Evaluation of cross-organizational business processes for data collection initiatives

Completed Research

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Abstract

The continuous specialization of the organization's activities towards its core competencies (Prahalad and Hamel 2000) and the adoption of digital business strategies (Bharadwaj et al. 2013) results in the emergence of a new type of cross-organizational business process. In the past few decades, cross-organizational business processes were reduced to their communication and coordination aspects (Scheckenbach 1997), without the need for real process ownership (Hirschmann 1998). Nowadays, digitalization across organizational borders brings brand new issues when it comes to inter-organizational information collection. Researchers have studied the technical and organizational issues around cross-boundary information sharing, mainly in the public sector (Pardo et al. 2006; Ramon Gil-Garcia et al. 2007). However, the collecting of information resulting from a cross-organizational business process lacking a designated process owner can be very difficult. This paper addresses this issue by presenting a three-part evaluation framework dedicated to assessing data collection initiatives across organizations.

Keywords

Business process, orchestration, cross-organizational.

Introduction

New forms of organizations favor competitive advantages by performing only those activities closest to their core competencies, and outsourcing other activities to external partners (Miles and Snow 1986). This form of organization implies the creation of specific communication and coordination tasks across organizational units in order to guarantee the business process flow (Thomas H. Davenport and James E. Short 1990). Werth (2008) classifies cross-organizational business processes into two groups: parallel and sequential processes. Parallel processes can be used to pool resources, replicating the same process in order to increase the throughput. For instance, airline alliances offer multiple flights in parallel to multiply travel routes for customers (Werth 2008). Sequential processes are used to build value chains or to outsource operational functions to external entities. Tightly integrated industries such as automotive rely on cross-organizational processes where each organization builds on the previous output to add value that will again be used to create more value further down the chain (Werth 2008). The resulting value chain is the sum of the contributions toward a goal defined by the organization owning the final product. In the case of outsourcing, a function or a process is outsourced to an external organization that runs it independently. Synchronization is less important, as each actor runs its own process, depending mostly on information from other parties. The outsourcing of facilities management or customer call-centers are two examples of cross-organizational processes where inter-process communication is sufficient to guarantee the overall quality. Each process exchanges information with the surrounding processes in order to guarantee the flow, without the need to exchange in-depth information on the progress of a

particular activity. This leads to information about one entity being disseminated across multiple organizations. The only information shared by the different organizations is the coordination information.

In this context of cross-organizational processes, it becomes difficult to collect comprehensive information about the entities. This problem is central for industries where traceability is mandatory, and various frameworks have been developed to address this issue (Thompson et al. 2005). However, most of these frameworks only exchange coordination information along the chain. For example, the Parmigiano Reggiano traceability system (Regattieri et al. 2007) can trace each portion of cheese back to the whole cheese, then to the dairy, the milk batch and finally the cow who produced the milk. This information is sufficient to trace the end product to the cow, but not to establish a complete picture of the fabrication process. Was the cow under special medication? Who runs the transformation in the dairy? How long was the cheese stored to mature? When comprehensive information is needed, for example in the case of a quality issue or external audit, there is little option than to create an ad-hoc process to collect this information across all organizations, as shown in Figure 1. Apart from product traceability, this occurs on many occasions where comprehensive information is not readily available. One example is elderly care, where various organizations provide some sort of service in an independent way, or master data initiatives where partial data owners are dispersed across multiple organizations. Confronted with these situations, organizations tend to create ad-hoc processes which have a lot in common with master data initiatives. There is a need to identify the right data owner in each organization, to assess the quality of the collected information and to maintain the data over a given period. In this work, we investigate the following research question: how do we assess the replication and industrialization potential of cross-organizational data collection processes?

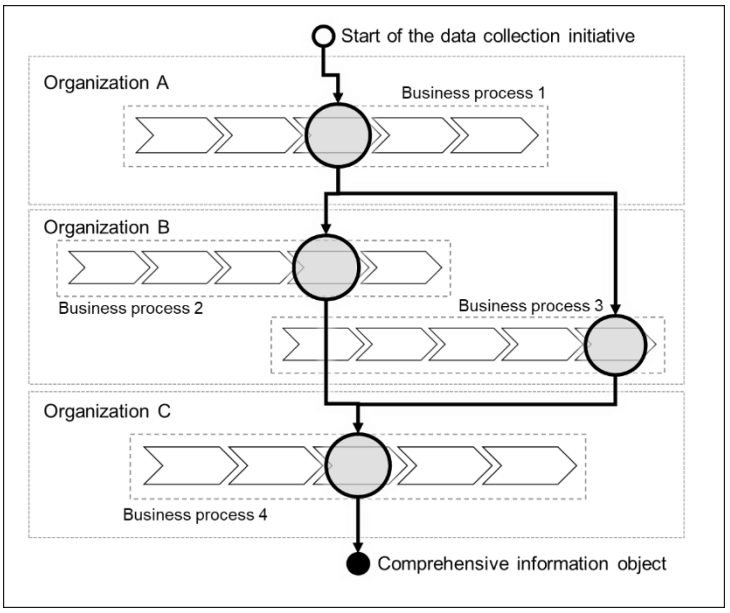

Figure 1. Cross-organizational data collection initiative

Coordination of information and processes beyond the boundaries of a single organization is an active field in information systems research (Schryen 2013). Most research focuses on the integration of business processes across organizational boundaries. Generally, it consists in extending IS support for business processes beyond a single firm, by structuring and automating the information flows between the different activities and actors involved in the definition, execution and monitoring of the process (Schubert and Legner 2011). This requires a high level of interoperability and the adoption of inter-organizational business standards, in order to enable organizations to align their goals and processes effectively (Im and Rai 2014; Zhao and Xia 2014). However, this approach is ill-suited to the type of cross-organizational processes described above, as the information objects resulting from process integration are tailored to the execution and monitoring of the operational activities of the underlying process. These information objects can therefore be irrelevant to the data collection initiative or insufficient to fulfill the goals of the data collection initiative. Information systems research and practice can benefit from tools and methods addressing these specific issues.

This paper presents a framework to assess whether a given cross-organizational process aimed at collecting comprehensive information about an entity can be efficiently industrialized when there is no clear process owner. We first present the state of the art and then our assessment framework. This framework outputs a process maturity level that informs about the possibility of industrializing the cross-organizational process. We follow this by presenting a case study about a master data initiative. Finally, we discuss our findings and present other fields of interest to apply our framework.

Literature review

The goal of this research is to build a framework to assess if a given cross-organizational process aimed at collecting comprehensive information about an entity can be efficiently industrialized.

Industrialization

Business processes are the core of an organization's activities. They can occur in an emergent fashion, being a combination of lower-level activities concurring to the same goal, or result from deliberate attempts to define the roles and structure of the activities in the realization of the organization's goals (Miles et al. 1978). Several methods exists as regards the management, design and redesign of business processes (van der Aalst et al. 2003; De Bruin et al. 2005). The structuring and optimization of business processes is a key element of industrialization. Industrial processes follow known activities paths and can be replicated in different contexts through incremental adaptations.

Process mining

The need for companies to learn more about how their processes operate in the real world is a major driver for the development and increasing use of process-mining techniques (Tiwari et al. 2008). These techniques aim at extracting information from event logs to capture a business process as it is being executed, and are useful for analyzing and understanding the effective flow of activities in organizations (van der Aalst et al. 2007; Tiwari et al. 2008). In our case, these techniques are of limited interest partly because the processes that we study have no defined owner and also because the activities from which data must be collected are part of different organizations, meaning that collecting and analyzing event logs is not feasible in our context.

Process quality

The domain of business process redesign provides us with a process performance measurement tool called the devil's quadrangle (Jansen-Vullers et al. 2007). This tool distinguishes four main dimensions in redesigning a business process: quality, cost, time and flexibility. Ideally, a business process decreases the time and the cost of execution while improving the quality of the service delivered and improving the ability of the business process to react to variation. Improving upon one dimension may have an effect on another.

The goal is to determine which dimension could be maximized and what consequences these decisions would have on the other dimensions. It can be concluded that the dimensions of the devil's quadrangle are suitable for measuring the performance of a process (Jansen-Vullers et al. 2007). Our study uses the four main dimensions as key performance indicators in order to evaluate a process.

The literature provides us with a large set of performance measures for the time dimension (Jansen-Vullers et al. 2007). In our study, we measured the throughput time, representing the time between completion of a task and completion of the next task.

The financial dimension is critical and therefore used in most frameworks. It is strongly attached to the time dimension, but also to quality and flexibility because such issues often result in cost increases. According to the literature (Jansen-Vullers et al. 2007) costs can be of different types: running costs, inventory costs, transport costs, administrative costs and resource utilization. In our study, the main source of cost is resource utilization. For this reason, we focused on the effective workforce cost (salary × worked hours) of a task during the setup, the service and the wait time of each task.

There are two kinds of quality: internal and external. Internal quality is considered as the social and psychological factors related to work. External quality is the degree to which products meet customers' requirements. Given our interest in the process quality and more precisely its internal quality, we chose the workers perspective as the most important measure for our study. Internal quality is commonly measured by a survey among employees and the literature (Jansen-Vullers et al. 2007) provides us with the following set of performance measures: skill variety, task identity, task significance, autonomy, feedback and co-worker relations.

Flexibility is the degree to which the process can adapt to changes in the environment. These changes can happened to the internal environment or to the external environment. This dimension determines whether the execution of the task is very rigid and can only be very slightly modified or conversely if the execution of the task is very flexible and an adaptation to particular cases is very easy.

Data quality

The literature provides a wide range of techniques for assessing and improving the quality of data and information (Batini et al. 2009). The terms data and information are often used synonymously, information being considered as data that has been processed in some manner. The systematic literature review carried out by Batini et al. (2009) identifies accuracy, completeness, consistency and timeliness as the most relevant dimensions for data quality assessment.

Data quality measures the timeliness, completeness, consistency, compliance and usability of data generated by a specific activity (Pipino et al. 2002). We are interested here in the quality of the dataset that was used by the activity (e.g. the finalized list of domains or the list of AGP institutes). This is a technical and objective measure. A validation rule is defined and the gap between the dataset and the defined rule is measured (e.g. the percentage of data that has not been transferred for more than 24 months).

A framework for the industrialization of cross-organizational processes

This section presents the three-part evaluation framework for assessment of data collection initiatives in cross-organizational business processes lacking a designated process owner. The key challenge in this setting lies in the replicability and stability of the data collection process. In the case of cross-organizational data collection initiatives – the goal being equal – there are still three degrees of freedom that can affect the transferability and replicability of the initiative: the organizational context, and the roles and activities constituting the data collection process.

As seen in the literature review, most process evaluation methods are quite generic, focusing on the ability of the process to achieve its goals effectively and efficiently, but without going into a detailed analysis of the process's unfolding. In regard to the issue we address in this paper, evaluation should cover the data collection process at two different levels: the overall process should produce the expected results and the individual activities should operate correctly.

At the process level, the main questions are whether the overall process is well defined and whether it provides the expected outcome. Generic methods are employed to evaluate the overall relevance and quality of the outcomes, as well as the general efficiency of the process. These generic methods are usually divided into two categories: quantitative and qualitative. By establishing quantitative measurements the performance of business objects such as time and costs can be measured. These quantitative measurements could in turn be used as qualitative indicators that evaluate overall quality and flexibility, see Table 1. Obtained values are compared with target values to determine whether or not desired objectives are achieved. Measurements can be made at various levels, such as executive, managerial or operational. Results are obtained using different techniques such as statistics and process mining.

Dimension	Observation criteria	Metric
Cost	Effective cost of the process, considering the costs of the workforce during the setup, the service and the wait time	Hours/days
Time	Total time required to complete the process, including waiting times	Hours/days
Flexibility	The degree to which the process can adapt to changes in the environment.	Likert 1–5: 1 Execution of the process is very rigid and can only be very slightly modified 5 Execution of the process is very flexible and an adaptation to particular cases is very easy
Internal quality	Quality of a process from an operator's perspective	Likert 1-5: 1 Process requires little skill variety and offers little visible outcome, direct impact on external environment, autonomy, poor feedbacks on performances and poor co-workers relation quality 5 Process requires high skill variety and offers high visible outcome, direct impact on external environment, autonomy, effective feedbacks on performances and high co-workers relation quality

Table 1. Process level evaluation metrics

Given the fact that the process's activities are performed in different organizations and that ownership of the overall process is not established, replicating the process in a different context calls for individual assessment of its activities. Therefore, the framework covers the definition of the data collection process, the evaluation of the individual activities and the evaluation of the process as a whole.

Process definition

First, the data collection process has to be defined. The goal of the data collection initiative consists of the comprehensive information object which is expected to be the process outcome. Once the goal is defined, the different organizations implied in the elaboration of the comprehensive information object need to be identified. These organizations are stakeholders for specific aspects of the comprehensive information object. Stakeholder analysis methods can be used for identifying the organizations and the specific roles that need to be included in the data collection initiative (Pouloudi and Whitley 1997). Analysis of the activities performed by these stakeholders allows us to narrow down the selection of activities that will compose the data collection process. Once the process's goal, roles and activities are established, the data collection initiative can be carried out. The activities can be evaluated as the data initiative progresses. At the end, the overall outcome and performance of the process is evaluated.

Assessment tool definition

We developed a survey-based tool, rooted in the above literature review, in order to evaluate the data collection initiative at the process and activities level. First, the activity execution quality (Table 2) focuses on the individual activity performance, using the same evaluation dimensions as at the process level (cost, time, flexibility, internal quality). In order to account for the possible changes in terms of context, roles or even in the activity itself, the flexibility of the activity is evaluated, among other standard evaluation criteria. Second, the information quality assesses the information resulting from performing the activity in the context of the data collection initiative, see Table 3. Third, the data quality concentrates on the data used by the activity, independently of the activity and its results, in order to establish the degree to which the activity can be formalized or automated, see Table 4.

Dimension	Observation criteria	Metric
Cost	Effective cost of the activity considering the costs of the workforce during the setup, the service and the wait time	Hours × hourly costs
Time	Total time required to complete the activity, including wait times	Hours or days
Flexibility	Degree to which the process can adapt to changes in the environment	Likert 1–5: 1 Execution of the activity is very rigid and can only be very slightly modified 5 Execution of the activity is very flexible and an adaptation to particular cases is very easy
Internal quality	Motivation, satisfaction fulfilling the activity	Likert 1–5: 1 Activity offering little satisfaction, badly identifiable, requiring few skills, requiring tedious collaborations 5 Very motivating activity, offering lots of satisfactions, very clearly identifiable, requiring various skills, offering interesting and easy collaborations

Table 2. Activity execution quality metrics

Dimension	Observation criteria	Metric
Intrinsic	Accuracy, trust, objectivity, reputation of information	Likert 1–5, 1 Difficult to trust the information (gaps, obvious faults, unreliable source, …) 5 Information has all the prerequisites to give full confidence
Accessibility	Information accessibility	Likert 1–5 , 1 Information is difficult to access (takes many queries – computer or human – to get all the information) 5 Information is in a single place (person, system, repository)
Contextual	Relevance, obsolescence, completeness, amount of information	Likert 1–5, 1 Information is irrelevant for its use in the process context (because of its age, gaps, partial or non-contextual results) 5 Information is fully in line with its use
Representation	Interpretability, comprehensibility, consistency, conciseness, manipulability of information	Likert 1–5, 1 Impossible to understand/ interpret correctly the information (too much information, difficult to manipulate or understand without outside help) 5 Information is sufficient to have a good understanding and/or be able to interpret it correctly

Table 3. Information quality metrics

Dimension	Observation criteria	Metric
Timeliness (freshness)	Is the data up to date?	Percentage of data (if all data up to date, 100%)
Completeness	Is the necessary data available? Is it missing data?	Percentage of data (if all data is available, 100%)
Non-duplication (consistency)	Is the data unduplicated?	Percentage of data (if there are no duplicates, 100%)
Compliance (accuracy)	Is the data compliant with the dictionary?	Percentage of data (if all data is compliant, 100%)

Usability	Is the data usable and used by the trade? Does it say something? Does it give the right information?	Percentage of data (if all data is usable, 100%)

Table 4. Data quality metrics

The evaluation results in a maturity score. A common design principle in the conception of maturity models (CMM) is to represent maturity as a number of cumulative stages where higher stages build on the requirements of lower stages with 5 representing high maturity and 1 low (De Bruin et al. 2005). In this study, we'll rely on this same design principle in order to evaluate the process, the quality of information and the quality of the data. We defined our stages based on the required adaptation effort to replicate the process, see Table 5. At the highest maturity stage, the process is sufficiently robust that the same roles and activities can be used in the new context, allowing for direct replication of the data collection process, level 3 in our framework. Level 2 corresponds to a situation where activities or roles will need to be redefined to apply the process to a different context. Level 1 represents the situation where the overall structure of the data collection process can be reused but the detailed roles and activities need to be adapted. Level 0 corresponds to the situation where the process needs to be built entirely from the ground up.

Maturity level	**Definition**
Level-0: Not possible	Achieving the data collection initiative in another context requires building the process from scratch
Level-1: Possible	Overall process architecture (main stakeholders and meta-activities) can be used as a template to achieve the data collection initiative in a different context
Level-2: Indirect replication	Comparable activities and roles are present in the new context, enabling almost direct replication of the overall process
Level-3: Direct replication	New context comprises the same roles and activities; the data collection initiative can be carried out by application of the existing process

Table 5. Maturity level definitions

A case study in the context of a federation of organizations

A large federation of higher education organizations was confronted with data quality issues when attempting to aggregate information from various members of the federation. The problem was not that the individual data was of poor quality; it was more that every organization in the federation had a particular way of entering, processing and storing information. Each organization was able to run their own processes smoothly with the expected quality, as long as no aggregation was required across different entities, even if some information was shared by multiple organizations. To solve this issue the federation decided to establish master data for the entities addressed by core business processes run in parallel across all organizations.

The project started by defining a process able to gather all information across multiple organizations for one specific entity: the fields of study. Each organization was offering multiple fields of study to its students and some of the fields of study were offered by multiple organizations in the federation. At the level of the federation, the fields of study were managed by the office of the vice-president, students. The office was in charge of the accreditation of the fields of study as well as delivering the diplomas. On the other side, each organization was responsible for the admissions, the curriculums and the examinations. Inside organizations, curriculums and examinations were the responsibility of the faculties. This repartition of the responsibilities between the federation, the organizations and the faculties led to the development or adaptation of business processes at each level. These processes are generating operational information about and around each field of study, depending on the specific needs of each entity.

Thus, collecting information about the fields of study implied to collect information from many entities, each managing a portion of the information in a quasi-independent way. The main activities of the

process were: defining the perimeter (attributes and data sources), creation of the dictionary (identify data owners across organizations, collect and consolidate data, create master data, define update process), data quality (business rules, technical rules, measure of quality) and quality improvement (define initiatives).

The goal of this process was to assess the feasibility of collecting all the required information in order to create a master data repository of all fields of study, for the whole federation. After the first run of this process, we evaluated the process itself, based on our framework. Each participant had to fill out a survey based on its implication in the process. The consolidation of the results was followed by six interviews with people involved in the process. These people were affiliated to four different organizations within the federation. These interviews were conducted in order to qualitatively understand the feasibility of the process based on the survey results. Different issues were raised, such as the difficulty of meeting all stakeholders across multiple organizations in an efficient way. Owing to the geographic dispersion, it was difficult to meet multiple people on the same day. It was also difficult to convey a clear message across organizations, as each organization has its own particular way of defining things. Despite these comments, the first results showed that the ratio between the cost (resources utilization) and the throughput time was unfavorable. We designed the first version of the data collection process in a linear way, making it sensitive to move time and queue time, as defined by Jansen-Vullers (2007). In order to reduce this sensitivity, we adapted the process to support, when adequate, the parallelization of activities. Quality and flexibility were found to have good ratings (4.2 and 4.8), probably due to the fact that the first run of the data collection process was very experimental and that few rules were defined initially. Due to these concerns, we rated the overall maturity level of the process at level 1, given that the process architecture can be reused as a template to achieve the data collection initiative for different entities.

In order to test our ability to assess the replication and industrialization potential of the data collection process adapted from the first run, it was decided to spin multiple processes in parallel in order to build master data for schools, domains and institutes, and to evaluate the impact of applying this process to more entities. Each process was under the control of one process owner, responsible for coordinating activities among the actors carrying out the activities. The processes took place between May and December 2016. Each actor involved in the process was asked to fill out the survey in order to evaluate the part of the process under their responsibility. We also conducted interviews with the three process owners, in order to gather more in-depth information regarding each instance of the process.

Discussion

Results of the second run showed that the evaluation was consistent across the processes and the actors, which signifies that the framework can be applied consistently across evaluators. The second finding of the second run is that the only deviation across processes concerns the data quality, which is also consistent with the goal of our framework. Indeed, data quality issues, as measured by our framework is a symptom of malfunctioning business processes at the operational level. Again, as we are trying to evaluate the possibilities of replicating data collection initiatives on a large scale, data quality issues, as measured by our framework, are signals that, due to the diversity of governances across organizations, a large-scale initiative will be negatively impacted by these issues.

When it comes to the data collection initiative for the master data management project inside a large federation of higher education organizations, the application of our framework allows several conclusions. First, the evaluation framework has shown good potential for industrialization, as comparable activities and roles exist inside the different organizations. Second, the different evaluation dimensions (activity execution, information and data quality, as well as overall process quality) allow for the investigation of different aspects of the process replication.

This research shows practical implications for organizations, mainly the self-assessment framework aimed at evaluating the level of industrialization capabilities of their data collection initiatives. To our knowledge, it is the first time that a practical multi-level (process and activities) framework has been presented. Thus, by using our results, organizations can assess and mitigate the risks associated with the implementation of such large-scale initiatives. Due to the pressure to better monitor compliance and traceability across not only their supply chain, but also their value chain, these initiatives will become

more and more frequent in the future, requiring extensive collection of information from cross-organizational processes.

A lot of research on cross-organizational processes in recent years has focused on automation and process mining (Brocke and Rosemann 2015; Liu et al. 2009). However, with the emergence of postmodern ERP or eXtended ERP (Romero and Vernadat 2016) we are faced with new challenges based on information sharing across loosely connected processes. Recent research proposes to address this issue with blockchain solutions (Weber et al. 2016). Our results suggests that traditional approaches are viable alternatives. By using our results, researchers can focus on extending their frameworks to support loosely connected processes, having a method to evaluate their results.

Conclusion

In this paper, we have presented a maturity model, based on the process evaluation and process industrialization literature. This evaluation tool assesses whether a cross-organizational process aimed at collecting comprehensive information about an entity can be efficiently industrialized.

This research has some limitations. First, the maturity model has been fully applied in a single study. While this demonstration has shown that the evaluation tool can be effectively applied to a real world case (Vaishnavi and Kuechler 2015), this tool needs to be used in more situations and in different contexts to better assess its validity. Secondly, most metrics used are self-reported by the actors. The result of the evaluation can be negatively impacted by the subjectivity of the actors. This can impact the ability to compare evaluation scores across multiple applications of the framework.

As discussed, this framework shows promising results. We will apply it in another data collection initiative, in the context of a project aimed at reducing the information opacity and administrative obstacles regarding social protection benefits. In this project, the expected comprehensive information will consist of sets of legal bills, rules and decision criteria related to a specific social protection benefit. As this project will encompass all available social rights across several legally independent regions, we expect to see an important variety as to how the required information is produced. The degrees of freedom in the replication of the process in terms of context, roles and activities should change from region to region. Regarding the conceptual foundations of our framework, further research is needed to establish its generalization to other problems than data collection initiatives.

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