71-71-71-63	**0.45**	**0.00**	**different**	.	.	.
7	ieSi0-ieSi0-ieSi0-ieSi0	71-71-71-71	0.66	0.73	equal	0.60	0.68	equal
8	ieSi0-ieSi0-ieSi0-ieSi1	71-71-71-72	0.75	0.81	equal	0.77	0.84	equal
9	ieSi0-ieSi0-ieSi1-ieS001	71-71-72-66	.	.	.	0.42	0.45	equal
10	**ieSi0-ieSi0-ieSi1-ieS100**	71-71-72-63	**0.44**	**0.00**	**different**	**0.00**	**0.46**	**different**
11	ieSi0-ieSi0-ieSi1-ieSi0	71-71-72-71	0.67	0.75	equal	0.84	0.83	equal
12	ieSi0-ieSi0-ieSi1-ieSi1	71-71-72-72	0.50	0.62	equal	0.53	0.65	equal
13	**ieSi0-ieSi1-ieSi0-ieR**	71-72-71-50	.	.	.	**0.00**	**0.49**	**different**
14	**ieSi0-ieSi1-ieSi0-ieS001**	71-72-71-66	.	.	.	**0.40**	**0.00**	**different**
15	ieSi0-ieSi1-ieSi0-ieS100	71-72-71-63	.	.	.	0.40	0.43	equal
16	ieSi0-ieSi1-ieSi0-ieSi0	71-72-71-71	0.53	0.64	equal	0.70	0.69	equal
17	**ieSi0-ieSi1-ieSi1-ieSi0**	71-72-72-71	.	.	.	**0.00**	**0.44**	**different**
18	**ieSi0-ieSi1-ieSi1-ieSi1**	71-72-72-72	**0.00**	**0.42**	**different**	**0.00**	**0.51**	**different**
19	**ieSi1-ieS100-ieSi0-ieSi0**	72-63-71-71	.	.	.	**0.00**	**0.41**	**different**
20	ieSi1-ieSi0-ieSi0-ieSi0	72-71-71-71	0.62	0.65	equal	0.78	0.80	equal
21	**ieSi1-ieSi0-ieSi0-ieSi1**	72-71-71-72	**0.00**	**0.42**	**different**	**0.55**	**0.73**	**different**
22	ieSi1-ieSi1-ieSi0-ieSi0	72-72-71-71	0.46	0.47	equal	0.48	0.60	equal
23	**ieSi1-ieSi1-ieSi1-ieSi0**	72-72-72-71	.	.	.	**0.00**	**0.43**	**different**
24	**ieSi1-ieSi1-ieSi1-ieSi1**	72-72-72-72	**0.00**	**0.42**	**different**	**0.00**	**0.44**	**different**
1	ieR-ieSi0-ieSi0-ieSi1-ieSi0	50-71-71-72-71	.	.	.	0.52	0.41	equal
2	**ieSi0-ieSi0-ieSi0-ieSi0-ieSi0**	71-71-71-71-71	0.55	0.50	equal	**0.00**	**0.45**	**different**
3	ieSi0-ieSi0-ieSi0-ieSi0-ieSi1	71-71-71-71-72	0.56	0.57	equal	0.46	0.59	equal
4	**ieSi0-ieSi0-ieSi0-ieSi1-ieSi0**	71-71-71-72-71	0.51	0.43	equal	**0.00**	**0.47**	**different**
5	**ieSi0-ieSi0-ieSi0-ieSi1-ieSi1**	71-71-71-72-72	**0.00**	**0.46**	**different**	**0.00**	**0.48**	**different**
6	**ieSi0-ieSi0-ieSi1-ieSi0-ieR**	71-71-72-71-50	.	.	.	**0.00**	**0.42**	**different**
7	**ieSi0-ieSi0-ieSi1-ieSi0-ieSi0**	71-71-72-71-71	**0.00**	**0.46**	**different**	0.55	0.56	equal
8	**ieSi0-ieSi0-ieSi1-ieSi1-ieSi1**	71-71-72-72-72	.	.	.	**0.00**	**0.44**	**different**
9	**ieSi0-ieSi1-ieSi0-ieSi0-ieSi0**	71-72-71-71-71	**0.00**	**0.43**	**different**	0.48	0.52	equal
10	**ieSi1-ieSi0-ieSi0-ieSi0-ieSi0**	72-71-71-71-71	**0.00**	**0.44**	**different**	0.47	0.57	equal
11	ieSi1-ieSi0-ieSi0-ieSi0-ieSi1	72-71-71-71-72	.	.	.	0.50	0.49	equal
12	**ieSi1-ieSi1-ieSi0-ieSi0-ieSi0**	72-72-71-71-71	.	.	.	**0.00**	**0.44**	**different**

(continued on next page)

1	**ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi0**	71-71-71-71-71-71	**0.41**	**0.00**	**different**	.	.	.
2	**ieSi0-ieSi0-ieSi0-ieSi0-ieSi0-ieSi1**	71-71-71-71-71-72	.	.	.	**0.00**	**0.43**	**different**
3	**ieSi0-ieSi0-ieSi1-ieSi0-ieSi0-ieSi0**	71-71-72-71-71-71	.	.	.	**0.00**	**0.44**	**different**

Note. The 109 teams were parted into three groups of the same size according to their performance (low – medium – high). Results are presented for the two extreme groups: all the teams with the lowest performance and all the teams with the highest performance on day one, respectively on day two.

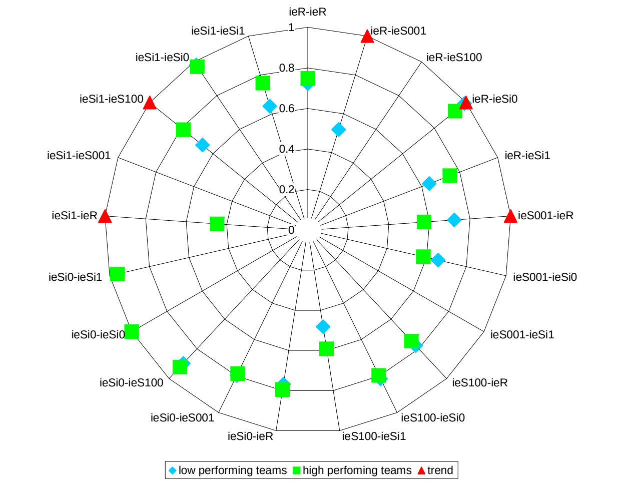
8.3 Sequences Detected on Day One and Day Two

The following figures for specialists A and B contain the graphical representation of the support values and the information if they statistically significant differ.

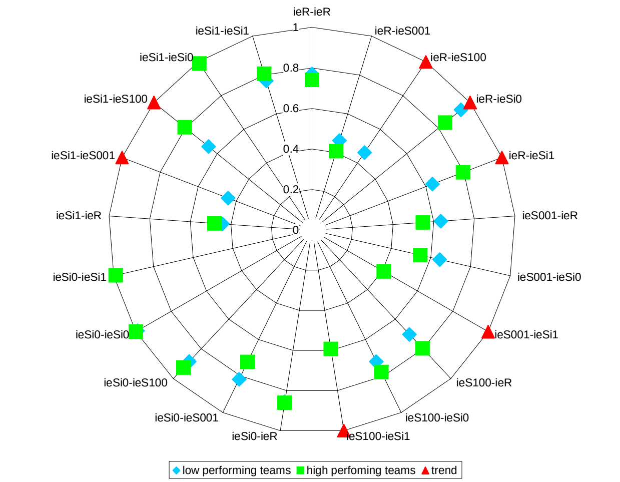
The graphical representations for commanders are found in Figure 50 (page 224).

Figure 56 Sequences for specialists A of low and high performing teams (triple) for day one and day two.

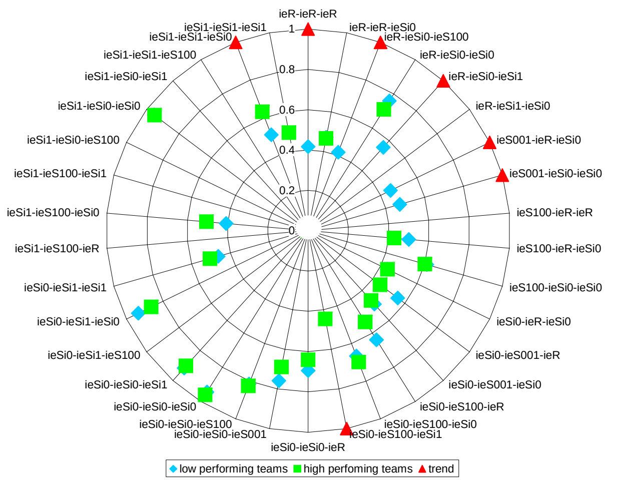
sequences of 2 events – day one



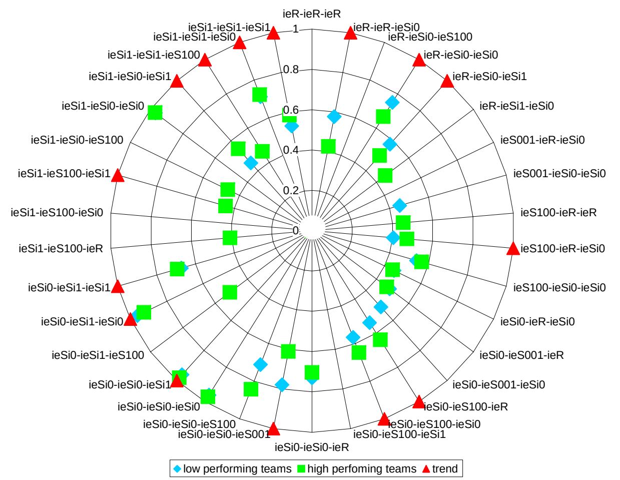
sequences of 2 events – day two



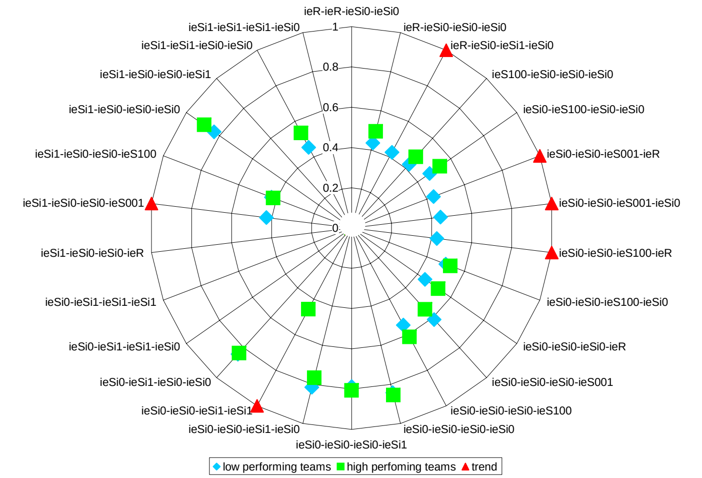
sequences of 3 events – day one



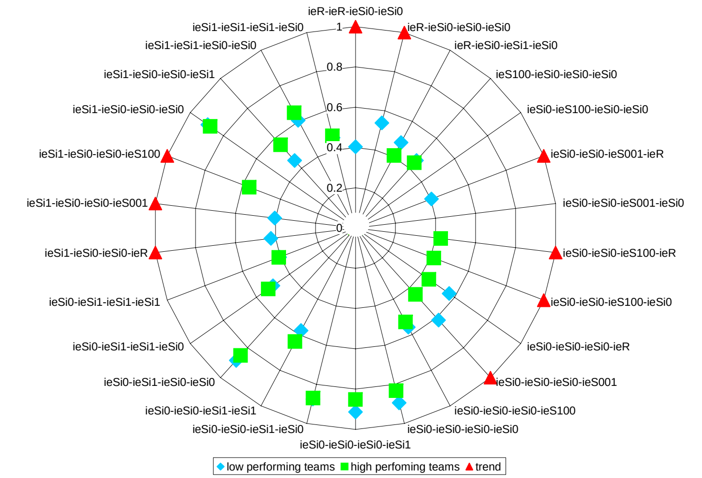
sequences of 3 events – day two



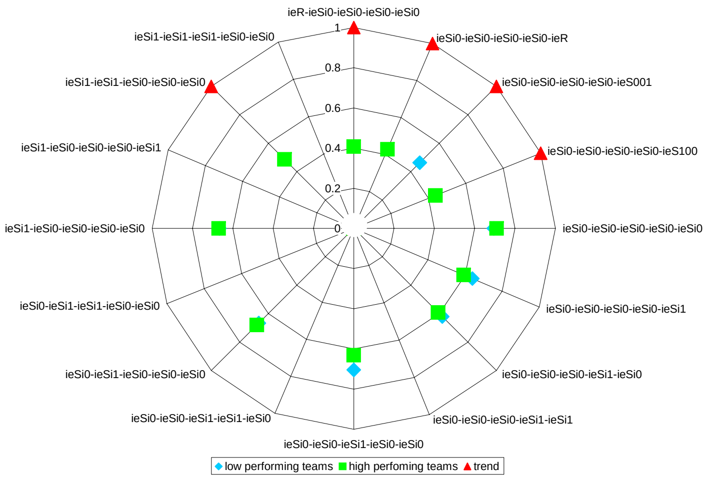
sequences of 4 events – day one



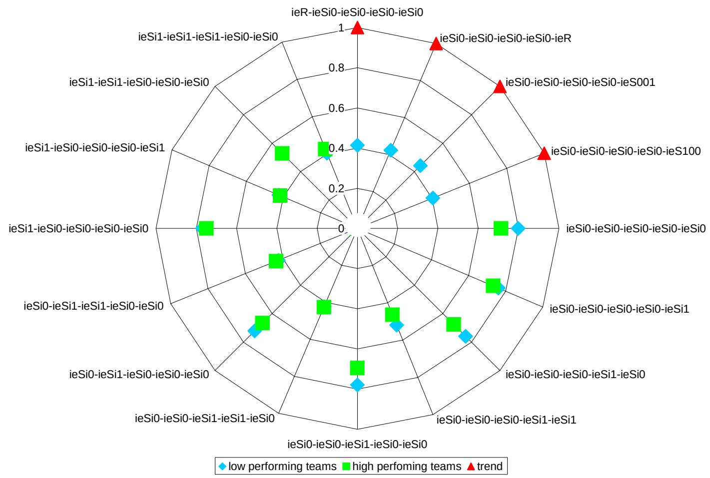
sequences of 4 events – day two



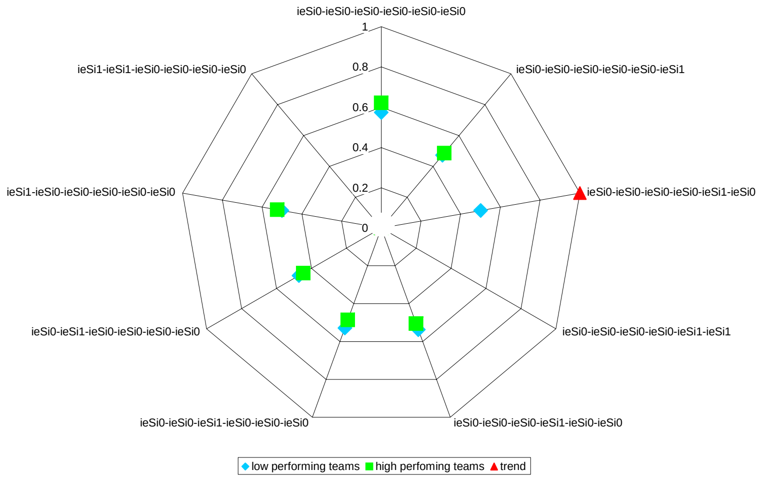
sequences of 5 events – day one



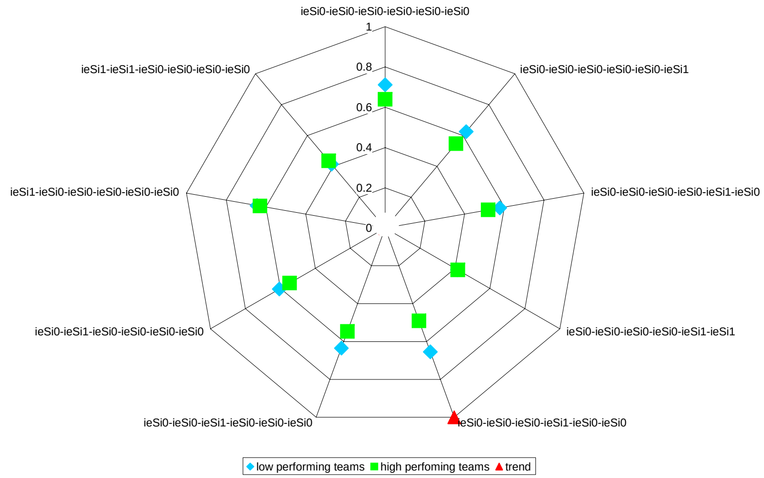
sequences of 5 events – day two



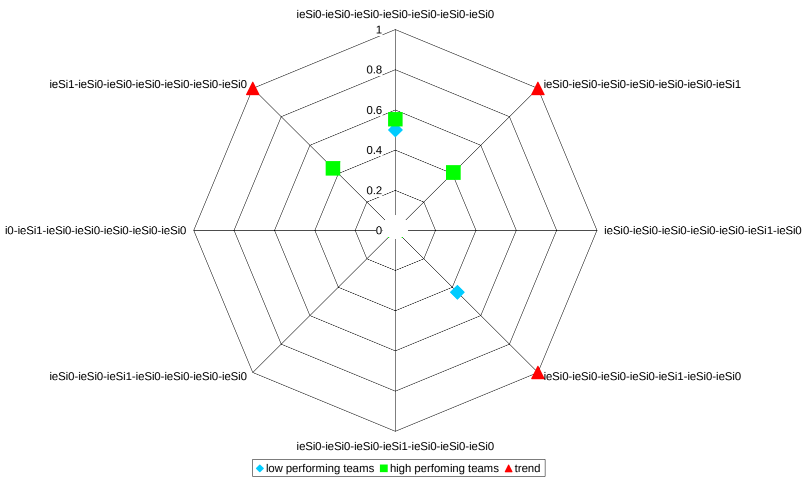
sequences of 6 events – day one



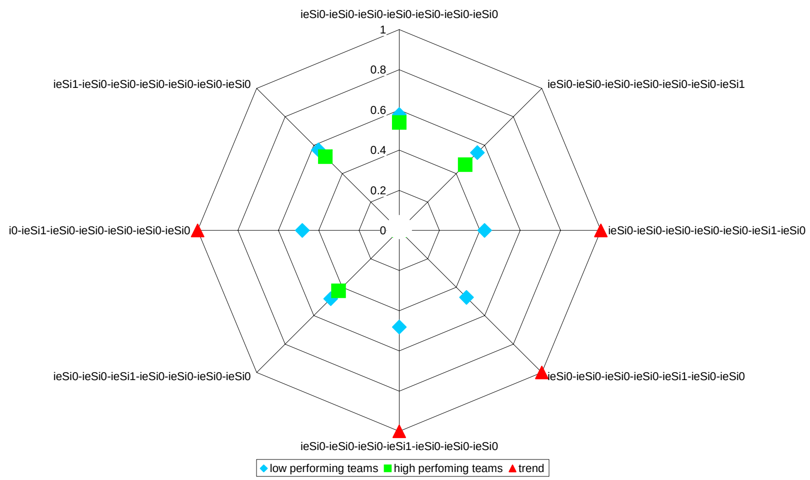
sequences of 6 events – day two



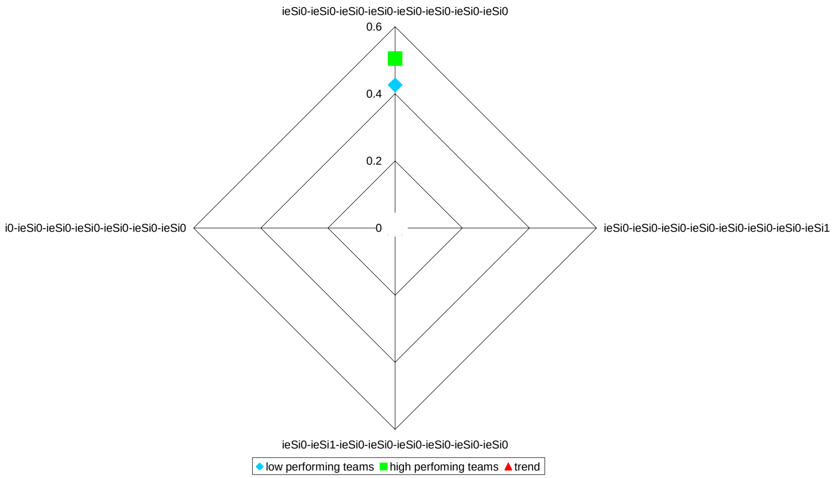
sequences of 7 events – day one



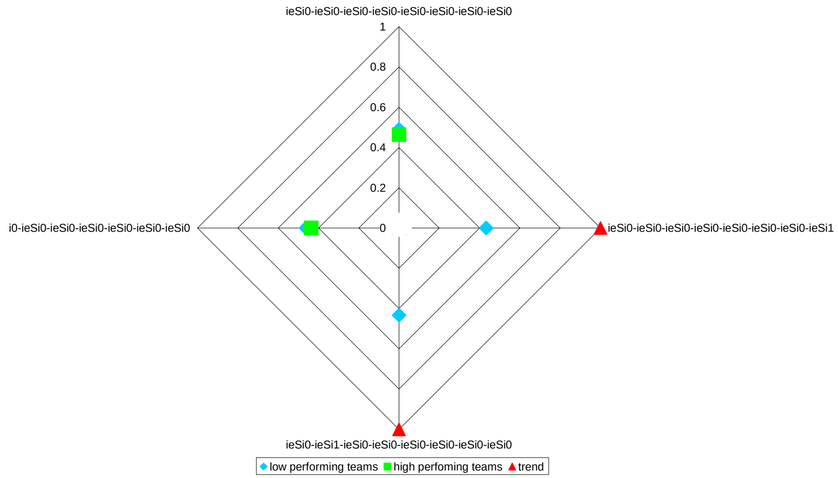
sequences of 7 events – day two



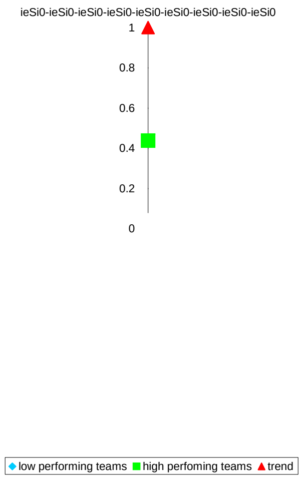
sequences of 8 events – day one



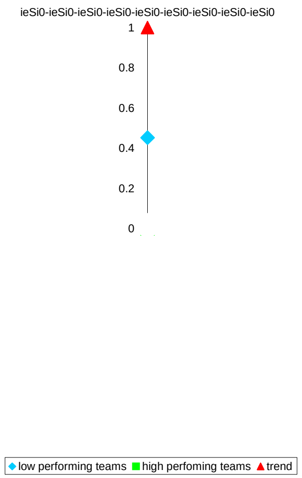
sequences of 8 events – day two



sequences of 9 events – day one

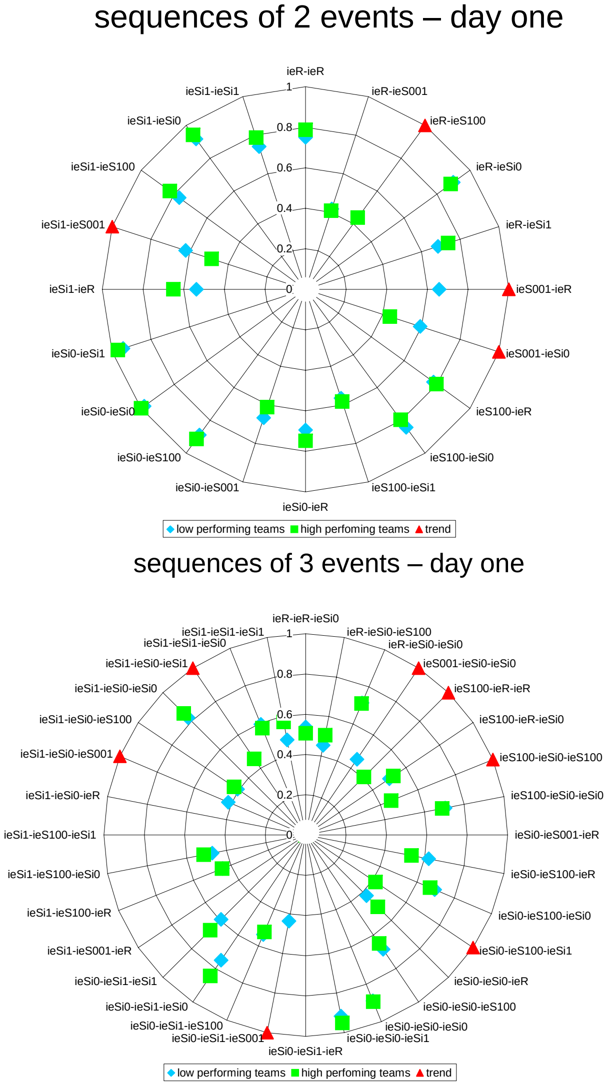


sequences of 9 events – day two

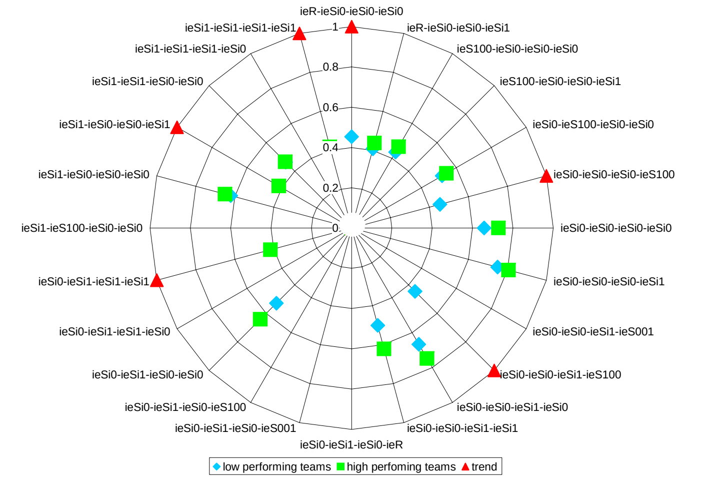


Note. Results are presented for the two extreme groups: all the teams with the lowest performance and all the teams with the highest performance on day one and day two. N = 108 streams day one low performance, 103 streams day one high performance, 104 streams day two, low performance, 108 streams day two, high performance.

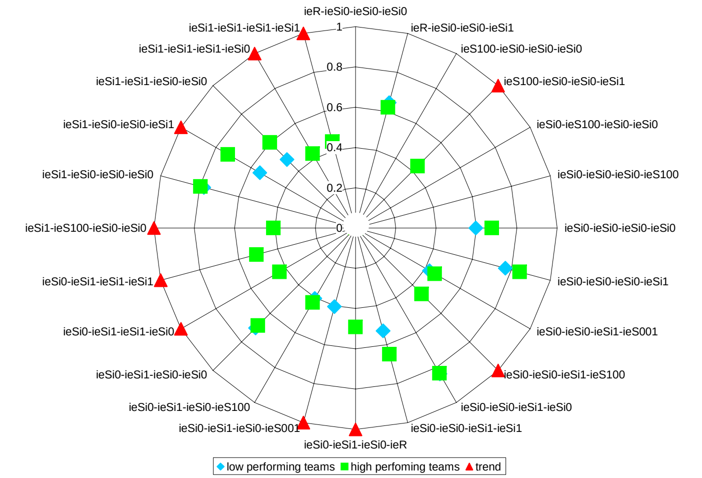
Figure 57 Sequences for specialists B of low and high performing teams (triple) for day one and day two.



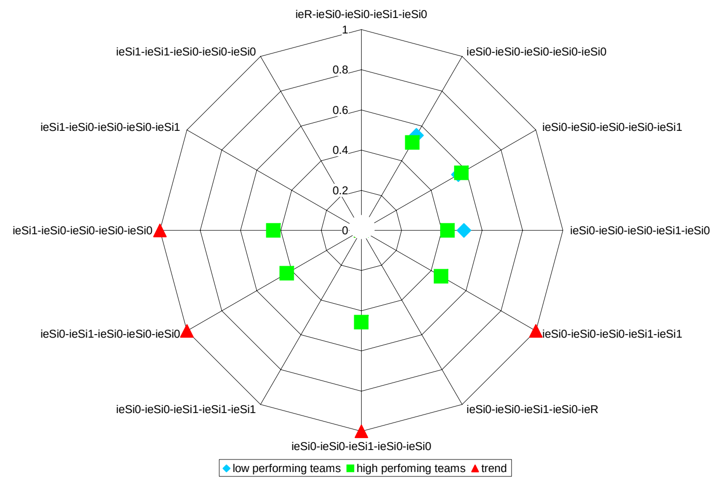
sequences of 4 events – day one



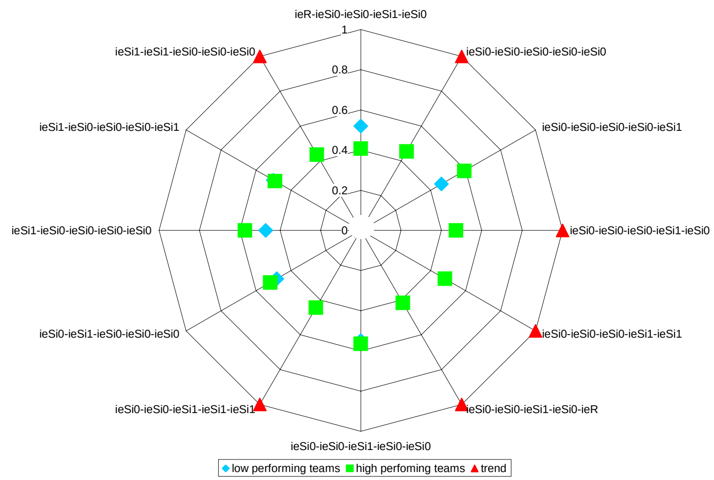
sequences of 4 events – day two

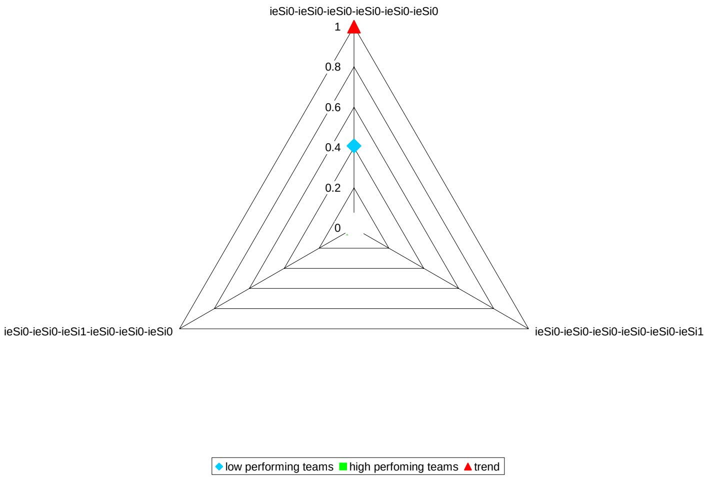
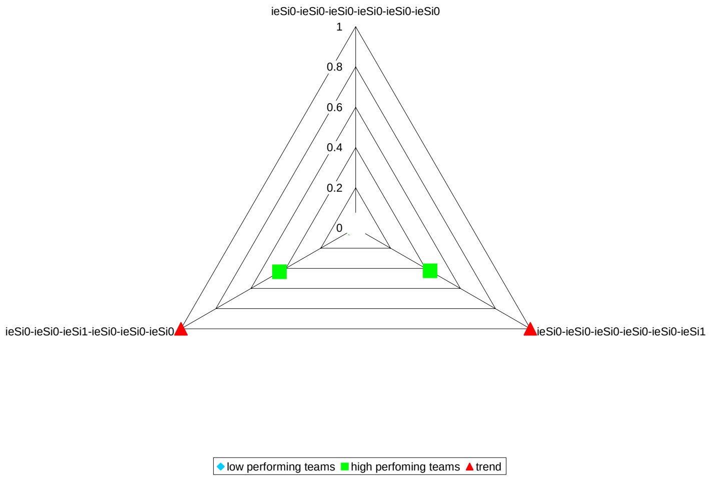


sequences of 5 events – day one



sequences of 5 events – day two



sequences of 6 events – day one	sequences of 6 events – day two
	
sequences of 7 events – day one	sequences of 7 events – day two
-	-
sequences of 8 events – day one	sequences of 8 events – day two
-	-
sequences of 9 events – day one	sequences of 9 events – day two
-	-

Note. Results are presented for the two extreme groups: all the teams with the lowest performance and all the teams with the highest performance on day one and day two. N = 108 streams day one low performance, 103 streams day one high performance, 104 streams day two, low performance, 108 streams day two, high performance.

8.4 Predicting Performance: Data Mining

The following tables contain all information on the details of the regression analyses run to predict performance using sequences found with data mining techniques. There are always two regression equations per shift. The fist equation predicts performance taking only sequences as predictors. The second equation controls for preceding performance, *input variables* and *summary-level process variables*.

Table 176 Results of multiple regression, predicting performance shift 1 with *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.094	.086	.094	11.17	1	107	.001	11.16	1	107	.001
2	.170	.155	.076	9.675	1	106	.002	10.87	2	106	.000
3	.216	.194	.046	6.164	1	105	.015	9.66	3	105	.000
4	.261	.233	.045	6.295	1	104	.014	9.18	4	104	.000
5	.303	.269	.042	6.211	1	103	.014	8.96	5	103	.000
6	.340	.301	.037	5.734	1	102	.018	8.76	6	102	.000
7	.366	.322	.026	4.096	1	101	.046	8.23	7	101	.000
8	.391	.343	.025	4.189	1	100	.043	8.04	8	100	.000
9	.406	.352	.015	2.511	1	99	.116	7.53	9	99	.000
10	.426	.368	.020	3.401	1	98	.068	7.28	10	98	.000
11	.440	.377	.014	2.455	1	97	.120	6.94	11	97	.000
12	.455	.387	.015	2.633	1	96	.108	6.68	12	96	.000

Predictors in trimmed model	Beta	t	Sig.
(1) ieH-ieSi1, commander EC25S1	.247	2.879	.005
(2) ieH-ieS100, commander EC23S1	.270	3.388	.001
(3) ieSi1-ieSi0-ieSi1. specialist B EB330S1	.169	2.126	.036
(4) ieS100-ieR-ieH, commander EC318S1	.191	2.184	.031
(5) ieS001-ieR, specialist A EA26S1	-.350	-3.305	.001
(6) ieS001-ieR-ieSi0, specialist A EA37S1	.230	2.144	.035
(7) ieSi1-ieSi1, commander EC218S1	.169	2.098	.039
(8) ieS100-ieR, specialist B EB28S1	.127	1.602	.112
(9) ieSi1-ieSi1-ieSi1-ieSi0-ieSi0, specialist A EA516S1	-.203	-2.359	.020
(10) ieS001-ieSi0-ieSi0, specialist B EB34S1	-.169	-2.069	.041
(11) ieSi0-ieSi0-ieSi0-ieSi1-ieSi1, specialist A EA58S1	.144	1.649	.102
(12) ieSi0-ieSi0-ieSi1-ieS001, specialist B EB49S	.127	1.623	.108

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15

Table 177 Results of multiple regression, predicting performance shift 1, with *input*, *summary-level process* variables, and *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.076	.067	.076	8.812	1	107	.004	8.82	1	107	.004
2	.112	.095	.036	4.242	1	106	.042	6.60	2	106	.002
3	.130	.105	.018	2.204	1	105	.141	5.23	3	105	.002
4	.201	.170	.071	9.285	1	104	.003	6.55	4	104	.000
5	.259	.223	.058	7.993	1	103	.006	7.19	5	103	.000
6	.289	.248	.031	4.411	1	102	.038	6.93	6	102	.000
7	.304	.256	.015	2.115	1	101	.149	6.30	7	101	.000
8	.321	.267	.017	2.509	1	100	.116	5.91	8	100	.000
9	.370	.313	.049	7.669	1	99	.007	6.46	9	99	.000
10	.401	.340	.031	5.142	1	98	.026	6.57	10	98	.000
11	.424	.359	.023	3.848	1	97	.053	6.50	11	97	.000
12	.441	.371	.017	2.888	1	96	.092	6.31	12	96	.000
13	.455	.380	.014	2.369	1	95	.127	6.09	13	95	.000
14	.470	.391	.015	2.671	1	94	.106	5.95	14	94	.000
15	.482	.398	.012	2.176	1	93	.144	5.76	15	93	.000

Predictors in trimmed model	Beta	t	Sig.
(1) education, specialist A	.152	1.923	.058
(2) education, commander	-.094	-1.152	.252
(3) computer expertise, commander	.167	2.053	.043
(4) duration Send Message, specialist A	-.275	-3.446	.001
(5) number Handle Threat, commander	.110	1.243	.217
(6) duration Send Message, commander	-.137	-1.646	.103
(7) number Read Message, specialist B	.066	.738	.463
(8) duration Read Message, specialist A	-.060	-.690	.492
(9) ieSi1-ieSi0-ieSi1, specialist B EB330S1	.245	3.084	.003
(10) ieS100-ieR-ieH, commander EC318S1	.198	2.263	.026
(11) ieH-ieS100, commander EC23S1	.168	1.972	.052
(12) ieS100-ieR, specialist B EB28S1	.143	1.699	.093
(13) ieSi1-ieSi1, commander EC218S1	.134	1.697	.093
(14) ieS100-ieR-ieR, specialist A EA39S1	-.147	-1.818	.072
(15) ieSi1-ieSi1-ieSi1-ieSi0-ieSi0, specialist A EA516S1	-.118	-1.475	.144

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15

Table 178 Results of multiple regression, predicting performance shift 2 with *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.157	.149	.157	19.97	1	107	.000	19.97	1	107	.001
2	.230	.215	.073	9.990	1	106	.002	15.82	2	106	.000
3	.276	.255	.046	6.655	1	105	.011	13.23	3	105	.000
4	.316	.290	.040	6.111	1	104	.015	12.01	4	104	.000
5	.355	.324	.039	6.204	1	103	.014	11.33	5	103	.000
6	.400	.365	.045	7.710	1	102	.007	11.34	6	102	.000
7	.438	.400	.038	6.883	1	101	.010	11.27	7	101	.000
8	.461	.418	.023	4.195	1	100	.043	10.69	8	100	.000
9	.481	.434	.020	3.794	1	99	.054	10.19	9	99	.000
10	.507	.456	.026	5.127	1	98	.026	10.07	10	98	.000
11	.530	.477	.024	4.871	1	97	.030	9.96	11	97	.000
12	.557	.501	.026	5.671	1	96	.019	10.04	12	96	.000
13	.572	.514	.016	3.472	1	95	.065	9.77	13	95	.000
14	.619	.563	.047	11.62	1	94	.001	10.92	14	94	.000
15	.639	.581	.020	5.133	1	93	.026	10.98	15	93	.000
16	.653	.593	.014	3.676	1	92	.058	10.82	16	92	.000
18	.661	.598	.008	2.189	1	91	.142	10.45	17	91	.000
18	.670	.604	.009	2.479	1	90	.119	10.16	18	90	.000

Predictors in trimmed model	Beta	t	Sig.
(1) ieH-ieSi1, commander EC24S2	.714	5.567	.000
(2) ieR-ieR-ieR-ieH-ieR, commander EC59S2	.107	1.207	.230
(3) ieR-ieH-ieSi1, commander EC36S2	-.547	-4.056	.000
(4) ieSi0-ieSi1-ieR, specialist B EB317S2	-.204	-3.187	.002
(5) ieSi1-ieSi1, specialist A EA221S2	.195	2.975	.004
(6) ieS001-ieSi1, specialist A EA28S2	-.092	-1.349	.181
(7) ieR-ieR-ieR-ieR-ieR-ieR, commander EC66S2	-.237	-3.363	.001
(8) ieH-ieR-ieR-ieR, commander EC43S2	.154	1.938	.056
(9) ieSi0-ieSi0-ieSi1-ieSi0, specialist A EA415S2	-.231	-2.594	.011
(10) ieR-ieSi1-ieH, EC315S2	.137	1.920	.058
(11) ieH-ieR-ieR-ieH-ieR, commander EC52S2	-.309	-3.326	.001
(12) ieR-ieH, commander EC25S2	.264	2.186	.031
(13) ieSi0-ieSi0-ieSi0-ieSi1-ieSi0-ieSi0, specialist A EA65S2	.598	4.799	.000
(14) ieSi0-ieSi0-ieSi1-ieSi0-ieSi0-ieSi0-ieSi0, specialist A EA76S2	-.521	-4.548	.000
(15) ieSi1-ieSi0-ieSi0-ieS100, specialist A EA422S2	-.175	-2.476	.015
(16) ieR-ieS001, specialist B EB22S2	-.124	-1.796	.076
(17) ieSi1-ieS100-ieSi0-ieSi0, specialist B EB419S2	-.117	-1.737	.086
(18) ieSi0-ieSi0-ieS100, specialist B EB314S	.107	1.575	.119

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15

Table 179 Results of multiple regression, predicting performance shift 2, with preceding performance, *input*, *summary-level process* variables, and *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.212	.205	.212	28.81	1	107	.000	28.81	1	107	.000
2	.236	.222	.024	3.303	1	106	.072	16.37	2	106	.000
3	.299	.279	.063	9.499	1	105	.003	14.95	3	105	.000
4	.320	.294	.021	3.178	1	104	.078	12.24	4	104	.000
5	.337	.305	.017	2.664	1	103	.106	10.48	5	103	.000
6	.394	.359	.057	9.638	1	102	.002	11.07	6	102	.000
7	.455	.417	.060	11.13	1	101	.001	12.03	7	101	.000
8	.478	.437	.024	4.553	1	100	.035	11.46	8	100	.000
9	.509	.464	.030	6.079	1	99	.015	11.38	9	99	.000
10	.531	.483	.022	4.622	1	98	.034	11.08	10	98	.000
11	.547	.495	.016	3.463	1	97	.066	10.64	11	97	.000
12	.565	.511	.018	4.000	1	96	.048	10.39	12	96	.000
13	.584	.527	.019	4.396	1	95	.039	10.27	13	95	.000
14	.622	.566	.038	9.387	1	94	.003	11.05	14	94	.000
15	.644	.586	.022	5.710	1	93	.019	11.21	15	93	.000
16	.661	.602	.017	4.593	1	92	.035	11.12	16	92	.000
17	.673	.612	.012	3.354	1	91	.070	11.01	17	91	.000
18	.687	.625	.014	4.171	1	90	.044	11.00	18	90	.000

Predictors in trimmed model	Beta	t	Sig.
(1) performance shift 1	.274	4.183	.000
(2) gender, commander	-.001	-.016	.988
(3) frequency Handle Threat, commander	.192	2.043	.044
(4) frequency Read Message, specialist B	-.117	-1.675	.097
(5) frequency Show Information, commander	.065	.973	.333
(6) ieH-ieR-ieR-ieH-ieR, commander EC52S2	-.280	-3.385	.001
(7) ieH-ieSi1, commander EC24S2	.624	5.057	.000
(8) ieR-ieR-ieR-ieH-ieR, commander EC59S2	.164	2.072	.041
(9) ieR-ieH-ieSi1, commander EC36S2	-.467	-3.660	.000
(10) ieSi0-ieSi1-ieR, specialist B EB317S2	-.149	-2.219	.029
(11) ieR-ieR-ieR-ieR-ieR-ieR, commander EC66S2	-.219	-3.203	.002
(12) ieH-ieR-ieR-ieR, commander EC43S2	.183	2.409	.018
(13) ieSi0-ieSi0-ieSi1-ieSi0-ieSi0-ieSi0-ieSi0, specialist A EA76S2	-.468	-4.152	.000
(14) ieSi0-ieSi0-ieSi0-ieSi1-ieSi0-ieSi0, specialist A EA65S2	.654	4.437	.000
(15) ieSi1-ieSi0-ieSi0-ieS100, specialist A EA422S2	-.168	-2.457	.016
(16) ieSi0-ieSi0-ieSi0-ieSi1-ieSi0, specialist A EA57S2	-.261	-2.074	.041
(17) ieSi1-ieSi1, specialist A EA221S2	.138	2.110	.038
(18) ieS001-ieSi1, specialist A EA28S	-.129	-2.042	.044

Note. Trimmed model. N = 109 teams, preceding performance entered in the first step with method enter, *input variables* entered in the second step with method forward, *summary-level process variables* entered in the third step with method forward, sequences entered in the fourth step with method forward, PIN = 0.15

Table 180 Results of multiple regression, predicting performance shift 3 with *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.090	.082	.090	10.59	1	107	.002	10.59	1	107	.002
2	.162	.146	.072	9.120	1	106	.003	10.26	2	106	. 000
3	.216	.194	.054	7.220	1	105	.008	9.65	3	105	. 000
4	.270	.242	.054	7.753	1	104	.006	9.64	4	104	. 000
5	.316	.282	.045	6.787	1	103	.011	9.50	5	103	. 000
6	.347	.308	.031	4.881	1	102	.029	9.03	6	102	. 000
7	.381	.338	.034	5.498	1	101	.021	8.86	7	101	.000
8	.413	.366	.032	5.535	1	100	.021	8.80	8	100	.000
9	.441	.390	.028	4.950	1	99	.028	8.68	9	99	.000
10	.468	.413	.027	4.911	1	98	.029	8.61	10	98	.000
11	.489	.431	.021	4.064	1	97	.047	8.44	11	97	.000
12	.504	.442	.015	2.983	1	96	.087	8.14	12	96	.000
13	.526	.461	.022	4.346	1	95	.040	8.11	13	95	.000
14	.547	.479	.020	4.249	1	94	.042	8.10	14	94	.000
15	.560	.489	.013	2.769	1	93	.099	7.88	15	93	.000
16	.574	.499	.014	2.993	1	92	.087	7.74	16	92	.000
17	.589	.512	.015	3.301	1	91	.073	7.66	17	91	.000

Predictors in trimmed model	Beta	t	Sig.
(1) ieS100-ieS100, commander EC214S3	-.289	-3.655	.000
(2) ieS100-ieSi1, specialist A EA211S3	.209	2.486	.015
(3) ieR-ieSi0-ieS100, specialist B EB32S3	-.251	-3.509	.001
(4) ieSi1-ieR, commander EC216S3	.327	4.121	.000
(5) ieSi1-ieS100-ieSi1, specialist B EB325S3	.203	2.658	.009
(6) ieR-ieR, specialist B EB21S3	.225	2.855	.005
(7) ieSi0-ieSi0-ieS001-ieSi0, specialist A EA47S3	-.234	-3.146	.002
(8) ieSi1-ieSi1-ieSi1-ieSi0, specialist B EB423S3	.147	1.944	.055
(9) ieSi1-ieS001, specialist B EB217S3	-.375	-3.745	.000
(10) ieR-ieS010, commander EC28S3	.216	2.841	.006
(11) ieR-ieSi1, commander EC210S3	-.161	-1.982	.050
(12) ieSi0-ieSi0-ieR, specialist A EA319S3	.169	2.231	.028
(13) ieSi0-ieR, specialist B EB211S3	-.225	-2.641	.010
(14) ieR-ieSi1, specialist B EB25S3	.171	2.205	.030
(15) ieR-ieS100, specialist A EA23S3	-.161	-1.918	.058
(16) ieR-ieS100-ieR-ieR, commander EC412S3	.150	1.916	.058
(17) ieSi0-ieSi1-ieS001, specialist B EB318S	.175	1.817	.073

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15.

Table 181 Results of multiple regression, predicting performance shift 3, with *input*, *summary-level process* variables, and *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.323	.316	.323	50.94	1	107	.000	50.94	1	107	.000
2	.380	.368	.057	9.768	1	106	.002	32.44	2	106	.000
3	.407	.390	.028	4.882	1	105	.029	24.05	3	105	.000
4	.435	.413	.027	5.034	1	104	.027	19.99	4	104	.000
5	.468	.443	.034	6.557	1	103	.012	18.16	5	103	.000
6	.493	.463	.025	4.994	1	102	.028	16.55	6	102	.000
7	.523	.490	.029	6.229	1	101	.014	15.80	7	101	.000
8	.553	.518	.031	6.835	1	100	.010	15.48	8	100	.000
9	.576	.538	.023	5.380	1	99	.022	14.96	9	99	.000
10	.597	.556	.021	5.096	1	98	.026	14.53	10	98	.000
11	.617	.573	.019	4.933	1	97	.029	14.19	11	97	.000
12	.631	.585	.014	3.767	1	96	.055	13.69	12	96	.000
13	.642	.593	.011	2.898	1	95	.092	13.11	13	95	.000
14	.656	.605	.014	3.787	1	94	.055	12.80	14	94	.000

Predictors in trimmed model	Beta	t	Sig.
(1) performance shift 1-2	.449	6.621	.000
(2) gender, commander	.132	1.950	.054
(3) age, specialist A	-.154	-2.445	.016
(4) frequency Send Message, commander	-.071	-.800	.426
(5) frequency Read Message, specialist B	-.088	-.686	.494
(6) ieR-ieSi0-ieS100, specialist B EB32S3	-.198	-3.074	.003
(7) ieS100-ieS100, commander EC214S3	-.283	-3.675	.000
(8) ieSi1-ieR, commander EC216S3	.197	3.111	.002
(9) ieSi1-ieS100-ieSi1, specialist B EB325S3	.155	2.311	.023
(10) ieSi1-ieS001, specialist B EB217S3	-.195	-2.937	.004
(11) ieR-ieSi1, specialist B EB25S3	.163	2.196	.031
(12) ieR-ieR, specialist B EB21S3	.271	2.426	.017
(13) ieSi1-ieSi1-ieSi1-ieSi0, specialist B EB423S3	.133	2.015	.047
(14) ieSi0-ieSi0-ieS001-ieSi0, specialist A EA47S3	-.134	-1.946	.055

Note. Trimmed model. N = 109 teams, preceding performance entered in the first step with method enter, *input variables* entered in the second step with method forward, *summary-level process variables* entered in the third step with method forward, sequences entered in the fourth step with method forward, PIN = 0.15.

Table 182 Results of multiple regression, predicting performance shift 4 with *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.079	.070	.079	9.130	1	107	.003	9.13	1	107	.003
2	.144	.128	.065	8.076	1	106	.005	8.91	2	106	. 000
3	.200	.177	.056	7.301	1	105	.008	8.72	3	105	. 000
4	.236	.207	.036	4.965	1	104	.028	8.03	4	104	. 000
5	.285	.250	.049	7.049	1	103	.009	8.21	5	103	. 000
6	.350	.312	.065	10.21	1	102	.002	9.15	6	102	. 000
7	.387	.344	.037	6.079	1	101	.015	9.10	7	101	.000
8	.412	.365	.025	4.215	1	100	.043	8.75	8	100	.000
9	.435	.383	.023	4.024	1	99	.048	8.46	9	99	.000
10	.458	.403	.024	4.267	1	98	.041	8.29	10	98	.000
11	.479	.420	.021	3.916	1	97	.051	8.12	11	97	.000
12	.497	.434	.018	3.395	1	96	.068	7.91	12	96	.000
13	.527	.462	.030	5.961	1	95	.016	8.13	13	95	.000
14	.550	.483	.023	4.793	1	94	.031	8.20	14	94	.000
15	.578	.510	.028	6.215	1	93	.014	8.49	15	93	.000
16	.594	.524	.016	3.679	1	92	.058	8.42	16	92	.000
17	.612	.539	.018	4.117	1	91	.045	8.43	17	91	.000
18	.624	.549	.012	2.904	1	90	.092	8.30	18	90	000
19	.635	.558	.012	2.841	1	89	.095	8.17	19	89	000
20	.653	.575	.018	4.528	1	88	.036	8.29	20	88	000
21	.663	.581	.010	2.461	1	87	.120	8.15	21	87	000
22	.674	.590	.011	2.871	1	86	.094	8.07	22	86	000

Predictors in trimmed model	Beta	t	Sig.
(1) ieR-ieR-ieS100-ieR-ieR, commander EC512S4	.021	.167	.868
(2) ieSi1-ieSi1, specialist A EA221S4	.137	1.861	.066
(3) ieR-ieR-ieR-ieR-ieH-ieR, commander EC65S4	.411	4.241	.000
(4) ieR-ieR-ieR-ieSi1, commander EC410S4	-.211	-2.832	.006
(5) ieH-ieR-ieR-ieH-ieR, commander EC52S4	-.177	-2.233	.028
(6) ieR-ieS010-ieR, commander EC313S4	-.304	-4.364	.000
(7) ieSi1-ieSi0-ieSi0-ieSi0, specialist B EB420S4	.332	4.449	.000
(8) ieSi0-ieSi1-ieS100, specialist B EB319S4	.217	3.328	.001
(9) ieS100-ieS100, commander EC214S4	-.376	-3.200	.002
(10) ieH-ieR-ieH-ieR, commander EC41S4	-.200	-2.772	.007
(11) ieS100-ieS100-ieR, commander EC320S4	.321	2.678	.009
(12) ieSi0-ieSi0-ieSi0-ieS001, specialist A EA411S4	.875	4.533	.000
(13) ieSi0-ieSi0-ieSi0-ieSi0-ieS001, specialist A EA53S4	-.741	-3.904	.000
(14) ieR-ieSi0-ieSi0, specialist B EB33S4	-.178	-2.472	.015
(15) ieR-ieR-ieR-ieH-ieR-ieR, commander EC64S4	-.294	-2.847	.006
(16) ieR-ieR-ieR-ieS100, commander EC49S4	.316	3.126	.002
(17) ieR-ieR-ieS100, commander EC310S4	-.299	-1.835	.070
(18) ieR-ieR-ieS100-ieR, commander EC411S4	.243	1.412	.162
(19) ieR-ieS001, commander EC27S4	.375	3.124	.002
(20) ieR-ieS001-ieR, commander EC312S4	-.304	-2.544	.013
(21) ieS001-ieSi0-ieSi0, specialist A EA38S4	-.161	-1.903	.060
(22) ieSi0-ieSi0-ieSi0-ieS100, specialist B EB46S	-.119	-1.694	.094

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15

Table 183 Results of multiple regression, predicting performance shift 4, with *input*, *summary-level process* variables, and *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.235	.228	.235	32.93	1	107	.000	32.93	1	107	.000
2	.281	.268	.046	6.791	1	106	.010	20.75	2	106	.000
3	.299	.279	.018	2.674	1	105	.105	14.95	3	105	.000
4	.319	.293	.020	3.072	1	104	.083	12.20	4	104	.000
5	.337	.304	.017	2.694	1	103	.104	10.46	5	103	.000
6	.353	.314	.016	2.505	1	102	.117	9.26	6	102	.000
7	.400	.358	.047	7.922	1	101	.006	9.61	7	101	.000
8	.419	.372	.019	3.317	1	100	.072	9.01	8	100	.000
9	.438	.387	.019	3.346	1	99	.070	8.57	9	99	.000
10	.457	.401	.019	3.413	1	98	.068	8.24	10	98	.000
11	.470	.410	.013	2.442	1	97	.121	7.83	11	97	.000
12	.527	.468	.057	11.53	1	96	.001	8.91	12	96	.000
13	.551	.490	.024	5.156	1	95	.025	8.98	13	95	.000
14	.574	.511	.023	5.082	1	94	.027	9.06	14	94	.000
15	.604	.541	.030	7.045	1	93	.009	9.47	15	93	.000
16	.630	.565	.025	6.333	1	92	.014	9.78	16	92	.000
17	.650	.585	.020	5.308	1	91	.024	9.95	17	91	.000
18	.662	.594	.011	3.051	1	90	.084	9.78	18	90	.000

Predictors in trimmed model	Beta	t	Sig.
(1) performance shift 1-3	.311	4.406	.000
(2) computer expertise, commander	.258	3.885	.000
(3) gender, specialist A	-.107	-1.664	.100
(4) Control Condition 1	-.101	-1.552	.124
(5) age, commander	-.194	-2.938	.004
(6) education commander	.181	2.684	.009
(7) duration Read Message, specialist B	-.098	-1.330	.187
(8) duration Send Message, specialist A	-.198	-2.774	.007
(9) frequency Handle Threat, commmander	-.180	-2.356	.021
(10) frequency Show Information, specialist B	.194	2.897	.005
(11) duration Read Message, commander	.052	.651	.517
(12) ieR-ieR-ieR-ieR-ieH-ieR, commander EC65S4	.289	3.983	.000
(13) ieR-ieS001, commander EC27S4	.354	3.289	.001
(14) ieR-ieR-ieR-ieSi1, commander EC410S4	-.257	-3.733	.000
(15) ieR-ieS010-ieR, commander EC313S4	-.230	-3.310	.001
(16) ieH-ieR-ieR-ieH-ieR, commander EC52S4	-.236	-3.091	.003
(17) ieR-ieS001-ieR, commander EC312S4	-.253	-2.376	.020
(18) ieR-ieS001, specialist A EA221S	.124	1.747	.084

Note. Trimmed model. N = 109 teams, preceding performance entered in the first step with method enter, *input variables* entered in the second step with method forward, *summary-level process variables* entered in the third step with method forward, sequences entered in the fourth step with method forward, PIN = 0.15

Table 184 Results of multiple regression, predicting performance shift 5 with *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.168	.160	.168	21.55	1	107	.000	21.55	1	107	.000
2	.302	.289	.134	20.36	1	106	.000	22.91	2	106	. 000
3	.385	.368	.083	14.26	1	105	.000	21.93	3	105	. 000
4	.417	.395	.032	5.673	1	104	.019	18.60	4	104	. 000
5	.446	.419	.029	5.347	1	103	.023	16.57	5	103	. 000
6	.470	.439	.024	4.666	1	102	.033	15.08	6	102	. 000
7	.501	.467	.031	6.295	1	101	.014	14.50	7	101	.000
8	.522	.483	.020	4.283	1	100	.041	13.63	8	100	.000
9	.540	.498	.018	3.894	1	99	.051	12.90	9	99	.000
10	.559	.514	.019	4.266	1	98	.042	12.42	10	98	.000
11	.572	.524	.013	2.995	1	97	.087	11.79	11	97	.000
12	.583	.531	.011	2.479	1	96	.119	11.18	12	96	.000
13	.592	.537	.009	2.206	1	95	.141	10.62	13	95	.000
14	.617	.560	.025	6.121	1	94	.015	10.83	14	94	.000
15	.628	.568	.010	2.567	1	93	.112	10.45	15	93	.000
16	.639	.576	.012	2.952	1	92	.089	10.19	16	92	.000
17	.653	.588	.014	3.635	1	91	.060	10.08	17	91	.000

Predictors in trimmed model	Beta	t	Sig.
(1) ieH-ieSi1, commander EC24S5	.482	5.502	.000
(2) ieR-ieS010-ieR, commander EC313S5	-.335	-5.102	.000
(3) ieSi0-ieSi0-ieS100, specialist B EB314S5	.123	1.644	.104
(4) ieSi1-ieSi1-ieSi0-ieSi0-ieSi0, specialist B EB512S5	.247	3.294	.001
(5) ieSi1-ieSi0-ieSi1, specialist A EA332S5	.155	2.323	.022
(6) ieR-ieH-ieSi1, commander EC36S5	-.291	-2.872	.005
(7) ieR-ieSi0-ieSi0, specialist A EA34S5	-.152	-2.270	.026
(8) ieR-ieR-ieH, commander EC37S5	.091	1.072	.286
(9) ieR-ieSi0-ieSi0, specialist B EB33S5	-.105	-1.356	.179
(10) ieSi0-ieSi0-ieR, specialist B EB313S5	.118	1.422	.158
(12) ieR-ieSi1, specialist B EB25S5	-.166	-2.291	.024
(13) ieS100-ieSi0, specialist A EA210S5	.115	1.465	.146
(14) ieR-ieR-ieR-ieS100, commander EC49S5	-.303	-3.088	.003
(15) ieR-ieS100-ieR-ieR, commander EC412S5	.230	2.810	.006
(16) ieR-ieS100, specialist A EA23S5	.184	2.193	.031
(17) ieR-ieR-ieR-ieR-ieH-ieR, commander EC65S5	.159	1.984	.050
(18) ieSi1-ieSi0, specialist B EB219S	.152	1.906	.060

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15

Table 185 Results of multiple regression, predicting performance shift 5, with *input*, *summary-level process* variables, and *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.271	.264	.271	39.75	1	107	.000	39.75	1	107	.000
2	.308	.295	.037	5.655	1	106	.019	23.57	2	106	.000
3	.326	.307	.018	2.844	1	105	.095	16.93	3	105	.000
4	.370	.345	.044	7.181	1	104	.009	15.24	4	104	.000
5	.411	.383	.042	7.317	1	103	.008	14.40	5	103	.000
6	.431	.397	.019	3.469	1	102	.065	12.87	6	102	.000
7	.446	.407	.015	2.705	1	101	.103	11.60	7	101	.000
8	.496	.455	.050	9.918	1	100	.002	12.28	8	100	.000
9	.535	.493	.039	8.334	1	99	.005	12.65	9	99	.000
10	.569	.525	.034	7.828	1	98	.006	12.95	10	98	.000
11	.597	.552	.028	6.787	1	97	.011	13.08	11	97	.000
12	.625	.578	.028	7.106	1	96	.009	13.34	12	96	.000
13	.648	.600	.023	6.178	1	95	.015	13.45	13	95	.000
14	.668	.619	.020	5.650	1	94	.019	13.51	14	94	.000
15	.685	.634	.017	4.961	1	93	.028	13.47	15	93	.000
16	.695	.643	.011	3.229	1	92	.076	13.13	16	92	.000
17	.706	.651	.010	3.117	1	91	.081	12.83	17	91	.000
18	.726	.671	.020	6.646	1	90	.012	13.24	18	90	.000
19	.734	.677	.008	2.684	1	89	.105	12.92	19	89	.000

Predictors in trimmed model	Beta	t	Sig.
(1) performance shift 1-4	.352	5.439	.000
(2) computer expertise, commander	.074	1.100	.274
(3) gender, commander	.178	2.810	.006
(4) frequency Show Information, specialist AB	-.030	-.293	.770
(5) frequency Show Information, specialist A	-.184	-2.792	.006
(6) duration Send Message, commander	-.102	-1.474	.144
(7) frequency Handle Threat, commander	.060	.940	.350
(8) ieSi0-ieSi0-ieR, specialist B EB313S5	.198	2.744	.007
(9) ieR-ieSi1, specialist B EB25S5	-.199	-3.172	.002
(10) ieSi1-ieSi1-ieSi0-ieSi0-ieSi0, specialist B EB512S5	.308	3.192	.002
(11) ieH-ieSi1, commander EC24S5	.331	4.032	.000
(12) ieR-ieS010-ieR, commander EC313S5	-.180	-2.757	.007
(13) ieSi1-ieSi0-ieSi1, specialist A EA332S5	.170	2.932	.004
(14) ieS100-ieSi0, specialist A EA210S5	.315	3.821	.000
(15) ieSi0-ieS001-ieSi0, specialist A EA315S5	.129	2.048	.044
(16) ieR-ieH-ieSi1, commander EC36S5	-.224	-2.600	.011
(17) ieR-ieR-ieR-ieS100, commander EC49S5	-.242	-2.980	.004
(18) ieR-ieS100-ieR-ieR, commander EC412S5	.195	2.557	.012
(19) ieSi1-ieS100-ieSi0, specialist A EA328S	-.131	-1.638	.105

Note. Trimmed model. N = 109 teams, preceding performance entered in the first step with method enter, *input variables* entered in the second step with method forward, *summary-level process variables* entered in the third step with method forward, sequences entered in the fourth step with method forward, PIN = 0.15

Table 186 Results of multiple regression, predicting performance shift 6 with *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.125	.117	.125	15.28	1	107	.000	15.28	1	107	.000
2	.201	.186	.076	10.04	1	106	.002	13.31	2	106	. 000
3	.269	.248	.068	9.764	1	105	.002	12.86	3	105	. 000
4	.300	.273	.032	4.708	1	104	.032	11.16	4	104	. 000
5	.324	.291	.024	3.581	1	103	.061	9.87	5	103	. 000
6	.361	.323	.037	5.894	1	102	.017	9.60	6	102	. 000
7	.388	.346	.028	4.570	1	101	.035	9.17	7	101	.000
8	.414	.367	.025	4.281	1	100	.041	8.82	8	100	.000
9	.438	.387	.024	4.286	1	99	.041	8.57	9	99	.000
10	.460	.405	.022	3.944	1	98	.050	8.34	10	98	.000
11	.478	.419	.018	3.383	1	97	.069	8.07	11	97	.000
12	.495	.432	.017	3.236	1	96	.075	7.84	12	96	.000
13	.511	.444	.016	3.107	1	95	.081	7.64	13	95	.000
14	.528	.458	.017	3.440	1	94	.067	7.52	14	94	.000
15	.541	.468	.013	2.703	1	93	.104	7.32	15	93	.000
16	.554	.476	.012	2.534	1	92	.115	7.14	16	92	.000
17	.573	.493	.019	4.064	1	91	.047	7.18	17	91	.000
18	.594	.513	.022	4.802	1	90	.031	7.33	18	90	.000
19	.609	.525	.014	3.267	1	89	.074	7.29	19	89	.000
20	.623	.538	.015	3.417	1	88	.068	7.29	20	88	.000
21	.635	.547	.012	2.811	1	87	.097	7.22	21	87	.000
22	.644	.553	.009	2.151	1	86	.146	7.08	22	86	.000
23	.664	.573	.020	4.981	1	85	.028	7.30	23	85	.000
24	.672	.579	.008	2.135	1	84	.148	7.18	24	84	.000
25	.683	.587	.011	2.777	1	83	.099	7.15	25	83	.000
26	.694	.597	.011	3.052	1	82	.084	7.16	26	82	.000

Predictors in trimmed model	Beta	t	Sig.
(1) ieSi1-ieSi1-ieS100, specialist A EA333S6	.204	2.733	.008
(2) ieSi1-ieSi0, specialist B EB219S6	.224	3.147	.002
(3) ieH-ieSi1, commander EC24S6	.223	2.602	.011
(4) ieS100-ieSi1, specialist B EB210S6	.112	1.281	.204
(5) ieS100-ieR, specialist A EA29S6	-.403	-3.733	.000
(6) ieS100-ieR-ieSi0, specialist A EA310S6	.245	2.580	.012
(7) ieR-ieS100-ieR, commanderEC314S6	.235	3.156	.002
(8) ieSi0-ieR, specialist A EA212S6	-.159	-1.920	.058
(9) ieSi0-ieS001-ieR, specialist A EA314S6	-.172	-2.405	.018
(10) ieSi1-ieS100-ieSi0-ieSi0, specialist B EB419S6	-.138	-1.707	.092
(11) ieR-ieH-ieSi1, commander EC36S6	-.212	-2.511	.014
(12) ieSi0-ieS100-ieSi0-ieSi0, specialist B EB45S6	.085	1.031	.306
(13) ieR-ieS010, commander EC28S6	.123	1.753	.083
(14) ieR-ieH-ieR-ieH-ieR, commander EC54S6	.235	2.667	.009
(15) ieR-ieSi0-ieS100, specialist B EB32S6	-.091	-1.108	.271
(16) ieSi0-ieSi1-ieSi0, specialist A EA325S6	.721	3.987	.000
(17) ieSi0-ieSi0-ieSi1-ieSi0, specialist A EA415S6	-.659	-3.606	.001
(18) ieSi0-ieSi0-ieSi0-ieSi0-ieS001, specialist A EA53S6	.170	2.321	.023
(19) ieR-ieS100, specialist B EB22S6	-.171	-2.126	.037
(20) ieR-ieR-ieH-ieR-ieH, commander EC57S6	-.221	-2.490	.015
(21) ieSi1-ieS100-ieR, specialist A EA327S6	.157	1.856	.067
(22) ieR-ieR, specialist B EB21S6	.246	2.728	.008
(23) ieR-ieR, specialist A, EA21S6	-.207	-2.376	.020
(24) ieR-ieR-ieR-ieR, commander EC48S6	-.221	-2.308	.024
(25) ieH-ieS100-ieR, commander EC33S6	-.124	-1.841	.069
(26) ieH-ieR-ieH-ieR-ieR, commander EC510S6	.167	1.747	.084

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15

Table 187 Results of multiple regression, predicting performance shift 6, with *input*, *summary-level process* variables, and *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.405	.400	.405	72.89	1	107	.000	72.89	1	107	.000
2	.423	.412	.017	3.196	1	106	.077	38.79	2	106	.000
3	.443	.427	.021	3.917	1	105	.050	27.88	3	105	.000
4	.464	.443	.020	3.968	1	104	.049	22.49	4	104	.000
5	.478	.453	.015	2.889	1	103	.092	18.90	5	103	.000
6	.489	.459	.011	2.186	1	102	.142	16.29	6	102	.000
7	.502	.467	.013	2.557	1	101	.113	14.55	7	101	.000
8	.515	.476	.013	2.601	1	100	.110	13.25	8	100	.000
9	.555	.514	.040	8.880	1	99	.004	13.70	9	99	.000
10	.578	.535	.024	5.520	1	98	.021	13.44	10	98	.000
11	.599	.554	.021	5.080	1	97	.026	13.19	11	97	.000
12	.614	.566	.015	3.621	1	96	.060	12.72	12	96	.000
13	.626	.575	.012	3.025	1	95	.085	12.22	13	95	.000
14	.636	.582	.010	2.673	1	94	.105	11.74	14	94	.000
15	.652	.596	.016	4.207	1	93	.043	11.61	15	93	.000
16	.702	.650	.050	15.44	1	92	.000	13.54	16	92	.000
17	.709	.654	.007	2.141	1	91	.147	13.03	17	91	.000
18	.716	.659	.007	2.223	1	90	.139	12.59	18	90	.000
19	.728	.670	.012	3.893	1	89	.052	12.52	19	89	.000
20	.736	.676	.008	2.705	1	88	.104	12.26	20	88	.000
21	.743	.681	.007	2.390	1	87	.126	11.97	21	87	.000
22	.749	.685	.007	2.255	1	86	.137	11.69	22	86	.000
23	.756	.690	.007	2.318	1	85	.132	11.46	23	85	.000
24	.762	.694	.006	2.188	1	84	.143	11.22	24	84	.000
25	.773	.705	.011	3.948	1	83	.050	11.31	25	83	.000

Predictors in trimmed model	Beta	t	Sig.
(1) performance shift 1-5	.404	5.996	.000
(2) age, commander	-.050	-.827	.411
(3) computer expertise, commander	.140	2.270	.026
(4) education, commander	.082	1.360	.178
(5) duration Read Message, specialist B	-.288	-3.247	.002
(6) frequency Send Message, specialist A	.245	3.324	.001
(7) frequency Read Message, specialist B	.068	.850	.398
(8) frequency Read Message, specialist B	.166	1.810	.074
(9) ieR-ieS010, commander EC28S6	.100	1.750	.084
(10) ieSi1-ieS100-ieSi0-ieSi0, specialist B EB419S6	-.166	-2.314	.023
(11) ieR-ieH-ieR-ieH-ieR, commander EC54S6	.207	3.077	.003
(12) ieSi0-ieS100-ieSi0-ieSi0, specialist B EB45S6	.063	.859	.393
(13) ieR-ieSi0-ieS100, specialist B EB32S6	-.034	-.479	.633
(14) ieSi0-ieSi0. specialist A EA215S6	-.337	-4.136	.000
(15) ieSi1-ieSi1-ieSi0-ieSi0-ieSi0-ieSi0, specialist A EA69S6	.964	4.260	.000
(16) ieSi1-ieSi1-ieSi0-ieSi0-ieSi0, specialist A EA515S6	-.849	-4.067	.000
(17) ieSi1-ieSi1-ieS100, specialist A EA333S6	.183	2.579	.012
(18) ieS100-ieR, specialist A EA29S6	-.199	-2.329	.022
(19) ieS100-ieR-ieSi0, specialist A EA310S6	.198	2.255	.027
(20) ieR-ieR-ieR-ieR, commander EC48S6	-.163	-2.136	.036
(21) ieH-ieR, commander EC22S6	-.161	-2.186	.032
(22) ieSi0-ieS001-ieR, specialist A EA314S6	-.119	-1.987	.050
(23) ieSi0-ieSi0-ieSi0-ieSi0-ieS001, specialist A EA53S6	.138	1.956	.054
(24) ieSi0-ieSi1-ieSi0, specialist A EA325S6	.136	2.185	.032
(25) ieR-ieSi0-ieSi1, specialist A EA35S6	-.144	-1.987	.050

Note. Trimmed model. N = 109 teams, preceding performance entered in the first step with method enter, *input variables* entered in the second step with method forward, *summary-level process variables* entered in the third step with method forward, sequences entered in the fourth step with method forward, PIN = 0.15

Table 188 Results of multiple regression, predicting performance shift 8 with *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig $\triangle$ F	F	df1	df2	Sig.
1	.226	.219	.226	31.24	1	107	.000	31.24	1	107	.000
2	.306	.293	.080	12.26	1	106	.001	23.39	2	106	. 000
3	.373	.355	.067	11.14	1	105	.001	20.80	3	105	. 000
4	.413	.391	.041	7.230	1	104	.008	18.33	4	104	. 000
5	.451	.424	.037	6.998	1	103	.009	16.91	5	103	. 000
6	.480	.450	.030	5.812	1	102	.018	15.72	6	102	. 000
7	.507	.473	.027	5.518	1	101	.021	14.86	7	101	.000
8	.531	.493	.024	5.039	1	100	.027	14.15	8	100	.000
9	.551	.510	.020	4.372	1	99	.039	13.49	9	99	.000
10	.565	.520	.014	3.153	1	98	.079	12.72	10	98	.000
11	.580	.533	.015	3.563	1	97	.062	12.19	11	97	.000
12	.592	.542	.012	2.885	1	96	.093	11.63	12	96	.000
13	.617	.564	.024	6.059	1	95	.016	11.77	13	95	.000
14	.631	.576	.014	3.476	1	94	.065	11.46	14	94	.000
15	.644	.586	.013	3.482	1	93	.065	11.21	15	93	.000
16	.656	.596	.012	3.277	1	92	.074	10.97	16	92	.000
17	.668	.606	.012	3.370	1	91	.070	10.79	17	91	.000

Predictors in trimmed model	Beta	t	Sig.
(1) ieSi1-ieSi1-ieS100, specialist A EA333S8	.204	2.733	.008
(2) ieSi0-ieSi0-ieSi0-ieS100, specialist B EB46S8	.224	3.147	.002
(3) ieSi1-ieSi0-ieSi0, specialist B EB329S8	.223	2.602	.011
(4) ieR-ieS001, specialist A EA22S8	.112	1.281	.204
(5) ieR-ieS010, commander EC28S8	-.403	-3.733	.000
(5) ieR-ieSi0-ieSi1, specialist A EA35S8	.245	2.580	.012
(6) ieSi0-ieSi0-ieSi1-ieS100, specialist B EB410S8	.235	3.156	.002
(7) ieSi0-ieSi1-ieSi0-ieSi0, specialist B EB416S8	-.159	-1.920	.058
(8) ieS100-ieR-ieR, specialist B EB35S8	-.172	-2.405	.018
(9) ieS001-ieR, specialist B EB26S8	-.138	-1.707	.092
(10) ieSi1-ieS100-ieSi0-ieSi0, specialist B EB419S8	-.212	-2.511	.014
(11) ieSi1-ieSi0-ieSi0-ieSi1, specialist A EA424S8	.085	1.031	.306
(12) ieSi1-ieSi0-ieSi0-ieSi0-ieSi1, specialist A EA514S8	.123	1.753	.083
(13) ieR-ieSi1-ieH, commander EC315S8	.235	2.667	.009
(14) ieS001-ieR-ieR, commander EC316S8	-.091	-1.108	.271
(15) ieR-ieS001-ieR, commander EC312S8	.721	3.987	.000
(16) ieSi1-ieSi1, commander EC218S	-.659	-3.606	.001

Note. Trimmed model. N = 109 teams, method = forward, PIN = 0.15

Table 189 Results of multiple regression, predicting performance shift 8, with *input*, *summary-level process* variables, and *data mining sequences*.

step	R^2	$R^2_{adj.}$	$\triangle R^2$	F_{change}	df1	df2	sig △ F	F	df1	df2	Sig.
1	.331	.325	.331	52.89	1	107	.000	52.89	1	107	.000
2	.359	.347	.028	4.655	1	106	.033	29.68	2	106	.000
3	.388	.370	.029	4.902	1	105	.029	22.15	3	105	.000
4	.412	.390	.025	4.345	1	104	.040	18.23	4	104	.000
5	.429	.402	.017	3.111	1	103	.081	15.50	5	103	.000
6	.442	.409	.013	2.350	1	102	.128	13.48	6	102	.000
7	.455	.417	.013	2.344	1	101	.129	12.04	7	101	.000
8	.508	.468	.053	10.75	1	100	.001	12.89	8	100	.000
9	.549	.508	.041	9.002	1	99	.003	13.38	9	99	.000
10	.563	.518	.014	3.137	1	98	.080	12.62	10	98	.000
11	.620	.577	.057	14.67	1	97	.000	14.40	11	97	.000
12	.640	.595	.020	5.274	1	96	.024	14.22	12	96	.000
13	.660	.614	.020	5.725	1	95	.019	14.21	13	95	.000
14	.677	.629	.016	4.763	1	94	.032	14.06	14	94	.000
15	.691	.641	.014	4.294	1	93	.041	13.87	15	93	.000
16	.713	.663	.021	6.871	1	92	.010	14.25	16	92	.000
17	.734	.685	.022	7.474	1	91	.008	14.80	17	91	.000
18	.746	.695	.012	4.196	1	90	.043	14.70	18	90	.000
19	.759	.708	.013	4.823	1	89	.031	14.77	19	89	.000

Predictors in trimmed model	Beta	t	Sig.
(1) performance shift 1-6	.338	5.217	.000
(2) Control Condition 2	-.198	-3.453	.001
(3) education, commander	.097	1.663	.100
(4) computer expertise, commander	.160	2.762	.007
(5) computer expertise, specialist A	.056	.986	.327
(6) computer expertise, specialist B	-.023	-.405	.686
(7) education, specialist B	.168	2.785	.007
(8) duration Read Message, specialist A	-.139	-2.348	.021
(9) duration Send Message, specialist A	-.251	-4.127	.000
(10) frequency Show Information, specialist B	.076	1.170	.245
(11) ieR-ieS010, commander EC28S8	.293	4.849	.000
(12) ieSi1-ieSi1-ieS100, specialist A EA333S8	.247	3.932	.000
(13) ieH-ieR-ieH-ieR-ieR, commander EC512S8	-.183	-3.155	.002
(14) ieSi0-ieS001-ieR, specialist A EA314S8	.130	2.098	.039
(15) ieS001-ieR-ieR, commander EC316S8	-.375	-4.385	.000
(16) ieR-ieS001-ieR, commander EC312S8	.261	3.123	.002
(17) ieSi0-ieSi1-ieSi1-ieSi0, specialist B EB417S8	.190	3.162	.002
(18) ieR-ieSi1-ieH, commander EC315S8	-.125	-2.246	.027
(19) ieSi1-ieS100-ieSi0-ieSi0, specialist B EB419S8	-.128	-2.196	.031

Note. Trimmed model. N = 109 teams, preceding performance entered in the first step with method enter, *input variables* entered in the second step with method forward, *summary-level process variables* entered in the third step with method forward, sequences entered in the fourth step with method forward, PIN = 0.15

9 Index of Tables and Figures

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Appendix

Appendix