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DIGITAL SUPPORT FOR HEALTH BEHAVIORAL INTERVENTIONS

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Digital Support for Health Behavioral Interventions

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Abstract

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Digital Support for Health Behavioral Interventions

Non-communicable diseases (NCDs) are still the leading cause of death worldwide. NCDs kill 41 million individuals each year, accounting for 71% of all deaths. According to the World Health Organization (WHO) simple interventions, allowing individuals to change their behavior, might have prevented many of these tragedies. Among the various risk factors, tobacco alone is responsible for more than 8 million deaths per year. Research points to several evidence-based interventions to support smoking cessation which, if applied widely, would considerably reduce premature deaths. Such interventions include providing advice and behavioral support. Digital systems that could be powerful catalysts to provide this support exist. But questions about how they affect behaviors and how they could be improved remain unresolved.

This thesis explores digital support for health behavioral interventions through six studies split into three parts. Part I, aims to provide an understanding of digital support for health interventions through two studies. The first study provides a landscape of mobile applications for smoking cessation, while the second investigates digital smoking cessation communities. Part II investigates how digital systems can leverage gamification to support the design of effective health interventions. The first study investigates the effectiveness of a digital escape room as a prevention tool for addictions and for risky behaviors. The second study leverages gamification to engage and to improve performance of a population of students, while holding them back from engaging in a particular unwanted behavior. Part III investigates

how the underlying relevant data in the context of health behavioral interventions should be managed. A first study proposes a methodology that could allow the individualization of Swiss public health statistical data. Such individualization is potentially a first step in providing personalized feedback and appropriate courses of action to individuals wishing to improve their health behavior. A second study reviews the literature that examines existing techniques for visualizing and interacting with Linked Data, a technological solution of interest for obtaining this individualized view of Swiss public health statistical data.

The overall findings of this thesis suggest that the process of smoking cessation behavior change can be supported by digital artifacts. Few mobile apps offer evidence-based, engaging and credible support, but digital smoking cessation communities offer support that can be considered effective for people who want to stop smoking. Gamification has been found to help in health prevention interventions allowing knowledge to be conveyed and behavior to be influenced. Also, game design elements allow individuals to engage in activities and improve their performance, while diverting them from unwanted behavior. This latter result could be of great benefit when applied to smokers who are determined not to relapse while making a smoking cessation attempt. Efforts to raise awareness and provide personalized feedback specific to each individual's situation still need to be undertaken. Currently the possibilities to automate, visualize and interact with such personalized data, allowing to better understand one's own situation and to compare it with similar profiles, are still understudied and they open the path to further investigations.

Keywords : information systems, human computer interaction, digital support, health interventions, smoking cessation, digital communities, gamification, engagement, motivation, data analysis.

Résumé

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Digital Support for Health Behavioral Interventions

Les maladies non transmissibles restent la principale cause de décès dans le monde, elles tuent 41 millions de personnes chaque année, ce qui représente 71% de tous les décès dans le monde. Selon l'Organisation Mondiale de la Santé, des interventions simples, permettant de modifier le comportement des individus, auraient pu éviter nombre de ces tragédies. Parmi les facteurs de risque, le tabac est à lui seul responsable de plus de 8 millions de décès par an. La recherche met en évidence plusieurs interventions basées sur des preuves scientifiques pour soutenir le sevrage tabagique qui, si elles étaient appliquées à grande échelle, permettraient de réduire considérablement les décès prématurés. Ces interventions comprennent à la fois des conseils et un soutien comportemental. Il existe des systèmes numériques qui pourraient être de puissants catalyseurs pour fournir ce soutien. Pourtant, bon nombre de questions sur la manière dont ils affectent les comportements et sur la façon dont ils pourraient être améliorés restent sans réponse.

Cette thèse explore le support numérique pour les interventions comportementales en matière de santé à travers six études réparties en trois parties. La partie I, vise à fournir une compréhension du support numérique pour les interventions de santé à travers deux études. La première étude présente le paysage des applications mobiles pour le sevrage tabagique, tandis que la seconde étudie les communautés en ligne de sevrage tabagique. La partie II étudie comment les systèmes numériques peuvent tirer parti de la gamification pour soutenir la conception d'interventions efficaces. La première étude porte sur l'efficacité d'une escape room numérique comme outil de prévention des addictions et des comportements à risque. La seconde étude exploite la gamification pour engager et améliorer les performances d'une population d'étudiants, tout en les empêchant d'adopter un comportement indésirable particulier. La partie III étudie comment gérer les données pertinentes sous-jacentes dans le contexte des interventions en matière de santé et de comportement. Une première étude propose une méthodologie qui pourrait permettre l'individualisation des données statistiques de la santé publique suisse. Une telle individualisation est potentiellement une première étape pour offrir un retour d'information personnalisé et des pistes d'action appropriée aux individus souhaitant améliorer leur comportement en matière de santé. Une deuxième étude passe en revue la littérature qui examine les techniques existantes de visualisation et d'interaction avec les Linked Data, une solution technologique intéressante pour obtenir cette vue individualisée des données statistiques de la santé publique.

Les conclusions générales de cette thèse suggèrent que le processus de changement de comportement en matière d'arrêt du tabac peut être soutenu par des artefacts numériques. Peu d'applications mobiles offrent un soutien fondé sur des preuves scientifiques, engageant et crédible, mais les communautés numériques de désaccoutumance au tabac offrent un soutien qui peut être considéré comme efficace pour les personnes qui veulent arrêter de fumer. La gamification s'est avérée être utile dans les interventions de prévention aux addictions, permettant de transmettre des connaissances et d'influencer les comportements. De plus, les éléments de gamification permettent aux individus de s'engager dans des activités et d'améliorer leurs performances, tout en les détournant des comportements indésirables. Ce dernier résultat pourrait être très utile lorsqu'il est appliqué aux fumeurs qui sont déterminés à ne pas rechuter alors qu'ils font une tentative de sevrage tabagique. Des efforts de sensibilisation et de feedback personnalisé, spécifiques à la situation de santé de chaque individu, doivent encore être entrepris. Actuellement, les possibilités d'automatiser, de visualiser et d'interagir avec ces données personnalisées, permettant de mieux comprendre sa propre situation et de la comparer à des profils similaires, sont encore peu étudiées et ouvrent la voie à de nouvelles perspectives de recherche.

Mots-clés : systèmes d'information, interaction homme-machine, soutien numérique, interventions en matière de santé, sevrage tabagique, communautés numériques, gamification, engagement, motivation, analyse de données.

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Contents

List of Abbreviations

ACM	**A**ssociation for **C**omputing **M**achinery
API	**A**pplication **P**rogramming **I**nterface
ASCII	**A**merican **S**tandard **C**ode for **I**nformation **I**nterchange
AVE	**A**verage **V**ariance **E**xtracted
BOW	**B**ag **o**f **w**ords
CR	**C**omposite **R**eliability
CT	**C**omputational **t**hinking
EA	**E**scape **A**ddict
FOPH	**F**ederal **O**ffice of **P**ublic **H**ealth
FSO	**F**ederal **S**tatistical **O**ffice
HCI	**H**uman-**c**omputer **I**nteraction
HTMT	**H**etero**t**rait-**m**ono**t**rait
IS	**I**nformation **S**ystems
LD	**L**inked **D**ata
LDA	**L**atent **D**irichlet **A**llocation
LIWC	**L**inguistic **I**nquiry and **W**ord **C**ount
LOD	**L**inked **O**pen **D**ata
M	**M**ean
mHealth	**M**obile **h**ealth
ML-KNN	**M**ulti**l**abel **k** **N**earest **N**eighbours
NCDs	**N**on-**c**ommunicable **d**iseases
NLTK	**N**atural **L**anguage **T**ool**k**it
OLS	**O**rdinary **L**east **S**quares
PHQ	**P**atient **H**ealth **Q**uestionnaire
PLS	**P**artial **L**east **S**quares
PUS	**P**erceived **U**serfulness **S**cale
PSS	**P**erceived **S**tress **S**cale
SD	**S**tandard **D**eviation
RDF	**R**esource **D**escription **F**ramework

SDMX	**S**tatistical **D**ata and **M**etadata E**x**change
SDT	**S**elf-**d**etermination **t**heory
SEM	**S**tructural **E**quation **M**odeling
SIGCHI	**S**pecial **I**nterest **G**roup on **C**omputer-**H**uman **I**nteraction
SIMS	**Si**tuational **M**otivation **S**cale
SPARQL	**S**parql **P**rotocol **a**nd **Q**uery **L**anguage
SLHS	**S**wiss **L**earning **H**ealth **S**ystem
STAI	**S**tate-**T**rait **A**nxiety **I**nventory
STEM	**S**cience, **t**echnology, **e**ngineering and **m**athematics
SUS	**S**ystem **U**sability **S**cale
TF	**T**erm **F**requency
TF-IDF	**T**erm **F**requency **I**nverse **D**ocument **F**requency
TTM	**T**rans**t**heoretical **m**odel
URI	**U**niform **R**esource **I**dentifier
URL	**U**niform **R**esource **L**ocator
UTC	**C**oordinated **U**niversal **T**ime
VIF	**V**ariance **I**nflation **F**actor
W3C	The **W**orld **W**ide **W**eb **C**onsortium
WHO	**W**orld **H**ealth **O**rganization

Dedicated to my beloved
sons, Elvio and Enea — May
you never stop learning.

Chapter 1

Introduction

1.1 Motivation and scope

Partially founded by the Swiss Learning Health System (SLHS), a collaborative project to establish a national platform for health systems and services research, policy and practice, this research aims to make a contribution related to the public health domain.

The World Health Organization (WHO) reports that the leading cause of death worldwide is non-communicable diseases (NCDs). NCDs, also known as chronic diseases, are diseases not directly transmissible from one person to another. They are of long duration and generally slow progression. The four main types of non-communicable diseases are cardiovascular diseases, cancer, chronic respiratory diseases and diabetes. NCDs kill 41 million people each year, equivalent to 71% of all deaths globally [1]. According to the WHO, through simple interventions, more than 40% (16 million) of these deaths could have been prevented [2]. Many of these risk factors, such as smoking, unhealthy diet, physical inactivity, stress, depression, heavy drinking, excess weight and obesity can be modified by simple interventions enabling individuals to change their behavior.

To support individuals to adopt healthier behaviors, the use of digital artifacts has recently seen a rapid growth. Worldwide, the ever-increasing adoption of mobile devices, such as smartphones and connected devices, has spurred a swift expansion in the field of electronic health. New technologies are giving individuals the potential to engage with their healthcare decision-making, opening new possibilities for improving their health outcomes [3]. These technologies can provide some advantages over traditional face-to-face methods and could represent a significant opportunity to promote health and prevent addictions or dependencies.

1.1.1 Smoking cessation

Beginning of 2019, when I first started working on this particular topic, the WHO was attributing 7 million annual deaths worldwide to tobacco, with the potential to reach 8 million deaths by 2030 if left unchecked [4]. Less than four years later, in 2022, we are already seeing 8 million deaths per year [5]. The figures are frightening. Four people die every second through smoking [5], and 50% of long-term smokers will die as a result of smoking [6]. Smoking is one of the biggest public health problems, killing more people than HIV/aids, malaria and tuberculosis combined [7]. And yet tobacco is still one of the most widely abused substances in the world.

In Switzerland, more than one in seven deaths are directly smoke-related [8]. Unlike many other European countries, the number of smokers in Switzerland has not decreased over the past ten years and they still represent around 27% of the population [9], [10]. While some legislative steps have been taken, Switzerland is doing less on tobacco and nicotine prevention than other European countries [11]. Most smokers, who are aware of the dangers of tobacco, would like to quit but they need help to do so [2]. Simple behavior change interventions can considerably reduce premature deaths of tobacco users [2]. Face-to-face counseling has proven to be the most successful and effective means of helping people quit [12]–[14]. At the same time, participation rates in these intimate and personal programs are usually low [15] and they are not affordable globally [16].

Digital support can potentially provide helpful complementary support for smoking cessation [12]. For instance, it can improve these participation rates by leveraging features such as real-time data collection, feedback and low-cost dissemination [17]. New technologies are giving individuals the potential to engage in their healthcare decision-making, opening possibilities of improving health outcomes [3]. These technologies can offer some advantages over traditional face-to-face methods and could represent a particular interest in health promotion and disease prevention.

1.2 Problem statement

The general problem statement of this thesis might be summarized as follows: *How can digital system be designed to support health behavioral interventions?* We break down this question into six sub-questions before delivering some answers:

Q1. *what is the landscape of smoking cessation mobile applications?*

Q2. *how do digital smoking cessation communities support the process of behavior change?*

Q3. *how can prevention designers improve interventions by leveraging gamification?*

Q4. *how can gamified feedback decrease unwanted behavior?*

Q5. *how should Swiss public health statistical data be managed to provide individuals with tailored information?*

Q6. *how can Linked Data be leveraged to make sense of health information?*

1.2.1 Smoking cessation – What works? what does research say? and what currently exists?

Government organizations, medical societies, research networks and research centers establish guidelines to provide a comprehensive review of the scientific evidence for treating tobacco use and dependence [18]. A review of 26 current guidelines allowed us to identify globally recommended smoking cessation interventions, with four of them providing strong evidence of efficacy: *brief advice*, *behavioral support*, *pharmacotherapy* and *abstinence evaluation* [19]. Early studies [20], [21] recommended that future development should strongly adhere to such guidelines and other evidence-based practices. Several years after these first findings, we wonder if the situation has improved and if the actual mobile applications are more credible and adhere better to the recommendations made in the guidelines, or if they are more engaging. Raising the following question:

Q1. *what is the landscape of smoking cessation mobile applications?*

1.2.2 Behavioral support through digital communities

Evidence suggests that when smokers try to stop, they require behavioral support [19]. Providing behavioral support can be done in three ways: (1) self-help material, (2) peer group meetings, (3) health professional counseling. The first option, self-help, can assist patients without the need for outside assistance, and it is considered beneficial if it is tailored to individual smokers [22]. In the second method, peers meet regularly and provide each other with support and encouragement. Compared to self-help, peer group support is more effective in helping smokers quit [22], [23]. In the third method, health professionals provide individual counseling through face-to-face appointments. This patient-centered approach is the most effective [12] but, currently, participation rates in these programs are low [15] and they are not affordable globally [16].

Digital interventions potentially offer several evidence-based interventions. For instance, digital communities have been found to contribute to significant long-term positive health outcomes through their information-providing role (self-help material) [24], [25]. However, it is not yet clear how engagement in such communities is linked to the actual process of behavior change. Digital interventions also offer supportive peer group meetings. Unfortunately, research results are not yet conclusive [23]. A better differentiation of social support concepts and causal pathways is awaiting further investigation to demonstrate the effective value of social relationships in increasing smokers' likelihood of cessation [26]. This raises the question:

Q2. *how do digital smoking cessation communities support the process of behavior change?*

1.2.3 Gamification of digital health intervention

Certainly one of the best ways to stop an addiction is to never let it happen in the first place. Raising people's awareness about addictive behaviors is one of the primary objectives of public health organizations, the sooner the better. According to the WHO, young people who adopt healthy habits early on, tend to maintain these over the long term and thereby have a lower risk of behavioral addiction, and a reduced risk of non-communicable diseases in adulthood [27]. People of younger ages are also often the target of products that can be harmful and addictive, making adolescents a prime target for prevention and health promotion measures [28].

Unfortunately, interventions in school tend to disappear as a result of funding constraints [29]. This context supports the development of effective lightweight interventions employing digital technologies. The opportunity is particularly salient because even though digital technology is becoming almost ubiquitous, the digital technologies that teenagers frequently interact with (e.g., social media) are rarely used as a vehicle for smoking prevention [29]. Among such potential interventions, activities using digital escape rooms have recently gained attention as offering promising collaborative and playful learning experiences for higher education [30]. Digitalization of educational escape rooms contributes to offering a cost-efficient, portable and easy-to-use learning experience [31], potentially lowering barriers of actual funding, time and human resources in school-based health promotion [29]. Past research on escape rooms has mostly focused on physical escape rooms, digital escape rooms being a novel phenomenon, still to be academically explored [32]. With this in mind, this work will explore this opportunity by investigating the following question:

Q3. *how can prevention designers improve interventions by leveraging gamification?*

Stanford psychologist Albert Bandura first talked about "self-efficacy" in 1977, expressing the belief that individuals hold the power and resources to achieve certain goals by themselves [33]. Bandura theory recognizes that giving individuals specific information about themselves, where they stand and where they want to get to, tends to encourage behavior change. Bandura suggested that to change behaviors such as substance abuse, people need to set specific goals and track their status and progress toward these benchmarks. Bandura theory also suggests that an individual's behavior is the consequence of feedback from a variety of personal factors, actions and the environment [33]. By tailoring the feedback received, Bandura believes that behavior can be successfully changed. Such monitoring keeps people mindful of how they are progressing. Since Bandura first proposed his self-efficacy model more than 30 years ago, feedback has emerged showing it to be one of the most powerful tools for behavior change [34]. In the digital realm, feedback mechanisms can be seen as digital nudges (i.e., digital artefacts steering users in a certain direction without limiting their choices). Over the past few years, the literature on digital nudges has exploded by an order of magnitude. An interesting aspect of digital nudges is that they could be personalized. One such approach is gamification, the inclusion of game-like features in non-game systems [35], [36] that provide personalized feedback. Typical features in gamified systems include points, leaderboards, achievements, themes, levels, rewards, goals, progress, challenge and also feedback [37]. Nevertheless, despite gamification research repeatedly calling for more theory-driven studies, most studies in the context of health behavior change still focus on the overall effects of gamification such as engagement, motivation or participation without understanding its underpinnings [38]. Thus, the role of gamification in the process of health behavior change is still unclear since the integration of gamification with health behavior change theories needs to be explored more profoundly [38]. In that respect, this work addresses this issue by giving an answer to the question:

Q4. *how can gamified feedback decrease unwanted behavior?*

1.2.4 Swiss public health statistical data

In Switzerland, an overview of the country's health determinants is published in a report every five years. In addition to the printed and PDF versions of the report, data is available as a machine-readable spreadsheet. Even though these statistics are under government mandate and are intended to monitor population health and improve the effectiveness of policy measures, they open opportunities for individuals to find specific information about where they stand in comparison with their peers and possibly to encourage behavior change. A data management methodology to leverage these opportunities is investigated through the following question:

Q5. *how should Swiss public health statistical data be managed to provide individuals with tailored information?*

Enabling individuals to visualize and interact with public health statistical data is a crucial and challenging step to bring the individualized view of public health statistical data forward. Linked Data (LD) represent a technological solution of interest for obtaining such individualized view. LD has been envisioned as an essential element for the Semantic Web, listing a set of best practices for publishing and connecting structured data on the Web. Despite focus on Human-Computer Interaction (HCI) has always been part of the Semantic Web vision, only few research have been led in HCI community regarding the central notion of the LD. In this regard, this work responds to the following question:

Q6. *how can Linked Data be leveraged to make sense of health information?*

1.3 Contributions

Inspired by the above-stated questions, the contributions of this thesis are bundled as a collection of studies in the present document. These studies include (1) a smoking cessation mobile applications review, (2) a novel theoretical model revealing the underlying connections between an individual's motivation to participate in digital smoking cessation communities, engagement and process of behavior change, (3) an evaluation of an experimental digital tool for addiction prevention, (4) an evaluation of gamified digital artifacts on individuals' engagement and on unwanted behavior, (5) a methodological proposition for individualizing Swiss public health statistical data, and (6) a systematic literature review about Linked Data (LD) visualization and interaction.

More concretely, the next sections summarize the major contributions obtained through the studies led during this thesis.

1.3.1 Understanding digital support for health interventions

The first major contribution is the outcome of the review of 99 popular smoking cessation mobile applications. Only two applications, according to the findings, originate from a reliable source, encourage user engagement with sophisticated motivational affordances and have been evaluated for efficacy. There is still a lot of space for development in today's popular smoking cessation applications. As prior study has shown, adherence to evidence-based standards and best practices remains low.

The second major contribution of this first part is a better understanding of individuals' motivation to join digital smoking cessation networks, the motivational factors that influence individuals toward online engagement and assist the process of behavior change. More specifically, we contributed to the literature by providing a novel research model based on the transtheoretical model as well as the uses and gratification approach. Our model allows us to determine smokers' motivation to join digital smoking cessation communities while figuring out how such online activities might support smokers' process of change. By examining user interaction data over the course of a decade, we gained insights into the beliefs and habits of members of one of the biggest digital smoking cessation communities, and have understood, among other things, the impact of the COVID-19 crisis on this digital community.

1.3.2 Designing digital support for health intervention

The third major contribution relies on the evaluation of digital escape rooms that appear to be a promising strategy for addiction prevention in schools. Such a solution encouraged students to discuss the intervention and, to a lesser extent, the preventative message; it also enabled people to learn new information and to alter some of their behaviors.

The fourth major contribution of this thesis is the demonstration of how gamification can contribute to the avoidance of unwanted behaviors. In the context of active learning, an experiment was conducted that found that gamified feedback positively influenced students' performance and engagement, while negatively influencing unwanted behavior. The gamification designs evaluated in this experiment were built with the problem of smoking cessation in mind, with the aim of encouraging smokers in their attempt to quit while helping them to avoid a relapse.

1.3.3 Managing data for digital support for health interventions

The fifth contribution is the introduction of a methodology that would allow individuals to visualize tailored Swiss Public Health statistical data in a way that would help them to gain a better understanding of where they stand in comparison to other Swiss residents with the same characteristics. This starting point, along with tailored feedback, follows what was suggested by Bandura [33] and potentially provides the first steps to lead to a behavior change supported by a digital artifact.

The sixth major contribution relies on the results of a literature review to better understand how the Human-Computer Interaction community has contributed to enabling humans to interact with LD technologies. The results showed that despite LD being a topic of interest to a variety of stakeholders, there are few possibilities for end-users to query, browse and visualize LD, underlining the need for further investigations. Enabling humans to interact with this data is a crucial and challenging step to bring the Semantic Web forward and potentially allow the representation of one's own situation in relation to the aggregated Swiss public health statistical data.

1.4 Form and structure

This thesis is organized as a series of essays rather than as a monograph. This approach has both advantages and disadvantages. On the plus side, each chapter of the thesis may be read as a stand-alone piece. On the downside, it leads to redundancy and some differences in the descriptions that have developed during the course of this work. The contributions of this thesis have been divided into a number of scientific articles that have been published or are currently under review with international peer-reviewed journals or conferences in the domains of computer science and information systems. This collection of essays is presented in this thesis and is split into three parts. Each article is a chapter and they are arranged by the topic they discuss. Each chapter tackles one of the questions defined in the problem statement section.

Part I provides a better understanding of digital support for health interventions. More specifically, Chapter 2 investigates digital support provided by mobile applications and provides a landscape of smoking cessation mobile applications (Q1). Chapter 3 aims to better understand how digital smoking cessation communities support the process of behavior change (Q2). Part I is based on the following studies:

- De Santo Alessio and Holzer Adrian. Assessing Digital Support for Smoking Cessation. In *the proceedings of the 16th European Mediterranean & Middle Eastern Conference on Information Systems (EMCIS)*, Dubai, UAE. 2019. Springer.
- De Santo Alessio, Moro Arielle, Kocher Bruno and Holzer Adrian. Helping Each Other Quit: A Look at Motivational Factors and User Interaction on the r/StopSmoking Digital Smoking Cessation Community. Submitted to *the International Journal of Transactions on Social Computing 2022. (fast-track extension of the above-mentioned publication)* Association for Computing Machinery (ACM)
- De Santo Alessio, Moro Arielle, Kocher Bruno and Holzer Adrian. From Digital Community Engagement to Smoking Cessation: Insights from the Reddit r/StopSmoking Thread. In *the Proceedings of the 54th Hawaii International Conference on System Sciences (HICSS)*, Honolulu, Hawai'i, USA. 2021. Association for Computing Machinery (ACM)

In Part II, gamified designs of digital support for health intervention are evaluated. Chapter 4 looks into how successful a digital escape room may be as a tool for preventing addictions and dangerous behaviors, providing prevention designers potential ways to improve the design of prevention interventions leveraging gamification (Q3). Chapter 5 is an illustration of how gamified feedback might decrease unwanted behaviors (Q4) through an experiment on a population of students. Part II includes two experimental studies:

- Bezençon Valéry*, De Santo Alessio*, Lanz Bruno and Holzer Adrian. Escape Addict: A Digital Escape Room for the Prevention of Addictions and Risky Behaviors in Schools. Submitted to *the International Journal of Computers & Education*. Elsevier
- De Santo Alessio, Farah Juan Carlos, Lafuente Martínez Marc, Moro Arielle, Bergram Kristoffer, Purohit Aditya Kumar, Felber Pascal, Gillet Denis, and Holzer Adrian. Promoting Computational Thinking Skills in non-STEM Students. Submitted to *the International Journal IEEE Transactions on Learning Technologies (TLT).* IEEE

In Part III, suggestions about public health statistical data management for further research in the context of digital support for health behavioral interventions are made. Chapter 6 provides an answer on how could Swiss public health statistical data be managed to provide individuals with tailored information (Q5), while Chapter 7 reviews the literature to investigate available approaches for visualizing and interacting with Linked Data and how might such data be leveraged to make sense of health information (Q6).

- De Santo Alessio, Cotofrei Paul, Stoffel Kilian. Personalized view of Swiss Public Health Statistical Data. In *the Book of Abstracts, Posters and Industry papers of the 7th International Conference on Health and Social Care Information Systems and Technologies (HCist)*. Lisbon, Portugal. 2018. SciKa
- De Santo Alessio and Holzer Adrian. Interacting with Linked Data: A Survey from the SIGCHI Perspective. In *the Proceedings of the 28th ACM Conference on Human Factors in Computing Systems (CHI).*, Honolulu, Hawai'i, USA. 2020. Association for Computing Machinery (ACM)

Finally, Chapter 8 wraps up this work and point the way to future study potential.

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Part I

Understanding digital support for health interventions

Chapter 2

Assessing Digital Support for Smoking Cessation

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Abstract

Tobacco still kills more than 7 million people each year. Research points to several evidence-based interventions to support smoking cessation which, if applied widely, could considerably reduce premature deaths. There is a huge range of mobile apps targeting this concern, which could potentially be powerful catalysts to provide this support. Yet it is unclear how much of their design is evidence-based and how effective they are. To address this issue, this paper provides an analysis of 99 popular smoking cessation apps. The results show that only two apps come from a credible source, provide support for user engagement through advanced motivational affordances and have been evaluated for efficacy.

2.1 Introduction

Do you think smoking is a public health concern of the past? Think again. According to the World Health Organization (WHO) tobacco use is still the single biggest preventable cause of death in the world today [1]. Tobacco kills 7 million people a year, which could potentially increase to more than 8 million by 2030 if left unchecked [1]. Most smokers, aware of the dangers of tobacco, would like to quit but they need help [1]. Simple behavioral change interventions can considerably reduce premature deaths of tobacco users [2].

Digital resources are increasingly available to support individuals in adopting healthier behaviors [3], [4]. An ever-increasing global adoption of mobile devices, such as smartphones and connected devices, has spurred rapid growth in the field of electronic health. New technologies are giving individuals the potential to engage more fully in their healthcare decision-making, opening possibilities to improve health outcomes [5], [6].

Face-to-face counseling is the most universally effective means of helping people quit [5] but, currently, participation rates in these programs are low [7] and they are not affordable globally [8]. Digital solutions to support smoking cessation can provide some advantages over traditional face-to-face methods, for example in terms of scalability and user proximity. Participation rates could be improved by leveraging features such as real-time data collection, feedback and low-cost dissemination [9].

Current literature establishes mobile phones as potentially useful in helping smokers quit [5]; however, among the thousands of mobile applications (apps) it is unclear how much of their design is evidence-based and how effective their use is. To address this issue, this paper provides a critical analysis of the most popular smoking cessation apps and identifies open research gaps and future promising research avenues.

2.2 Smoking Cessation – What Works

Government organizations, medical societies, research networks and research centers establish guidelines to provide a comprehensive review of the scientific evidence for treating tobacco use and dependence [10]. A review of 26 current guidelines allowed us to identify globally recommended smoking cessation interventions, with four of them providing strong evidence of efficacy: *brief advice*, *behavioral support*, *pharmacotherapy* and *abstinence evaluation* [11].

- *Brief advice.* Brief advice is 5 to 10 minutes of advice to encourage smokers to improve their health by quitting their smoking habit, primarily by triggering a cessation attempt. Some frameworks, such as the 5A's and the ABC framework, provide a structure for providing brief advice. The 5A's stands for *Ask*, *Assess*, *Advise*, *Assist* and *Arrange* a follow-up. The ABC stands for: (A) *Ask* all people about their smoking status, (B) provide *Brief advice* to stop smoking to all people who smoke, (C) make an offer of evidence-based *Cessation treatment*.

- *Behavioral support.* Often when smokers try to quit, they need behavioral support to avoid relapses. There are three main methods of providing behavioral support: (1) self-help material, (2) peer group meetings, (3) health professional counseling. The first method, self-help information, can support patients without outside help. When self-help is personalized it is even more effective [12]. In the second method, peers meet regularly and provide each other with support and encouragement. Compared to self-help, peer group support is more effective in helping smokers quit [12], [13]. In the third method, health professionals provide individual counseling through face-to-face appointments. This patient-centered approach is the most effective. Providing multiple and longer sessions also increases the effectiveness [12].
- *Pharmacotherapy.* Guidelines suggest the use of pharmacotherapy such as nicotine replacement therapy, bupropion and varenicline to assist patients with nicotine withdrawal [11]. In situations such as abruptly quitting smoking, a combination of behavioral support and pharmacotherapy is recommended [12].
- *Abstinence evaluation.* Guidelines suggest that abstinence evaluation confirmed by objective measurements is providing strong evidence in smoking cessation programs [11]. Measurement forms include various techniques such as tracking systems, biochemical markers and clinical tests. Even though tracking systems can in principle be bypassed, research suggests that increasing smoking awareness and providing tools such as goal setting [14] and tailored feedback [15] helps smokers to quit. These tools are important, since smokers are generally unaware of their daily smoking patterns [16].

2.3 Smoking Cessation Apps – What Research Says

Early attempts to assess mobile support for smoking cessation have primarily rated apps according to their adherence to smoking cessation treatment guidelines [17]–[21]. Overall, apps identified by Abroms et al., [17], [18] presented low adherence to established US guidelines for smoking cessation. The recommendation of Abroms et al., [17], [18], for future development, was to greatly adhere to such guidelines and other evidence-based practices. Bennett et al., [19] provided conclusions consistent with those of Abroms et al., [17], [18]. These US findings were echoed around the world, as smoking cessation apps also have low levels of adherence to Chinese [20] and Australian smoking cessation treatment guidelines [22].

Research suggests that the more a smoking cessation app is opened and accessed, the more likely the user is to quit smoking [23]. Thus, factors that might influence routine use are particularly important to consider for mobile app interventions, as 26% of apps are discontinued after first use, and 74% are used no more than 10 times [24]. *User engagement* and *source credibility* are two dimensions that appear to be important aspects of mHealth routine use [24]–[26].

In this paper, we build on these findings and critically assess existing digital smoking support solutions not only on their adherence to guidelines, but also on how their design encourages user engagement, and on their source credibility. The source credibility of an app relates to the emitting authority and significantly influences mHealth routine use [25]. *Competence* and *trustworthiness* are the main subdimensions of source credibility [27]. Competence refers to expertise, while trustworthiness is a function of the perceived character and integrity of the source. An app's emitting authority is not always mentioned, making the evaluation of its competence and trustworthiness difficult. Note, however, that source credibility refers to a user's perception of the credibility of an emitting authority, reflecting nothing about the app itself.

User engagement can be measured through the activity of an user on the app (number of visits, time spent, actions performed, etc.). It can be enhanced through motivational affordances, i.e. design features that trigger psychological levers such as intrinsic motivation, sociometric status and reciprocity [26]. Suh et al., [26] identified four types of motivational affordance, leading people to be better engaged in an activity:

- *Rewards.* By obtaining points as a pay-off for completing pre-designed tasks, users reach levels or milestones rewarded by virtual badges and trophies demonstrating their accomplishments.
- *Competition.* Users have the opportunity to compare with, and compete against, other people through components such as leaderboards, permitting them to visualize their standing against other users or friends.
- *Self-expression.* Personal identities can be created by users, through avatars and emoticons, enabling them to express their emotions.
- *Altruism.* Points and virtual goods can be exchanged between users.

Figure 5.13 provides an overview of the three-dimensional perspective for building an evidence-based app that will potentially encourage user engagement and routine use.

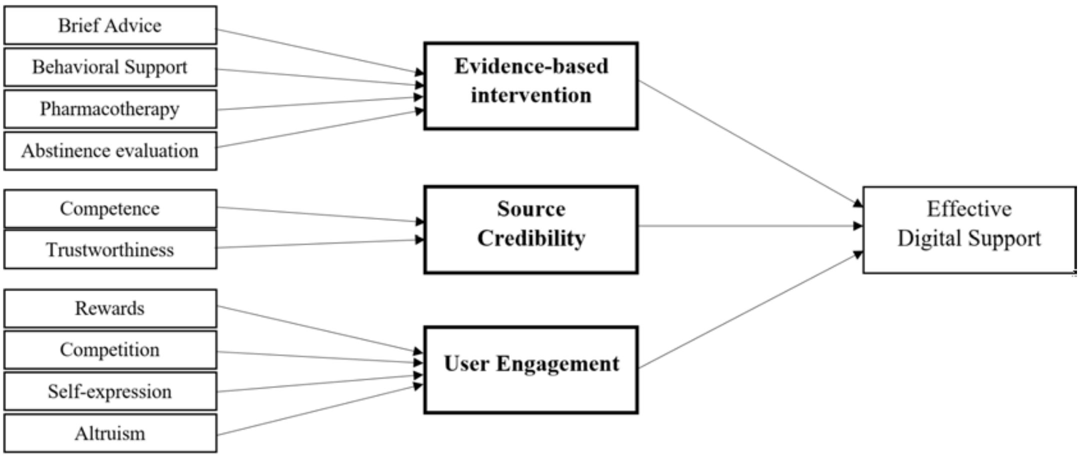

FIGURE 2.1: Research three-dimensional perspective.

2.4 App Landscape – What Currently Exists

To identify current practices, we collected a subset of the most popular apps and reviewed them on: *evidence-based* practice adherence, *source credibility* and motivational affordance that encourages *user engagement*. We also investigated whether apps were *validated* through evaluation studies. The app collection was conducted through the Explorer research tool provided by 42Matters (`https://42matters.com/`), on 19 November 2018. The following search terms were used to perform the queries on the title and description of the apps: *quit smoking*, *smoking cessation* and *stop smoking*. For each search

TABLE 2.1: Inclusion and exclusion criteria.

Inclusion criteria
Apple iOS and Google Android app
only apps available in the English language
only apps published in the Apple App Store or the Google Play Store
only apps containing in their description or title “quit smoking", “smoking cessation" or “stop smoking"
Exclusion criteria
unrelated app
general health and wellbeing app
exact duplicates between different app stores

term, the 40 most popular apps were retrieved on the number of downloads and on a rating basis, resulting in 120 Android apps and 120 iOS apps. Duplicate apps were removed, resulting in 92 iOS apps, 78 Android apps and 18 apps available on both platforms. Inclusion and exclusion criteria, as presented in Table 2.1, were applied to exclusively select smoking cessation apps. Figure 2.2 depicts the results of the process. The remaining 99 apps were then manually coded by parsing the app description, screenshots and website (where available).

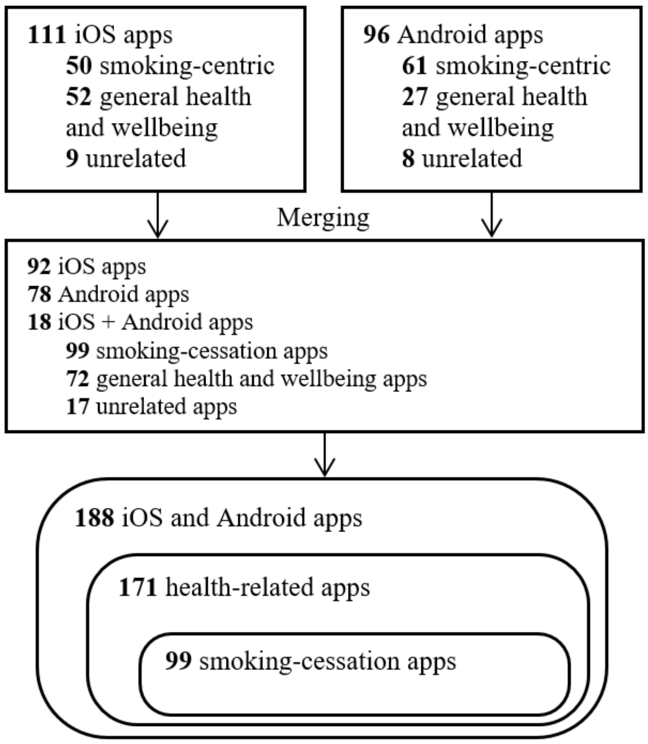

FIGURE 2.2: Procedure for our smoking cessation app sample selection.

2.4.1 Adherence to Evidence-Based Practices

As a first dimension of our review, apps were coded in respect of adherence to evidence-based practices: *brief advice*, *behavioral support*, *pharmacotherapy* and *abstinence evaluation*. The coding process was inspired by grounded theories and open coding techniques [28], [29], making the categories emerge by their proximity.

For the *brief advice* subdimension, we coded whenever apps provided smoking cessation *tips*, *pieces of advice* or *recommendations*. Apps' descriptions and screenshots were parsed, looking for this specific content addressed to smokers and representing brief advice interventions. Brief advice in a smoking cessation app can, for instance, be "Rejecting is easier if you do it with someone who has the same problem and understands you completely. [...]" (Ex Smoker, Sopharma AD), or when a smoker is reporting a craving, tips such as "drink something (water, juice)", "eat some fruit" or "brush your teeth" (Stop-tobacco, Université de Genève).

Concerning the *behavioral support* subdimension, we identified three different levels of support: (1) apps providing *self-help* support with cessation facts, (2) apps having a *social* dimension and (3) apps providing a guided smoking cessation *program*. Self-help cessation facts, are usually related to monitoring information and provide smokers with statistics about their behavior. For instance, apps can inform about the time elapsed since their last cigarette, the number of cigarettes smoked daily, or empowering facts triggered after quitting, such as "You have no more physical dependence on nicotine" (Qwit, Team Geny) or "Taste and smell senses regained" (Smoke – quit, NikNormSoft). Apps providing peer group support offer features such as community chat, permitting sharing and the discovery of peer experience, but also features allowing smokers to share their progress and achievements about smoking cessation on social networks such as Facebook and Twitter. Apps can also rely on specific programs, conducting smokers through the use of the app. Programs can have different formats, such as animated video clips, audio sessions including interactive exercises and mindfulness sessions. Finally, indications of *validation* studies were sought on the app description and website.

The *pharmacotherapy* subdimension was coded on whether apps provided information about existing pharmacotherapies. For instance, apps can provide tablet intake instructions or support.

The *abstinence evaluation* subdimension was coded by categorizing the various self-monitoring possibilities offered by the apps. Most of the apps provided monitoring features such as an *unsmoked cigarettes* counter, *unsmoked days* representing the number of days since the smoker quitted, the number of *cigarettes smoked* since the installation of the app, the *interval* of time between two smoked cigarettes or the report of *cravings and urges*.

2.4.2 Source Credibility as Routine Use Influencer

As a second dimension of our review, the source credibility of each app was coded. Apps could be developed and published by everyone, enabling developers of any kind to come with their batch of smoking cessation interventions. Metadata found in an app's description, screenshots and website allowed the identification of the emitting authority of the app. Competence and trustworthiness are the two consistently emerging dimensions of source credibility [27]. Trustworthiness is a function of the perceived character and integrity of the source and can therefore not be universally categorized. Competence refers to expertise of the source. Coding was simply categorized as follows:

- *Unspecified.* No information about the people involved in the development process of the app is found.
- *Peer.* A smoker or an ex-smoker developed or participated in the development of the app.
- *Specialists.* The creation of the app involved medical professionals, researchers or universities.
- *Governmental.* A governmental institution, such as the public health department, mandated or participated in the development of the app.

2.4.3 User Engaging Motivational Affordance

As a third dimension of our review, user engagement was evaluated. According to Suh et al., [26]: *rewards*, *competition*, *self-expression* and *altruism* provide motivational affordance, being meaningful antecedents of needs satisfaction, stimulating intrinsic motivation (enjoyment) and causing users to engage more deeply in target activities within a gamified app. User engagement was coded by noting the presence of the following motivational affordances in the apps:

- *Rewards.* Through using the app, points are obtained as a pay-off for completing pre-designed tasks, such as staying smoke-free. By obtaining points, users can also reach levels or milestones rewarded by virtual badges and trophies demonstrating their accomplishments. Associated design elements are: points, levels and badges/trophies.
- *Competition.* Users engage in competition with each other through components such as leaderboards, enabling them to compare points, levels or badges. Associated design elements are: points, levels, badges and leaderboards.
- *Self-expression.* Personal identities can be defined through dynamics, allowing users to, for instance, create an avatar, upload a personal profile photo or communicating with emoticons expressing their emotions. Associated design elements are: points, levels, badges, leaderboards, avatars and emoticons.
- *Altruism.* Points and virtual goods can be exchanged between the users. For instance, a user can make a present by offering a virtual gift to another user. Associated design elements are: points and virtual gifts.

2.5 Results

The content of 99 apps was reviewed and coded, following the three previously presented dimensions: *evidence-based* practices adherence and *validation* studies, *user engagement* and *source credibility*. Table 2.3 presents the results of the analysis, with the supported subdimension and scores. Scores allow us to compare evaluated apps on the evidence-based, user engagement and source credibility dimensions. Each category sub-score goes from 0 to 2, 0 representing the lowest level of adherence, 2 corresponding to the highest level of adherence. The addition of evidence-based, user engagement and source credibility scores provides the total score. Detailed attribution of scores is further detailed in Table 2.2.

Figure 2.3 provides an overview of the cumulative scores. The maximum achievable total score is 6. Two apps of our sample (2%) obtained the maximum score, while the average total score was 2.17. The average score for evidence-based adherence is 1.01. The average score for user engagement is

TABLE 2.2: Attribution of the dimensions' scores.

Score	*Evidence-Based*	*User Engagement*	*Source Credibility*
0	no use of any evidence-based practices	no use of motivational affordance	unknown emitting authority
1	use of at least one evidence-based practice	use of at least one motivational affordance design element	peer (e.g. ex-smoker) emitting authority
2	use of at least one evidence-based practice AND the app is backed up by scientific validation	use of two or more motivational affordances	specialists or governmental emitting authority

0.74. Of the reviewed apps, 10.1% do not support any evidence-based practice or any motivational affordance stimulating user engagement. The average score for source credibility is 0.42. Of the sample, 24.2% support some form of evidence-based practices without implementing any motivational affordances to increase user engagement. Finally, 72.7% of the reviewed apps do not provide enough information to clearly identify the emitting authority and therefore the source credibility. Note that only 11% of the apps indicated that their efficacy was validated through a scientific study.

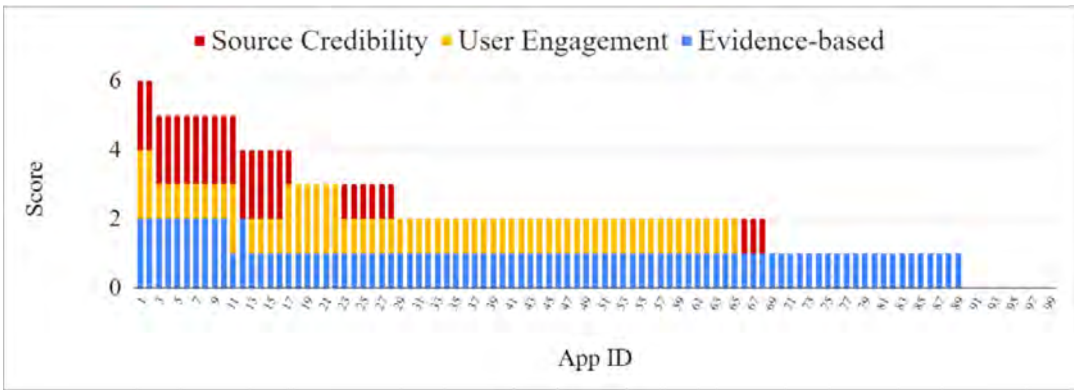

FIGURE 2.3: Overview of the reviewed apps' scores.

TABLE 2.3: Overview of the reviewed apps sorted by score.

id	App name (Editor)	OS			Evidence-based										User Engagem.				Source Cred.			Scores			
						Behav. Supp.				Abstinence Evaluation															
		Android	iOS	Validation	Brief Advice	Self-help	Peer-support	Program	Pharmacotherapy	Unsmoked cig.	Unsmoked days	Smoked cigarettes	Cigarettes Interval	Urges/Cravings	Rewards	Competition	Self-expression	Altruism	Peer	Specialists	Governmental	Evidence-based	User Engagement	Source Credibility	**Total**
1	Stop-tobacco (Université de Genève)	✓		✓	✓	✓	✓				✓				✓		✓			✓		2	2	2	6
2	Quit Genius - Best way to quit smoking for good (Digital Therapeutics)	✓	✓	✓		✓	✓	✓			✓				✓		✓			✓		2	2	2	6
3	Stoptober (Public Health England)	✓	✓	✓	✓	✓	✓	✓		✓	✓				✓				✓		✓	2	1	2	5
4	Craving To Quit! (Claritas MindSciences/Goblue International LLC)	✓	✓	✓	✓		✓	✓				✓			✓					✓		2	1	2	5
5	Quit Smoking - Stop Tobacco Mobile Trainer (Iteration Mobile S.L)		✓	✓	✓			✓				✓			✓					✓		2	1	2	5
6	Quit smoking - Smokerstop (Dr. med. Titus Brinker)	✓		✓	✓	✓				✓					✓					✓		2	1	2	5
7	Smoke Free - Stop Smoking Now (David Crane)		✓	✓	✓	✓					✓				✓					✓		2	1	2	5
8	2MorrowQuit (was SmartQuit) (2Morrow, Inc.)	✓	✓	✓				✓						✓	✓					✓		2	1	2	5
9	Smoke Free, quit smoking now and stop for good (The Quit Smoking Specialists)	✓		✓		✓	✓				✓				✓					✓		2	1	2	5
10	Stay Quit Coach (US Department of Veterans Affairs (VA))	✓	✓	✓		✓					✓				✓					✓		2	1	2	5
11	Quit Now: My QuitBuddy (ANPHA)	✓			✓	✓	✓					✓			✓		✓		✓		✓	1	2	2	5
12	Stop Tobacco Mobile Trainer. Quit Smoking App Free (Iteration Mobile & Vialsoft Apps)	✓		✓	✓	✓		✓				✓								✓		2	0	2	4
13	Smokefree (Public Health England)	✓	✓		✓			✓		✓				✓	✓						✓	1	1	2	4
14	Tabac info service, l'appli (l'Assurance Maladie)	✓	✓		✓	✓	✓								✓				✓		✓	1	1	2	4
15	Ex Smoker (Sopharma AD)	✓			✓	✓			✓	✓					✓					✓		1	1	2	4
16	Sacabo (Amarutek S.L.)	✓			✓				✓	✓					✓					✓		1	1	2	4
17	QuitNow! (Fewlaps, S.C)	✓	✓		✓	✓	✓			✓	✓				✓		✓		✓			1	2	1	4
18	Quit It - stop smoking today (digitalsirup)		✓			✓	✓			✓					✓	✓						1	2	0	3
19	Quit It Lite (digitalsirup)		✓			✓	✓			✓					✓	✓						1	2	0	3
20	Quitbit - Quit Smoking Cigarettes And Gently Stop (Quitbit, Inc)		✓			✓	✓					✓			✓		✓					1	2	0	3
21	Stop Smoking - EasyQuit free (Mario Hanna)	✓				✓				✓					✓		✓					1	2	0	3
22	Stop tabac - Quit smoking and cigarette cessation (Cedric Martin)		✓							✓					✓		✓					1	2	0	3
23	Quit Smoking Now: Quit Buddy! (HQmedia)	✓			✓	✓	✓	✓			✓				✓				✓			1	1	1	3
24	My Quit Smoking Coach (Andreas Jopp)	✓			✓	✓		✓		✓					✓				✓			1	1	1	3
25	Quit Smoking Pro (EpicLapps)	✓				✓	✓			✓					✓				✓			1	1	1	3
26	Quit Smoking: Cessation Nation (Ron Horner)	✓				✓	✓			✓	✓				✓				✓			1	1	1	3
27	Stop Smoking – quit smoking, be smoke free (The Quit Smoking Professionals)	✓				✓	✓			✓					✓				✓			1	1	1	3
28	LIVESTRONG MyQuit Coach (LIVESTRONG.COM)		✓				✓					✓			✓				✓			1	1	1	3
29	SmokeFree – quit smoking slowly (MotiveBite)	✓			✓	✓		✓		✓		✓	✓		✓							1	1	0	2
30	Quit Pro (Etago)		✓		✓	✓	✓			✓	✓				✓							1	1	0	2
31	quitSTART - Quit Smoking (ICF International)	✓	✓		✓	✓	✓				✓			✓	✓							1	1	0	2
32	101 days to quit smoking for good Free (GreenTomatoMedia)		✓		✓	✓					✓				✓							1	1	0	2
33	Quit Smoking - Quit now (Dhurandhar apps)	✓			✓	✓				✓					✓							1	1	0	2
34	Quit-Smoking Coach (Brainlag Studios)	✓			✓	✓				✓					✓							1	1	0	2
35	Quit-Smoking Coach Free (Brainlag Studios)	✓			✓	✓				✓					✓							1	1	0	2
36	QuitGuide - Quit Smoking (ICF International)	✓	✓		✓	✓								✓	✓							1	1	0	2
37	Smoke – quit (NikNormSoft)	✓			✓	✓				✓					✓							1	1	0	2
38	Quit Smoking Now: Stop Forever (TreePie)		✓		✓					✓					✓							1	1	0	2
39	Stop Smoking 3D (World Cloud Ventures)		✓			✓		✓			✓				✓							1	1	0	2
40	Drop It! Quit Smoking (Nikola Mladenovic)	✓				✓	✓			✓					✓							1	1	0	2
41	Kwit – quit smoking for good - smoking cessation (Kwit SAS)	✓	✓			✓	✓			✓	✓				✓							1	1	0	2
42	Smoke FREE Finally Non Smoking (sg-pages - Marcus Steller)	✓				✓	✓			✓					✓							1	1	0	2
43	Smoke Revoke - Gradually Quit Smoking (Alek Branch)		✓					✓				✓			✓							1	1	0	2
44	Cigarette Analytics (Alvakos)	✓				✓						✓			✓							1	1	0	2
45	Get Rich or Die Smoking (Tobias Gruber)	✓				✓				✓					✓							1	1	0	2
46	I Give Up Smoking (Stand Dev)	✓				✓				✓					✓							1	1	0	2
47	myQuitTime (Arete World Enterprises)		✓			✓				✓	✓				✓							1	1	0	2
48	myQuitTime Free (Arete World Enterprises)		✓			✓				✓	✓				✓							1	1	0	2
49	Quit Smoking - Goodbye Tobacco (Your Health)	✓				✓				✓	✓				✓							1	1	0	2
50	Quit Smoking - My Last Cigarette (Mastersoft)		✓			✓				✓					✓							1	1	0	2
51	Quit Smoking !!! (Dennis Ebbinghaus)		✓			✓				✓	✓				✓							1	1	0	2
52	Quit Smoking (Luis Salcedo)	✓				✓					✓				✓							1	1	0	2
53	Quit Smoking (Morisson Software)	✓				✓					✓				✓							1	1	0	2
54	Quit Tracker: Stop Smoking (despDev)	✓				✓				✓					✓							1	1	0	2

TABLE 2.3: Overview of the reviewed apps sorted by score.

id	App name (Editor)	OS			Evidence-based										User Engagem.				Source Cred.			Scores			
						Behav. Supp.				Abstinence Evaluation															
		Android	iOS	Validation	Brief Advice	Self-help	Peer-support	Program	Pharmacotherapy	Unsmoked cig.	Unsmoked days	Smoked cigarettes	Cigarettes Interval	Urges/Cravings	Rewards	Competition	Self-expression	Altruism	Peer	Specialists	Governmental	Evidence-based	User Engagement	Source Credibility	**Total**
55	Qwit (Quit Smoking) (Team Geny)	✓				✓				✓					✓							1	1	0	2
56	Smoke FREE - Non Smoking (sg-pages)		✓			✓				✓	✓				✓							1	1	0	2
57	Stop & Quit Smoking – Smoke & vaping Cessation Now (Ibrahim Khalil)		✓			✓						✓			✓							1	1	0	2
58	Stop smoking helper (Roxoft)	✓				✓				✓					✓							1	1	0	2
59	Time To Quit Smoke (VantusMantus)	✓				✓				✓	✓				✓							1	1	0	2
60	Non Smoking Timer (LinQ)	✓									✓				✓							1	1	0	2
61	Quit Smoking - Butt Out (Ellisapps Inc.)		✓								✓	✓		✓	✓							1	1	0	2
62	Quit Smoking - Butt Out Pro (Ellisapps Inc.)		✓								✓	✓		✓	✓							1	1	0	2
63	Smoking reduction free (hashisoft)	✓										✓			✓							1	1	0	2
64	Smoking reduction Trial (hashisoft)	✓										✓			✓							1	1	0	2
65	Tabex – quit smoking (Sopharma Ukraine Limited Liability Company)	✓							✓						✓							1	1	0	2
66	Stop Smoking In 2 Hours (Juice Master)	✓	✓		✓			✓											✓			1	0	1	2
67	Quit Smoking Audio Help Tips Stop Now and Forever (Pitashi! Mobile Imagination.)		✓		✓		✓												✓			1	0	1	2
68	Stop Smoking Personal Stories of Success Quit Now (Pitashi! Mobile Imagination.)		✓		✓		✓												✓			1	0	1	2
69	Quit Smoking with Willpower (Pocket Pixels)		✓		✓	✓		✓					✓									1	0	0	1
70	Smoktivation : Ma motivation pour arrêter de fumer (JCD Software)		✓		✓	✓				✓	✓											1	0	0	1
71	Can I Smoke? (Steven Dakh)		✓			✓		✓					✓									1	0	0	1
72	Ecig-Coach (E-CIG GROUP)		✓					✓				✓										1	0	0	1
73	No smoking (antonfil84)	✓				✓	✓			✓	✓											1	0	0	1
74	Quit Smoking Hypnosis (Mindifi)	✓			✓			✓														1	0	0	1
75	Quit Smoking NOW - Max Kirsten (Life Change Media Ltd)		✓					✓		✓												1	0	0	1
76	iQuit - Stop Smoking Counter (Vidal de Wit)		✓			✓				✓	✓											1	0	0	1
77	Nextlater (App2Bizz)		✓			✓						✓										1	0	0	1
78	NoSmokingLife (bamboo)		✓			✓				✓												1	0	0	1
79	Quit Smoking (Azati)	✓				✓				✓		✓										1	0	0	1
80	Quit Smoking (HC)	✓				✓				✓	✓											1	0	0	1
81	Smokenote - Quit Smoking (NXCARE)	✓				✓						✓										1	0	0	1
82	Smoking Log - Stop Smoking (Cory Charlton)	✓										✓										1	0	0	1
83	Quit Smoking with Andrew Johnson (Michael Schneider)		✓			✓		✓														1	0	0	1
84	iCan Stop Smoking: learn self hypnosis and quit smoking (iCan Hypnosis)		✓					✓														1	0	0	1
85	Quit and Stop Smoking Hypnosis (Mindifi)		✓					✓														1	0	0	1
86	Quit Smoking Hypnosis Program (Mindifi)		✓					✓														1	0	0	1
87	Quit Smoking in 28 Days Audio Program (Pitashi! Mobile Imagination.)		✓					✓														1	0	0	1
88	Smoking Cessation Hypnosis (Hyptalk)		✓					✓														1	0	0	1
89	Stop Smoking! (On Beat Limited)		✓					✓														1	0	0	1
90	Cigarette Smoke Simulator Free (Gravy Baby Media)	✓																				0	0	0	0
91	Help You to Quit 100% (Nightingale WebApp)																					0	0	0	0
92	Roll and Smoke 3D FREE (Sakis25)	✓																				0	0	0	0
93	Simulator Cigarette Vape Joke (StarApps7)	✓																				0	0	0	0
94	Smoke a virtual cigarette (MaxZieli)	✓																				0	0	0	0
95	Smoke Cigarette Simulator (Yami Apps)	✓																				0	0	0	0
96	Smokerface (Dr. med. Titus Brinker)	✓																				0	0	0	0
97	Smoking virtual cigarettes (ScreenPranks)	✓																				0	0	0	0
98	Virtual cigarette (SmileTools)	✓																				0	0	0	0
99	Virtual Hookah/Shisha (Iris Studios and Services)	✓																				0	0	0	0
		61.6%	49.5%	11%	31.3%	61.6%	24.2%	25.3%	3.0%	43.4%	29.3%	19.2%	3.0%	6.1%	64.6%	2.0%	7.1%	0.0%	13.1%	12.1%	4.0%				
																				Average		1.01	0.74	0.42	2.17

2.6 Discussion

This research has shown that even though the subject is well-known, and smoking cessation apps are plentiful, research that provides information for system designers, users and medical professionals is not yet mature. One main issue is the lack of evaluation of smoking cessation apps. Of the 99 applications reviewed, only 11 (11%) were validated by scientific research, seven other apps (7.1%) claimed to be scientifically based, but no proof of this claim was found on the developer website. The lack of large empirical studies on effectiveness of smoking cessation apps provides an open avenue for future research. Furthermore, at this stage, most of the research papers referenced by the reviewed apps deal with the effectiveness of cognitive and behavioral theories [3], [30], but none deal with the app itself.

Current popular smoking cessation apps still have much room for improvement. Adherence to evidence-based guidelines and best practices continues to be low, as mentioned by previous research. It is often difficult to evaluate the source credibility, as most of the time the source is unknown or no guarantee of legitimacy is available. Regarding user engagement, the great majority of apps automatically reward smokers without requiring their intervention or being based on their actual behavior. In terms of motivational affordances, providing rewards is the most used mechanism. Although rewards are recognized as motivational affordances that encourage user engagement, they only weakly contribute to it when they are not coupled with other mechanisms (such as competition or self-expression) [26]. To maximize user engagement, future apps should consider such combinations.

The findings of this study should be interpreted in the context of certain limitations, the main limitation being that the apps were reviewed on the sole basis of the information provided by their developer (description, screenshots and website), which could be incomplete, erroneous or outdated. For a more comprehensive assessment, each app should be installed and used just as a smoker would.

While actual apps are potentially useful, they vastly underutilize the potential of mobile technologies. Mobile technology provides an unprecedented environment for reaching and interacting with smokers. Arguably the greatest strength of mobile technology is its ability to infer user activity, potentially providing a better idea of the smoker's actual behavior and in turn delivering personalized content in an appropriate context, in terms of space and time.

Such technology also enables ubiquitous connectivity, enabling communication with peers and experts. Currently, popular apps only poorly implement such possibilities; for instance, only 2% permit smokers to engage in competition with peers and only one app (Quit Now: My QuitBuddy, ANPHA) provides access to experts through a quitline.

Future research should further exploit the opportunity of the device being in the smoker's pocket anytime and anywhere, thus providing an inconspicuous, accurate and efficient monitoring of smoking activity. Of the reviewed apps, only one (Quitbit, Quitbit Inc) uses a connected device (lighter) to monitor smoked cigarettes. There is a lack of research into the evaluation of such tracking devices and their efficiency. These devices would definitely introduce an important feedback loop for the smoker's actual behavior with potentially high effectiveness [12], [15]. In addition, the sensors (e.g. GPS) already built into most smartphones make it possible for apps to provide sophisticated just-in-time and in-the-moment intervention for smoking cessation. Evaluation of previous smoking activity monitoring and digital support tailorization should be further investigated. A major challenge with such features is the privacy concern that they raise. It is therefore crucial to understand how to best find trade-offs to enable privacy-by-design while enabling personalization through data analytics.

Future work could also investigate social media interactions, which have been found to be poorly implemented. Designing interactions with peers (behavioral support functionalities) would not only reinforce the evidence-based practices, but would also facilitate the design, evaluation and understanding of what additional motivational affordances (competition, self-expression, altruism) are most effective besides rewards.

Finally, a majority of reviewed apps were emitted by an unspecified authority, leading to concerns of source credibility. Emitting sources of mHealth apps could be certified to help smokers in their choice. As interest in using apps for smoking cessation grows, it may become more difficult for consumers to find an app that is likely to be helpful. Further research should investigate how the emitting source could be legitimated and how sensitive content such as pharmacotherapy could be integrated.

2.7 Conclusion

This study provides an updated review of the most popular smoking cessation apps and suggests directions for further research to improve the efficacy of future digital support for smoking cessation. As interest in using apps for smoking cessation grows, it may be difficult for consumers to find an app that is likely to be helpful. Helping individuals quit smoking is a challenging task that requires an interdisciplinary approach. The volume of available apps makes the process of selecting a smoking cessation app difficult. The information systems community can provide support for this challenge by investigating how to best design digital support systems to help smokers quit. Even though there are a significant number of apps to help smokers quit, most of them are not aligned with evidence-based guidelines, nor are they encouraging user-engagement and source credibility, and there is also a lack of research for evaluating their effectiveness.

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Chapter 3

Helping Each Other Quit: A Look at Motivational Factors and User Interaction on the r/StopSmoking Digital Smoking Cessation Community *

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Abstract

Despite decades of prevention, tobacco addiction is still a widespread health concern responsible for around 8 million deaths per year. Existing digital solutions such as social media are becoming increasingly popular and represent a novel approach for people to find community support. However, little is known about how they affect smoking behavior. This research investigates

*Study 1 of this research was published under the title of "From Digital Community Engagement to Smoking Cessation: Insights from the Reddit r/StopSmoking Thread", the full article is currently under second-round review for the International Journal of Transactions on Social Computing, Association for Computing Machinery (ACM), submitted on April 15, 2021 with a minor revision sent on January 21, 2022 how an online smoking cessation community can help. A multimodal analysis of one of the biggest communities, namely the Reddit r/StopSmoking thread, was conducted in three complementary studies. Using the transtheoretical model and the uses and gratification theory, Study 1 predicts online engagement and the smoking cessation process of change. Study 2 provides insights into the attitudes and behaviors of the r/StopSmoking community by analyzing 10 years of user interaction data. Study 3 focuses on the effect of the COVID-19 pandemic on r/StopSmoking. Our findings suggest that engagement in such communities has a positive relationship with the process of change. Providing social support was found to be the most important motivational factor to engage in r/StopSmoking. This finding is important because previous research suggests that helping others can be an important factor in helping oneself. User interactions analysis validated that the responses given through surveys were indeed consistent with actual user behavior. Regarding the impact of the COVID-19 pandemic, we could suggest that it increased levels of stress and depression among the community while active engagement dropped, indicating that there might be room for improvement in the community, to face difficult situations.

3.1 Introduction

According to the World Health Organization (WHO), tobacco use is the starting point for many non-communicable diseases (NCDs) and is responsible for over 8 million deaths annually [1]. Most smokers, who are aware of the dangers of tobacco, would like to quit but need help to do so [2]. Simple behavioral change interventions can considerably reduce the premature deaths of tobacco users [2]. Past research has investigated which interventions can effectively reduce the premature deaths of tobacco users. According to primary care guidelines, brief advice, behavioral support, pharmacotherapy and abstinence evaluation are the only four interventions providing strong evidence of efficacy [3]. Unfortunately, these evidence-based interventions are still largely underused [4]. For instance, face-to-face counseling, which is the most effective way to help smokers to quit [5], has only low participation rates [6] and is also not affordable globally [7]. Reaching smokers with this efficient intervention will require novel approaches to enhance the effectiveness of existing cessation interventions, and to increase their adoption.

To support individuals in adopting healthier behaviors, digital artifacts are increasingly available [8]–[10]. Social networks [11], social support [12], and social integration [13] appear to play important roles in smoking behavior and can potentially provide helpful complementary support for smoking cessation [5]. Among available digital resources, social media are becoming increasingly popular for people in search of health information and support [14], [15]. On these platforms, the digital community, i.e., the group of people interacting on the platform, can potentially provide 24/7 behavioral support and brief advice through messaging. However, evidence on the specific factors that enable digital communities to support tobacco cessation are still limited [16], [17].

We address this issue by investigating how such digital communities provide support for smokers who are attempting to quit. This research provides an understanding of motivation to participate in digital smoking cessation communities and of its behavioral impact on individuals' online engagement and offline smoking cessation process of change. More specifically, this paper is subdivided in three studies. In the main study, Study 1, we contribute to the literature by providing a novel research model based on the transtheoretical model as well as the uses and gratification approach. Our model aims to predict online engagement and eventually the progress in smokers' behavioral process of change towards becoming an ex-smoker. This study also aims at understanding how online activities support smokers' process of change. We instantiate this model using insights from users of a real social media community (r/StopSmoking on Reddit) which includes more than 100k members, and 865k messages (i.e., 115k posts and 750k comments). In Study 2, we provide further insights into the r/StopSmoking community's attitudes and behaviors by exploring all publicly available user interaction data over the course of a decade. Finally, Study 3 aims at understanding the impact of the COVID-19 crisis on the online community. This study takes a multimodal analytics approach combining survey results with activity traces.

3.2 Literature review and hypotheses

This section reviews the relevant literature for our work and presents five hypotheses that will be evaluated.

3.2.1 Towards smoking cessation

The director of the O2 Foundation, a regional anti-tobacco agency, explains that "on average it takes around seven attempts before someone manages to quit for good". To quit smoking seems to be more a process than a single act following a decision. A useful theoretical model, matching this idea of process, is the transtheoretical model (TTM) [18]. This model, based on stages, differs from many other behavioral theories that based on so-called continuum models. According to continuum models, interventions could be applied in any order, or even simultaneously, and do not include any notion of progression [19]. Stage models imply that different interventions are appropriate at different stages of health behavior change [19], making for instance TTM a frequently used model for smoking cessation intervention [20]. Even if stage models have also been criticized [21], [22], arguing that the notion of stages might be flawed or circular, in that the stages are not genuinely qualitative, they still embed this notion of progression, which goes beyond the sole variation of intention including the action and post-action spectrum. The TTM hypothesizes that this change occurs in six distinct steps, also called *stages of change*:

- Stage 1, *precontemplation*, i.e. no intention to take action within the next six months;
- Stage 2, *contemplation*, i.e. intention to take action within the next six months;
- Stage 3, *preparation*, i.e. intention to take action within the next 30 days with some behavioral steps in this direction already taken;
- Stage 4, *action*, i.e. changed overt behavior for less than six months;
- Stage 5, *maintenance*, i.e. changed overt behavior for more than six months;
- Stage 6, *termination*, no temptation to relapse and 100% confidence.

The TTM further suggests a set of 10 *processes* mediating the progress between stages (see Table 3.1). Empirical integration [23] suggests that, in early stages, smokers rely on cognitive, affective and evaluative processes to progress through the stages. In later stages, smokers work more on commitments, conditioning, contingencies, environmental controls and support for progressing toward maintenance or termination.

3.2.2 Evidence-based interventions

Four interventions for smoking cessation have been found to be supported by evidence [3]: (1) pharmacotherapy, (2) brief advice, (3) behavioral support

Process of Change	***Description***
Consciousness raising *(Stage 1 → 2)*	Increasing awareness via information, education and personal feedback about the healthy behavior
Dramatic relief *(Stage 1 → 2)*	Feeling fear, anxiety or worry because of the unhealthy behavior, or feeling inspiration and hope when they hear about how people are able to change to healthy behaviors
Environmental reevaluation *(Stage 1 → 2)*	Realizing the negative impact of the unhealthy behavior or the positive impact of the healthy behavior on one's proximal social and/or physical environment
Self-reevaluation *(Stage 2 → 3)*	Realizing that the behavior change is an important part of one's identity as a person
Self-liberation *(Stage 4 → 5)*	Making a firm commitment to change
Helping relationships *(Stage 5 → 6)*	Seeking and using social support for the healthy behavior change
Counterconditioning *(Stage 5 → 6)*	Substitution of healthier alternative behavior and cognition for the unhealthy behavior
Reinforcement management *(Stage 5 → 6)*	Increasing the rewards for the positive behavior change and decreasing the rewards of the unhealthy behavior
Stimulus control *(Stage 5 → 6)*	Removing reminders or cues to engage in the unhealthy behavior and adding cues or reminders to engage in the healthy behavior
Social liberation *(no specific Stage)*	Realizing that the social norms are changing in the direction of supporting the healthy behavior change

TABLE 3.1: Processes of change that mediate progression between the stages of change

and (4) abstinence evaluation. Examples of pharmacotherapy include nicotine replacement therapy and the use of bupropion or varenicline to assist patients with nicotine withdrawal. A brief advice is 5–10 minutes of advice to encourage smokers to improve their health by quitting their smoking habit, primarily by triggering a cessation attempt. Behavioral support includes: self-help material, peer group meetings and health professional counseling. *Self-help information* can support patients without outside help. When self-help is personalized, it is even more effective [24]. With *peer group meetings*, smokers who attempt to quit meet regularly and provide each other with support and encouragement. *Health professional counseling* generally consists of one-on-one face-to-face appointments between a medical professional and a smoker. Enhancing the motivation to stop smoking through behavioral support has been identified as an important aspect of the overall treatment for tobacco addiction [24]. Finally, abstinence evaluation is the confirmation of abstinence through either self-reporting or objective measures such as biochemical markers or clinical tests.

3.2.3 Digital communities for smoking cessation

Several studies have analyzed online smoking cessation communities [16], [25]–[27]. Some studies investigated the effectiveness of health behavior interventions on online social communities, finding none, very modest or ambivalent evidence of efficacy [25], [27]. Others used observational rather than interventional approaches to understand peer-generated content and interactions [26], [28]. From this perspective, emerging results suggest that peer support is helpful in avoiding smokers relapsing [16] or to motivate them to quit [3]. Researchers argue that digital communities can be perceived as a "safe space" for smokers to talk about day-to-day challenges, cravings or relapses [26]. Furthermore, the relative anonymity of the Internet can facilitate discussion and mutual support [26]. A wide variety of peers can be available at any time to provide help and support through various activities, such as sharing information, sympathizing, cheering, coaching or celebrating. Some of these peers, potentially further along the line, can be considered as *expert patients*. They can provide firsthand experience about how to cope, what to expect and how things feel [27].

Digital interventions can be seen as potentially supporting several evidence-based interventions. For instance, digital communities have been found to contribute to significant long-term positive health outcomes through their information-providing role (*self-help material*) [29], [30]. However, it is not yet clear how engagement in such communities is linked to the actual process of behavior change. Digital interventions can also be seen as potentially supportive *peer group meetings*. Unfortunately, research results are not yet conclusive [31]. A better differentiation of social support concepts and causal pathways is awaiting further investigations to demonstrate the effective value of social relationships in improving smokers likelihood of cessation [12].

We argue that one of the important factors to assess the impact of online communities is participant (i.e. user) engagement. User engagement in a digital community can be defined as the different activities users perform in an online community. These activities can be divided into active contributing activities (e.g. posting messages, reacting to a comment, sharing a video) and passive consuming activities (e.g. viewing content, visiting a page) [32], [33]. Based on these definitions and the aforementioned literature, we make the following hypotheses:

H1: Overall engagement in digital smoking cessation communities is positively linked to the process of change.

H1a: Active engagement in digital smoking cessation communities is positively linked to the process of change.

H1b: Passive engagement in digital smoking cessation communities is positively linked to the process of change.

3.2.4 Motivation for digital community engagement

To understand the motivational factors influencing engagement in digital communities, the *uses and gratifications theory* is widely relied upon [34], even though it was originally developed to examine how and why individuals use and adopt mass media in their daily lives [35]. As depicted in Table 3.2, this theory describes four motivational factors to predict engagement in digital communities [33], [34], [36]: *information-seeking*, *status-seeking*, *entertainment* and *socialization*.

While the uses and gratifications theory already stands as a valid means of examining the motivations sought and obtained by users of online communities [33], [34], [36], recent literature is still calling for contributions to further expand this approach by, for instance, examining new needs and motivations [33]. To expand this model, one possibility is to integrate recent findings about behavior change [33], in this case the evidence that providing support is even more useful than receiving support [40], [41]. Smoking cessation being a process in which one is not immune from relapsing, providing support may have a twofold positive impact, for people receiving the support but also for people providing it. To reflect the dual aspect of seeking and providing support discussed above, we suggest expanding the socialization factor into two relevant subfactors: (1) *Providing social support* and (2) *Seeking social support*. Providing social support is measuring users' motivation to support others in their smoking cessation process, which would represent "expert" users who are further ahead on the withdrawal journey and are willing to provide firsthand experience and support [27]. Seeking social support aims to measure a user's motivation to engage in online communities to exchange

Motivational factor	***Description***
Information seeking	Seeking and obtaining useful information is one of the primary motivations for Internet use [37]. Information seeking has been positively associated with social networks participation in past studies [34], [38]. Online communities represent a wealth of information, providing smokers with self-help material.
Status-seeking	Improving one's social status has been shown to be a strong motivating factor from a uses and gratifications perspective in studies of social network usage [33], [34].
Entertainment	The need for pleasurable, emotional and aesthetic experiences has been found to be a strong motivation factor in Internet and social network usage [33], [36]. Studies have indicated that reading and sharing content may also meet entertainment needs for users [39].
Socialization	Previous studies have found socialization as strong motivations among users [33], [36], [38]. Building and maintaining social contacts are among the most prevalent reasons for participation in online communities [33], [36]. Smokers may also use such channels to share about their quitting journey and to exchange peer support.

TABLE 3.2: Motivational factors to participate in online smoking cessation communities

with others in order to receive support. These observations lead to the following hypotheses:

H2: Uses and gratification motivational factors will be positively linked to engagement in online smoking cessation communities.

H3: Seeking and providing social support are motivational factors that increase participation in online smoking cessation communities.

3.3 Study 1: Understanding how a digital community supports smoking cessation

This study focuses on a particular digital smoking cessation community, the popular Reddit social media platform, and in particular its r/StopSmoking subreddit, which is one of the largest and most active communities dedicated to smoking cessation (more than 100k users, 115k posts and 750k comments). A subreddit can be seen as a shared forum where users can post messages, reply with comments and vote messages up or down. Each Reddit user, also known as a redditor, can join r/StopSmoking and ask for or give advice, share stories or encourage someone who is trying to quit. The following sections provide a description of the survey, a presentation of the model and method used to analyze the data, and a description of the participants, through key data.

3.3.1 Survey

This study employed a survey designed to assess individuals' motivation to participate in r/StopSmoking, their level of engagement and the perceived influence of the community on their process of behavior change. The survey was validated by the University of Neuchâtel ethics committee, and asked for informed consent of participants. Respondents were anonymous and could stop the study at any time. Besides asking for informed consent, demographics and some descriptive facts in the first section, the survey aimed at measuring engagement, motivation and process of change.

Measuring engagement

The second section focused on engagement in r/StopSmoking. Engagement was measured by asking participants how frequently they performed the following types of activities: visiting, reading, posting, commenting and voting. The first two activities are considered passive engagement, whereas the last three are instances of active engagement. These activities were measured using a five-point scale: "never", "almost never", "occasionally/sometimes", "almost every time" and "every time". Frequency of visiting was measured through a question asking for the average monthly number of visits with possible answers ranging from "less than 1" to "30 or more".

Measuring motivation

The third section of the survey measured the motivation to participate in r/StopSmoking. Motivation to participate was measured through four factors, according to the uses and gratification approach: information-seeking, status-seeking, socialization and entertainment. The information-seeking, status-seeking and entertainment factors were directly taken and adapted from prior instruments employed in uses and gratifications research [33], [34], [36]. The socialization factor was also adapted from previous research, but the questions were linked to the novel factors *providing social support* or *seeking social support* according to the direction of the interaction. For instance, one of the questions used for the *providing social support* factor asked whether the respondent participated in the r/StopSmoking subreddit to help others. In contrast, one of the questions used for *seeking social support* factor asked if the respondent participated in the r/StopSmoking subreddit to gain peer support from others. All factors were measured with multiple questions, using five-point Likert scales.

Measuring process of change

The fourth section of the survey focused on the behavior change process. The process of change was measured through the individual's accomplishment of the various processes mediating the progression between the stages of change of the TTM process of change (see Table 3.1). For instance, to measure whether r/StopSmoking helped people to move from precontemplation to contemplation we inquired if r/StopSmoking allowed users to accomplish the corresponding processes of change: consciousness raising, dramatic relief and environmental reevaluation. For instance, consciousness raising accomplishment was measured by asking participants if the digital community allowed them to increase their awareness via information, education and personal feedback about smoking cessation (see Table 3.1). For each process, the accomplishment was measured with the same question structure, and individuals could then answer through a five-point Likert scale. Each stage of change was finally measured as a formative construct – based on the various processes that would allow them to progress beyond it – giving indicators measured through five-point Likert scales. As there are no clear processes allowing people to move on from the preparation and termination stages, they were not included in our model.

Participants

Users of the r/StopSmoking subreddit were invited to participate in the survey through links posted directly to the site. The survey was completed on a voluntary basis and no compensation was given to respondents. A total of 173 responses were collected from 11 February to 11 April 2020. To maintain the visibility of the invitation among other posts, invitations to participate in the survey were randomly re-posted 18 times throughout the data collection period. After preliminary analyses and data preparation to remove incomplete surveys and surveys with inconsistencies in the control questions, 169 participants were included in the analysis (85 males, 83 females and 1 preferred not to say; mean age 34). The average age when participants started to smoke was 16.6 years old. The average number of years of smoking was 16.1 (min 1 – max 45). Respondents smoked on average 16.8 cigarettes per day before quitting.

3.3.2 Model and data analysis

Partial least squares (PLS), a variance-based structural equation modeling (SEM) analysis technique, was used for assessing our model and our hypotheses. PLS is an increasingly popular technique in IS research to analyze explanation and prediction of IS phenomena [42]–[44]. Central to PLS is the path model, a diagram that displays the hypotheses and variable relationships to be estimated in an SEM analysis [45].

The construction of our path model (Figure 3.1) includes three main dimensions: (1) *Motivation to Participate*, referring to motivational factors influencing the participation in the digital community, (2) *Engagement (online behavior)*, referring to engagement in the digital community and (3) *Process of Change (offline behavior)*, referring to the process of behavior change. To evaluate our model and test our hypotheses we used a three-stage approach. First, as advocated by Hair et al. [44], we evaluated the reliability, validity and significance of our model. Second, we analyzed the overall results, focusing on a macro view of the model to test hypotheses H1 and H2. Finally, we tested hypotheses H1a, H1b and H3 with an in-depth path analysis from a micro view of the model. SmartPLS was used as the analysis tool.

To evaluate the reliability of our *reflective constructs* (i.e. information-seeking, status-seeking, entertainment, providing social support and seeking help) we used composite reliability (CR) and average variance extracted (AVE) as

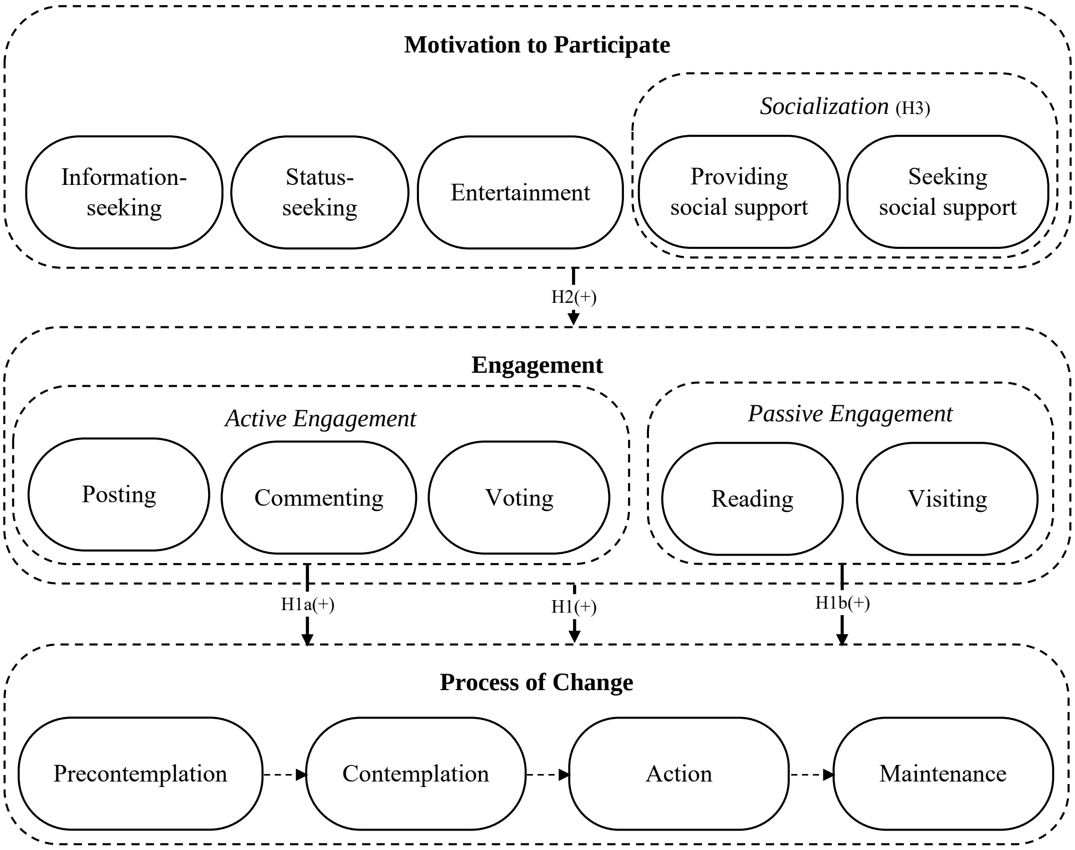


FIGURE 3.1: Research model

indicators. As shown in Table 3.3, the CR of all the constructs was greater than 0.7 and the AVE greater than 0.5, hence these constructs are considered reliable [44].

	rho_A	*CR*	*AVE*	*Cronbach's Alpha*
Information-seeking	0.860	0.890	0.730	0.822
Status-seeking	0.583	0.765	0.527	0.553
Entertainment	0.711	0.793	0.568	0.646
Prov. social support	0.880	0.940	0.887	0.873
Seek. social support	0.712	0.874	0.776	0.711

TABLE 3.3: Evaluation of reflective constructs

To evaluate the convergent validity of the reflective construct, we considered outer loadings and the AVE of the indicators [46]. The outer loadings of all our reflective variables were above 0.7 (the standard threshold [46]), apart from one indicator in status-seeking and another in entertainment that were above 0.6. As this study is an exploratory research, we decided to keep indicators between 0.4 and 0.7, as recommended by Hair et al. [46].

To measure the discriminant validity of our reflective constructs, we measured the Heterotrait-Monotrait Ratio (HTMT) [44]. The rule of thumb accepts values lower than 0.85 for conceptually distinct constructs and below 0.90 for conceptually similar constructs. As shown in Table 3.4, all values were lower than 0.85, demonstrating the discriminant validity of our constructs.

	Entertainment	Information-seek.	Prov. social support	Seek. social support	Status-seek.
Entertainment					
Information-seeking	0.384				
Prov. social support	0.323	0.152			
Seek. social support	0.585	0.527	0.755		
Status-seeking	0.414	0.298	0.686	0.611	

TABLE 3.4: Heterotrait-monotrait ratio (HTMT)

To validate our formative constructs, we measured the variance inflation factor (VIF), defined as the reciprocal of the tolerance. The VIFs of our formative constructs indicating values lower than 5 (Table 3.5) exclude potential collinearity problems [46].

Weights express a formative indicator's relative importance in forming the construct. Significance indicates whether formative indicators truly contribute to forming the construct. The results presented in Table 3.5 depict the indicator's weight and significance for each formative construct. All the indicators of the motivation to participate construct were highly significant ($p<0.001$). Concerning the engagement indicators, the frequency of posting and voting were not significant ($p>0.05$) in the determination of individuals' active engagement. In the same way, consciousness raising was not found to be a significant determinant in the users' progression from precontemplation to contemplation stage. As recommended by Hair et al. [46], we verified that for outer loadings of non-significant indicators found in our study, all values were high (>0.5) and indicators were eventually retained, bearing in mind that such indicators had an absolute and not relative importance. To assess the high-level hypotheses (H1 and H2), we extracted latent variable scores of motivation to participate, engagement and process of change constructs.

Construct	*Indicator*	*Outer Weight*	*t-value*	*p-value*	*VIF*
Motivation to Participate	Information-seeking	0.259	4.812	<0.001	1.284
	Status-seeking	0.251	7.090	<0.001	1.377
	Prov. social support	0.340	9.452	<0.001	1.783
	Seek. social support	0.328	14.609	<0.001	2.129
	Entertainment	0.245	8.598	<0.001	1.343
Active Engagement	Posting	0.303	1.238	0.216	1.871
	Commenting	0.584	2.561	0.010	1.908
	Voting	0.324	1.745	0.081	1.219
Passive Engagement	Reading	0.613	2.799	0.005	1.145
	Visiting	0.602	2.845	0.004	1.145
Precontemplation	Consciousness raising	0.198	1.133	0.257	1.343
	Dramatic relief	0.415	2.993	0.003	1.236
	Environm. reevaluation	0.666	5.247	<0.001	1.234
Maintenance	Counterconditioning	0.302	3.115	0.002	1.426
	Helping relationships	0.476	4.880	<0.001	1.180
	Reinforcement managem.	0.374	3.907	<0.001	1.257
	Stimulus control	0.253	2.321	0.020	1.303

TABLE 3.5: Evaluation of formative constructs

3.3.3 Results

Figure 3.2 shows that the link between engagement and process of change is significant and positive. The more users are engaged in the community, the higher their process of change. H1 is supported.

Figure 3.2 shows that motivation to participate influences significantly and positively engagement. The more motivated users are to participate, the more they actually participate. H2 is supported.

Looking further into the motivation to participate construct enabled us to further test hypotheses H2 and H3. Motivation to participate in r/StopSmoking was found to be significantly influenced (see Table 3.5) by all uses and gratification factors: information-seeking, status-seeking, providing social support , seeking social support and entertainment factors. The most influential motivational factors are: providing social support (0.340), followed by seeking social support (0.328), information-seeking (0.259), status-seeking (0.251)

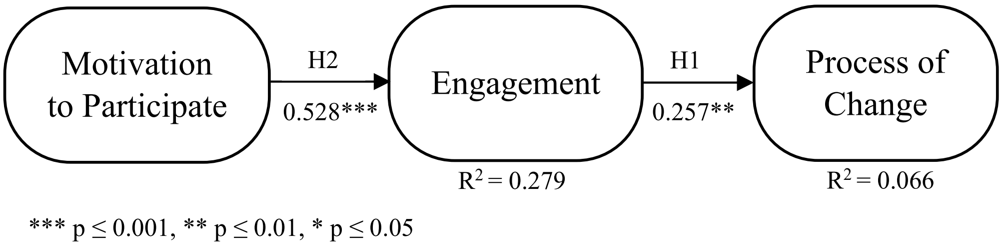


FIGURE 3.2: Overall results from macroscopic view of the model

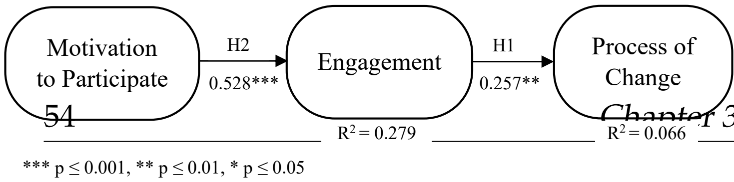
and entertainment (0.245). Thus, providing and seeking social support are the most influential motivational factors. H3 is supported.

Path coefficients of our model indicate that the motivation to participate in r/StopSmoking has a strong effect on the individuals' active engagement (0.496) and on individuals' passive engagement (0.335), both being highly significant ($p<0.001$) (Figure 3.3).

Engagement explains 6.6% of the total variance of the overall process of change. The quite poor influence of r/StopSmoking overall engagement on the process of change is not surprising as it is difficult to exert an influence on every stage of the process at the same time. It is for this reason that we tested hypotheses H1a and H1b at a lower level of granularity and analyzed the influence of both active and passive engagement on each stage independently. Both H1a and H1b are supported, with different influences on the stages of change whenever individuals perform active or passive engagement. Active engagement influenced only processes of change moving on maintenance in a strongly significant manner, while passive engagement influenced processes of change moving on precontemplation and maintenance with high levels of significance (see Figure 3.3). However, engagement did not significantly influence processes of change moving from contemplation to action, neither for moving from action to maintenance.

3.4 Study 2: Understanding interactions on the digital community

Whereas Study 1 built a model based on survey data linking motivation to participate to engagement and eventually to smoking cessation, Study 2 seeks to assess actual behavior and to provide further insights to the model by looking at all publicly available user interaction data such as comments,



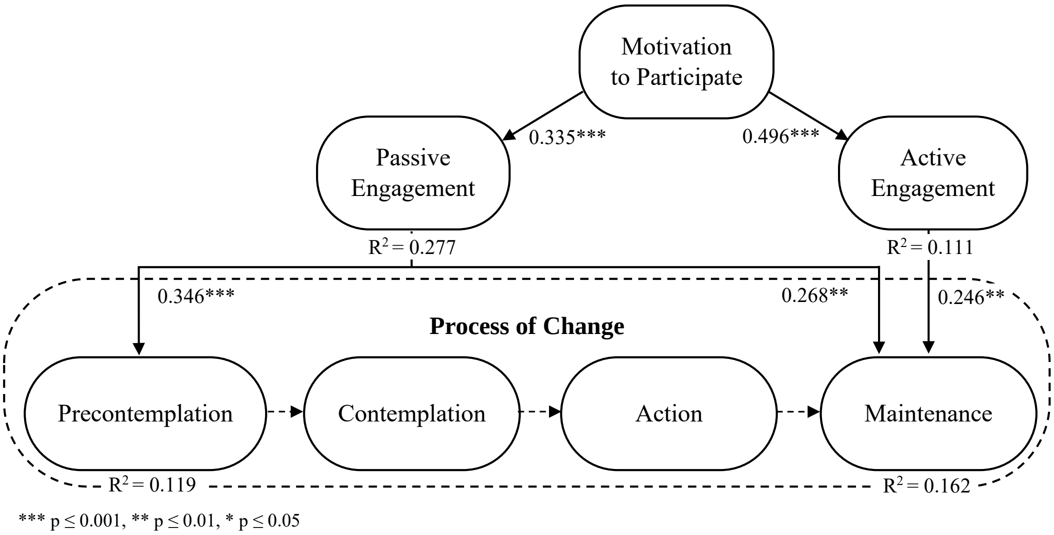


FIGURE 3.3: Influence of active and passive engagement on the stages of change

posts and scores, from the r/StopSmoking thread by addressing six open questions (see Table 3.6). First, Study 2 aims to shed light on the motivational factors of participating in r/StopSmoking. As Study 1 found that providing social support, seeking social support and information-seeking were the most influential motivational factors, Study 2 seeks to verify whether the interactions of the users of this community contain what motivated the users to come. To investigate if these motivational triggers are indeed satisfied, we analyzed the community's interactions, paying particular attention to: (1) the kind of information available and (2) the proportion of messages aiming to provide or seek social support (Q1, Q2). Second, Study 2 aims to give an overview of the general trend of the community in terms of engagement. Engagement has been found in Study 1 to be helpful for the quitting process. Thus, it may be important to look at the dynamics of this engagement: Is the community growing or decreasing? What kind of contributors are participating? Specifically, Study 2 focused on active engagement (e.g. commenting on a post), which was shown in Study 1 to have a significant impact on cessation maintenance. Unfortunately, passive participation could not be measured through the available data. Study 2 therefore investigated active engagement both in terms of users (Q3) and interactions (Q4). Third, as Study 1 indicated community support for several stages of the process of change, Study 2 aims to understand what stage users are at and the stage targeted by messages (Q5, Q6).

To extract the data from r/StopSmoking the Pushshift API was employed.

Dimensions	**Questions of interest**
Motivation to Participate	**Q1:** What type of information is available? **Q2:** How much social support is provided?
Engagement	**Q3:** How has the community evolved in terms of active users? **Q4:** How has the community evolved in terms of active engagement?
Process of Change	**Q5:** What stage of their process are the contributing authors at? **Q6:** Which stage of the smoking cessation process is targeted by the messages?

TABLE 3.6: Study 2 questions of interest.

Pushshift is a big-data storage and analytics project containing the copy of Reddit comments and posts [47]. The use of this API has been chosen over the official Reddit API as it allows to export large quantities of Reddit data without quantity limitation. We downloaded 125,349 posts and 803,611 comments resulting in a sample of messages going from the creation of the subreddit to 31 December 2020. As a first step in pre-processing the collected data, deleted posts and comments were removed from the dataset. Deleted posts and comments are still present in Reddit but are easily identifiable as the text message contains a "[deleted]" mention. Orphan comments, i.e., comments belonging to a deleted message, were kept as they could still contain content of interest. The final dataset consisted of 86,554 posts and 745,428 comments written by 92,046 different authors from 6 November 2009 to 31 December 2020.

3.4.1 Q1: What type of information is available?

To answer Q1, a topic modeling technique was used to identify the key topical interests. The notion of topic has to be understood as a mixture of words used together in similar contexts, that potentially allow to determine the main streams of discussion in r/StopSmoking. As previous studies suggested that the topic of an online discussion is prone to change as the discussion progresses [48], we considered each post and comments distinctly as messages, as we expect many of the longer discussions to have multiple topics. To reduce noise and extract key words from messages, the data was preprocessed to clean and normalize the text messages. The URLs were removed from the messages and each message was then tokenized. From the list of tokenized words, non-ASCII characters were removed, characters were converted to lowercase, the punctuation and English stopwords were removed. Stopwords are high-frequency words such as *the*, *to*, and, *also* that are usually filtered out of texts as they provide little lexical content. In addition to the usual English language stopwords provided by the stopwords corpus of the Python Natural Language Toolkit (NLTK), we added a list of additional stopwords related to the context of smoking cessation. In fact, words such as *quit*, *smoking*, *cigarette* or *pack* are extensively used in all topics as they are part of the main concern of the community. Excluding such contextual stopwords allowed us to emphasize less common lexical content to widen the gap between the different topics. Finally, a validity check performing a systematic analysis over 5000 randomly selected messages confirmed our position in the topic modeling. To code topics, we used the Latent Dirichlet Allocation (LDA) approach [49], which is one of the most widely used methods to understand the key topics from a large quantity of documents. LDA is an unsupervised algorithm that uses a generative model that uncovers topics by considering the posterior probability of the topics. The lack of a ground truth dataset and the effectiveness LDA demonstrated in previous studies assured us in our choice. Indeed, the analyses of multiple health-related digital communities have demonstrated the effectiveness of LDA topic modeling, such as in the analysis of cannabis consumption influence [50], symptoms and medical usages analysis [51] or general health discussions [52]. Furthermore, using LDA as opposed to most other unsupervised clustering techniques allows to consider each message with multiple topics. Unfortunately, using LDA requires a predetermined number of topics to be set. However, an interactive topic model visualization tool called pyLDAvis [53] provides help in fitting the LDA models with the optimal number of topics. After fine-tuning this number, the following five topics emerged:

Topic 1 – *Encouragement*

Messages featuring common usage of the terms *congrats*, *congratulations*, *strong*, *proud* or *easier*. Such *encouragement* messages usually follow the publication of an accomplishment by a community member, as for instance “day 1 wish me luck!” or “3 days without smoking! First two days were horrible, I feel I’m about to relapse.” Users easily congrat the accomplishment of other members and provide them with some encouragement such as “Congrats! Stay strong! It will get easier with time!”

Topic 2 – *General information*

Features the words *addiction*, *brain* or *understand*. These terms seem to refer to authors trying to provide a better understanding of the addiction. Community members share information about what they know or they heard regarding tobacco addiction. For instance "It's the addiction to smoking that caused you to feel so terrible in the first place. For a decade, you have been feeding your brain dopamine by smoking those poisonous things. Your brain will have a chemical imbalance for some time after quitting. You have to power through that and your brain will rewire itself to produce dopamine normally. Some say it can take 30 to 90 days at most."

Topic 3 – *Personal experience*

Features terms relating to personal experience over smoking cessation process. Words like *weight*, *eat*, *water* or *exercise* are among the most relevant ones in this cluster. Messages describing personal experience such as "exercise really helped me, gave me purpose and a great feeling 4 times a week."

Topic 4 – *Nicotine substitute*

Most relevant featured terms are *nicotine*, *vape*, *gum* or *patches*. In this topic, users seem to discuss nicotine substitutes. As it is a hard step to get rid of the nicotine addiction, smokers may share solutions to fight the addiction once they are trying to keep smoke free. A typical message might be "I hated the control smoking had over how I lived my life. I used a vape as a method to quit." or "I've tried quitting a few times over the past few years using patches, nicotine gum, cold turkey, chewing tobacco [...] finally had enough with smoking and started taking Chantix on 4/4."

Topic 5 – *Pieces of Advice*

Reading the Allen Carr's book "The easy way to stop smoking" is among the top advice that community members receive on r/StopSmoking. Topic 5 contains words like *allen*, *carr* and *way*, but also *app*, *audiobook* or *advice*, and seems to refer to all sorts of advice given when people are willing to quit. For instance: "Allen Carr's book, The Easy Way To Stop Smoking. Read it, believe it, set yourself free from the slavery of nicotine addiction."

3.4.2 Q2: How much social support is provided?

In order to answer Q2, 5000 randomly selected messages were manually tagged by two researchers in search of "providing social support" and "seeking social support" messages. The 5000 messages were divided in two for the two researchers, checking inter-rater reliability on 10% of the whole sample. A Cohen's kappa greater than 0.6 was found. On the basis of these 5000 tagged messages, we trained multi-label classification algorithms to be able to classify messages providing social support, messages seeking social support, but also messages doing both (providing and seeking) or neither. Two thirds of these 5000 messages (3500) were used to train the algorithms while one third (1500) was used to test and evaluate results obtained. Examples of providing social support and seeking social support messages could be for instance "Congratulation on your first day without smoking!" and "Wish me luck, I quit smoking today!" Messages were first cleaned and normalized by converting them to lowercase, removing html-tags, punctuation and non-alphabetic characters. Then, stopwords were removed using the same technique as for the clustering under Q1. Next, stemming was applied, transforming words with roughly the same semantics to one standard form. After splitting the dataset into train and test sets, we summarized the messages into numerical vectors using the Term Frequency Inverse Document Frequency (TF-IDF) technique. TF-IDF picks the most frequently occurring terms (term frequency or TF) but also measures how unique a word is, i.e. how infrequently the word occurs across all messages (inverse document frequency IDF). We were indeed interested in extracting features corresponding to the terms that frequently occur in the messages belonging to the category we wanted to analyse. Compared to other techniques such as bag of words (BOW), the TF-IDF technique is well adapted to extract adapted features for a text classification task because it solves the problem of less frequent words. Multiple multi-label algorithms were then tested in search of the best accuracy, recall and precision: One-vs-Rest, Binary Relevance, Classifiers Chains, Label Powerset and ML-KNN. The One-vs-Rest algorithm provided the best performance and was therefore selected. Classification of messages providing social support provided an accuracy of 0.76, a recall of 0.79 and a precision of 0.76 with the following confusion matrix (Table 3.7). Classification of seeking social support messages did not provided sufficient performance quality and was then discarded. Figure 3.4 illustrates the ratio of messages providing social support in respect of the total amount of messages. The results show that the proportion of messages providing social support is slightly growing over time and represents in 2020 more than one third of the total messages. Figure 3.5 also shows the proportion of authors providing social support among total number of contributing authors. From 2010 to 2020 the proportion of authors providing social support increased from 23% to 28%.

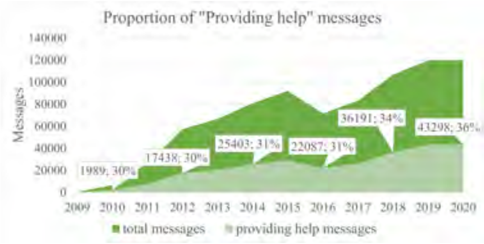


FIGURE 3.4: Proportion of "Providing social support" messages in relation to the total number of messages per year.

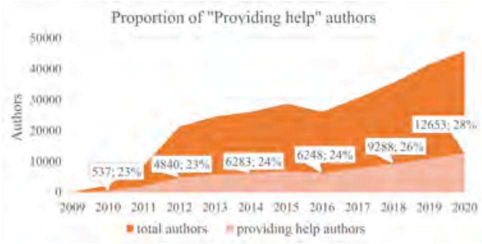


FIGURE 3.5: Proportion of "Providing social support" authors in relation to the total number of contributing authors per year.

		Predicted	
		Positive	Negative
Actual	Positive	542	195
	Negative	159	604

TABLE 3.7: Confusion matrix of the "Providing social support" messages classifier

3.4.3 Q3: How has the community evolved in terms of active users?

In year 2020, 45,819 distinct authors posted a message on r/StopSmoking, from which 15,720 were new on that thread. To have a better idea of the community evolution, the annual number of contributing authors and of first-time contributing authors have been extracted.

This allowed us to identify four main stages of evolution for the r/StopSmoking community: (1) From 2010 to 2012, the number of authors and new contributing authors exploded, with for instance an increase of 279.5% first-time contributing authors from 2010 to 2011. (2) From 2013 to 2015, the annual growth rate of the community appears to have stabilised. For that period, the mean growth rate of the number of authors contributing was 10.6% with a 4.9% standard deviation (SD), while the mean growth rate of the number of first-time authors was 5.4% with a 0.6% standard deviation. (3) In 2016 there is a growth rupture. Topic extraction could not reveal anything different for that specific year and this decreased growth remains at this point unexplained. (4) From 2017 to 2020, a stable period in terms of growth starts again. In fact, the weekly mean growth rate from 2017 to 2020 is 15.1% with a standard deviation of 3.1% for overall contributing authors and 21.4% with a 10.6% standard deviation for the first-time contributing authors. Figure 3.6 allows to visualize these four stages.

To have a better idea of the author rollover, yearly means of first-time contributing authors have been extracted. Figure 3.7 presents the average number of first-time authors per year. Another interesting insight concerning community authors comes from Figures 3.8 and 3.9, which show that a greater part of the authors contribute only a few times in r/StopSmoking, with a large part contributing only once.

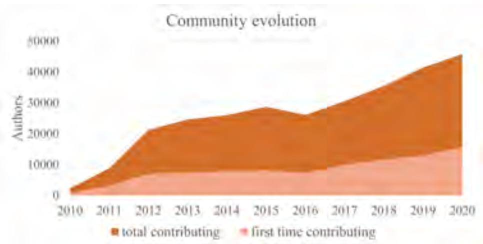


FIGURE 3.6: Community evolution in term of contributing authors and first-time contributing authors.

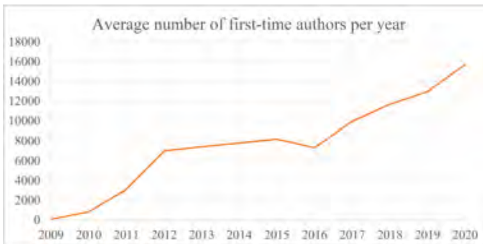


FIGURE 3.7: Average number of first-time contributing authors per year.

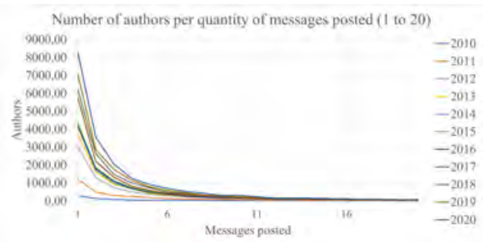


FIGURE 3.8: Comparison by years of the number of authors having posted the same quantity of messages.

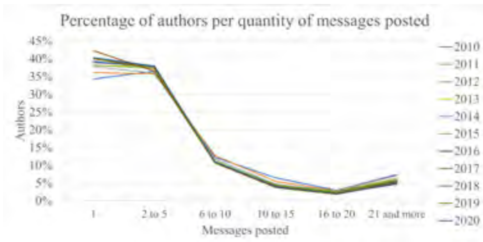


FIGURE 3.9: Comparison of the percentage of authors per year having posted the same amount of messages.

3.4.4 Q4: How has the community evolved in terms of active engagement?

During 2020, the r/StopSmoking community registered 12,344 new posts and 107,663 new comments, with an average of 233 posts and 2031 comments per week. Figures 3.10 and 3.11 present the evolution of such figures from the beginnings of r/StopSmoking until end of 2020. The evolution of the amount of posts and comments registered every year appears to follow the same four-stage pattern of the community evolution presented in Q3. To have a better idea of the frequency of participation we extracted weekly figures. The weekly mean number of posts is illustrated in Figure 3.12, the weekly mean number of comments in Figure 3.13 and the weekly mean number of contributing authors in Figure 3.14. Regarding the votes that a message on r/StopSmoking can receive, Figure 3.15 illustrates the mean score obtained by messages per year, the score of each message represents the addition of upvotes with the subtraction of downvotes, that are voluntarily assigned by the community. The comments scores appears to be stable through the years, while the posts score seems be more subject to variation, with a minimum reached in 2020.

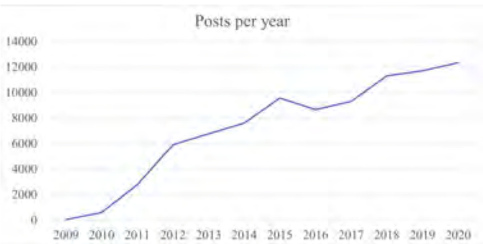


FIGURE 3.10: Total number of posts per year.

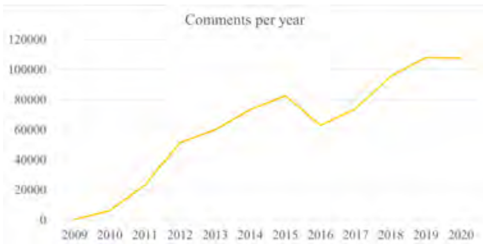


FIGURE 3.11: Total number of comments per year.

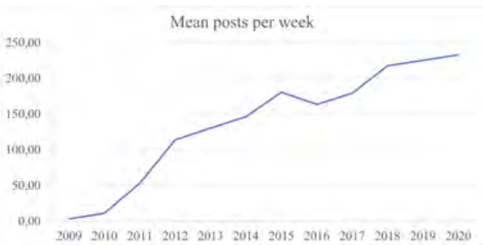


FIGURE 3.12: Average weekly posts year on year.

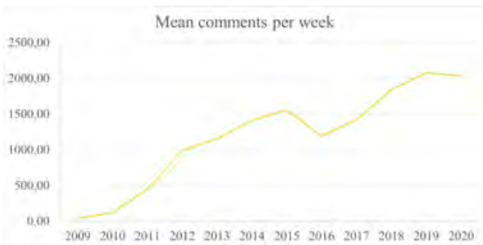


FIGURE 3.13: Average weekly comments year on year.

To investigate the possible activity cycles, we plotted the average number of messages posted on r/StopSmoking week by week (Figure 3.16). We could see that the first weeks of years 2012, 2013, 2015, 2016 ,2017, 2018, 2019 and

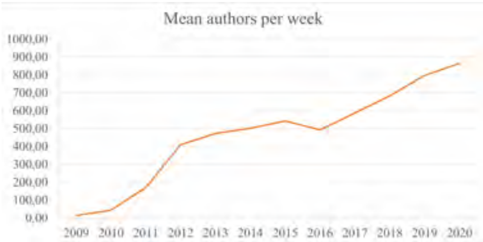


FIGURE 3.14: Average weekly number of contributing authors year on year.

FIGURE 3.15: Mean messages score per year.

2020 is marked by a peak in activity. After manually analyzing the messages, we could attribute these peaks of activity to the new year resolutions, smokers deciding to quit smoking for the new year and then seeking for socialization, information, status or entertainment on r/StopSmoking. Further analysis of the community attendance allowed us to determine that the community is more active during the working days (Figure 3.17), particularly Tuesday and Wednesday. Peak hours of activity are from 4pm to 8pm (UTC) (Figure 3.18).

FIGURE 3.16: Overall number of posts and comments per week day.

3.4.5 Q5: What stage of their process are the contributing authors at?

To answer Q5, the 5000 randomly selected messages were manually tagged by two researchers whether they were written by smokers, by former smokers, or if it was not specified or deducible. For instance, an example of a smoker's message would be "saw all the class stories on here about people quitting and was looking for some tips. I've wanted to quit smoking for a long time, but always fall back into it", while an example of former smoker's message would be "I've also been smoke-free for 1 month today. What can

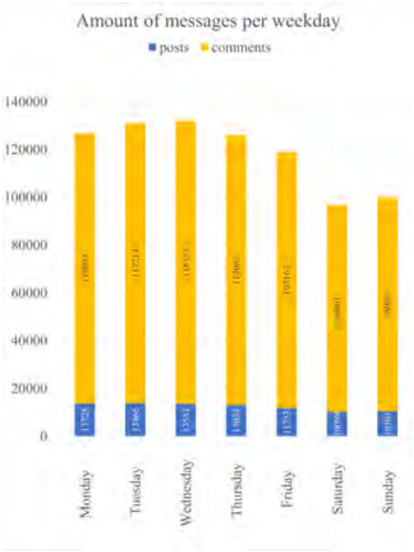


FIGURE 3.17: Overall number of posts and comments per week day.

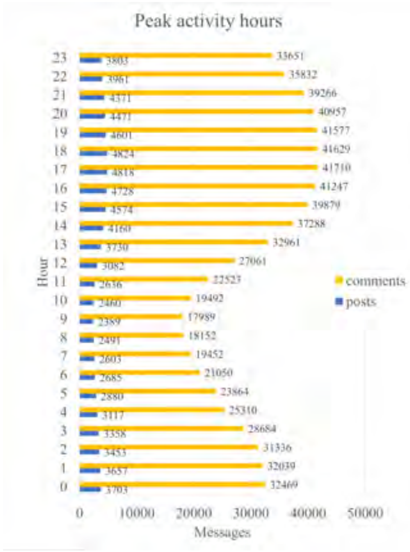


FIGURE 3.18: Overall number of posts and comments per hour (UTC).

we expect in terms of benefits of quitting going forward?" The 5000 messages were divided into two for the two researchers checking inter-rater reliability on 10% of the whole sample. A Cohen's kappa greater than 0.65 was found. On the basis of these 5000 tagged messages, we trained a classification algorithm to be able to classify messages according to the status of its author. Messages were first cleaned and normalized by converting them to lowercase, removing html-tags, punctuation and non-alphabetic characters. Then, stopwords were removed using the same technique as for the clustering under Q1. Stemming was then applied, transforming words with roughly the same semantics to one standard form. After splitting the dataset into train and test sets we summarized the messages into numerical vectors using TF-IDF technique. The One-vs-Rest algorithm was used to classify the messages. Classification of messages authored by current smokers did not provide sufficient performance quality and were then discarded. Classification of messages authored by former smokers, provided an accuracy of 0.77, a recall of 0,62 and a precision of 0,64 with the following confusion matrix (Table 3.8). As classifying former smokers messages performed better, we applied this classifier on the whole dataset obtaining results illustrated in Figure 3.19. The results of our analysis indicates that 67% of messages posted in 2020 were authored by users classified as former smokers, which suggests that much of the activity on this community is conducted by individuals in the maintenance stage of their TTM process of change.

		Predicted	
		Positive	Negative
Actual	Positive	868	164
	Negative	178	290

TABLE 3.8: Confusion matrix for messages authored by former smokers classifier.

3.4.6 Q6: Which stage of the smoking cessation process is targeted by the messages?

The 5000 randomly selected messages were manually tagged by two researchers looking for timing usefulness messages. Timing usefulness was classified as "pre stop-smoking", if the message was useful before the action stage of the TTM process of change, and as "post stop-smoking" if it was useful after the action stage of the TTM process of change. For instance, a message useful before the action of quitting could be "Just say no, start doing something else to take your mind off it. You need to read Allen Carr's book." A message useful after the action of quitting could be "Sometimes, when I'm very stressed (it's been a stressful week at work), or when I see someone smoking, I feel a strong craving, but I remind myself that I've been good for 18 days, and I don't want to throw it all away." The 5000 messages were divided in two for the two researchers checking inter-rater reliability on 10% of the whole sample. A moderate inter-rater reliability was found among researchers with a 0.45 Cohen's Kappa. On the basis of these 5000 tagged messages, we trained multi-label classification algorithms to be able to classify messages on the basis of their timing usefulness on the smoking cessation process of change. Messages could contain information or advice useful before quitting (pre stop-smoking), after quitting (post stop-smoking) but also for both situations or neither of them. Multi-label algorithms were then tested in search of the best accuracy, recall and precision. The One-vs-Rest algorithm was selected as it provided the best performance compared to Binary Relevance, Classifiers Chains, Label Powerset, and ML-KNN. Messages were preprocessed by lowercasing them, removing html-tags, punctuation and non-alphabetic characters. Then, stopwords were removed using the same technique as for the clustering under Q1. Next, stemming was applied, transforming words with roughly the same semantics to one standard form. After splitting the dataset into train and test sets we summarized the messages into numerical vectors using TF-IDF technique. Classification of messages useful before action, provided an accuracy of 0.76, a recall of

		Predicted	
		Positive	Negative
Actual	Positive	917	134
	Negative	229	220

TABLE 3.9: Confusion matrix of the pre stop-smoking messages

		Predicted	
		Positive	Negative
Actual	Positive	835	170
	Negative	207	288

TABLE 3.10: Confusion matrix of the post stop-smoking messages

0.50 and a precision of 0.62 with the following confusion matrix (Table 3.9). Classification of messages useful after action, provided an accuracy of 0.75, a recall of 0.58 and a precision of 0.63 with the following confusion matrix (Table 3.10). Figure 3.20 illustrates the proportion of messages being useful before having stopped smoking, after having stopped smoking, in both or in neither situation. It appears that a majority of messages are useful in both pre and post stop-smoking situations. Comparing messages that are exclusively useful before or after having stopped smoking, figures suggest that messages being useful to people before they stop smoking are increasingly present year on year.

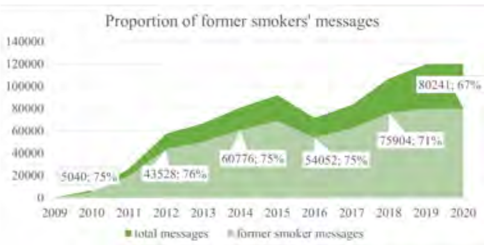


FIGURE 3.19: Proportion of former smokers messages in relation to the total number of messages per year.

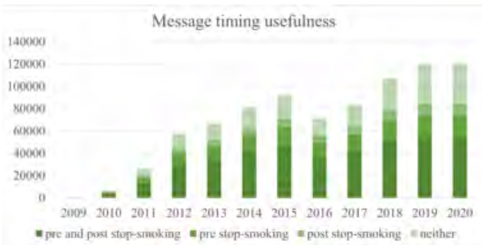


FIGURE 3.20: Estimation of the message timing usefulness year by year.

3.5 Study 3: Understanding the impact of COVID-19 on the digital community

In 2020, the COVID-19 pandemic shook the whole world by killing several million people around the globe and affecting billions indirectly through economic hardship or politically imposed lockdowns. As a result, stress levels and conditions like anxiety and depression can be expected to increase [54], [55]. Furthermore, with social distancing, highly effective support relying on a face-to-face setting will probably have lower participation rates than usual [6]. Because of this, it has been suggested that social media could fulfil a compensatory function by substituting physical touch with a virtual touch and extending social contacts beyond the physical boundaries of COVID-19 confinement [56]. These findings and predictions about the impact of the COVID-19 crisis in general led to the following hypotheses regarding its impact on the r/StopSmoking community in particular:

- **H4a:** During COVID-19 crisis, stress levels have increased among r/StopSmoking users.
- **H4b:** During COVID-19 crisis, anxiety levels have increased among r/StopSmoking users.
- **H4c:** During COVID-19 crisis, depression levels have increased among r/StopSmoking users.
- **H5:** r/StopSmoking engagement has increased during COVID-19 crisis.
- **H6:** Perceived usefulness of r/StopSmoking has increased during COVID-19 crisis.

Several methodological steps were taken to study the influence of the COVID-19 crisis on the r/StopSmoking community. First, we submitted a new dedicated survey to the community. Second, we further analyzed the data collected in Study 2.

The survey employed for Study 3 was designed to assess individuals' perceived stress, anxiety and depression levels, but also the perceived usefulness of the r/StopSmoking community during and before the COVID-19 crisis. In this survey, we first probed the community's general concern and feeling about the COVID-19 crisis. Then, r/StopSmoking user engagement, before and during the COVID-19 crisis was assessed. Engagement was measured by asking participants how frequently they performed the following types of activities: visiting, reading, posting, commenting and voting. Next, respondents evaluated the perceived usefulness of r/StopSmoking as well as the perceived stress, anxiety and depression levels during, and if applicable before the COVID-19 crisis. The "before" section was only displayed if the respondents confirmed their having engaged in r/StopSmoking before the COVID-19 crisis. In that case, before and during subsections were randomized. To measure the perceived usefulness of r/StopSmoking, we used the validated Perceived Userfulness Scale (PUS) from the work of David et al. [57]. The self-reported perceived stress of respondents was measured thanks to the Perceived Stress Scale (PSS) [58] in its short form, PSS-4, as validated by the study of Warttig et al. [59]. To monitor self-reported perceived depression, we used the Patient Health Questionnaire (PHQ-2), a two-item questionnaire suggested and validated by Löwe et al. [60]. To self-report perceived anxiety, we used one of the most frequently used measures of anxiety in applied psychology research, the Spielberger State-Trait Anxiety Inventory (STAI) [61], in its short form, STAI-6, as presented and validated by Marteau et al. [62]. All of these validated scales were adapted to the context. As with the first survey, it was validated by the University of Neuchâtel ethics committee, asked for informed consent, and participants were free to stop at any time. Users of the r/StopSmoking subreddit were invited to participate in the survey through links posted directly to the site. The survey was completed on a voluntary basis and no compensation was given to respondents. A total of 211 responses were collected from 20 January to 21 March 2021. To maintain the visibility of the invitation among other posts, invitations to participate in the survey were randomly re-posted throughout the data collection period. After preliminary analyses and data preparation 57 respondents were retained as they were engaged in r/StopSmoking before and during COVID-19 crisis, most of other respondents did not engage in r/StopSmoking before the crisis.

3.5.1 H4a: During COVID-19 crisis, stress levels have increased among r/StopSmoking users.

The four-item instrument asks respondents to rate how often they experienced stressful situations on a Likert scale ranging from 0 to 5 where 0 = never and 5 = very often. Two of the PSS-4 items are reverse scored, and so, these variables were recoded. Higher values on the PSS-4 indicate more stress. As presented in Table 3.11, on a maximum score of 5, the perceived stress of our sample increased from 2.74 to 3.01 with standard deviations of respectively 0.73 and 0.77 representing an increase of 10%. According to a two-tailed repeated-measures t-test, we can affirm that r/StopSmoking users appear to perceive themselves significantly ($p < 0.05$) more stressed. Looking more in detail at respondents' answers, we noted that PSS-4 Score increased for 58% of our sample.

	Before COVID-19		During COVID-19		Significance
	Mean	**SD**	**Mean**	**SD**	**two-tailed t-test**
PUS-6 Score	3.71	0.72	3.88	0.75	1.50 (not significant)
PSS-4 Score	2.74	0.73	3.01	0.77	2.64 (significant at p <0.05)
STAI-6 Score	3.11	0.55	3.21	0.67	1.02 (not significant)
PHQ-2 Score	2.02	0.74	2.46	0.84	3.54 (significant at p <0.01)

TABLE 3.11: Perceived usefulness, stress, anxiety and depression before and during COVID-19 crisis

3.5.2 H4b: During COVID-19 crisis, anxiety levels have increased among r/StopSmoking users.

The six-item measure asks respondents to rate how they felt on a Likert scale going from 0 to 5 where 0 = not at all and 5 = very much so. Respondents had to rate whether they felt calm, tense, upset, relaxed, content or worried. Three of the STAI-6 items are reverse scored, and so these variables were recoded. Higher values on the STAI-6 indicate more anxiety. As shown in Table 3.11, on a maximum score of 5, the perceived anxiety of our sample increased from 3.11 to 3.21 with standard deviations of respectively 0.55 and 0.67 representing an increase of 3.1%. Looking in more detail, STAI-6 Score increased for 46% of our sample. However, according to a two-tailed repeated-measures, this perceived anxiety growth is not significant.

3.5.3 H4c: During COVID-19 crisis, depression levels have increased among r/StopSmoking users.

The two-item questionnaire, PHQ-2, asks respondents how often they were affected by (1) having little interest or pleasure in doing things or (2) feeling down, depressed or hopeless, on a Likert scale going from 0 to 4 where 0 = not at all and 4 = nearly every day. Higher values on the PHQ-2 indicate higher level of depression. As shown in Table 3.11, on a maximum score of 4, the perceived depression of our sample increased from 2.02 to 2.46 with standard deviations of respectively 0.74 and 0.84 representing an increase of 22%. According to a two-tailed repeated-measures t-test we can affirm that r/StopSmoking users appear to perceive themselves significantly ($p < 0.05$) more depressed. More specifically, PHQ-2 Score increased for 49% of respondents.

3.5.4 H5: r/StopSmoking engagement has increased during COVID-19 crisis.

To verify this effect, we relied directly on data retrieved during Study 2. We defined the COVID-19 period of relevance for r/StopSmoking from 24 January 2020 to 31 December of 2020. These dates were chosen because the first time that a user of r/StopSmoking talked about the COVID-19 disease was on week 4 of 2020, 24 January 2020: "Another reason to quit - Wuhan Virus - This virus puts a great toll on the respiratory system - lung function is very important", and because the data collected stopped on 31 December 2020. Then we compared the COVID-19 period with the past ordinary evolution of the r/StopSmoking community. But the community has a global yearly natural growth trend and eventual seasonality, which should be taken into consideration. Study 2 suggested in fact a seasonal effect, with peaks of activity in the early weeks of each year (probably due to new year resolutions). Therefore, we made predictions on the COVID-19 period, based on the previous growth trend and seasonality. To establish predictions we focused on data from 2017 to 2019, as according to Study 2, they belong to the same stage of evolution of the community. The general evolution trend of users' interactions was therefore extracted by identifying the regression line. The seasonality was then added by calculating the seasonal index of every week. For instance, in Table 3.12, we present the weekly number of posts recorded in r/StopSmoking for years 2017 to 2019. On that basis, the mean for each week for years 2017 to 2019 was calculated. Then with the 52 weekly means the overall total mean (207.3) was calculated. Finally, the seasonal index of each week is calculated by dividing the week mean by the total mean (e.g. for Week 1 293.3/207.3 = 1.4). Predicted mean number of posts and comments

	Week 1	***Week 2***	***Week 3***	...	***Week 12***	***Week 13***	***Week 14***	...	***Week 50***	***Week 51***	***Week 52***	*total mean*
2017	245	189	173	...	148	172	169	...	154	142	160	
2018	307	213	229	...	185	215	232	...	203	189	190	
2019	328	268	270	...	217	249	261	...	221	222	208	
mean	293.3	223.3	224.0	...	183.3	212.0	220.7	...	192.7	184.3	186.0	207.3
season coeff.	1.4	1.1	1.1	...	0.9	1.0	1.1	...	0.9	0.9	0.9	

TABLE 3.12: Seasonality calculus.

for COVID-19 period were calculated, making use of the regression line and multiplying each week estimation by the seasonal index of the corresponding week. To check if there was a statistically significant difference between calculated and measured values, we performed a bilateral Student test of the residuals with a hypothetical mean of zero. The residuals matrices of both posts and comments were normally distributed (Shapiro-Wilk test, $p>0.1$). The difference between measured and calculated numbers of comments was significantly different, but that was not the case for the number of posts. The actual numbers of comments per week during 2020 (M = 2033.0, SD = 334.0) demonstrated a significantly lower number of comments from what could have been calculated (M = 2262.0, SD = 153.0), $t(47) = 5.06$, $p<.001$. We suggest that the bias observed between calculated and measured number of comments may be due to the special situation of the COVID-19. Looking at the curves more closely (Figure 3.21), we could observe a sudden drop of the number of comments per week with two negative peaks on Week 29 (July 13–19 2020) and 39 (September 21–27 2020). Regarding the posts, we can still observe an interesting second peak of posts at the beginning of the COVID-19 period, that could not be predicted by the prediction curve.

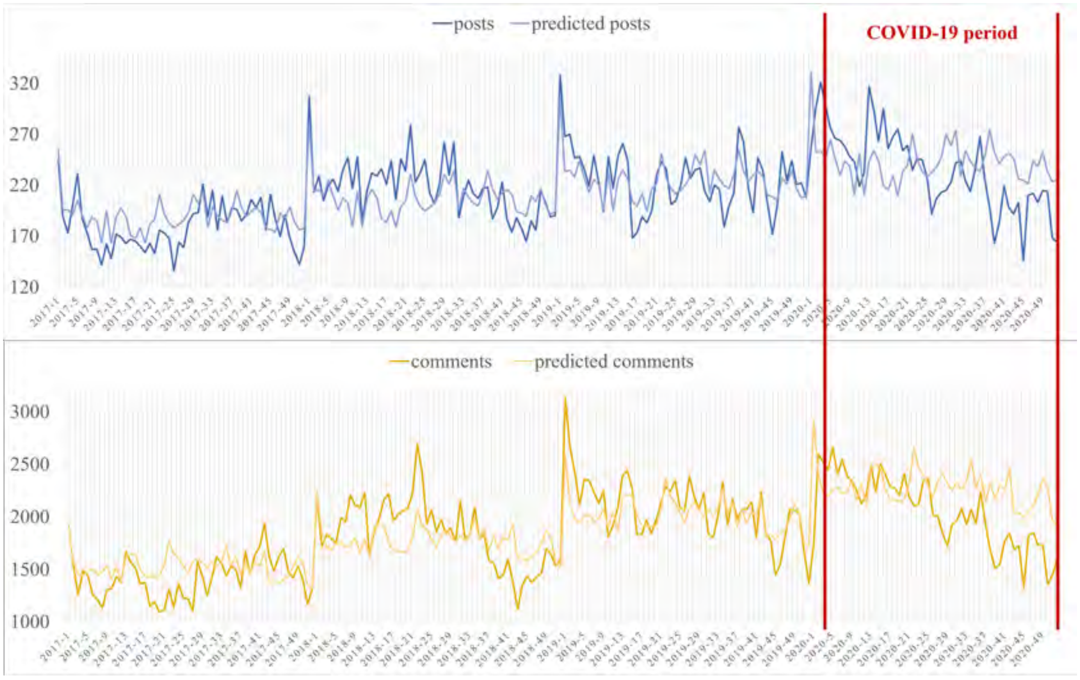


FIGURE 3.21: Predicted vs. effective interactions. On the top number of posts per week and on the bottom number of comments per week.

3.5.5 H6: Perceived usefulness of r/StopSmoking has increased during COVID-19 crisis.

The six-item instrument measuring the perceived usefulness (PUS-6) of r/StopSmoking was measured on a Likert scale going from 0 to 5 where 0 = strongly disagree and 5 = strongly agree. Questions measured whether r/StopSmoking made it easier to get support, improved willpower, increased the motivation, was useful in supporting them in their smoking cessation process and/or helped in making a quit attempt. Higher values on the PUS-6 indicate a higher level of perceived usefulness. As shown in Table 3.11, on a maximum score of 5, the perceived usefulness of our sample increased from 3.71 to 3.88 with standard deviations of respectively 0.74 and 0.84 representing an increase of 4.5%. More specifically, PUS-6 Score increased for 51% of respondents. However, according to a two-tailed repeated-measures this perceived usefulness growth is not significant.

3.6 Discussion

Our findings provide support that engagement in smoking cessation communities is positively correlated to the process of change (H1). This means that the frequency of participation in r/StopSmoking has an influence on the overall process of change. The results show a significant but modest relation between the overall engagement and the overall process of change. Engagement with such communities help smokers at the beginning of their process and also in the maintenance of their withdrawal. Therefore, encouraging smokers to engage in online smoking cessation communities should be considered as a good practice. In fact, such engagement could in a first instance increase their awareness of the unhealthy behavior, enable them to realize the negative impacts, feel fear about it but also feel hope when they hear about how people can change to healthy behaviors. These processes can potentially lead to a first success: a firm intention to quit smoking in the next six months. Engaging smokers who have already taken action and are trying to stay smoke free has also to be considered as a good practice, as this research provides further evidence that such engagement helps in staying smoke free. In fact, Study 1 indicates that active engagement is significantly correlated to the maintenance stage, which means, for instance, that the frequency of commenting or voting helps ex-smokers to not relapse. Active engagement allows to obtain social support from peers, but we might expect that it would also encourage people to provide social support in turn to peers in a lower level of accomplishment in their process of change. An additional line of inquiry might look at a possible feedback loop between such engagement and motivation to participate.

Looking at the user interactions (Study 2), we validate the consistency of results of Study 1 obtained through surveys by looking at actual behavior of the online community. Analyzing the conversations, we can observe that most of the active users engaged in r/StopSmoking have already stopped smoking (Q5) and are mainly sharing messages helping others to stop smoking and stay smoke free (Q6). About one third of authors and one third of messages are aimed at providing social support (Q2). This result further validates what was found in Study 1 on the motivational factors side. Providing social support is the main motivational factor to participate in r/StopSmoking (H3) and it represents one third of r/StopSmoking content. This result supports the presence of *expert patients* who are willing to provide experience and support to newcomers, and thereby helping themselves to stay smoke free [41]. By helping others, former smokers are helping themselves to stay smoke free. Former smokers should therefore also be encouraged to use such online smoking cessation communities.

Further results on motivational factors show that all uses and gratification motivational factors are positively linked to engagement in online smoking cessation communities (H2). Information-seeking, status-seeking, socialization (providing and seeking social support) and entertainment are all significantly and positively contributing to the motivation to participate and consequently to the online engagement of the user. A deeper analysis of the community interactions in Study 2 shows that r/StopSmoking keeps growing, with increasing numbers of weekly messages (Q4) and authors (Q3). More and more smokers are therefore helped. Even if most users seem to only seldomly actively engage in r/StopSmoking (Q3), the increasing quantity of messages generated every day provides ever-new material feeding individuals willing to get passively or actively engaged.

When analyzing more closely the content of such interactions, we can see that the main topics of conversation in r/StopSmoking (Q1) are: encouragement, general information, personal experience, nicotine substitute and pieces of advice. These topics fit surprisingly well with strong efficacy evidence based interventions for smoking cessation (brief advice, behavioral support, pharmacotherapy and abstinence evaluation) [3]. Brief advice can be found in general information, personal experience and pieces of advice. Behavioral support is potentially provided through encouragement and pieces of advice. Pharmacotherapy is discussed within the topic of nicotine substitute and personal experience. Abstinence evaluation is also frequently self-evaluated through relating personal experience, as one of the most common posts relates to the number of days since the author stopped smoking. These insights provided by the core content of the community could also partly explain some of the reason behind the finding established in Study 1 showing that the more frequently someone visits and reads content on r/StopSmoking the more likely they will be to express a firm intention to quit smoking or stay smoke free if they have already quit (H1b). The impact of the participants' engagement with topics supported by strong efficacy evidence based interventions could potentially provide more insight into the understanding of the smokers' progress in their process of change.

Finally, Study 3 investigates how the community reacted to a global crisis, namely the COVID-19 pandemic. Our results confirm that users seem to have increased stress levels (H4a) and increased signs of depression (H4c), but that was not true for anxiety (H4b). Furthermore, Study 3 hints at the fact that the community's perceived usefulness did not increase during the crisis (H6) and engagement even dropped (H5). The number of posts did not present a significant difference from what could have been predicted, but the number of comments did: fewer comments than predicted were found. This hints at the fact that the need for support has potentially increased in the pandemic, but the r/StopSmoking community has not been able to fully respond to these needs. Perhaps this decrease of comments is due to lack of time or a reordering of people's concerns [56]. This may mean that the number of people visiting the community to express themselves spontaneously has not significantly changed. But on the other hand, the number of people reacting to these messages has decreased. One might wonder if the online community has lost its usefulness, but according to our results there has been no significant change in the perceived usefulness of the online community. Furthermore, semantic analysis of messages posted during the COVID-19 period revealed that users who continued to use the community, took COVID-19 mostly as an opportunity to stop smoking. This latter result may be in line with a parallel research investigating the effect of the COVID-19 pandemic on smoking cessation success for patients admitted to clinics and those supported by phone [63]. This support provided remotely, whether by phone or via the online community, may have been used as a way to vent excess stress and depression during this period and although the community was less responsive, it was still perceived as useful. A more detailed and longer-term analysis would certainly shed more light on this change in dynamics and also determine whether it has persisted over time. Future work could also further investigate how design features of such communities could be adapted to better cope with such situations and avoid such engagement decrease.

3.6.1 Academic contributions

As a contribution to research, our work is a first step into a more nuanced understanding of motivation to participate in digital smoking cessation communities and its behavioral impact on individuals' online engagement and offline smoking cessation process of change. We were able to demonstrate the validity of a model measuring the influence of engagement in online smoking cessation communities on offline smoking behavior as well as potential motivational antecedents to such engagement. TTM's stages of change and its mediating processes have been used to measure the progress between the various stages, showing the significant support of online communities in the precontemplation to contemplation transition as well as on the maintenance to termination transition.

The uses and gratification approach allowed us to identify motivational factors of such digital communities. This research confirmed status-seeking and entertainment as relevant motivational factors of online engagement, these findings being consistent with previous literature [33], [36]. This research also found the information-seeking factor to be one of the most salient motivational factors examined, contradicting previous research on Reddit engagement [33], but being aligned with conclusions of other literature relating to Facebook online communities [38]. With Reddit containing such a variety of topics and therefore of different communities, we believe that uses and gratification can vary from one community to another. Especially when participating in a subreddit, such as r/StopSmoking, where the community is driven by a common health-related goal, the uses and gratifications may be different than another random community driven by a completely different goal. This research extended the uses and gratification approach by extending the socialization factor, giving a better understanding of social interaction motivation. This novel definition of the socialization factor, through providing and seeking social support subfactors, found them to be the most significant motivational predictors of the overall motivation to engage in r/StopSmoking.

This research also provides a multimodal analytics methodology combining survey results and activity traces over an extended period of time. Such analysis has demonstrated that users' motivational factors appear to be aligned with their acts, because we found that one third of the community has basically already stopped smoking and is providing social support to others. The r/StopSmoking community keeps growing in the number of users and the quantity of messages, but the information access infrastructure, i.e., the forum-style design of the Reddit platform, is only marginally adapted to the size and the context of this community, perhaps keeping out a potentially larger audience. For instance, there are no facilities to quickly find adequate messages, advice or other information personalized to one's situation and context. Insights revealed from this Study 2, i.e., a majority of former smokers among active users, may highlight a lack of design to attract a larger panel of smokers that is more representative of the TTM process of change in its entirety.

This research also offers a better understanding of the evolution of the r/StopSmoking online community through the COVID-19 crisis from different perspectives. For instance, our findings indicate that perceived levels of stress and depression increased among community users, which is in line with concerns raised by early COVID-related studies concerning smokers [54], [55]. However, smokers' perceived anxiety or perceived usefulness of the community have not significantly increased with the COVID-19 crisis, which is less in line with what we might have expected [54], [56]. In terms of activity on the platform, Figure 3.21 shows an increase of posts which coincides with the start of the first wave (March 2020), and this may indicate that at least at the start of the pandemic, people flocked to the community. However, there is a declining trend of posts and messages over the year 2020. These findings are in line with others who have found the COVID-19 pandemic to have been associated with information overload [64].

3.6.2 Implications for practice

In the various processes mediating the progress between stages of change, we observed that early and late stages of the overall process were significantly supported by online engagement. More specifically, we observed highly significant correlation between passive engagement and the stages of precontemplation and maintenance. This means that visiting and reading online communities could give smokers the intent to stop smoking within the next six months or help them to stay smoke free when they are not 100% confident about being able to do so. High significance correlation between the active engagement and maintenance stages further confirms the effectiveness of online communities in keeping ex-smokers away from temptation and relapses.

Encouraging smokers to share their experience on online smoking cessation communities could help them in their own process of change. It could also help them to potentially become expert patients who will then be even more helped [41]. Interestingly, the three most relevant factors of motivation to engage in digital smoking cessation communities are aligned with primary care interventions of strong efficacy [3]. Providing and seeking social support on online communities could be assimilated to peer-group behavioral support, while information-seeking could be assimilated to self-help material. Introducing smokers to these digital smoking cessation communities could trigger motivational factors, which in turn would be effective in the process of behavior change. Further research on a long-term basis is still needed to verify these assertions. User interaction data confirmed the potentially effective help that such communities could provide to smokers, as the topics of discussions are interestingly similar to the strong efficacy smoking cessation interventions as presented in primary care guidelines [3]. This is especially the case when the traditional support vectors cannot be reached for whatever reason, as is currently the case within the COVID-19 crisis. Related to COVID, we agree with recommendations made by the previous literature on this subject [54], [55]. Special attention must be given to smokers and former smokers during and after this period, not only because they present an increased risk but also because we have been able to show that potential risks of an increased level of stress and depression exist.

3.6.3 Limitations and future research

This research is not without limitation. A first limitation is that the model only includes a partial view of the smoking behavior of a user in a limited context (e.g. health conditions, demographic context, family context). A second limitation is the fact that we did not integrate the preparation stage in our research model because there is no clear process allowing people to move from preparation to action. This transition could warrant more attention in future work since it can be particularly challenging. A third limitation is the scope of the data, which unfortunately does not allow access to the identities of those users who engage more passively in the community. Neither the Reddit API nor the Pushshift API provide access to data such as the identity of users visiting, reading or even voting on a community message. A fourth limitation lies in the various classifier algorithms that can surely be further improved by including a larger quantity of features and tagged data. We could also extend the analysis of the Reddit messages with the extraction of semantic features and their polarity (i.e. sentiment analysis). A fifth limitation is related to the sample sizes of our surveys, which might not contain representative members of the community. This is particularly true for Study 3, where we could only find 57 participants that engaged with the community both before and during COVID-19 crisis.

Future work could investigate how to encourage passive users to become active and expert patients to become even more active online. Visualizing activity traces could be one way to motivate this behavior [65]. Finally, another interesting research topic would be to test if the model can be applied to other addictions or other behavioral problems (e.g. eating disorders).

3.7 Conclusion

In this research paper, we presented a novel model for investigating the influence of digital smoking cessation communities engagement on the behavior of actual smokers in their process of change. We also studied the motivational factors of such participation in online communities while extending the uses and gratification approach to fit the special context of smoking cessation. To do so, we undertook three distinct studies. The first, on the basis of a survey data from 169 Reddit contributors of the r/StopSmoking thread. The second, on the basis of ten years of user interaction data. The third, on the basis of a survey data from 57 Reddit users contributing to this thread from at least one year as they contributed before and during actual COVID-19 crisis. The results show that active and passive engagement in online smoking cessation communities has a significant influence on the process of change, mainly in the precontemplation and maintenance stages of the TTM stages of change. We identified that uses and gratification motivational factors are correlated to online smoking cessation communities engagement. The novel structure of the socialization factor, including providing and seeking social support, is relevant because they were found to be the main predictors of the individual's motivation to engage in such virtual communities. Indeed, providing social support was found to be a main motivational factor for contributing to the community, and the analysis of the user interaction data showed that a third of messages are indeed aimed at helping others. We also found that the main topics discussed in the community were tightly linked to strong efficacy evidence-based literature on smoking cessation, i.e., advice, information, pharmacotherapy and peer support. A broader analysis of the community shows that it is expanding as more users join, and we believe that such communities could be of great help to smokers and former smokers in general, especially in crisis situations, as recently with that of COVID-19. Nevertheless, our results highlight that participation during such a crisis is not to be taken for granted, as participation in the community dropped during that time, and future work should investigate how to better support users in such situations.

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Part II

Designing digital support for health intervention

Chapter 4

Escape Addict: A Digital Escape Room for the Prevention of Addictions and Risky Behaviors in Schools

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Abstract

Preventing addictive behaviors among teenagers is a crucial mission of public health organizations and public education institutions. However, it is challenging to design effective and portable interventions for classroom settings. This research evaluates the effects of a novel classroom intervention called Escape Addict. Escape Addict is a digital escape room learning activity that aims to prevent, and raise awareness of, addictive and risky behaviors. We conducted a controlled field experiment with 10 classes surveyed before (N=202 pupils) and after (N=199 pupils) the intervention, as well as 20 semi-structured interviews. Our results measured three weeks after the intervention show that Escape Addict significantly increased knowledge by 10%. Escape Addict also enabled pupils talk about addictions and risky behaviors. The intervention had no major effect on risk perceptions and other behaviors. However, Escape Addict had heterogeneous effects. For instance,

those pupils who enjoyed the intervention more, played fewer video games afterwards. Also, the effect on knowledge acquisition was stronger for pupils with higher educational achievement. Gender had limited effect. Our findings provide overall support that digital escape rooms represent interesting platforms to convey prevention messages in a compelling way.

4.1 Introduction

Adolescence is characterized by a relatively high level of risk-taking, sensation- and novelty-seeking, as well as by a strong need for experimentation [1], [2]. The path chosen during the rocky road through the teenage years can have long-term effects on people's health and well-being. For instance, (1) the vast majority of people using tobacco today began doing so when they were adolescents [3], (2) alcohol consumption among adolescents is a major concern in many countries [4], (3) particular patterns of video gaming are recognized as addictive behavior that may lead to psychological distress [5] and (4) increased consumption of energy drinks may also become a public health risk, especially among young people [6].

But adolescence is also a period of great opportunity [7], [8]. According to the World Health Organization (WHO) young people who adopt healthy habits early on, tend to maintain these over the long term and have a lower risk of behavioral addiction, and a reduced risk of non-communicable diseases in adulthood [9]. Adolescents are therefore a prime target for prevention and health promotion measures [10].

With this in mind, preventing addictive behavior among teenagers is a crucial mission of public health organizations and public education institutions [11]. It is particularly important to develop evidence-based interventions in the community, online, or in the classroom for a variety of addictions, such as smoking [11]–[13]. However, interventions in school tend to disappear as a result of funding constraints [11]. This context provides opportunities to design effective lightweight interventions using digital technology. The opportunity is particularly salient because even though digital technology is becoming almost ubiquitous, the digital technologies that teenagers frequently interact with (e.g., social media) are rarely used as a vehicle for smoking prevention [11]. Among such potential interventions, activities using digital escape rooms have recently gained attention as promising collaborative and playful learning experiences for higher education [14]. However, most of the research so far has focused on higher education in traditional fields such as computer science, engineering or medicine [14]. It is not clear how such experiences can be designed to support health promotion campaigns targeted at adolescents.

This paper seeks to address this gap by investigating the impacts of a novel digital escape room intervention in that particular context, namely the prevention of addictive and risky behaviors for teenagers.

4.2 Related Work

4.2.1 Educational escape rooms

Escape rooms can be described as games in which players, acting as a team, are trapped in a room and have to solve a series of enigmas to achieve a goal, usually to escape the room, within a limited amount of time [15], [16]. Escape rooms are usually theme-based and involve a recreational role play driven by a narrative.

Escape rooms used in educational contexts are called educational escape rooms. Recreational escape rooms and educational escape rooms share many similarities as well as having some important distinctions. The most important distinction is that enigmas and solutions of educational escape rooms are designed for a specific target group and focus on well-defined learning objectives, whereas recreational escape rooms are for enjoyment purposes only. Furthermore, recreational escape rooms are typically held in one or more physical rooms with teams playing one after the other. In educational contexts, facilitators have generally more limited amount of time and resources to design, set up and support activities since classrooms are utilized for different courses, and all teams play at the same time. Educational escape rooms offer participants an engaging and entertaining learning environment, encouraging collaboration, cultivating soft skills, and their intellectual development [17], while providing the facilitators a mobile and time-boxed learning experience.

Unsurprisingly, they have become an increasingly popular educational activity [18] and are integrated into many different educational disciplines, such as healthcare [19]–[21], computer science [22], chemical engineering [23], pharmacy [24], physics [25], mathematics [26], [27] and biology [28]. Research results show that these interventions can have significant positive outcomes on academic performance through improved motivation, positive behaviors and engagement [29].

4.2.2 Digital educational escape rooms

With the rise of digital technologies, the notion of the digital escape room also emerged. As suggested by [30], a digital escape room can be considered as "an innovative teaching approach incorporating digital materials with reality". For instance, digital artifacts such as video, QR codes, augmented reality can supplement physical escape rooms while bringing an additional technological dimension. Digitalization of educational escape rooms therefore contributes to reaching an even more cost-efficient, portable and easy-to-use learning experience [31], potentially lowering actual funding, time and human resources barriers for school-based health promotion [11]. At the extreme of this digitalization trend, fully digital escape rooms make use of computerized applications to simulate a series of locks to be opened, puzzles to be solved and missions to be carried out [32]. In this research, our definition of digital escape room does not exclude the use of a physical context.

Past research on escape rooms has mostly focused on physical escape rooms, digital escape rooms being a novel phenomenon still to be academically explored [29]. Furthermore, to our knowledge, research has not yet investigated how these lightweight, portable concepts could support prevention programs for teenagers. These observations lead to the following research question:

(RQ1) How effective are digital escape rooms at improving teenagers' knowledge and changing their perceptions and behaviors related to addiction and risky behaviors?

4.2.3 Effect of educational achievement

Previous research has shown that gameful interventions are more motivating for pupils with higher cognitive abilities [14]. This might be an issue, since those people who are less scholarly inclined are associated with an increased risk of addictive behaviors such as drug abuse [33]. Nevertheless, the design of escape rooms may also incorporate digital technologies such as virtual reality, augmented reality or embedded screens [34], [35]. Such use of digital technologies, with which adolescents like to engage, could make them feel more connected to a health promotion intervention [11]. Digital escape rooms represent a novel educational tool that may mentally transport pupils outside of the usual school setting and could benefit pupils who are less diligent at school. Overall, it remains unclear whether educational achievement conditions the impact of these interventions, leading to the following research question:

(RQ2) How does educational achievement influence the effectiveness of digital escape rooms aiming to prevent teenagers' addictive and risky behaviors?

4.2.4 Effect of gender

Males enjoy and play video games more than females [36]. Regarding serious games, the literature suggests less clear-cut results. Male pre-adolescents and adolescents seem more empowered and more engaged in the gameplay of serious games [37], but this does not seem to apply to escape games, which attract both genders equally [22]. Neither does gender seem to condition the effect of digital escape rooms on gameful experience, collaboration and motivation of elementary school students [14]. Previous work on gamification has identified several factors that should be considered when it comes to gender inclusion. For instance, identification with characters in the game seems to be an important process in explaining females' gaming motivations [38]. But also, game elements such as badges seem to have a positive relation with perceived playfulness and are more enjoyable for females [39]. However, it is still unclear if these conclusions apply to various contexts and scenarios, leading us to our third research question:

(RQ3) How does gender influence the effectiveness of digital escape rooms aiming to prevent teenagers' addictive and risky behaviors?

4.2.5 Effect of enjoyment

When playing games, the player is in a playful state of mind [40], also called playfulness [41] which procures enjoyment. Enjoyment can be described as an outcome but also as a dimension of the game experience. In an effective serious game, enjoyment acts as a catalyst to encourage learning initiative [42]. Previous research found that students were intrinsically motivated by educational digital escape rooms [14]. Research also indicates that intrinsic motivation is directly linked to enjoyment, the pleasure of the game or the desire to improve skills [43]. As a result, the role of enjoyment as a potential facilitator of knowledge acquisition or of behavior change in the prevention domain requires further exploration leading to our last research question:

(RQ4) How does enjoyment influence the effectiveness of digital escape rooms aiming to prevent teenagers' addictive and risky behaviors?

4.3 The Escape Addict Learning Experience

Escape Addict (EA) is a digital escape room learning experience that aims to raise awareness, provoke reflections and eventually lead to behavior change related to risky and addictive behaviors and their consequences. EA is not restricted to one specific addictive behavior, but rather seeks to address the underlying mechanisms of addiction that can be very similar from one addiction to another. EA exposes pupils to the problems of tobacco, alcohol, cannabis, screen use (social networking, video games) and related consequences (e.g., bullying, addiction). This experiential prevention approach confronts pupils with situations that they encounter or are likely to encounter in their daily lives, such as risk-taking opportunities, peer pressure or problematic behaviors on social media.

EA was designed by Promotion Santé Valais, a regional health promotion agency in Switzerland. It is a standalone intervention that can easily be deployed in a classroom and repeated across classrooms and schools. EA targets school pupils aged 12 to 15. It aims to reach the following learning outcomes: (a) raise awareness and elicit reflections in relation to addictive and risky behaviors, such as alcohol and tobacco consumption, or social media usage; (b) reduce or at least delay the start of any addictive and risky behavior; (c) connect at-risk pupils to available support. While achieving these educational goals, EA also aims to be fun, engaging, collaborative, portable and allowing active learning to foster depth.

4.3.1 The learning experience

An EA session lasts one hour and an half (i.e., two school periods), including fifteen minutes of instruction at the beginning and debrief at the end. The class is split up into self-selected groups of 4 to 6 pupils. Each group receives a digital tablet.

The game starts with a narrative audio recording setting the stage of the experience: the class is locked-down until pupils conduct a set of four investigations. Each investigation has its own scenario based around a teenager who has some issues related to risky or addictive behaviors and requires teams to perform certain tasks to correctly gives answers to quizzes (see Table 4.1 for an overview and Appendix A for a detailed presentation).

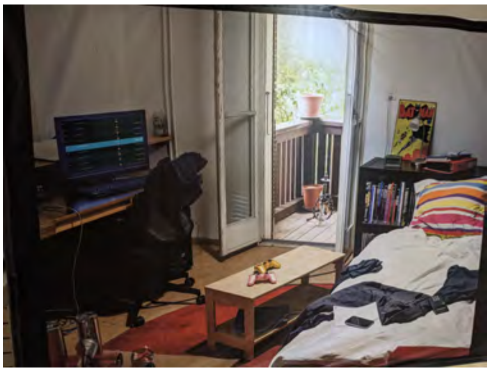
The experience provides different immersive interactions through the tablets (e.g., augmented reality, 360° camera). In addition to the tablets, the experience makes use of several physical artifacts to provide a richer experience. For instance, the classroom is set up with a transportable 300×235cm self-standing exhibition banner, illustrating a teenager's room (Figure 4.1a), a safe sealed with a padlock (Figure 4.1b), a digital clock with a countdown timer (Figure 4.1b), and a ribbon figuratively sealing the classroom (Figure 4.1c).

TABLE 4.1: Summary of Escape Addict investigation scenarios

	main character	**topics covered**	**digital content**	**estimated duration**
1	Adrien, 13, male	psychological dependencies such as video games addiction, sleep deprivation and energy drink consumption.	augmented reality, quiz	10–15 min.
2	Jordan, 12, male	alcohol and tobacco consumption, social networks cyber-bullying	360° video, videos, puzzle game, quiz	20–25 min.
3	Lyse, 13, female	alcohol and tobacco consumption, social networks and media manipulation	point and click, videos, photos, quiz	20–25 min.
4	Lisa, 12, female	co-addiction	audios, quiz	10–15 min.

Each group of pupils has to follow the instructions on their tablet to solve the four investigations. The same investigations are provided to each group. As groups are solving investigations, they collect pieces of a physical puzzle that the whole class will have to assemble at the end of the game to unlock the room (Figure 4.1d).

Finally, once all the teams have solved the four investigations, the class is brought together to solve the final puzzle. The resolution of the final puzzle provides access to the safe containing a pair of scissors which will be used to cut the ribbon that was locking the classroom. The session ends with a debrief led by the facilitator. The debrief aims to reinforce the key health messages following the game experience, but also to ask the pupils about their feelings, their learning and their future behaviors.



(A) Transportable standing banner illustrating a teenager's room.

(B) Safe to unlock to exit the room and countdown timer with remaining time to complete the game.

(C) Ribbon figuratively sealing the classroom.

(D) Puzzle pieces earned after each solved investigation.

FIGURE 4.1: Escape Addict physical setting

4.4 Field experiment

The field experiment aimed at evaluating the effect of EA on pupils' knowledge, risk perceptions and actual behaviors*. It also aimed to assess whether these potential effects interacted with gender, educational achievement or enjoyment of the experience.

4.4.1 Participants

We selected four schools within Canton of Valais to participate in the experiment – two schools in cities and two schools in suburbs. The four schools were randomly allocated to the control or treatment group, while ensuring the type of school was matched (i.e. one city school and one suburban school in each group). The allocation to the treatment or control groups was done by school rather than by class to minimize contamination effects. More specifically, the fact that control and treatment schools are geographically separate mitigates the possibility that the treatment affects post-test survey responses in the control group. Three classes from each city school and two classes from each suburban school were randomly selected to participate in the experiment and to receive the questionnaires. This led to five classes being allocated to the treatment group and five classes to the control group.†

4.4.2 Procedure

The field study included a pre-test and a post-test survey administered respectively before and after the intervention. The treatment group did the EA activity between the pre-test and the post-test surveys, while the control group did not do the EA activity but nevertheless received the pre-test and post-test surveys at about the same time and interval.

Staff in each school distributed the pre-test surveys (on paper) two weeks before the intervention, while the post-test surveys (also on paper) were distributed three weeks after the intervention. Pupils were informed that their answers were confidential and anonymous (their name was never requested). Following previous research [44], [45], we asked three personal questions to allow indirect identification and connect pre-test and post-test

*The evaluation of EA also measured for intentions, stereotypical perceptions and some other characteristics of the participants, which we do not discuss here to keep the focus on the most relevant measures.

†Classes belonging to the control group did the EA activity after the experiment was over.

surveys: first name of their paternal grandmother, parents car brands, name of their favorite pet. This allowed us to connect 81.3% of the pre-test and post-test surveys. The other questionnaires could not be connected, either because the pupils were absent in the pre- or post-test or because the connection questions did not match. The final dataset excludes data on these identification questions. The questionnaire was pre-tested by three teenagers from the same age group but from a different region (i.e., not belonging to the population) as well as by a teacher for that age group, in order to make sure the questions were clear and understandable. Minor adjustments were made based on the comments. The head of the schools participating in the experiment as well as the head of regional education services approved the evaluation approach and the distribution of the surveys to the pupils.

4.4.3 Measures

The surveys measured: (1) knowledge, (2) risk perception, (3) behaviors in the domain of addiction and risky behaviors. For the treatment group only, it also measured (4) EA experience. Pre-test and post-test surveys were similar for both treatment and control group, except for extra (5) gender and (6) educational achievement questions which were asked only in the pre-test survey. Table B.1 in Appendix B lists the measures and scales.

Factual knowledge

Knowledge was measured with five specific multiple choice questions, covering different domains considered in EA (shisha, tobacco industry, social network, video games, alcohol). Answers were coded as correct if they corresponded to the information provided in EA or more conservative from a health promotion perspective. Our knowledge variable is then defined as the proportion of correct answers across all five questions.

Risk evaluation

We adapted existing measures [46] to evaluate perception of risk associated to specific behaviors. Seven questions measured risk perception in different domains (smoking, cannabis consumption, alcohol consumption, social network and internet-related behaviors, video gaming) with an 11-point answer format anchored from 1 - low risk to 11 - high risk. Our risk perception variable consists of the average of the 7 items and is thus measured on a 1 to 11 scale.

Behavior

Three types of behaviors addressed in EA were measured: (1) how much pupils talked about the topic of addictions, (2) the time spent playing video games, and (3) the privacy settings on social networks. The first behavior was measured with three yes-no questions asking whether pupils had talked about the topic of addictions (not about EA) with (a) friends, (b) parents, (c) teachers in the previous two weeks, that is, not directly after EA, but between one and three weeks after EA. Based on these questions, we created an index measuring the number of different types of interlocutors, going from 0 whenever they spoke to none of the cited interlocutors to 3 if they spoke to all of them. The time spent playing video games was measured by combining information on the number of days in which they played during a normal week and how many minutes they played on average during those days. The privacy settings on social networks were measured specifically by asking whether pupils activated privacy protection settings on social networks on which they were active.

EA experience

The post-test survey of the treatment group also included questions on their experience with EA. In particular, we measured how much pupils enjoyed the experience with EA (from 1 - did not enjoy at all, to 7 - enjoyed a lot), how realistic they found the situations they were confronted with (from 1 - not at all realistic, to 7 very realistic), how much they had the impression that they participated to the discussions within their teams (from 1 - not at all, to 7 - a lot), how much they thought they acquired new knowledge (from 1 - very little, to 7 - a lot), whether they spoke about EA specifically to their parents, friends or teachers (from 0 - none of them, to 3 - all of them), and the fraction of questions asked during the game they thought they understood (from 0 to 100 percent).

Educational achievement

In region Valais, four educational subjects (math, French, German and science) have a basic and an advanced level. In each class, pupils will take the basic or the advanced level of these subjects depending on their own level in each particular subject. Based on this, we coded educational achievement as ranging from 0 if the pupil is advanced in none of the subjects to 4 if the pupil is advanced in all subjects.

4.4.4 Analysis

The objective of the analysis is to identify the impact of EA on the pupils in the treatment group relative to the control. This requires two steps. First, we estimate how each outcome changes following the EA intervention by computing the difference between pre-test and post-test values among treated pupils. Second, we subtract the corresponding change observed among control pupils. Intuitively, this approach of using double difference (or difference in differences) identifies the average treatment effect of the intervention (RQ1) by factoring out the trend observed among non-treated pupils. This is based on an assumption that, absent of treatment, treated pupils would have followed the same trend as those in the control group.

Statistical inference on these double differences is derived from a set of linear regression models. We start by denoting measured outcomes by Y_{it}, where i is an index for pupils and t stands for survey waves (pre- and post-test). The outcomes we consider are: (i) knowledge (ii) risk perception (iii) discussions with interlocutors, (iv) activating private settings and (v) total gaming time. For each outcome, we then estimate the following baseline regression model:

$$Y_{it} = \alpha + \beta \cdot treated_i + \gamma \cdot time_t + \delta \cdot treated_i \times time_t + \epsilon_{it} \tag{4.1}$$

where $treated_i$ is an indicator variable equal to one if i is in the treatment group, zero otherwise, $time_t$ is equal to one if t is after the EA intervention, zero otherwise, and ϵ_{it} is an error term. The term $treated_i \times time_t$ represents an interaction between the two indicator variables, so that it takes a value of one for treated unit in the post-test, zero otherwise.

The parameters α, β, γ and δ are estimated from the data using ordinary least square regression. The parameter α measures the average outcome for the control group in the pre-test, β is the pre-test difference in the average outcome between treated and control groups and γ is the difference in average outcome between pre- and post-test for the control group. Of particular interest is the parameter δ, which is the double difference estimator and therefore quantifies the average treatment effect of the intervention.

We further expand Equation 4.1 to estimate how EA differentially affected alternative groups of pupils, as discussed in RQ2 to RQ4. Formally, we define a moderating variable X_i that potentially affected the size of the treatment effect, namely (i) educational achievements, (ii) gender or (iii) enjoyment of EA. This gives the following regression:

$$\begin{aligned} Y_{it} = \alpha + &\beta \cdot treated_i + \gamma \cdot time_t + \delta \cdot treated_i \times time_t + \\ &\eta \cdot time_t \times treated_i \times (X_i - average(X)) + \theta \cdot X_i + \epsilon_{it} \end{aligned} \tag{4.2}$$

where the notation follows from above and η measures how the average treatment effect changes as the moderating variable increases by one unit.[‡] For example, if Y_{it} is our measure of knowledge and X_i is educational achievements, a positive and statistically significant estimate would indicate that EA leads to higher knowledge acquisition among students with high achievements (RQ2).

4.4.5 Results

This section reports the results from the field experiment. First, we provide a number of summary statistics on the sample and outcomes considered. Second, we report the results of Equation 4.1 focusing on the average treatment effects. Lastly, we report heterogeneous impacts across educational achievements, gender and EA enjoyment, based on Equation 4.2.

Descriptive statistics

A total of 401 surveys were distributed: 202 in the pre-test and 199 in the post-test. We could not connect 39 questionnaires in the pre-test and 36 in the post-test, leaving 163 pupils with matched pre- and post-test records. Of those, we discarded eight questionnaires because some pupils were not present in the class during the EA activity or because they did not engage

[‡]Note that we subtract the average of the variable X_i when we construct the interaction term. This ensures that the main effect δ still quantifies the average treatment effect. This normalization does not affect the interpretation of the parameter η.

TABLE 4.2: Descriptive statistics for control and treatment groups.

	Control group			Treatment group		
	N	Mean pre-test	Mean post-test	N	Mean pre-test	Mean post-test
% female	80	0.49	0.49	75	0.51	0.51
Educational achievement (0-4)	70	1.96	1.96	72	2.28	2.28
Knowledge (% correct)	80	0.59	0.57	75	0.60	0.67
Risk evaluation (1–11)	80	6.33	5.94	74	6.80	6.71
Addictions discussions (1–3)	80	0.37	0.37	74	0.36	0.46
Privacy settings (0–1)	78	0.79	0.73	69	0.72	0.71
Video games (min/week)	64	670.5	865.5	62	410.7	600.1
Enjoyment (1–7)	-	-	-	75	-	5.68
Realistic (1–7)	-	-	-	75	-	5.65
Participation (1–7)	-	-	-	75	-	5.77
Knowledge (1–7)	-	-	-	75	-	4.76
EA discussions (1–3)	-	-	-	75	-	0.64
Understanding (0–10)	-	-	-	75	-	7.96

Notes: This table reports summary statistics for the field experiment. See Table B.1 for the list of measures and scales. Due to outliers, the "Video games" characteristic of the pre-test populations presents a difference between control and treatment groups.

with the approach (not answering questions and writing jokes instead). This leads to a final sample of 155 pupils, including 80 in the control group and 75 in the treatment group.[§] Refer to Table 4.2 for the descriptive statistics.

Starting with the control group, our data suggests that pre- and post-test averages are very similar, with p-value from paired t-tests for differences being below conventional levels. The only exception is time spent playing video games, which increases from 670.5 to 865.5 minutes per week, with the difference being statistically significant (p-value$<$.05). More interestingly, the treatment group data suggest a statistically significant increase in knowledge, as the share of correct answers increases from 60 percent to 67 percent (p-value$<$.01). Similarly, we observe a significant increase of addiction-related discussions with teachers, parents or peers (p-value$<$.05) and also an increase in the time spent playing video game (p-value$<$.05). By contrast, we do not find a statistically significant change in risk assessment.[¶]

Regarding the EA experience, we can observe that pupils enjoyed the experience with EA, with a mean score of 5.68 on a maximum value of 7. Pupils also found the situations presented realistic (5.65 on 7). They also had the impression that they could participate actively to the discussions within their teams (5.77 on 7). The perceived knowledge acquired also seems interesting (4.76

[§]Note that the sample size slightly varies across variables due to missing values for individual variables.

[¶]We observe a large difference in gaming time between control and treatment (in both baseline and post-treatment). This is in part driven by the presence of some extreme gamers in the control group who play more than 7 hours per day on average over the week.

TABLE 4.3: Average treatment effect of EA intervention.

Outcome:	Knowledge % correct	Perceived risk 1–11 scale	Addictions discussions 0–3. diff. interlocutors	Privacy setting activated = 1	Video games Minutes / week
	(1)	(2)	(3)	(4)	(5)
Avg .treatment effect	0.098***	0.304	0.099*	0.050	−5.597
(δ)	(0.030)	(0.249)	(0.056)	(0.065)	(104.642)
Constant	0.588***	6.328***	0.367***	0.795***	670.469***
(α)	(0.019)	(0.166)	(0.040)	(0.046)	(105.152)
Treated (=1)	0.009	0.467*	−0.002	−0.070	−259.791**
(β)	(0.026)	(0.246)	(0.053)	(0.071)	(118.854)
Time (=1)	−0.019	−0.393*	0.000	−0.064*	195.000**
(γ)	(0.020)	(0.201)	(0.040)	(0.038)	(76.189)
N pupils	155	154	154	147	126
R^2	0.022	0.049	0.009	0.016	0.041

Notes: OLS regression coefficients reported. In Column 1 the outcome is proportion of correct answer. In Column 2 the outcome is perceived risk measured on a 1–11 scale. In Column 3 the outcome is the share of potential interlocutor. In Column 4 the outcome is an indicator variable equal to one if the privacy settings are activated. In Column 5 the outcome is the time spent playing video games in minutes per week. See Table B.1 for the list of measures and scales. Robust standard errors clustered at the pupil level reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

on 7). Finally, pupils spoke about EA on average with 0.64 parties (among parents, friends or teachers), and understood the questions asked during the game well (7.96 on 10).

Effects of EA on addiction prevention

In Table 4.3, we aim to answer our first research question by reporting ordinary least squares (OLS) regression results quantifying the average treatment effect of EA on five alternative outcomes (Equation 4.1). Specifically, Column 1 focuses on knowledge acquisition, Column 2 reports risk perception, and Columns 3 to 5 focus on behaviors, capturing respectively changes in the share of interlocutors, in the activation of privacy settings on social media, and in the time spent playing video games. Cluster-robust standard errors are reported in parenthesis.

Results in Raw 1 confirm that the intervention increased the proportion of correct answers by around ten percentage points on average (p-value$<.01$), and had a positive impact on the variety of interlocutors with whom the themes of EA were discussed (around 0.1 points, with p-value$<.1$). The intervention is also associated with higher risk perception, higher probability of activating privacy settings, and reducing gaming time, although these impacts are not statistically significant at conventional levels. Next, we discuss a set of OLS regressions documenting the role of alternative moderating variables (equation 4.2), to answer research questions two to four. Results for educational achievements are reported in Table 4.4, gender is considered in

TABLE 4.4: Effects of educational achievement on EA intervention impacts.

Outcome:	Knowledge % correct	Perceived risk 1–11 scale	Addictions discussions 0–3. diff. interlocutors	Privacy setting activated =1	Video games Minutes / week
	(1)	(2)	(3)	(4)	(5)
Avg .treatment effect	0.101***	0.280	0.097	0.027	−21.975
(δ)	(0.031)	(0.264)	(0.059)	(0.065)	(110.850)
× educational attainment	0.029**	0.052	0.024	−0.049	−8.880
(η)	(0.012)	(0.099)	(0.024)	(0.034)	(70.307)
Constant	0.563***	6.153***	0.388***	0.736***	792.734***
(α)	(0.027)	(0.217)	(0.054)	(0.068)	(179.264)
Treated (=1)	0.0003	0.384	−0.002	−0.083	−146.464
(β)	(0.027)	(0.258)	(0.055)	(0.073)	(116.007)
Time (=1)	−0.016	−0.385*	0.005	−0.044	214.636**
(γ)	(0.022)	(0.217)	(0.043)	(0.039)	(82.846)
Educational attainment	0.014*	0.121*	−0.011	0.031	−99.718**
(θ)	(0.007)	(0.068)	(0.016)	(0.022)	(47.645)
N pupils	142	142	142	136	116
R^2	0.123	0.064	0.020	0.018	0.078

Notes: OLS regression coefficients reported. In Column 1 the outcome is proportion of correct answer. In Column 2 the outcome is perceived risk measured on a 1–11 scale. In Column 3 the outcome is the share of potential interlocutor. In Column 4 the outcome is an indicator variable equal to one if the privacy settings are activated. In Column 5 the outcome is the time spent playing video games in minutes per week. See Table B.1 for the list of measures and scales. Robust standard errors clustered at the pupil level reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

Table 4.5, and the role of enjoyment in EA participation is in Table 4.6. Each table follows the same structure as above, including the five outcome variables, and reports cluster-robust standard errors in parenthesis.

Effects of educational achievement

Results for educational achievement (Table 4.4) suggest that the effect of the intervention on knowledge acquisition was stronger the higher the pupil's educational achievement. However, at the lowest level of educational achievement EA does not significantly impact the knowledge of pupils. By contrast, pupils with higher achievement tend to provide more correct answers to start with, and they also provide more additional correct answers after participating in EA (relative to pupils with lower school achievements). Educational achievement did not moderate the effect of EA on risk perceptions (η in Column 2) or behaviors (η in Columns 3–5). The only effect of educational achievement on behaviors was a main effect on gaming. Specifically, the higher the educational achievement, the less time pupils spend playing video games.

TABLE 4.5: Effects of gender on EA intervention impacts.

Outcome:	Knowledge % correct	Perceived risk 1–11 scale	Discussions 0–3. diff. interlocutors	Privacy setting activated =1	Video games Minutes / week
	(1)	(2)	(3)	(4)	(5)
Avg .treatment effect	0.098***	0.303	0.099*	0.050	−5.087
(δ)	(0.030)	(0.249)	(0.056)	(0.064)	(103.912)
× female (=1)	0.056	0.124	0.008	−0.262**	22.377
(η)	(0.043)	(0.336)	(0.081)	(0.112)	(210.689)
Constant	0.580***	6.313***	0.334***	0.776***	931.350***
(α)	(0.023)	(0.188)	(0.044)	(0.057)	(155.421)
Treated (=1)	0.009	0.466*	−0.004	−0.071	−268.207**
(β)	(0.026)	(0.248)	(0.053)	(0.072)	(111.409)
Time (=1)	−0.019	−0.393*	0.000	−0.064*	195.000**
(γ)	(0.020)	(0.202)	(0.040)	(0.038)	(76.498)
Female (=1)	0.016	0.031	0.066	0.038	−521.763***
(θ)	(0.023)	(0.232)	(0.051)	(0.070)	(148.595)
N pupils	155	154	154	147	126
R^2	0.071	0.048	0.027	0.022	0.142

Notes: OLS regression coefficients reported. In Column 1 the outcome is proportion of correct answer. In Column 2 the outcome is perceived risk measured on a 1–11 scale. In Column 3 the outcome is the share of potential interlocutor. In Column 4 the outcome is an indicator variable equal to one if the privacy settings are activated. In Column 5 the outcome is the time spent playing video games in minutes per week. See Table B.1 for the list of measures and scales. Robust standard errors clustered at the pupil level reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

Effects of gender

Gender had limited impact on the effect of EA, as reported in Table 4.5. Only two behaviors are worth mentioning in relation to gender. First, females were less likely than males to change their privacy settings following their participation in EA, as suggested by the negative and statistically significant coefficient on the interaction term reported in Column 4. Second, Column 5 shows that girls play significantly less video games relative to males, although gender did not affect the influence of EA on gaming.

Effects of enjoyment

Lastly, results on the role of EA enjoyment shown in Table 4.6 suggest that the impact of the intervention on knowledge acquisition did not change as a function of self-reported enjoyment (Column 1). We find, however, that the treatment effect on risk perception is positively affected by enjoyment (Column 2, p-value$<$.1). That is, the more pupils enjoyed EA, the more they increased their perception of risk (i.e., they found the behaviors they were asked to evaluate more risky). We also find that enjoyment reported during the intervention is associated with a lower likelihood of activating privacy settings (Column 4), and a decrease in gaming time following the intervention (Column 5). Therefore, while we do not observe an effect of the intervention on gaming time (compared to the control group), gaming time declines

TABLE 4.6: Effects of enjoyment on EA intervention impacts.

Outcome:	Knowledge % correct	Perceived risk 1–11 scale	Discussions 0–3. diff. interlocutors	Privacy setting activated =1	Video games Minutes / week
	(1)	(2)	(3)	(4)	(5)
Avg .treatment effect	0.098***	0.299	0.099*	0.052	−17.361
(δ)	(0.030)	(0.247)	(0.056)	(0.066)	(103.902)
× enjoyment (1–7)	−0.007	0.214*	0.007	−0.089**	−175.338**
(η)	(0.017)	(0.116)	(0.039)	(0.039)	(85.597)
Constant	0.588***	6.328***	0.367***	0.795***	670.469***
(α)	(0.019)	(0.166)	(0.040)	(0.046)	(105.365)
Treated (=1)	0.009	0.467*	−0.002	−0.070	−259.791**
(β)	(0.026)	(0.246)	(0.053)	(0.071)	(119.095)
Time (=1)	−0.019	−0.393*	0.000	−0.064*	195.000**
(γ)	(0.020)	(0.201)	(0.040)	(0.038)	(76.343)
N pupils	155	154	154	147	126
R^2	0.058	0.053	0.016	0.016	0.054

Notes: OLS regression coefficients reported. In Column 1 the outcome is proportion of correct answer. In Column 2 the outcome is perceived risk measured on a 1–11 scale. In Column 3 the outcome is the share of potential interlocutor. In Column 4 the outcome is an indicator variable equal to one if the privacy settings are activated. In Column 5 the outcome is the time spent playing video games in minutes per week. See Table B.1 for the list of measures and scales. Robust standard errors clustered at the pupil level reported in parentheses. *, ** and *** denote statistical significance at 10%, 5% and 1% respectively.

for pupils who enjoyed EA to a larger extent. This effect is independent of the control group as enjoyment was only measured ex-post in the treatment group. Thus, the difference in pupils gaming profile between treatment and control does not play a role in the effect of enjoyment.

4.5 Qualitative interviews

The aim of the qualitative interviews were (1) to gain additional insights on pupils' learning and engagement with EA, that is, to better understand the type of knowledge acquired and the behaviors performed; (2) to better understand the characteristics of the escape room that drives its potential effectiveness, (3) to provide recommendations to improve the intervention and related concepts. The first two objectives relate to our research questions and the willingness to understand EA's effects, whereas the last one is prescriptive.

4.5.1 Methods

We conducted 20 semi-structured interviews with pupils who participated in the EA activity. The interviews were inspired by the phenomenological approach, as we were interested in understanding pupils' shared experience of Escape Addict [47]. We let pupils describe their experience of the escape

TABLE 4.7: List of interviewees by gender, educational achievement and interview length

interview	class	gender	educational achievement (0: basic, 1: advanced)					interview length (min.)
			math	French	German	science	total	
[1]	1	M	1	0	0	1	2	26
[2]	1	M	1	1	1	1	4	21
[3]	1	M	1	1	1	1	4	30
[4]	1	M	0	0	0	0	0	20
[5]	1	F	0	1	1	1	3	31
[6]	1	M	0	0	0	0	0	27
[7]	1	F	1	1	1	1	4	26
[8]	1	F	1	1	1	1	4	29
[9]	1	F	1	1	1	1	4	26
[10]	2	M	1	1	1	1	4	26
[11]	2	F	1	1	1	1	4	24
[12]	2	F	0	0	0	0	0	20
[13]	2	M	1	1	0	1	3	31
[14]	2	F	1	1	1	1	4	25
[15]	2	F	0	1	1	1	3	39
[16]	2	M	1	1	0	0	2	28
[17]	2	M	1	1	1	1	4	29
[18]	2	M	0	0	0	1	1	28
[19]	2	F	1	1	1	1	4	26
[20]	2	F	0	1	1	1	3	26

room. The interviews occurred in the semester following the field experiment, with different pupils. Participants were drawn from two classes in two different schools. The pupils' parents were informed of the interviews several weeks before their child's participation in EA and were given the option to withdraw their child from the interview (one was withdrawn). The interviews were conducted on the school premises during one full day per class. They occurred five days after the pupils had been exposed to EA for the first class and 10 days after the second class. We randomly selected 9 pupils from one class and 12 from the other (in total, 10 boys, 10 girls and 1 absentee). Pupils were called during their normal lessons to the interview room. Given our access constraints, our interviews lasted between 20 and 40 minutes. Table 4.7 presents the list of interviewees by gender, educational achievement and interview length. The interview guide evolved after the first day of interviews. Appendix C presents the final version.

During the interviews, pupils were informed of the objectives of the study, the confidentiality of their response, and the option of not answering certain questions or of abandoning the interview at any time (which no one did). In addition to the parents' consent, the head of education services also consented to the interviews. The names of the pupils and any identifying information were deleted from the analysis files. Names were replaced with numbers. The interviews were recorded with pupils' permission and transcribed. They were analyzed by theme in order to identify patterns, commonalities, and points of divergence.

4.5.2 Results

The results are structured along four themes: experience with EA, recollection of EA puzzles, knowledge of health messages and capacity to trigger reflections, discussions and other behaviors. Results are illustrated with representative quotes from pupils which have been translated from French to English (the number refers to the interview number in Table 4.7).

Experience with Escape Addict

Overall, the qualitative interviews largely confirm that pupils enjoyed participating in EA. The escape room format was appreciated. Pupils particularly enjoyed the technological and multimedia features. One said “I found it very interesting and original to use a tablet, I didn’t expect that", then “I liked it when we had to go to the billboard and look for objects, I appreciated the music in the game" [7].

Pupils also appreciated getting away from a more prescriptive (or even moralizing) prevention model and move towards a more playful model: “I thought it was well done, because it was not centered on something like it’s bad to smoke and drink" [18]. Another one said that “it was not boring because we did not have to listen to the theories of someone" [11]. The teamwork helped to move away from the traditional model. For instance, someone noted: “It was interesting and funny. In addition, I could do it with my friends. It boosted us to succeed" [9].

Three pupils out of 20 mentioned that they disengaged towards the end (even if they spoke positively about EA during the interview) [1, 4, 5]. One person would have preferred doing the activity alone or that an expert talks about the topic instead, in particular because in team, “it raises embarrassing questions" [4]. The other two were in teams of six pupils, which may explain a certain disengagement towards the end (usually, teams were composed of four or five participants). Beyond these exceptions, doing the activity as a team was a valued feature.

Overall, EA was much appreciated, in particular for its playfulness, its technological features, its originality and the teamwork that it relied on.

The role of character gender and digital features on recollection

In the second day of the interviews, we asked pupils about the investigation that they found the most memorable. No one mentioned the investigation on video games (Investigation 1), four pupils mentioned the investigation that discussed harassment (Investigation 2), five mentioned the investigation on ethylic coma (Investigation 3), one mentioned the investigation on the alcoholic parents (Investigation 4) and one did not answer. Investigations 2 and 3 are the longest investigations (about 20–25 minutes each vs 10–15 minutes for Investigations 1 and 4). It is unsurprising that these two are more memorable. More interestingly, five out of six girls mentioned the investigations in which the main character was a girl (investigation 3 and 4) and three out of four boys mentioned the investigations in which the main character was a boy (investigation 2). Even though the sample is too small to be conclusive, this observation could hint that the gender of the character is important for the memorability of the investigation.

Another observation is that when pupils are asked to talk about the investigations, they first and foremost talk about the scenarios and the digital features and less about the prevention messages.

Overall, these preliminary findings point to the importance of specific design features, including who the main character is (gender and potentially other characteristics on which the intervention wants to be inclusive) and how the health messages are embedded in the scenario and the digital features.

Knowledge of health messages

The very large majority of interviewees think they have learned something useful. The field experiment also showed that their knowledge significantly improved. However, when the pupils are probed about the type of knowledge they gained, it mostly stays at a general level (e.g. “if you drink alcohol, you can do dumb things and ruin your life" [2]). Nevertheless, slightly less than half of the interviewees do mention at least one specific message such as “When there is an addiction, we should talk about it to someone. Also, there are phone numbers we can call when there is an emergency, such as the 144" [19].

Moreover, pupils with higher educational achievement seem more able to remember specific messages. About three-quarters of pupils with high achievement in all four disciplines managed to formulate specific messages learned through EA. Only one quarter were able to do it for the others. This is consistent with our field experiments which showed that the impact of EA on knowledge acquisition was stronger for pupils with higher (vs lower) educational achievement.

Capacity to trigger discussions, reflections and behaviors

A minority of interviewees mentioned explicitly that EA made them reflect ("It really made me reflect on substances" [4], "The stories make you think. It is shocking that 12–13 year old kids already do things like that" [9]). Some of them also mentioned that they would act differently, faced with a given situation: "If I have a buddy who is drunk, I will maybe better know what to do" [3]. Even if only a minority of pupils mention those reflections or implementation intentions, it is possible that EA had a similar effect on other pupils even if they are not necessarily able to explicit it during the interviews.

About three-quarters of the interviewees spoke about EA with their friends and even more with their parents, which echoes the descriptive results of the field study. However, the content of the discussion remains relatively shallow. With their parents, the discussion typically consisted of a brief description of EA, of its appreciation by the pupil and of some elements of gamification (solve puzzles, collect points, reward, etc.). Those who spoke about it with their friends also shared their opinion about the intervention, compared their scores or certain answers. The underlying health message has been less discussed. Two or three pupils discussed it with their parents.

It is interesting to note that although the content of the discussion remained shallow, the discussions may have occurred because of the playful and innovative features of EA. A traditional expert-based in-class prevention intervention would probably not have led a majority of pupils to talk about the intervention with their friends and parents several days after.

Several pupils had already had discussions with their parents in relation to addiction. Some parents seem very concerned about the topic. However, others seem unaware of how to approach addictions (and screen time most specifically): "I told my parents that we had that thing on EA. My mother was happy because I play a lot with video games" [3]. For those parents in particular, EA and serious games more generally could potentially help trigger discussions between parents and children or compensate for the powerlessness of parents or even disengagement. When asked whether their parents try to trigger a discussion on addictions, a pupil answered: "Yeah, but it is not like a serious topic. It's more for fun. I'm a teenager, so they think I do unhealthy stuff, which is not true, so they laugh at me thinking I do stuff." Then: "I told them that it [EA] was cool, that I learned things. They said it was a bit useless. Anyway, my parents are a bit closed-minded, I can't really talk about that kind of topic with them" [20].

Overall, EA triggered a lot of discussion, albeit relatively shallow.

4.6 Discussion

Through a mixed-method approach, this research is the first to show the effect of a school-based digital escape room in the domain of addictive and risky behaviors prevention. In current studies, most digital educational escape rooms audience targets are participants in higher education (pre-graduate, undergraduate, graduate, and post-graduate), with only few studies targeting primary or secondary education [29]. Our findings confirm the effectiveness of digital escape rooms for educational purposes for secondary education pupils in the particular context of addiction prevention. It also shows that digital escape rooms could help pupils talk about the topics of addictive and risky behaviors. It is a promising result, since addiction is not the primary interest of pupils in the studied age group. Overall, although EA did not affect all outcomes we measured, the significant effects on knowledge acquisition and discussion generation are powerful, given that the intervention lasted only 90 minutes and the outcomes were measured long after the intervention (three weeks).

There is however a caveat with digital escape rooms. Pupils may prefer to engage with interventions built with technologies and media that they like [11], but only pupils with higher (vs lower) educational achievement acquired knowledge with EA. This result is unfortunate but aligned with previous findings on physical escape games [14].

Overall, gender had little influence on the effect of EA, which is a positive indication that the design of the learning experience does not unwittingly disadvantage one gender over another. The only outcome that differed according to gender was privacy setting behavior. The limited effect of gender may also be attributed to how EA balanced the use of genders in representing the main characters of the puzzles. Our qualitative interviews indeed show that females and males are more struck by puzzles in which a female (male respectively) is the main character. This extends previous research on identification with game characters, showing that gender identification leads not only to more motivational strength [38], but also to more recall of the puzzle. This is also in line with previous research showing that people respond more positively to stimuli that are congruent with their identity [48], such as when the stimulus features a person with whom the person identifies [49]. Digital escape room designers, and prevention specialists in general, should carefully think about the characters they feature on the stimuli, not only in terms of gender, but more broadly in terms of characteristics on which the project should be inclusive (e.g. cultural communities, etc.).

Finally, our results show that enjoyment plays a significant role in driving EA's effectiveness. EA promoters feared that the playfulness of the concept would shift pupils' focus from the prevention messages to the gameplay. However, our results show that EA's effectiveness was stronger on some outcomes for people who enjoyed EA's experience to a larger (vs lesser) extent. In particular, pupils who enjoyed the experience played less video games after EA's exposure and marginally increased their perception of risk related to addictive behaviors.

4.6.1 Implications and recommendations for practitioners

Overall, digital escape rooms seem promising as school-based interventions. EA made pupils talk about the intervention and to some extent about the prevention messages. It also improved knowledge acquisition and changed some behaviors. However, our evaluation also shows that EA could be improved. In what follows, we discuss how to increase the effectiveness of future digital escape rooms, based on the findings of our research.

Overall, pupils had a fairly superficial memory of the prevention messages. A way to increase pupils recollection of the key messages is to make those messages inseparable from the investigation and the technological features. Indeed, when a message is well-integrated into a stimulus, knowledge about the message increases [50]. For instance, the health message related to the video 360° where pupils had to identify dangerous ads was well embedded, and pupils remembered it more.

Also, EA addressed a large array of topics, with many underlying messages. An overly ambitious and diverse prevention intervention (substances, video games, behaviors online, etc.) in only 90 minutes may make it more difficult for pupils to leave with a clear set of takeaways. Future digital escape rooms (and prevention programs more generally) may limit the number of messages and make messages easier to take home. For instance, rather than asking pupils to remember phone numbers (even if only three figures), it may be better to ask pupils to directly enter the numbers in their mobile phones (for those who have one) or distribute a sticker or list with important phone numbers.

Finally, to increase the extent and depth of the discussions that digital escape rooms trigger, the interventions could be complemented, for instance by developing content for parents or pursuing the game outside the classroom.

A last point to mention is that EA was motivating not only for pupils, but also for teachers, schools and facilitators. The digital escape room format made it easier for prevention specialists to convince schools and teachers to welcome it into their classrooms.

4.6.2 Limitations and future research

This research is not without its limits. Using a field experiment to robustly evaluate the effectiveness of a school-based digital escape room is difficult, resulting in limited sample sizes. Therefore, detecting effects is more difficult and the likelihood of false-positive or negative is increased. However, the qualitative and quantitative parts show overall convergence, which increases the confidence in our results.

Also, field experiments are subject to field incidents. One of the schools in the control condition could not be surveyed at the same time as the other schools, which makes external effects less adequately controlled. We could, however, keep the same interval between the two measurements. Results are similar with and without this school, which tempers this problem.

Another limit of our study is that we compared our intervention to a control group without intervention. Future research could investigate how digital escape rooms compare to other prevention models, such as expert presentation. In our research, we can only assert that the digital escape room had an effect, but not that this effect was superior to that of any other prevention model.

More broadly, future research could explore how to design digital escape rooms that are free from educational achievement bias. Like other formats [51], digital escape rooms seem to be more beneficial for teenagers with higher educational achievement. Future research could address this issue by investigating alternative delivery models that are appealing to and effective with all teenagers (or even more effective with teenagers with lower educational achievement, since they may start with a lower knowledge base, as our research shows).

Finally, our research points to the need to smoothly integrate the prevention messages in the puzzles and in the technology, so that remembering the technology or the puzzle becomes inseparable from remembering the message. Future research could explore how to optimally embed the messages in order to maximize impact.

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Chapter 5

Promoting Computational Thinking Skills in non-STEM Students — Gamifying Computational Notebooks to Increase Student Engagement

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Abstract

Computational thinking (CT) skills are becoming increasingly relevant for future professionals across all domains, beyond computer science. As such, increasingly more bachelor and masters programs outside of the science, technology, engineering, and mathematics (STEM) disciplines integrate CT courses within their study program. At the same time, tools such as notebooks and interactive apps designed to support the teaching of programming concepts are becoming ever more popular. However, in non-STEM majors, CT might not be perceived as essential, and students might lack the motivation to engage with such tools in order to acquire solid CT skills. This paper presents a field study conducted with 115 students during a full semester on

a novel computational notebook environment. It evaluates computational notebooks and CT skills in an introductory course on information technology for first-year undergraduates in business and economics. A multidimensional evaluation approach makes use of pre- and post-test surveys, lectures and self-directed lab sessions tracking analytics. Our findings suggest that, in the process of learning CT for non-STEM students, engagement in active learning activities can be a stronger determinant of learning outcomes than initial knowledge. Furthermore, gamifying computational notebooks can serve as a strong driver of active learning engagement; even more so than initial motivational factors.

5.1 Introduction

The use of computers, smartphones, or other connected devices is becoming the daily routine of an ever-increasing number of people around the world. The increased usage of computing devices and their processing power allows us to solve problems that we could not tackle before and, at the same time, this has complexified the way society works, leading to an increased presence of non-routine work [1]. Even people without computing skills need to use computers to carry out specific tasks in their daily lives. In this hyper-connected era, individuals must be aware of how to make the most of computers, which involves being fully capable of communicating with them and of extracting all their computing potential to solve complex problems in a wide range of domains [2]. As such, computational thinking (CT) is part of the essential skill set that a student should master in order to solve problems in the digital era [3], [4]. This may include several key concepts such as abstraction, decomposition, pattern recognition, and algorithms [5], [6]. However, the assessment of CT competence is not straightforward [7] due to the plethora of concepts involved, the fact that frameworks are different across authors, and the lack of validated tools. Furthermore, the recent COVID-19 health crisis has introduced additional complexity as many courses can no longer rely on in-class teaching support and have to be exclusively taught online. These different factors mean that educators should pay particular attention in engaging students in active learning to increase learning gains [8], and to promote specific pedagogies likely to increase their motivation, such as gamification [9], [10]. Indeed, in non-STEM majors, CT might not be perceived as essential, and students might lack the intrinsic motivation to engage fully in learning, which may prevent them from acquiring solid CT skills [11].

Promising tools to teach students how to solve complex problems using a programming language are computational notebooks [12], [13]. These tools allow students to recreate and simulate exercises in an interactive manner, where they can manipulate chunks of code and observe the results of their actions in real-time.

This study tackles this specific issue and brings new insights through a multi-dimensional evaluation approach of CT skills using multiple sources of data. Quantitative scores, insights of problem-solving strategies deployed by students, and usage data from the computational notebook used as course support have been analyzed. This study also includes a controlled experiment with a gamified feedback feature. In particular, it makes the following research contributions:

5.1.1 Contributions

First, the paper introduces a novel computational notebook environment using the Graasp open digital education platform with associated learning scenarios [14]. The computational notebook application offers a coding environment, integrated learning analytics, and modular gamification modules.

Second, the paper presents a field study conducted using data captured during a full semester introductory course on information technology for first-year undergraduate students in business and economics. More specifically, we analyzed the data of 115 students who took the lecture between February and June 2021 and who agreed to participate in this study.

Third, in the context of non-STEM undergraduate students, this paper investigates whether computational notebooks can support active learning scenarios for promoting CT skills in non-STEM students (RQ1), how engagement with computational notebooks is associated with student motivation (RQ2), and how gamification can contribute to increased engagement with computational notebook (RQ3).

5.1.2 Roadmap

The remainder of the paper is structured as follows: Section 5.2 defines CT and discusses related work about computational notebooks and related motivational aspects and gamification mechanisms that may influence engagement in the context of CT knowledge acquisition. Section 5.3 presents *Graasp*, the education platform used for this study, as well as the learning scenarios. Section 5.4 presents the research case study, the data used to carry out the analysis, and the techniques applied to address this research. Section 5.5 presents the results about each research question. Finally, Section 5.6 and 5.7 conclude the paper and summarizes the main insights.

5.2 Related Work

CT and its use in educational settings stems from the work of Seymour Papert at the Massachusetts Institute of Technology in the second half of the 20th century [15]. Papert proposed that computers should be an integral tool of young people's learning, and put forward the use of programming languages like Logo. The topic of CT has re-emerged as an increasingly relevant issue in education over the past few years. Jeanette Wing—considered to be the author that coined the term CT—asserts that it is a fundamental competence for everyone, not just for computer scientists [16], [17]. Although there is a plethora of definitions and conceptualizations of the term, Jeanette Wing has conceived CT as the thought processes involved in formulating problems and their solutions so that the solutions are represented in a form that can be effectively carried out by an information-processing agent. However, the promotion of CT in the classroom is challenging because—among other reasons—research on how to teach and learn CT in the classroom is very scarce [18]. If we want to improve these teaching practices at the university level, we must be able to distinguish effective methodologies and motivational affordances, such as gamification. The tools built up to now to evaluate CT in higher education are, to the best of our knowledge, still somewhat limited [19]. Literature review on computational notebooks, motivational aspects, gamification mechanics, and existing evaluation tools in a CT educational context are presented below.

5.2.1 Computational notebooks

Previous studies, demonstrated that students increase their conceptual comprehension, critical thinking, and interpersonal skills when they participate actively in their study, according to research [20]. Such active participation is better known in the literature as active learning and is a teaching method that pushes students to continually assess their understanding by doing things. Active learning is an effective alternative to more passive types of knowledge acquisition, such as attending lectures [20]. One way to apply active learning in CT-related knowledge acquisition relies in blended learning. Blended learning combines traditional face-to–face learning with digital interaction in class or at home [21]. The shift to blended learning has been a key trend in education in the past decade. Currently, most learning activities are delivered using a blended approach, to some degree [22], [23]. Blended learning also provides digital education platforms with the possibility to integrate learning analytics into the instructor's awareness and reflection processes, potentially allowing instructors—and other stakeholders (e.g., parents, researchers)—to assess how students are performing and to predict student success or failure early on in the course [24]. Furthermore, a blended learning approach can also potentially be used in a fully online learning context [25].

Blended learning is particularly applicable to introductory programming courses [26], [27], which often incorporate online programming tools such as computational notebooks. Computational notebooks, which are widely used in data science education [28], combine code snippets and text with other multimedia content to create rich interactive environments for data exploration and programming [29]. Combining an online coding environment without the need for external software, and the ability to run code embedded in text and multimedia content make computational notebooks a tool well suited to teaching CT [30]. Previous work has explored the use of computational notebooks to teach CT in different learning activities. For instance, researchers evaluated its usage for (i) lectures, (ii) reading, (iii) homework, and (iv) exams [30].

Jupyter Notebooks [31] (henceforth *Jupyter*)—a popular computational notebook—have seen a particularly significant increase in popularity over the past few years, becoming a valuable teaching tool. One of the keys for Jupyter's rise in popularity is its support of the Python programming language, whose simplicity and readability make it attractive as an introductory programming language [32]. As such, Jupyter is becoming more popular in introductory Python courses [33]–[35], despite the fact that there are many other web-based tools that have been suggested for teaching Python [36]–[38]. This preference for Jupyter could be explained by the fact that it offers many features aimed at students, including the ability to work on coding assignments without having to switch between the assignment's instructions and the coding software [39]. Furthermore, Jupyter includes many tools that are specifically made for teaching, such as grading modules [39]. Certain personalized learning environments (PLE) allowing the creation of rich interactive learning spaces, gamified learning experiences, and learning analytics, have also started to provide support for computational notebook integration [14].

Nevertheless, these notebooks can also have a negative effect on learning. Some argue that they encourage poor coding practices, given that it is not straightforward to break down code into smaller, reusable modules, and that it is hard to write and run tests [31]. Furthermore, the fact that computational notebooks are used both for exploratory and explanatory purposes can also lead to complications, since it takes a lot of effort to transform a messy exploratory notebook into a clean one that can be shared with others [40]. Moreover, these environments lack support to allow for greater interaction, collaboration, activity awareness, access control, and other features [29]. Therefore, it has been argued that while computational notebooks can be useful for introductory-level students, they are not suitable for more experienced learners [41], [42]. To address this issue, notebooks can be customized according to learning preferences, programming experience, and learning context [30]. The above observations lead to the following research question:

(RQ1) *Can computational notebooks support active learning scenarios for promoting CT skills in non-STEM students?*

5.2.2 Motivation

As active learning scenarios rely on voluntary student engagement, it raises the question of the underlying motivations that drive or hinder engagement. As non-STEM undergraduates may not perceive CT as essential, which could potentially make it difficult for them to develop strong computational thinking skills [11], it is critical to understand the motivational aspects of students engaging in active learning scenarios. This observation leads to the following research question:

(RQ2) *How is the engagement with computational notebooks associated with student motivation?*

Over the last 60 years, self-determination theory (SDT) has emerged as a fundamental theory of human motivation [43]. SDT's basic premises propose that motivation operates on three levels: global, contextual, and situational [44], [45]. Motivation on a global scale reflects how an individual interacts with his or her surroundings in general [45]. A motivating tendency toward a certain setting, such as job or education, is known as contextual motivation [44]. Situational motivation relates to the "here and now" of motivation, or the motivation felt when participating in a certain activity [44]. All three levels can be further refined and described by various constructs, among them the motivational factors proposed by SDT [46], [47]: intrinsic motivation, identified regulation, external regulation and amotivation, constituting a self-determination continuum from self-determined to non-self-determined motivation. Intrinsically motivated behaviors are those that are done for the purpose of doing them, or for the pleasure and satisfaction that comes from doing them. [46]. In contrast, extrinsic motivation refers to a wide range of behaviors in which the goals of action are not limited to those that are inherent in the activity. [46]. Different types of extrinsic motivations have been proposed by self-determination theory, these are external and identified regulations [46], [47]. External regulation happens when behavior is regulated by rewards or to keep away from negative consequences. Identified regulation, on the other hand, happens when a behavior is valued and viewed as one's own choice. However, the motivation still remains extrinsic because the activity is done as a means to an aim rather than for its own sake. Amotivation defines a completely non-autonomous behavior, with no drive to speak of and likely struggling to have any of oneself needs met. To measure a person's situational motivation the Situational Motivation Scale (SIMS) can be used as it demonstrates good reliability and factorial validity in the education context [48].

5.2.3 Gamification

For the use of gamified settings to promote CT, Kotini and Tzelepi [49] find that the use of gamification—e.g., using grading characteristics comparable with those of video games, such as points or levels—can increase engagement of students. There are many types of settings one can apply, and instructional design has to be careful to not only promote external goals such as points and prizes related to performance, because this would only lead to increasing extrinsic motivation of students. The educational setting also has to integrate aspects that can grow students interest in mastering their learning, thus leading to promoting intrinsic motivation as well. One key element is if gamification can provide feedback and scaffolding for students, and by which means. Providing feedback for learning activities has long been identified as an important component allowing students to identify gaps and to assess their learning progress [50]. Some experiments [51] have shown that gamified environments where the digital environment itself produces the scaffolds necessary for students acquisition of CT skills can be implemented. In another study where a mobile app game was used to promote CT [52], the authors found that, generally, the average time that students spent on a level in the game increased with the level of progression. In other studies [53], it is the didactic sequence itself that scaffolds the students to acquire CT, and the authors report an increasing learning rate in the experimental group compared to the control group.

However, the literature does not clarify what role gamification can play on learning outcomes and student engagement in the context of higher education, where it is non-STEM students that are learning CT skills. Given the different kinds of tools that appear in the literature, it seems wise to use a combination of tools that can provide greater reliability to evaluate students CT skills and cover the different facets of their competence. This is precisely the perspective that will be adopted in this paper, where we will use multiple instruments to assess a student's CT expertise based both on programming and non-programming activities. The above observations lead to the following research question:

(RQ3) *How can gamification contribute to increased engagement with a computational notebook?*

5.2.4 Tools for evaluating CT skills

Comptentency-based tests propose abstract items for assessing CT skills. For example, Gouws et al. created a test to evaluate CT performance in higher education students [54]. Sometimes, tests created for other purposes have been used as a tool to measure CT skills (e.g., including tasks related to conservation or probabilistic reasoning). That is the case for the GALT test [55], which was used for instance used in the context of higher education [56]. Recently, Lafuente et al. [57] developed a psychometric test to evaluate algorithmic thinking skills. The authors validated the test based on factor analyses and opinions of experts in the field, obtaining a 20-item test capable of discriminating experts in CT from students without any training in computational issues.

Self-assessment tools have been developed so that students can evaluate by themselves to what extent they have mastered different skills related to CT [58], [59]. These tests have been validated by researchers and used by students in higher education. However, self-reported questionnaires may yield measurement errors based on an overestimation of the student's own skills or lack of understanding of the concepts involved in the questionnaire [60]. This type of tools also includes interviews, which are used to extract qualitative evidence, mainly of the thought processes used by students to solve CT tasks [61].

Exams and other "ad hoc" tools are probably the most frequently used tools to evaluate CT [62]. The authors usually construct an artifact with tasks that resemble very much the ones used in the classroom for teaching and learning the subject (i.e., the evaluation tool is an exam), and very often the tools include the use of programming in a language that students have been learning in the class. These tools are mainly oriented to evaluating a student's CT-related knowledge. Likewise, portfolios and reports constructed by students are also used to evaluate CT competence, using evidence of understanding and achievement in CT-related activities [63]. Furthermore, the ability to properly assess a student's acquisition of CT skills could also provide valuable insight into how CT should be taught in the classroom, which is an active area of research [18].

This paper will make use of this body of research to design, implement and evaluate adequate support for promoting CT skills.

5.3 Graasp digital notebook

The digital notebook environment studied in the paper is built using the Graasp personalized learning environment. Graasp is an open digital education platform providing two interfaces [14]. An *Authoring View* allows instructors to combine and configure resources they use to create their online lessons, which we refer to as *learning capsules*. Learning capsules can then be broken down into step-by–step exercises, which can be contextualized with text, images, links, chatrooms, and other interactive content. The second interface is the *Live View*. This view is a student-oriented environment that can be accessed through a link. By clicking on the link, students can take part in the online lesson, navigating through pages that contain lectures and exercise materials prepared by the instructor.

To provide a context resembling computational notebooks, we designed an open source coding application (henceforth the *code app*[*]) to provide a ready-made Python environment within Graasp. The code app uses the Pyodide[†] library to execute Python directly on the browser without any additional dependencies. Students can read and write files, provide manual input, and generate graphics using libraries such as Matplotlib [64]. The code app also includes a command-line interface to display output and to allow students to navigate a virtual file system, as well as a feedback functionality that allows instructors to review and annotate the code written by students. To enable advanced features such as custom configuration, saving student-generated code, and tracking learning analytics, the code app can leverage application programming interfaces (APIs) exposed by digital education platforms. In our case, we use Graasp's API to preconfigure the code app with sample code, data files, and instructions for students. Within the live view, students could then write, execute and save code, review feedback provided by the instructor, and visualize any graphical output.

The *code app*, was then coupled with two others graasp apps to gamify the active learning experience. The first additional app is a simple *answer app*[‡], which allows students to enter an answer and get feedback if it is correct or not. The second app is a *point counter app*[§]. This point counter is a gamification app added to the learning space which reads the output of the answer app, i.e., it adds points to the score if an answer is correct, and removes points if a hint is displayed.

5.3.1 Learning scenario 1 — active lectures

This learning scenario supports knowledge transmission by an instructor in a live session, whether remote or in-class. It aims to make traditional lectures more interactive by providing dynamic slides to students who can write and execute their own code during the lecture. The goal is that in a first step,

[*]Code App: `github.com/graasp/graasp-app-code`
[†]Pyodide: `github.com/iodide-project/pyodide`
[‡]Answer App: https://github.com/graasp/graasp-app-submit-answer
[§]Point Counter App: https://github.com/alessio265/graasp-app-levelvis

students follow the code that the instructor presents. Then, in a second step, students are encouraged to deviate from the code presented, in order to test some corner cases or validate some expected behaviors. Using the computational notebook, this scenario allows instructors to structure the course content into blocks or slides, each with an independent space to write and execute code and possibly images, videos, or other interactive content. In this real-time learning scenario, it is expected that students move along the slides at the same pace as the instructor. Figure 5.1 shows a typical example of a learning capsule with different slides (e.g., definition, memory). In the selected slide (*Definition*) there is a block of static text with the interactive code app below. Concretely, the learning activity in Figure 5.1 depicts one of the Python lessons and showcases one of the hands-on exercises performed during the theoretical part of the course. In this example, students are presented with a variable they should print to discover its content, providing an introduction to the concept of variables.

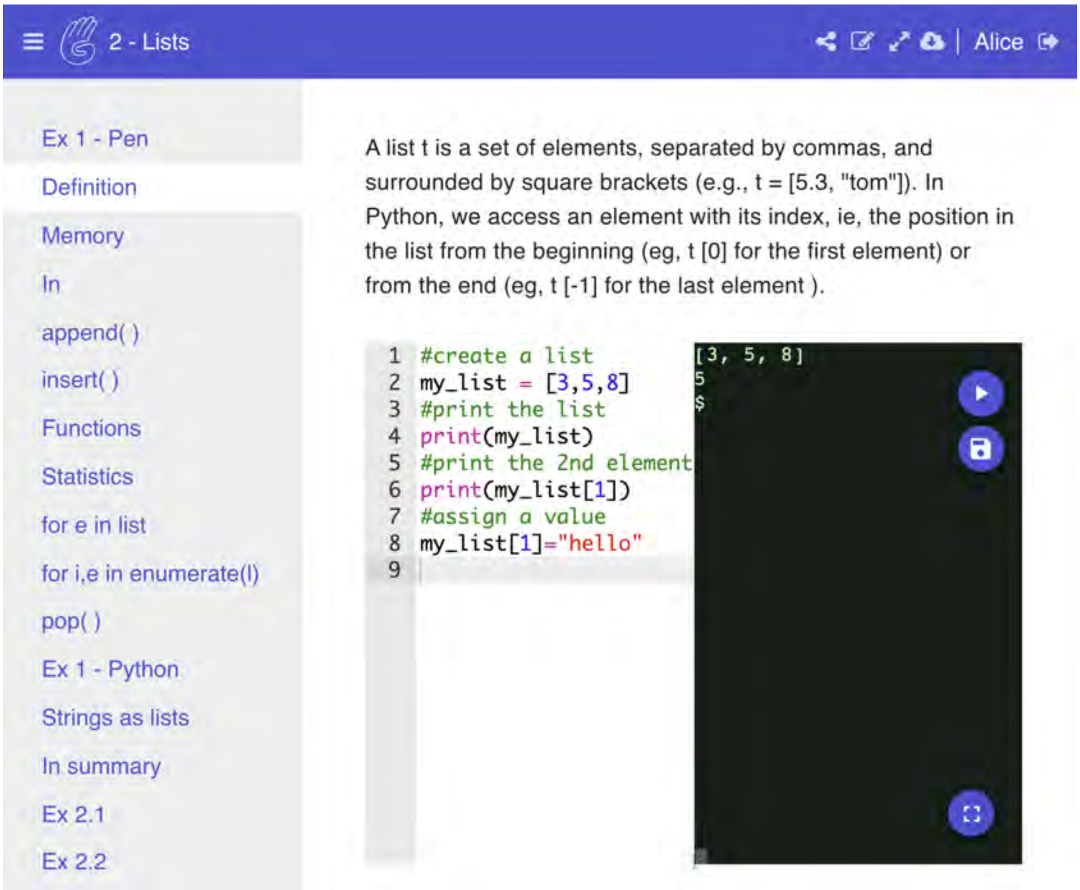

FIGURE 5.1: Interactive lecture — a computational notebook learning capsule on Graasp. The instructor and students can write and execute code during the course.

5.3.2 Learning scenario 2 — self-guided labs

This learning scenario aims to support self-guided knowledge acquisition during lab sessions. The idea is to present students with exercises and to include auto-correction and formative feedback. Several tools can be included within the learning capsule to provide formative feedback. A simple input app allows students to submit text, while a real-time communication app enables students to spontaneously ask questions and to respond to multiple-choice questions posed by the instructor. Students could also use the app to complete homework assignments and provide answers to the problems presented during the lab sessions. Figure 5.2 shows three apps in the learning capsule to support lab sessions. First is the *code app*, which allows students to run code. It should be noted that it can make use of hidden lines of code that can be executed before or after the visible code. Second there is the *answer app*, which allows students to enter an answer and get feedback if it is correct or not correct. This app also allows teachers to set a hint for each question. Such a hint can then be displayed by students if they wish. Third, there is the *point counter* on the right-hand side of the live view. This point counter reads the output of the answer app, illustrating accumulation of points for each correct answer given, but also the loss of points when asking for a hint. The goal was to increase the time spent by students on activities by decreasing their need for help, i.e., the number of hints asked for.

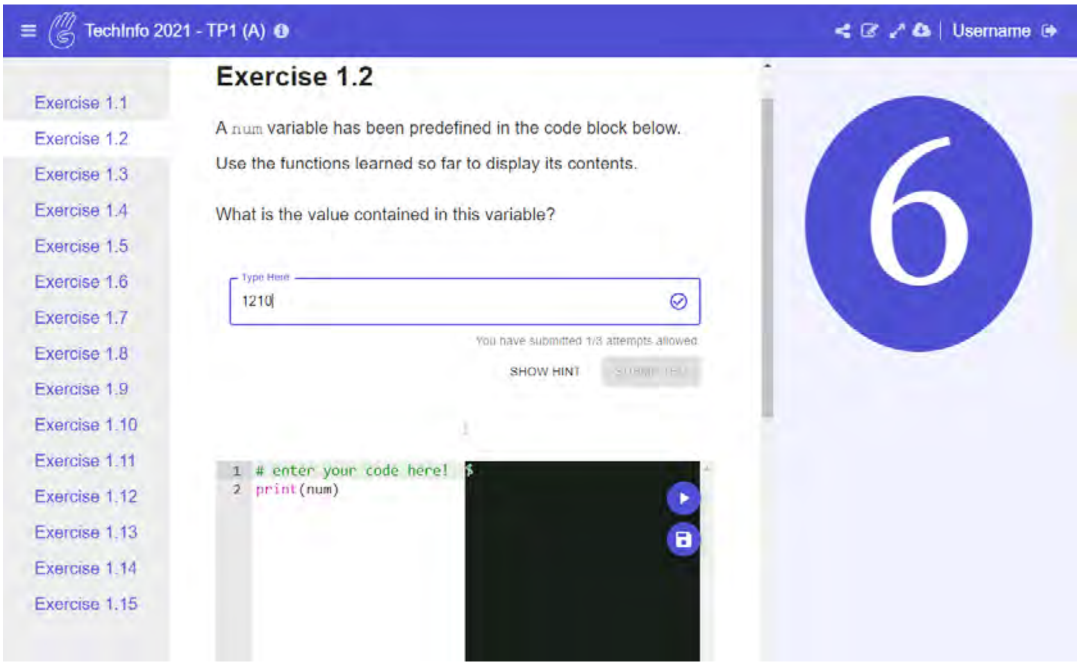

FIGURE 5.2: Lab support with Graasp. A self-guided learning activity with visual point feedback.

TABLE 5.1: Course outline

Week	Lecture	Lab session
1	Pre-test survey	CT concepts
2	CT concepts	
3	Spreadsheet formulas and computational models	
4		
5		
6		
7		
8		
9	Python – variables and conditions	
10	Python – loops	
11	Python – lists	
12	Python – functions	
13	Web technologies	
14	Questions & Answers	Post-test survey

5.4 Methodology

In this section, we present the research case study, the data we used to carry out this analysis, and the techniques we applied to address our research questions. The case study for this paper is a full semester introductory course on Information Technology for first-year undergraduate students in business and economics (February–June 2021). This course consisted of two 45-minute periods per week of theoretical lectures and two 45-minute periods per week of lab sessions (see Table 5.1). This course covers an introduction to CT concepts (2 weeks), introduction to spreadsheet formulas and computational models (5 weeks), Python programming (4 weeks), web technologies (2 weeks), and a final week with an exam dry run. The course is evaluated through a 1-hour online exam. During the first and the last week, respectively, students filled in a pre- and a post-test survey, which inquired about their CT skills and attitudes. Out of the 115 students in the course, 112 gave their consent for this study.

5.4.1 Learning outcome data

There were no prerequisites for this course, and the learning outcomes of the course were for students (1) to be able to conceptualize problems computationally, i.e., use CT principles to describe and attempt to solve problems, and (2) to be able to solve simple problems algorithmically using the Python programming language. These learning outcomes were measured informally at the beginning (pre-test) and at the end of the course (post-test), and formally during the written exam at the end of the semester.

The pre- and post-tests each were composed of six problem-solving questions and six Python programming questions (examples are given in Figures 5.3 and 5.4). The problem-solving questions were extracted from the Algorithmic Thinking Test for Adults [57]. For all questions, there was one correct answer. For all problem-solving questions, besides asking students for an answer, we asked them to provide a textual description of their problem-solving strategy for tackling the problem. This second part was not taken into account for the scoring of their answer, but allowed us to get an impression of how much CT concepts and higher levels of thinking were used in the process of solving or attempting to solve the questions.

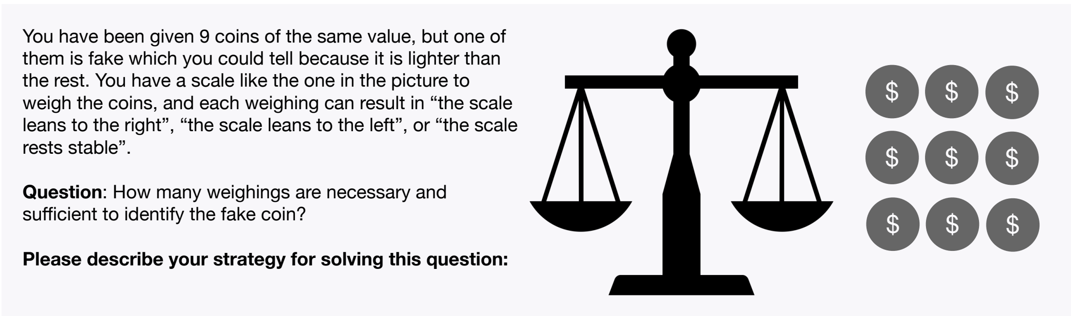

FIGURE 5.3: Example of a general problem-solving question. Note that the question has two components. The first is quantitative and requires a precise answer, the second is qualitative and requires an open-ended answer describing the problem-solving strategy.

More specifically, we analyzed the six problem-solving questions of the pre- and post-tests, where students had to explain their reasoning process. We sought to determine whether the key terms and concepts presented during the course had been assimilated and reused in the explanations given by the students using an approach inspired by grounded theory [65], [66] and open coding techniques, making the categories emerge from theoretical content of the courses, resulting in 22 different concepts:

What is the output of the code below:	What is the output of the code below:	What is the output of the code below:

`def lila(home, run, bat):`
`   home = home + 1`
`   return home + bat`
`print(lila(10, 50, 40))`
	`isGreat = False`
	`nb_students = 30`
	`travel = 0`
	`if isGreat or nb_students > 5:`
	`   travel = 9`
	`else:`
	`   travel = 5`
	`print(travel)`
		`grades = [1,2,3,4,5,10]`
		`print(grades[4])`

FIGURE 5.4: Example of three basic programming questions.
These questions require a precise answer.

decomposition, sub-problem, rule, specification, repetition, generalization, variables, function, instruction, abstraction, model, class, algorithm, loop, repeat, sequence, condition, trial, error, iteration, increment, test.

For each word of the student explanations and for each target concept presented here above, we performed lemmatization to transform words with roughly the same semantics to one standard form. Lemmatization was performed through WordNet corpus of the Python Natural Language Toolkit (NLTK). WordNet is a large freely and publicly available lexical database for the English language, establishing structured semantic relationships between words [¶].

The final exam consisted of five open-ended Python questions, asking for simple functions or programs, such as: "Write a function that takes two parameters as input (a string called word and an integer called n) and returns a new string made of n times the word".

5.4.2 Lecture data

During the lectures, we used learning analytics in Graasp to track student attendance and visual analysis to evaluate if the student followed the lecture. As an example, Figure 5.5 shows a learning dashboard to track user activity. More specifically, it shows the order in which each student has visited the pages available in the live view, as well as the time spent on each of them. If instructor use the live view at the same time, then the instructors' data can be compared against the students data. Each color represents a page inside the live view. If students were to be perfectly synchronized with the instructor, their color patterns would all be the same.

[¶] https://www.nltk.org/howto/wordnet.html

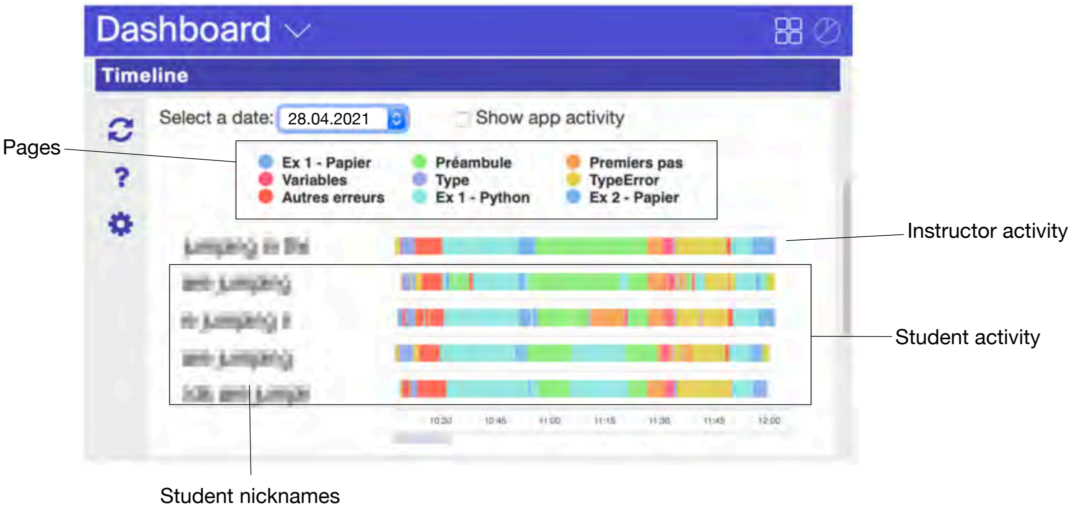

FIGURE 5.5: Activity dashboard.

5.4.3 Lab session data

During the Python programming lab sessions, students were randomly split into treatment (70 students) and control group (45 students). The students went through four series of 15 exercises, with a total of 60 exercises. The various series of exercises corresponding to the different topics introduced each week in the theoretical courses were: 1) variables and conditions, 2) loops, 3) lists, and 4) functions. The treatment group was provided with an extensive gamified feedback, including a level visualization, as shown in Figure 5.2, while the control group had limited feedback, only knowing if their answers were right or wrong. The gamified feedback appears on the right-hand side of the interface in the form of a chain of bubbles that scrolls along with the score. To help them in the resolution of the exercise, students could ask for hints. For each exercise, the code block of the computational notebook was preconfigured to perform a list of tests on the execution of students code, providing validation keys. Once the student's algorithm could execute properly, a validation key was returned back. For each exercise, two different validation keys could be received back by the students. In the first case, the algorithm acts as expected, while in the second one the algorithm does not act as expected. There were no limits on the number of tests and executions of the algorithms, and students were not aware of the meaning of the validation key received. Validation keys were randomly predefined and therefore different for each exercise. Theses validation keys should then be submitted by the students in the answer app. When submitting their validation key, a checkmark or a cross allowed feedback to be provided to the students on the correctness of their algorithm. Furthermore, for each correct answer on the first attempt, students get three points. For each correct answer provided after the first attempt, students get two points. For every hint revealed, students lose one point. The control group has no visual feedback of its score.

5.4.4 Psychometric and demographic data

In addition to the above data, we also collected demographic data, student motivation, and the computational notebook usability level.

Student motivation was assessed in the post-test survey and aimed to measure the motivation to perform the lab sessions through the computational notebook. Motivation was assessed using the 16-item *Situational Motivation Scale* (SIMS). SIMS is designed to assess intrinsic motivation, identified regulation, external regulation, and amotivation [48].

In order to evaluate the usability level of the computational notebook, the students answered ten questions about the computational notebook, based on the system usability scale (SUS) [67] at the end of the post-test.

5.4.5 Path model and analysis

To provide a global view of the different factors influencing the learning outcomes, we designed a path model and conducted a partial least squares (PLS) analysis technique. PLS is a variance-based structural equation modelling (SEM) analysis technique increasingly popular for analyzing explanation and prediction of information systems phenomena [68], [69]. Central to PLS is the path model, a diagram that displays the hypotheses and variable relationships to be estimated in an SEM analysis [70]. T-statistics are used to test the proposed hypotheses for the standardized path coefficients, by specifying the same number of cases that existed in the dataset and bootstrapping 1000 re-samples. The resulting design of the path model for this analysis is depicted in Figure 5.6. It contains three main independent variables: (1) initial skills, as measured by the score on the pre-test, (2) motivation, as measured by the SIMS scale, and (3) gamified feedback, which indicates whether the student was in the gamified feedback condition or not. Note that motivation can be further broken down into its four components (intrinsic motivation, identified regulation, external regulation, and amotivation). These variables potentially influence positively lab performance, as measured with the score on the lab exercises and the engagement on the online platform. Engagement is measured by tracking student interactions (i.e. number of clicks, number of code execution, text written) on the Graasp platform. "Need for help" construct is measured by the number of hints requested by a student (the more hints, the greater the need for help). It is expected that gamified feedback and motivation will reduce the need for help. In other words, this would mean that gamification of the activity, as well as increased motivation would lead students to try to get the answers on their own to get more points, without asking for hints. Finally, lab performance and initial skills potentially positively influence the learning outcome as measured by the grade of the exam.

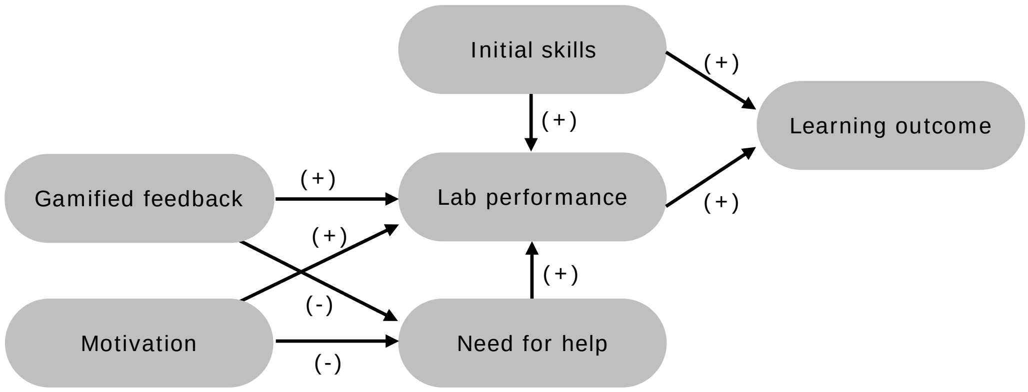

FIGURE 5.6: Path model. Positive influence (+) is expected among the linked constructs of the model.

To validate the reflective constructs of our path model (i.e. lab performance, intrinsic motivation, identified regulation, external regulation, and amotivation), we evaluated their reliability, convergence, and discriminant validity.

Reliability

we used composite reliability (CR) and average variance extracted (AVE) as indicators. As shown in Table 5.2, the CR of the constructs was greater than 0.7 and the AVE greater than 0.5, thus these constructs are reliable [69].

Convergent validity

we used the outer loadings and the AVE as convergent validity indicators [71]. The outer loadings of all our reflective variables were above 0.7, which is the standard threshold [71], except from one variable in amotivation construct which was only above 0.5. As this study should be deemed as exploratory research—indicators between 0.4 and 0.7 were kept, as recommended by Hair et al. [71].

TABLE 5.2: Evaluation of reflective constructs

	Cronbach's Alpha	*rho_A*	*CR*	*AVE*
Lab session perf.	0.727	0.761	0.878	0.783
Intrinsic motivation	0.887	0.921	0.920	0.742
Identified regulation	0.838	0.861	0.891	0.673
External regulation	0.762	0.715	0.820	0.553
Amotivation	0.784	0.921	0.856	0.606

Discriminant validity

We used the heterotrait–monotrait (HTMT) ratio as a measure of discriminant validity [69]. Values lower than 0.85 are considered as acceptable for conceptually distinct constructs [69]. As shown in Table 5.3, with the exception of Amotivation → Identified Regulation which scores 0.857 and thus is on the margin, all values were lower than 0.85, demonstrating the discriminant validity of our constructs.

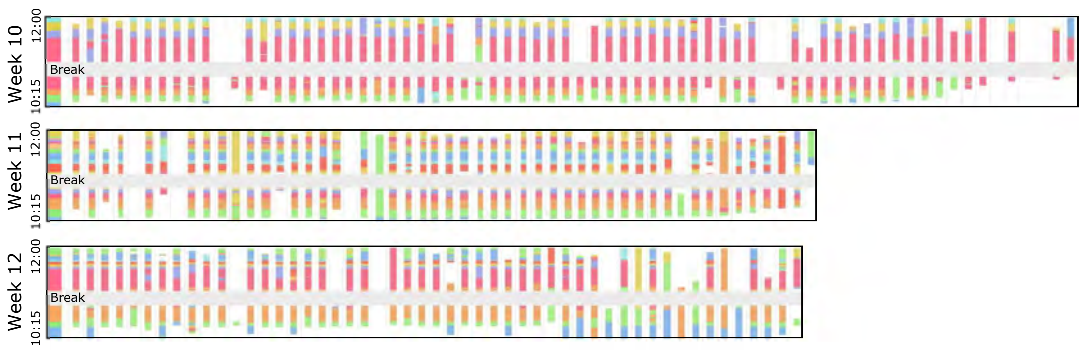

FIGURE 5.7: Visualization of students following the lectures in Weeks 10–12.

TABLE 5.3: Heterotrait-monotrait ratio (HTMT)

	Lab perf.	Int. motiv.	Iden. reg.	Ext. reg.	Amotiv.
Lab session perf.					
Intrinsic motivation	0.569				
Identified regulation	0.685	0.748			
External regulation	0.335	0.183	0.426		
Amotivation	0.544	0.688	0.857	0.413	

5.5 Results

5.5.1 Can computational notebooks support active learning scenarios for promoting CT skills in non-STEM students? (RQ1)

To answer the first research question we evaluate if the notebook was considered usable (yes), if it was used as intended in the learning scenarios (yes) and whether there were learning gains (yes).

Usability

The average SUS score is equal to 67.4 (N=64), which represents okay usability [72]. There is no significant gender difference in terms of usability.

Learning scenario

Using data from the learning dashboard presented in Figure 5.5, we examined usage patterns from Week 10 to Week 12 as shown in Figure 5.7.

The dashboard gives a visual impression of how synchronized students are during the lecture. Note that the first slide (blue on the bottom) is always a pen and paper exercise, which explains why students are not always looking at the slide on the computational notebook. A visual analysis shows that during the lecture on Week 10, 62 followed at least part of the lecture on the computational notebook and 40 of them (64.5%) followed actively (meaning that around 80% of the lecture material was followed in the same order as the instructor, switching slides at around the same time), the other 22 students are considered as following the course passively. In Week 11, there were a total of 49 students online, among them 39 were active (79.5%). In Week 12, there were a total of 50 online, of whom 39 were active again (78%), and 33 were the same as the previous lecture.

The overall engagement of students during the live online lecture is depicted in Figure 5.8. It shows how many students were mostly active, mostly passive, or absent during these three lectures ($N = 112$). Of the 112 students who at some point appeared on the course, 42 did not participate in the online lectures, 28 were passive, and 42 were active. Among the 96 who ended up taking the exam, 31 did not follow the lectures, 23 were passive, and 41 were active.

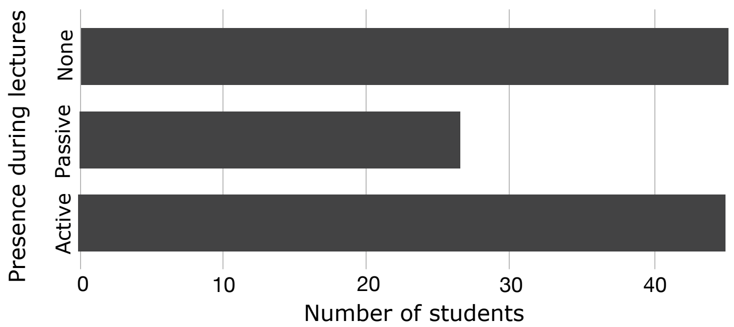

FIGURE 5.8: Bar-chart of lecture presence during Weeks 10–12 ($N = 112$).

Finally, we also analyzed whether students watched the recordings of the course that were put online after the lecture. Figure 5.9 shows student engagement with the lecture (live on the computational notebook and after the lecture viewing videos) over three weeks. Real-time activity is reported as a percentage of active participation in the real-time lecture discussed above. Video watching activity is reported as a percentage of the total time of the videos posted for the three weeks capped at a 100%.[11] The total number of videos posted was 149 minutes for the three lectures. The results show that a significant number of students (around 20%) did not participate actively in the live lessons, but nevertheless watched the videos at home. One student spent more than 900 minutes watching videos.

Learning gains

The main goal of this analysis is to explore the evolution of the CT skills of the students and to see if we can observe differences between their initial knowledge and their learning outcomes (Python score, CT score). To answer this

[11] Students could watch videos several times, which could lead to some playing times exceeding 100%.

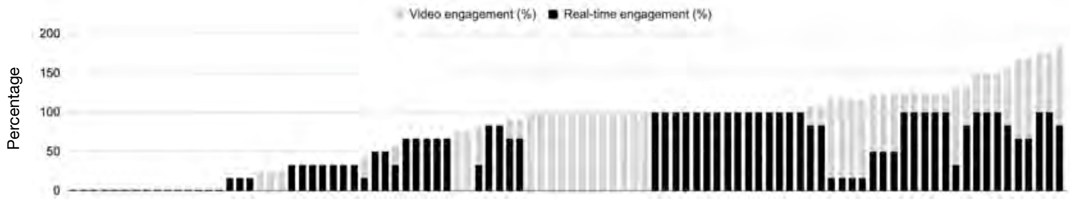

FIGURE 5.9: Student engagement with the lecture in number of minutes of attention, live on the computational notebook, or later by watching videos ($N = 112$).

question, we compared student scores on the pre- and post-tests as well as the evolution of their problem-solving strategies (CT concepts). Figure 5.10 provides a visual overview of the results of the mean scores in percentage points with pre-test results as baseline. To perform the analysis, mean scores were normalized and ranged between 0 and 1, which represents the maximum achievable score.

When it comes to the Python score, a statistically significant difference was found for the Python exercises ($t(59) = 11.25, p < 0.01$) between the pre- ($N = 60, M = 0.16, SD = 0.24$) and post-test ($N = 60, M = 0.61, SD = 0.29$) scores.

Regarding CT score, a paired t-test revealed that there is a statistically significant difference ($t(59) = 3.73, p < 0.01$) in problem-solving exercises between the pre- ($N = 60, M = 0.39, SD = 0.25$) and post-test ($N = 60, M = 0.52, SD = 0.27$) scores.

Finally, in terms of CT concepts, we analyzed student answers to the CT questions from a semantic and linguistic point of view. To observe the potential evolution of the use of such conceptual terms in the problem-solving explanations given by the students, we compared the appearance frequency of each concept in students pre- and post-test explanations. The results show a statistically significant ($t(59) = 2.31, p < 0.05$) positive evolution between the pre- ($N = 60, M = 0.43, SD = 0.79$) and post-test ($N = 60, M = 0.97, SD = 1.65$) scores.

Learning outcome

Figure 5.11 gives an overview of the final grades of the course ($N = 96$) between 1 (worst) and 6 (best) with the passing grade being 4. The pass rate for this course was 60.4%. There is also no significant difference in grades between gender.

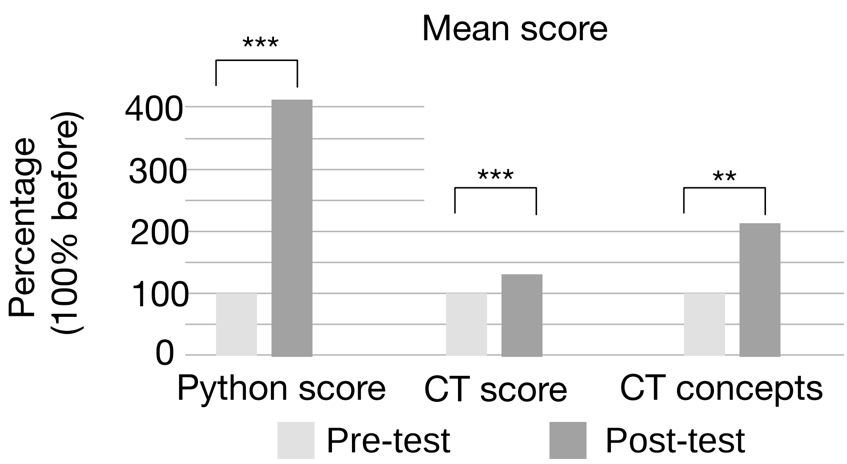

FIGURE 5.10: Pre-test and post-test results (pre-test used as baseline). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Looking at engagement with the lecture material in real-time on the computational notebook a median-split of the student grade results (pass/fail) ordered according to the time they spent following the lecture created two natural groups: one with high engagement and one with low engagement. A χ^2 test of independence indicated a significant association between lecture engagement and having a passing final grade in the course $\chi^2\ (1, n = 96) = 6.27, p = .012$. In fact, the group with high lecture engagement was about 50% more likely to pass the course (35 students had a passing grade (76%) in the high engagement group compared to 23 (48%) in the low engagement group. To assess whether engagement with videos was also associated with a higher pass rate, we performed a median-split of student grade results (pass / fail) ordered according to the time spent watching the videos. However, no significant difference was found.

5.5.2 How is the engagement with computational notebooks associated with students motivation (RQ2)

To answer this second research question we evaluate if the engagement with computational notebooks is associated with students intrinsic motivation (yes), identified regulation (yes), external regulation (somehow), and amotivation (no). The analysis was performed on the subsample of 84 students which filled the pre-test survey, counting 46 males and 38 females. As measured by the SIMS scale, the mean of student motivational aspects were calculated. Figure 5.12 presents student motivational aspects in participating to

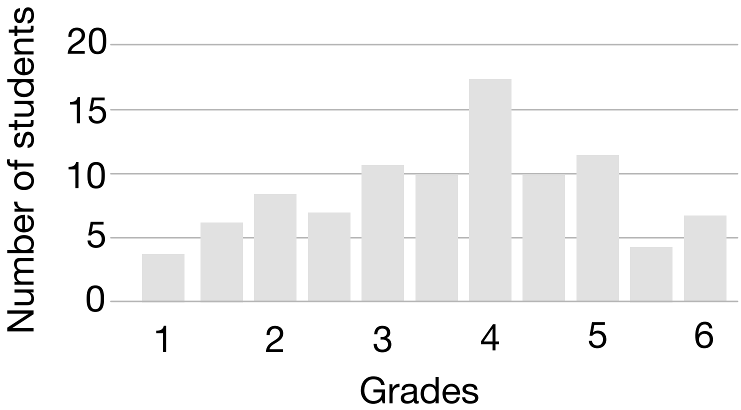

FIGURE 5.11: Distribution of raw grades. M = 3.88, SD = 1.30, N = 96.

lab sessions during week 10 to 12. The highest motivational aspect has been found to be identified regulation (M=3.93, SD=0.73), followed by the external regulation (M=3.54, SD=0.76) and then the intrinsic motivation (M=3.37, SD=0.82), with only little overall amotivation (M=2.24, SD=0.73). To evaluate

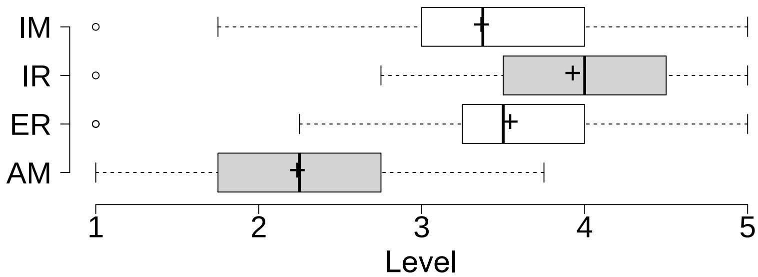

FIGURE 5.12: Student mean intrinsic motivation (IM), identified regulation (IR), external regulation (ER) and amotivation (AM), as measured by the SIMS scale, to use computational notebooks in the context of weeks 10 to 12 lab sessions.

the outcome of this research question, we performed a Path Model Analysis using SmartPLS. The Path Model Analysis aims to evaluate how the constructs of intrinsic motivation, identified regulation, external regulation, and amotivation [48] influence the students behavior on computational notebook activities. More precisely, we aim to investigate how the students behavior is influenced by motivational aspects during the lab sessions. We were particularly interested in the influence on student lab performance and on students need for help. As illustrated in Figure 5.13, coefficients of our path analysis indicate that intrinsic motivation had a significant effect ($p < 0.05$) on lab session performance (0.272). Intrinsic motivation did not have any significant influence on the need for help (i.e., hints requested). Identified regulation influenced (0.323) significantly ($p < 0.05$) students lab session performance, but not the amount of hints requested. While external regulation influenced (0.347) significantly ($p < 0.01$) the students quantity of hints requested but not the final lab session performance. Amotivation does not have any influence on students lab session performance or on the amount of hints requested.

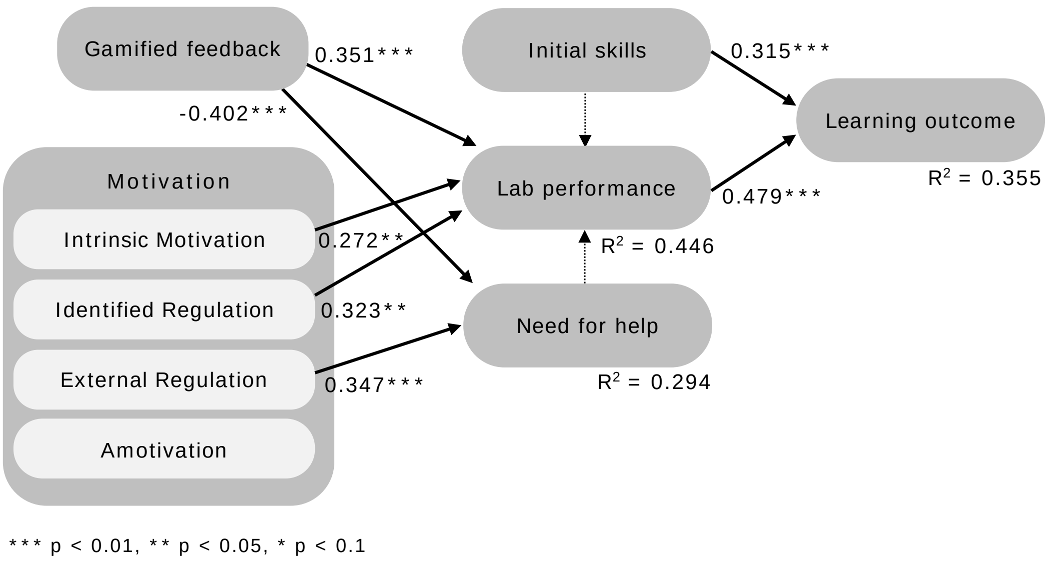

FIGURE 5.13: PLS Model results.

5.5.3 How can gamification contribute to increased engagement with a computational notebook? (RQ3)

To answer this research question we evaluate if the gamification of the lab sessions contributed to increase the lab session performance (yes) and allowed to decrease undesired behavior, in this case need for help (yes). The analysis was performed on the same subsample and the same Path Model as for RQ2 (Figure 5.13). The gamified feedback functionality was implemented as shown in Figure 5.2, rewarding students on accurate answers and penalizing them on hints revealed. A control group (N=29) was defined with no visual gamified feedback. The aim was two-fold: (1) increase lab session engagement, through scoring system and number of interactions, and (2) decrease the need for help (hints requests).

Increase lab session engagement

Figure 5.13 shows that the link between gamified feedback and lab session performance is significant ($p < 0.01$) and positive (0.351). Furthermore, gamified feedback has been found to be the most influencing construct on the lab performance, more influential than identified regulation or intrinsic motivation. Overall lab performance was predicted at 44.6%. As depicted in Figure 5.15 students receiving gamified feedback performed significantly ($t(82) = 1.82, p < 0.05$) better (M=87.6, SD=61.06) in the lab sessions than students from the control group (M=63.24, SD=51.74. The number of interactions did not vary significantly ($t(82) = 0.42, p > 0.1$) with (M=14473.24, SD=13862.91) for treatment group and (M=13128.83, SD=13329.82) for control group 5.14.

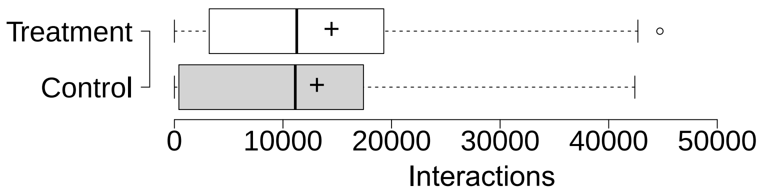

FIGURE 5.14: Lab session engagement, resulting from activity tracking on Graasp, for students with gamified feedback (treatment) versus students without gamified feedback (control).

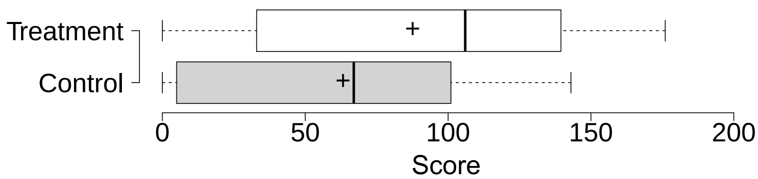

FIGURE 5.15: Lab session scores for students with gamified feedback (treatment) versus students without gamified feedback (control).

Decrease need for help

Figure 5.13 shows that the link between gamified feedback and need for help is significant ($p < 0.01$) and negative (-0.402). During the lab sessions, students receiving gamified feedback requested fewer hints (M=4.78, SD=7.73) than students from the control group (M=14.62, SD=20.82) (Figure 5.16). A Mann–Whitney test indicated that this difference is slightly significant, $U(N_{treat.} = 54,\ N_{ctrl} = 30) = 655.5, z = -1.33, p < 0.1$.

5.6 Discussion

This study provides the results of a semester-long field study with 115 non-STEM students on the use and the gamification of an innovative computational notebook environment aimed at developing CT skills. The field study

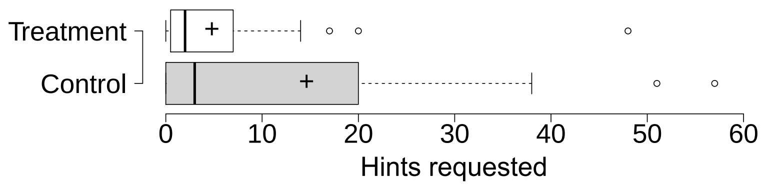

FIGURE 5.16: Need for help (i.e., hints requested) for students with gamified feedback (treatment) versus students without gamified feedback (control).

was conducted in an introductory course on information technology for first-year undergraduates in business and economics, where CT may not be seen as necessary by the students. This research assessed computational notebooks and CT skills making use of pre- and post-test surveys, learning analytics, and student-generated data from lab sessions. We showed that it is feasible and valuable to teach CT competence to non-STEM students, and that computational notebooks are an appropriate tool for introducing CT and programming to students with less technical academic backgrounds. A detailed discussion is presented below, with limitations and potential further work.

5.6.1 Computational notebooks in a distance learning context

The pre-post approach and the multifaceted pool of assessment tools that we used, allowed us to find that students gained CT skills both in terms of general problem-solving (CT score) and programming skills (Python score), as well as in terms of adopting more analytical problem-solving strategies (CT concepts). As such, this study endorses the notion that computational notebooks can support active learning scenarios for promoting CT skills in non-STEM students (RQ1). Unsurprisingly, we found that initial knowledge—operationalized with the programming scores of the pre-test—was strongly linked to the learning outcomes. Yet, this study demonstrated that self-directed lab performance was even a more important predictor to the learning outcomes. The better a student performed in the online labs, the better their final grades. Furthermore, initial knowledge was not a significant predictor of self-directed lab performance, which indicated that students were not put off by the technology.

Our analyses showed that participating in the real-time lecture was associated with an increased pass rate compared to students who chose not to attend or only had limited engagement in the live online lectures. This finding supports previous research that finds that active learning is more effective for knowledge acquisition [20]. However this finding is not completely aligned with literature claiming the importance of active learning in both live and remote learning context [73], [74]. In fact, we emit some reservations about remote offline active teaching scenarios which did not, in this context and in contrast with real-time scenarios, have links with learning outcomes. These distance teaching observations have been made in the particular context of COVID-19 in which this study took place, where in-class teaching was at that time not possible. Students could either follow the course in real-time online or watch recorded videos of the course at home. This study showed that the students pass rate of the more active students was 76%, whereas the pass rate of the less active was only 47%. It should be noted that around 32% of the students who took the exam were not engaged at all with the real-time lectures. This result should be seen in perspective with a previous preliminary study that showed around 90% of students actively following the lecture in a *physical* in-class setting [12].

This work is not without limitations. Indeed, although this study covered one course during a full semester with 115 students, the conclusions could be more generalizable if the results integrated more courses with more instructors. From the point of view of remote learning, this study was able to demonstrate the strengths of tools such as Graasp, however the measure of remote engagement is always subject to variables that cannot be easily controlled. For instance, remote engagement via videos replayed offline is potentially subject to overcounting or undercounting as a video can be viewed by a student without him or her paying attention to it. Finer-grained learning analytics and links between several dissociated learning systems (LMS, computational notebook, and video repository) could inform about such differences. It would be interesting to conduct a similar study over a longer period of time with a larger number of participants allowing the positive long-term results to be verified. Future work could investigate the added value of lectures played on replay and on what kind of scenarios, the student's learning can be supported. This is especially important with remote teaching becoming more prevalent.

Another limitation lay in the simple but innovative approach used to measure the evolution of students CT concepts. The approach was to ask participants to adopt a kind of think-aloud approach to describe how they approached the problem. The strategy used for the analysis was rudimentary (counting the frequency of keywords) and could be extended and improved in future work. This syntactic analysis of the cognitive approach to solve CT problems seemed to be an interesting line of investigation and would also deserve to be explored further. It should be noted that we first conducted an analysis using advanced lexical analysis tools, such as the software called Linguistic Inquiry and Word Count (LIWC) to extract linguistic features [75], more precisely the 2015 version of the LIWC dictionary [76]. However, such tools did not appear to generate valid results as a simple and inconsistent problem-solving strategy description such as "Yes" received a higher score than some obviously more appropriate ones such as "By trial and error". Future research making use of problem-solving reflections and interpretation of these advanced tools such as LIWC deserve, in our opinion, to be conducted further.

5.6.2 Computational notebooks motivational aspects and gamification

This study has found motivation and gamified feedback to be strong predictors of lab performance. This finding supports previous research that finds that technological platforms can provide scaffolding for CT skills acquisition in gamified settings [52]. This study has shown how various motivational aspects may influence student performance and behavior in gamified settings. The results of this research have shown that the engagement with computational notebooks is associated with student motivation (RQ2). Specifically, we found that the influences of intrinsic and extrinsic motivation were completely different: while intrinsic motivation led to better lab performance and better learning outcomes, extrinsic motivation (as understood by external regulation) decreased a student's self-regulation making them look for more hints to quickly solve the task. Moreover, this study demonstrated that gamification can contribute to increase better quality engagement with the computational notebook (RQ3). This study showed that gamified feedback influenced positively self-directed lab performance while influencing negatively unwanted behavior, such as the hints requested to complete the exercises in a quick and possibly less thoughtful way. We believe that the use of computational notebook environments such as Graasp, integrated with other applications, especially those introducing gamification, can open doors to other interesting avenues of research. The results presented in this article have already demonstrated the benefits of such a gamification approach, aligning with previous studies [51], [52] showing that the technological environment itself can successfully encourage feedback to drive CT skills learning in gamified settings. These results demonstrate that learning activity designers can encourage certain desired behaviors and at the same time discourage certain undesirable ones by using a well designed gamification mechanism. Computational notebooks environments, used in combination with multiple instruments allowing to assess students CT expertise and covering different facets of students knowledge acquisition, are clearly opening a new perspective but it still need to be further investigated further.

Unfortunately, even though the sample size was adequate for the results presented above, it was too small to assess more fine-grained group differences and interaction effects (e.g., Female vs. Male, Advanced vs. Beginners). Future research should assess whether the effects of gamification play out in a similar direction for such subgroups. It is particularly important to confirm that students with less initial knowledge or who are less inclined toward CT are not left behind or negatively affected by certain gamification features. Based on such finer grained analysis, personalized gamification mechanisms could be deployed to adequately motivate students if no one-size-fits-all mechanism is found. We believe that future research and development on more integrated computational notebooks environments would be encouraged by our results. The combination of learning analytics with real-time coding support and gamification features was central to our study. Nevertheless, most computational notebooks do not yet allow the composition of such rich learning activities. Open format and the availability of tracking data on student activities should be encouraged across the various computational notebooks environments; this would potentially open the doors to further improvements in knowledge acquisition of complex skills such as those comprising CT.

5.7 Conclusion

This paper addressed the issue of teaching CT to non-STEM students. We conducted a field study in a real classroom with 115 students using a computational notebook app as support. This study evaluated computational notebook support for non-STEM students from multiple perspectives. In order to evaluate the progression of the students in terms of competence in CT, we carried out a pre- and a post-test composed of problem-solving and programming questions. Students were also monitored during live lectures and self-directed lab sessions, allowing us to observe differences between real-time and replayed student engagement, but also influences of motivational aspects and gamified feedback on lab performance and learning outcome. We conclude by noting that computational notebooks can support active learning scenarios for promoting CT skills in non-STEM students, engagement with computational notebooks is associated with student motivation, and that gamification can contribute to better quality engagement with the computational notebook. Finally, this study underlines the importance of continuing to investigate methods to engage people with little apparent interest in CT with active learning, computational notebooks and gamification mechanisms.

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Part III

Managing data for digital support for health interventions

Chapter 6

Personalized view of Swiss Public Health Statistical Data

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Abstract

In recent years, the number of governmental initiatives and directives aiming to put more statistical data into the public domain has increased rapidly. Statistical data has become one of the most important sources of information for a wide range of stakeholders. More and more frequently, governments' statistical data is made accessible to the public through Web portals. This open access is formalized using various file formats depending on the country. In this paper, we study the case of statistical data on the determinants of health, provided by the Swiss Federal Statistical Office. Health, and more particularly public health, is one of the significant beneficiaries of government statistics. At the same time, the customization of health services and the measures taken to put the patient at the center of the process are multiplying. Why not give a generic individual more advantage of government statistics by giving them the opportunity to benefit from statistics that directly concern them? This paper presents a methodology for achieving an automated

personalized view of Swiss government statistics, offering a benchmark that could encourage personal action to improve personal health.

6.1 Introduction

In recent years, the number of governmental initiatives and directives aimed at putting more statistical data into the public domain has increased rapidly. The possibilities for offering open access data on the Internet are very varied and are continually evolving. Even if governments were capable of publishing data long before the Web was created, the linking abilities that this global network offers have decisively started a global move towards releasing government data via the Internet. The two most notable movements are probably the launch of data.gov in the USA and of data.gov.uk in the UK. Sir Tim Berners-Lee, best known as the inventor of the World Wide Web, acted as a government adviser when the UK data website, data.gov.uk, was built. Consequently, W3C standards and in particular Linked Data standards and approaches were used for publishing UK government data on the Web [1].

Although the Semantic Web and Linked Data communities encourage the use of RDF (Resource Description Framework) and Linked Data as a standardized data publication format, only a small fraction of the open data is available in RDF. Currently, most of the government's statistical data published on the Web is in the form of tabular data, such as CSV files or Excel sheets [2]. Through surveys and population surveillance activity, governments acquire exciting data statistics leveraging new knowledge of the population's health. Statistics permit summarizing, as numbers or graphical form, quantitative information about the population [3].

Health is one of the main concerns of communities and individuals. A combination of factors affect a person's health; access to and use of health care services, place of living, environment, genetics, income, education level, and even relationships with friends and family, have considerable impacts on health. These factors are known as the determinants of health. Determinants of health can be grouped into three categories: social and economic environment, physical environment, and the person's characteristics and behaviors [4].

In Switzerland, an overview of the country's health determinants is published in a report every five years. In addition to the printed and PDF versions of the report, data is available as a machine-readable spreadsheet. Even though these statistics are under government mandate and are intended to monitor population health and improve the effectiveness of policy measures, they open in our opinion, a number of opportunities of which we can take advantage. In this paper, we explore the opportunity of a personalized view of these statistics in a way that could in due time leverage engagement of the population. This paper introduces a methodology that would allow us to visualize individualized Swiss Public Health statistical data in a way that would help people to know better their own situation in comparison to other Swiss residents who have the same characteristics. This starting point, along with personalized recommendation, could lead to behavior change [5], which is one of the best health decisions we can make [6].

6.2 Proposed methodology

This paper proposes a methodology to implement a personalized view of statistical data. Based on data published by the Swiss FSO, this personalized view allows individuals to situate themselves with regard to their health determinants characteristics and behaviors. This methodology aims (1) to identify data of interest, (2) to extract a machine-readable version of this data, (3) to build a semantical understanding out of it, and finally, (4) to exploit the interlinking and structure of the data in order to achieve to a personalized and future-proof view of the data. This methodology must be understood iteratively, allowing the semantic data to evolve and allowing more and more automation at each cycle. In Switzerland, aggregated data used to establish the statistical report are published on a Web portal (http://www.portal-stat.admin.ch/ges/). The statistical data is made available to the public. Not all available data concerns characteristics and behaviors of health determinants.

A first step consists therefore in the identification and selection of such data. As the data is published as Excel spreadsheets without respecting any structure nor standard, we manually identified and selected the data of interest. On a new iteration, the detection of key concepts referring to health determinants characteristics and behaviors should be automatically detected using semantical comprehension of the Excel files. As we are starting from a proprietary machine-readable structured set of data (Excel files) that don't share a common structure, we first need to adopt such a structure to be able, in a second stage, to make links between the data. In fact, the number of tables, the number of characteristics and sub-characteristics, and the irregular format of the tables make it difficult to make this machine processable. To automate the process, a customized algorithm has to be developed. The detection of the tabular(s) data (H, D) consisting in a tuple header (H) and a tuple data (D) is the key of the algorithm. Headers can be composed of categories and subcategories, but also units of measure. The algorithm should be able to make the distinctions to understand the data correctly. Works such as Ermilov [2] present interesting inputs heading in that direction.

Once the data is extracted, we need a tool to identify the underlying concepts allowing us to make connections between the datasets. In other words, we need a tool that understands the semantics to correctly categorize the data. Given the limited scope of this project, a first domain ontology could be created manually by the understanding of the categories, as suggested in Petrou's methodology [7]. Through the next iterations, as described in Best Practices for Publishing Linked Data [8], we propose to use existing vocabularies and interoperability standards. The RDF Data Cube vocabulary [9] is a standardized vocabulary for the ontological representation of statistical data. Its design has been influenced by earlier efforts such as SCOVO and by the Statistical Data and Metadata Exchange (SDMX) data model. The RDF Data Cube vocabulary was published by the W3C Government Linked Data working group. Semantical data provides a structure to uniquely identify each characteristic, facilitate the process of making connections and makes the implementation future-proof [8], [10]. New characteristics could be integrated in further data release, and it will certainly offer new opportunities to make links even beyond our data set. Resulting data could then be part of Linked Open Data (LOD) paradigm. LOD is a set of directives and technologies thought to encourage people – and more particularly governments' data owners – to go further than just putting data on the Web by providing data such that links can be made openly by other people or machines [10]. In other words, using a world common vocabulary, understandable by the machines, permits links to be made with statistics or health topics related to our dataset.

Based on the concepts and vocabulary from the previous step, we are able to represent the selected statistical data in a way that facilitate data linking and visualization. The Semantic Web and Linked Data communities are advocating the use of RDF. RDF is a data-modeling framework for the Semantic Web technology describing resources that belong to a well-defined domain ontology. The domain ontology created in the previous step helps us in converting resulting tabular data from step 2 to RDF. Using an existing approach like the one of Sharm [11], the links between the ontological concepts and the available data should emerge.

6.3 Conclusion and future work

In this paper, we proposed a methodology for working through the Swiss Public Health Statistical Data to achieve an individualized representation of this data. We believe that providing an individualization of the statistical data will offer a synthesized and comparative view of the concerned person that could represent the first step in a behavioral change. The work on this project is in the early stages, the aim of this publication is to gather feedback and opinion of experts on the methodology proposal. The methodology is being tested in a first iteration involving multiple human interventions, we aim to automate this process as much as possible for the following iterations. Future work, also, includes implementation of the personalized view.

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Chapter 7

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Abstract

The Semantic Web can be defined as an extension of the current Web, in which data is given well-defined meaning, better-enabling computers and people to work together. Linked Data (LD) has been envisioned as an essential element for the Semantic Web, listing a set of best practices for publishing and connecting structured data on the Web. Enabling humans to interact with this data is a crucial and challenging step to bring the Semantic Web forward. In order to better understand how the Human-Computer Interaction community has contributed to this effort, this late-breaking work presents a review focusing on the ACM Special Interest Group on Computer-Human Interaction (SIGCHI) venues. Our findings show that despite LD being a topic of interest to a variety of stakeholders, there are missing possibilities for end-users to query, browse and visualize LD, underlying the need for further investigations.

7.1 Introduction

Tim Berners-Lee not only made a major contribution to the invention of the World Wide Web but also envisioned its next step: the "Web of Data". This early vision – also known as the Semantic Web – dates back to the early 2000s [1]. The Semantic Web can be defined as an extension of the current Web in which data is given well-defined meaning, better-enabling computers and people to work together. The W3C leaders pushed the Linked Data (LD) technology as an essential element for the Semantic Web. Nowadays, emerging standards, technologies and other tools are starting to turn Berners-Lee's initial vision into reality [2].

Linked Data
The term Linked Data (LD) refers to a set of best practices for publishing and connecting structured data on the Web [3]. The basic idea of LD is to apply the general architecture and fairly simple set of rules of the World Wide Web to the task of sharing structured data on global scale. Two major rules are: (1) the use of Universal Resource Identifier (URI) as identifiers for resources, (2) the use of standards such as Resource Description Framework (RDF) to provide both the resource and metadata about the resource. RDF being a family of W3C specifications, originally designed as a metadata data model and representing now the main mechanism to describe resources in the Semantic Web. LD may also be Open Data, in which case they are called Linked Open Data (LOD) making it possible to link datasets with existing one on the Web.

In the past decade, the Web of Data has raised strong interest among governments and organisations, leading to the publication of large amount of data in a machine-readable format. Only considering the Linked Open Data (LOD), more than 5.8 billion triples reside in a central connected Cloud.* Ubiquity of mobile devices, the widespread of connected devices and automatic production of LD make this amount of data grow quickly. Part of this data, such as governmental statistics, is produced for end-user consumption but making sense of such data presents huge challenges. The mass of edges linking into resources often results in information overload. Furthermore,

*https://lod-cloud.net/

querying LD with languages such as SPARQL, requires an understanding of query language's syntax and basic knowledge of data content and structure.

To unleash its full potential, it is necessary to study LD principles from a technical perspective, but it is also crucial to take a human-centered approach [4]. Human-computer Interaction (HCI) has been part of the vision from the beginning, "User Interaction and Applications" was even formally introduced into the Semantic Web framework [5], further strengthening the importance of human-centered approaches. Stakeholders should understand how to best design systems making use of LD [6] as the vision of the Web of Data is ultimately targeted towards human users. To understand what has been done and what remain to be investigated, this late-breaking work is the first step of a systematic literature review on the topic of LD interaction and it is scoped to the contributions published in ACM SIGCHI venues.†

7.2 Related Work

While the utility of LD to non-technical audiences is evident, LD also aims to be a machine-readable technology. Human uptake and consumption could therefore requires technical knowledge and understanding of the intricacies of the semantic technology stack. To overcome this hurdle, a key solution is to access LD in a consistent and legible manner, allowing non-tech savvy users to have a good understanding of its structure, to identify resources and discover new pieces of information through their links. Dadzie et al. [7] identify two main types of users, which the visualization of LD must function for: *lay-users* and *tech-users*. While several works aimed to systematically review the literature related to LD technologies, a focus on end-users is lacking. Existing literature reviews can be categorized in (1) *domain-specific* literature reviews [8]–[12] and (2) *technical-related* literature reviews [13]–[15].

7.2.1 Domain-specific literature reviews

Domain-specific literature reviews focus on specific business domains where LD is used to leverage, discover or interconnect knowledge. End-user interaction with LD is drawn in domain-specific processes, making HCI contributions little emphasized. For instance, Pinto and Parreiras [8] present a comprehensive literature review about the applications of LD in corporate

† `https://dl.acm.org/sig/sigchi`

environments, pointing out that integrating external LD leverages organizations competitive intelligence process. In health-related research, Tew et al. [9] highlight the potential of LD in term of costs and health policy improvement. Jevsikova et al. [10] establish that LD technologies can be used to support and personalize student learning processes.Other researches [11], [12], [16] studied the use of LD in digital libraries, identifying issues and barriers faced by libraries to implement LD technologies, along with motivating factors to start these projects and challenges in implementing them. Domain-specific literature reviews focus on LD consumption to improve business processes but it translates merely as machine-consumption of LD.

Lay-users. (mainstream) users who do not necessarily understand the intricacies of RDF and other Semantic Web technologies. Such users are computer literate and are able to find information through online resources and may have an interest in the data they explore, but only a fraction will have indepth domain knowledge.
Tech-users. expert users who are literate with Semantic Web and other advanced technologies, have experience in using RDF as a data format, and know how to interpret an ontological model.

7.2.2 Technical-related literature reviews

Technical-related literature reviews aim to establish the state of the art of a computer science technique enhanced with LD principles. Figueroa et al. [13] for instance evaluate the efficiency of LD use in recommender systems. Figueroa et al. [13] classify systems according to how LD contributed to the recommendations. Feitosa et al. [14] conducted a literature review focusing on the publication of LD and the techniques used to do so, finding among other things that there is empirical evidence of the benefits of using best practices such as re-use of vocabularies and use of machine-readable formats. Khalili and Auer [15] specifically evaluated the quality of semantic content authoring tools. They proposed a set of quality attributes and features facilitating the evaluation and development of these authoring tools, including aspects such as usability, automation, generalizability, collaboration, customizability and evolvability. Among technical-related literature reviews, the same conclusion persists, past studies have mainly investigated machine-consumable LD. The only exception is the Khalili and Auer [15] research that takes a user-centered usability approach, nevertheless this study focused solely on tech-users semantic content authoring tools. So far, to the best of our knowledge, despite the fact that interaction with LD has been identified as a crucial research aspect, no literature review has specifically looked at how LD has been studied from an HCI perspective including lay-users perspective.

7.3 Methodology

This work is a first step towards a comprehensive literature review of LD interaction and focus on SIGCHI published venues. This work assess how the SIGCHI community contributed to the LD research, more particularly on HCI solutions allowing end-users to discover, interact and uptake LD. The search string used in the ACM Digital Library.[‡] was: *"Linked Data" OR "Linked Open Data"* and was conducted on the 3rd of September 2018. The research questions addressed by this study are: (RQ1) Who are the end-users in SIGCHI LD research? (RQ2) What is the context in SIGCHI LD research? (RQ3) Where are the design contributions in SIGCHI LD research? and (RQ4) How is SIGCHI LD research validated? In Table 7.1, a set of inclusion and exclusion criteria is defined in order to determine whether or not a study should be included.

7.4 Results

A total of 60 papers were returned by the research request. The oldest paper dated back to 2005 while the latest one is from 2018, both mean and median publication year were 2014. Seventeen results (28.3%) were excluded according to our exclusion criteria. No journal publications appeared in the research results. Resulting in the 43 entries presented in Table 7.2. Figure 7.1 depicts the main venues among reviewed papers.

7.4.1 Who are the end-users in SIGCHI LD research?

To answer RQ1, studies were coded according to LD users presented by Dadzie et al. [7] (Table 7.3). Ten papers (23.3%) aimed to make LD accessible by lay-users. For instance, Freitas et al. [17] provide a natural language interface and an associated semantic index to support an increased level of vocabulary independency for queries over LD. Dumas et al. [18] present a

[‡]ACM Digital Library: https://dl.acm.org

tool allowing non-expert to visualising and exploring large RDF datasets. Four papers (9.3%) present novel solutions for tech-users LD interaction. For instance, Vigo et al. [19] made a attempt to understand the effectiveness of existing Semantic Web authoring tools. Four reviewed papers (9.3%) targeted a (sub-)category of users which are not necessarily expert of Semantic Web technologies, but are domain-specific experts and therefore likely to have very good understanding of data structure and content in their domain. For instance, Kotoulas et al. [20] presented a LD-based approach to access and surface information across domains of Social Care and Healthcare. Most of the reviewed papers (21 papers; 48.8%) were machine-consumption oriented, investigating for instance how LD technologies contribute to interlink datasets, enrich data or improve system recommendation. Finally four papers (9.3%) did not have specific LD end-user as they were only discussing argument such as LD future challenges [21] or current uses [22].

Inclusion criteria
Only studies published in the English language;
Only studies published in SIGCHI ACM-DL community;
Studies with the terms Linked Data or Linked Open Data;
Articles or conference papers.
Exclusion criteria
Studies not relevant to Linked Data;
Proceedings adjuncts;
Workshop, student consortium and talk papers.

TABLE 7.1: Inclusion and exclusion criteria.

7.4.2 What is the context in SIGCHI LD research?

For RQ2, we used grounded theories [60], [61] and open coding techniques, to make categories emerge, resulting in six different contexts (Table 7.4). The main topic of interest was *semantic enhancement* using LOD Cloud (22 papers; 51.2%). In semantic enhancement research, authors typically enrich data using LOD. For instance, Pellegrini [57] describe how the BBC (British Broadcasting Corporation) could improve their news production process by pulling related data from open repositories like DBpedia (the LOD version of Wikipedia). *Interlinking datasets* represented a large proportion of investigation related to LD (15 papers; 34.9%). These researches investigated for instance how to structure and standardize a dataset. As an example, Ding et al. [43] built a core accessibility dataset out of multiple data sources and

Ref.	**End-user**				**Context**						**Eval.**		**Contrib.**	
	Lay-users	*Tech-users*	*Expert-users*	*Machine*	*LD Querying*	*LD Vis.*	*LD Browsing*	*Sem. Enhanc.*	*Dataset Interl.*	*Rec. Sys.*	*Qualitative*	*Quantitative*	*Practical*	*Theoretical*
[17]	✓				✓			✓				✓	✓	✓
[23]	✓				✓			✓	✓		✓		✓	
[24]	✓					✓		✓					✓	
[25]	✓					✓		✓					✓	
[18]	✓						✓						✓	
[26]	✓						✓						✓	
[27]	✓						✓				✓		✓	
[28]	✓						✓				✓		✓	
[29]	✓				✓		✓				✓		✓	
[30]	✓						✓						✓	
[31]		✓						✓					✓	✓
[32]		✓				✓	✓				✓	✓		✓
[19]		✓			✓	✓	✓				✓			✓
[33]		✓			✓							✓	✓	✓
[34]			✓						✓				✓	
[35]			✓						✓		✓	✓	✓	
[36]			✓					✓					✓	✓
[20]			✓				✓					✓	✓	
[37]				✓					✓					✓
[38]				✓					✓				✓	
[39]				✓					✓			✓	✓	✓
[40]				✓					✓	✓	✓		✓	✓
[41]				✓				✓			✓		✓	
[42]				✓				✓					✓	
[43]				✓				✓	✓				✓	
[44]				✓				✓		✓		✓	✓	✓
[45]				✓				✓		✓		✓		✓
[46]				✓				✓		✓		✓	✓	
[47]				✓				✓		✓		✓	✓	
[48]				✓				✓		✓		✓		✓
[49]				✓				✓		✓		✓	✓	
[50]				✓				✓		✓		✓	✓	
[51]				✓				✓		✓		✓	✓	
[52]				✓				✓		✓		✓	✓	
[53]				✓				✓	✓	✓	✓		✓	
[54]				✓		✓			✓		✓		✓	✓
[55]				✓		✓			✓		✓	✓	✓	
[56]				✓				✓		✓	✓	✓		✓
[57]				✓				✓	✓				✓	✓
[58]									✓					✓
[21]									✓				✓	
[22]								✓	✓	✓				✓
[59]						✓								✓
	23.3%	9.3%	9.3%	48.8%	11.6%	16.3%	20.9%	51.2%	34.9%	30.2%	30.2%	39.5%	79.1%	41.9%

TABLE 7.2: Overview of the reviewed papers

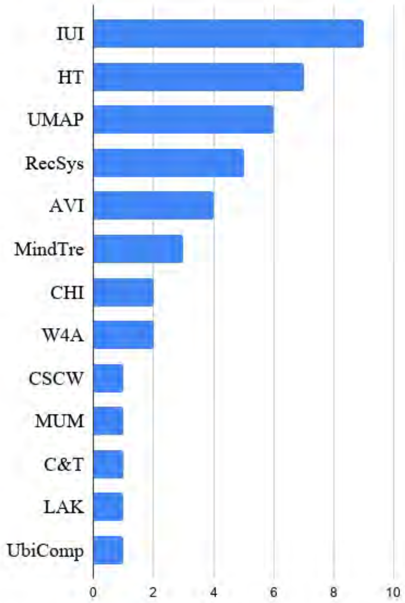

FIGURE 7.1: Publications per SIGCHI conference.

ontologies, addressing the gap between users' special needs and accessibility data. Thirteen papers (30.2%) considered the use of LD to improve the performance of *recommender systems*. For instance, Musto et al. [48] proposed a hybrid recommendation framework based on classification algorithms such as Random Forests and Naive Bayes, investigating to what extent features gathered from the LOD Cloud impact the overall accuracy of the recommendations. Nine papers (20.9%) presented *LD browsing* solutions. In such studies, researchers presented tools and approaches to assist users in exploring data and discovering relationships of a given LD dataset. Several tools, such as Rel-Finder [27], Vidax [18] and Filter-Dials [26] presented solutions to assist users in exploring LD, unfortunately such tools are not anymore maintained or even accessible. Seven papers (16.3%) made use of LD to feed or generate *LD Visualizations*. LD Visualization differs from LD Browsing as it do not directly permits to navigate through a given datasets, but it instead makes use of LD principles, such as vocabularies, to enhance existing visualizations. For instance, Burel and Cano [25] made use of LD and semantics to visually augment the knowledge presented in a Web document. Five papers (11.6%) investigated *LD querying*. These studies explored new ways of querying LD. Authors contributed with an algorithm to efficiently retrieve answers to property path queries over LD. Freitas et al. [17] worked on the semantic gap between the way users express their information needs and the representation of the data, providing a natural language interface to support queries over LD datasets.

End-user	*Theoretical*	*Practical*	*Both*
Lay-users	0	9	1
Tech-users	0	2	2
Expert-users	0	3	1
Machine	4	12	4
None	3	1	1

TABLE 7.3: Number of contributions per LD end-user.

Context	*Theoretical*	*Practical*	*Both*
LD Querying	1	2	2
LD Visualization	1	3	3
LD Browsing	2	7	0
Semantic Enhancem.	4	13	5
Dataset Interlink.	3	8	4
Recomm. System	4	7	2

TABLE 7.4: Number of contributions per context.

Evaluation	*Theoretical*	*Practical*	*Both*
No eval.	10	4	3
Qualitative	7	1	2
Quantitative	7	2	4
Both	1	2	0

TABLE 7.5: Number of contributions per evaluation.

7.4.3 Where are the design contributions in SIGCHI LD research?

To answer RQ3, we analyzed the contributions of the various articles, checking whether they contained: (1) practical implementation, (2) theoretical frameworks, models or design recommendations. Most of the research papers (34;

79.1%) described the implementation of a specific software artifact, measuring the impact of LD technologies. Only 18 (41.9%) research papers presented a theoretical model, design guidelines or a framework. On one side, studies like the one of Ding et al. [43] depict step by step, from data selection to data interlinking, the mapping approach proposed to generate a Linked Open accessibility repository. This repository being linkable to other resources on the LOD Cloud, associates geographical data to data related to travel accessibility issues. Ding et al. [43] work aims to benefit people with disabilities when travelling but also gives a concrete, practical contribution to the establishment of a LOD in the accessibility context. On the other side, there are researches like the one of Pellegrini et al. [59] or Vigo et al. [19] that introduces new theoretical concept. For instance, Pellegrini et al. [59] introduced the concept of LD Business Cube, allowing to model, visualize and analyze business models for LD assets, revenue and stakeholders.

7.4.4 How is SIGCHI LD research validated?

The type of evaluations presented in the papers (RQ4) is rather diverse (Table 7.5). The majority of reviewed papers (17 papers; 39.5%) contained no evaluation, focusing mainly on the description of the process. The remaining papers were fairly split equally between quantitative (13 papers; 30.2%) and qualitative (10 papers; 23.3%) evaluations. A few papers presented both quantitative and qualitative evaluations (3 papers; 7.0%). Quantitative evaluations focused on increased performances compared to classical approaches; for instance, Piao and Breslin [52] measured the quality of top-N recommendations comparing the ranking of relevant items between classical and LD techniques. Qualitative evaluations were interested in usability, usefulness and suitability. For instance, Paulheim and Meyer [28] measured the usability of user interfaces with 22 volunteers who had to perform different complexity tasks to then fill a questionnaire about their experience. Authors made their evaluations through observation and user feedback collection through techniques such as walk through, think aloud and debriefs. Some authors used semi-structured interviews techniques, in this case, the sample size varied from around 5 to 30 participants, often depending on the level of expertise required. Few authors made use of social networks and crowd-sourcing platforms to recruit participants, submitting them, in this case, questionnaires. None of the researches made use of control groups to validate their observation.

Context	*Lay-users*	*Tech-users*	*Expert-users*	*Machine*
LD Quer.	0.32	0.38	0.12	0.35
LD Vis.	0.06	0.29	0.14	0.18
LD Brows.	0.53	0.23	0.03	0.50
Sem. Enh.	0.12	0.17	0.17	0.40
Dataset Int.	0.29	0.23	0.10	0.16
Rec. Sys.	0.36	0.21	0.21	0.57

TABLE 7.6: Cramer's V correlation between Context and LD end-users (<0.05: no or very weak, 0.05-0.10: weak, 0.10-0.15: moderate, 0.15-0.25: strong, >0.25: very strong).

7.5 Discussion and Conclusion

This late-breaking work presented a survey on how papers from SIGCHI venues deal with LD. This review has discussed 43 papers with regard to LD end-users, context of contribution, evaluation type and contribution design.

This review revealed that in the last decade, LD in SIGCHI community research were mostly used for machine consumption. In that prospect, LD principles were mostly used by algorithm aiming to provide semantic enhancement or improve their recommendation systems. LD demonstrated to increase the performance of many of those algorithms. These studies actually represent the main source of theoretical and practical contributions, with also high rates of qualitative and quantitative validation. In comparison, little research has investigated how to best support human end-user to query, browse and visualize LD, leaving various challenges still open. For instance, allowing lay-users to filter LD relationships on multiple views [27] or normalising and creating appropriate visualisations for a specific set of RDF data [18]. Table 7.6 further confirms the weak involvement of SIGCHI community regarding LD lay-users visualization research. Furthermore, end-user oriented research rarely include artefact validation or theoretical take-aways. For instance, no theoretical contribution could be found on lay-users LD browsing. Only two studies explored lay-users LD visualization, which are furthermore not providing any kind of validation. Very few researches on lay-users LD querying have also been led, these later explored natural language solutions. Studies aiming tech- and expert-user also represent a small part of the research corpus. Domain-specific experts are likely to be major contributors to LD-based systems, however studies allowing such category of user to query, visualize and browse LD is weak to moderate (Table 7.6). Expert-users having a very good understanding of data structure and content in their domain should be given more consideration in future research. This state of the research leaves several important research questions unresolved about LD interaction usability as well as LD literacy.

This late-breaking work presents inherent limitations as the scope of the review was voluntarily limited to SIGCHI venues. Future iterations of this work are planned as the continuation of our research investigating human interactions with LD. Further iterations will look into HCI contributions coming from other communities and outlet, hopefully some existing tools or approaches could be added and confronted to the present study. This late-breaking work also opens a breach for SIGCHI researchers, inviting them to further investigate means to improve lay-users interactions with LD. For instance, technologies such as virtual reality or natural language interfaces are only minimally exploited in the LD context, these topics could potentially open up interesting avenues of further research.

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Chapter 8

Conclusion

8.1 Summary of contributions

The aim of this thesis was to better understand how digital systems can be designed to better support health behavioral interventions. In short, we conclude that digital support can contribute to health behavioral interventions when they are aligned with evidence-based guidelines, but also when implementing designs that encourage individuals to actively participate. These designs might, for example, rely on gamification, which have been shown in our research to have an influence on not just digital engagement but also on individual behavior.

In detail, we provided a study subdivided in three parts providing (1) a better understanding of digital support for health interventions, (2) designs and evaluations of digital support for health interventions, and (3) technological solutions to manage data for digital support for health interventions.

Understanding digital support for health interventions. Along that line, we assessed 99 popular smoking cessation applications and provided a deeper understanding of inherent behavioral dynamics of digital smoking cessation communities. Results demonstrated that few applications adhere to strong efficacy evidence-based health interventions or are validated by scientific research. Most of the applications also failed to provide credibility or engaging designs. Regarding digital smoking cessation communities, we believe that such communities are of great help to smokers and former smokers in general. Our findings providing support for the idea that engagement in digital smoking cessation communities is positively correlated to the process of change. Providing social support was found to be the most important motivational factor for engaging in these communities, suggesting that helping others can be an important factor in helping oneself.

Designing digital support for health intervention. In order to evaluate how digital support health interventions could be improved, we conducted two field experiments experimenting with gamified designs. Specifically, in the first experiment, we evaluated a digital escape room as a digital support for addiction prevention in schools. Such a solution encouraged students to discuss the intervention and the preventative message; it also aided in the learning of new information and altered behaviors. In the second experiment, we investigated how specific gamification designs could contribute in avoiding unwanted behaviors. This latter experiment was conducted in the context of active learning, and it was discovered that gamified feedback impacted positively on student engagement and performance while adversely affecting undesirable behavior. The gamification designs reviewed in this study were created with the goal of motivating smokers to quit and also to avoid relapsing, which sounds promising for future research.

Managing data for digital support for health interventions. In order to encourage individuals toward behavior change, we wanted to offer a starting point that could exploit the Swiss public health statistical data to provide an individualized representation of one's own situation in comparison with a population group sharing the same characteristics. Therefore, we investigated possibilities of managing the Swiss public health statistical data and the opportunities of making it intelligible and engaging for everyone. A Swiss public health statistical data management methodology and a systematic literature review investigating how to enable humans to interact with this data were undertaken. The methodology provides the steps and the underlying technologies envisioned in order to build an individualized view of Swiss public health statistical data. We believe, as suggested by Bandura's self-efficacy theory [1], that providing an individualization of the statistical data will offer a synthesized and comparative view of the concerned person which could represent the first step in a behavioral change. Consequently, W3C standards and in particular LD standards and Semantic Web approaches appear to offer a possible technical solution to achieve this individualized view of Swiss public health statistical data. Unfortunately, the subsequent literature review demonstrated that at the moment there are few possibilities for end-users to query, browse or visualize LD, underlining the need for further investigations. Enabling humans to interact with this data is a crucial and challenging step to bring the Semantic Web forward and potentially to allow the representation of oneself situation among the aggregated governmental health statistics.

8.2 Future research

Besides having provided implications for practice and contributed to the academic literature through the six studies of this thesis, this research has also resulted in the identification of various unexplored research areas. Here, we detail potential avenues of research to continue investigating the topic of digital support for health behavioral interventions. There are, in our opinion, three main avenues of research, under the umbrella of digital feedback, that are worthy of further investigation: (1) gamified feedback, (2) social feedback, and (3) feedback mediation.

Gamified feedback. On the basis of our results, we strongly believe that gamified feedback has an influence on individuals' engagement, performance and behavior. However, suggested gamified elements evaluated in an academic context in Chapter 5 need now to be tested on real case scenarios aiming to support smokers in their smoking cessation attempts. Hundreds of dedicated apps are already aiming to provide feedback to smokers in the process of quitting. But most of these applications only provide limited feedback features such as an unsmoked cigarettes counter, unsmoked days representing the number of days since the smoker quit, the number of cigarettes smoked since the installation of the app, the interval of time between two smoked cigarettes, or the reporting of cravings and urges. Additional investigations should more precisely tackle the promising, yet largely untapped, research avenue of personalized digital feedback [2]. Current literature suggests that gamification seems to hold the potential for a low-cost, highly effective solution that may supplement the behavioral support component in smoking cessation apps [3]. Nevertheless, despite gamification research repeatedly calling for more theory-driven studies, most studies in the context of health behavior change still focus on the overall effects of gamification such as engagement, motivation or participation without understanding its underpinnings [4]. Thus, the role of gamification in the process of health behavior change is still unclear since the integration of gamification with health behavior change theories needs to be explored more profoundly [4]. As shown in Chapter 2, whereas gamification has become ubiquitous and typically used in 74% of smoking cessation apps, research on the subject is not yet fully mature. Moreover, it is unclear under what circumstances such interventions are helpful, especially when it comes to gamifying peer support. While gamification encourages the engagement of individuals with a technological solution using game-style techniques and has demonstrated its efficiency in different contexts, gamification must still be carefully included in a technological solution because of its high sensitivity to the users and the context of application [5], [6]. Regarding smoking addiction, two studies investigated gamification in this specific context. El-Hilly et al. [3] found three important factors for game-engagement in the mobile health context and in the smoking cessation context in particular: (i) purpose, (ii) user alignment, and (iii) functional utility. Blok et al. [7] used different gamification strategies with unmotivated smokers in order to study the evolution of their engagement to stop smoking. The authors developed several gamified health tools and discovered that smokers prefer choosing an application according to their personal preferences (e.g., stressful vs. not stressful gamification technique). Consequently, a generic approach seems not to be recommended. We argue that innovative feedback combining personal and social levers could best match the requirements for an efficient impact on behavior.

Social feedback. Through this research, it has been demonstrated that digital social support has been identified as a potentially effective means of progress in the process of behavior change. We believe that there is a strong interest in further investigating smoking cessation online communities and exploiting their rich content to derive feedback loops applicable to any individual allowing them to situate, compare, compete and track personal progress in relation to a knowledgeable community. A common factor of many game mechanics is the reliance on data generated by individuals and their contextual peers. In that respect, social feedback would allow individuals to compare themselves to a specific community. Individuals engage in social comparisons to assess their own abilities and social standing. These social comparisons impact individuals' self-esteem, well-being, motivation and behaviors [8], [9]. Programs such as Weight Watchers have demonstrated that feedback is not the only factor working in favor of behavioral change, with the other common component being "the magic of the meeting" [10]. Group meetings have long been considered a worthwhile tool for improving behavior. Smoking cessation is no exception, with strong evidence demonstrating the efficacy of peer-support interventions [11]. Despite these principles having been known for decades, they often include entry barriers that prevent individuals from taking advantage of feedback and peer groups that would help them. Smoking log journals are examples of feedback artifacts that often fail because of the additional effort required on top of the initial behavior change commitment [10]. It might also be enough of an obstacle to get people to haul themselves to a meeting room every week. Hence, a new catalyst or mechanism to make it easier for smokers to get feedback and to gather with peers is needed. Hence, self-monitored collective data-driven learning experiences could lead to novel opportunities to engage in collective empowerment. New technologies are leveraging features such as real-time data collection, feedback and low-cost dissemination, giving individuals the opportunity to engage more fully in their healthcare decision-making, opening possibilities to improve health [12]–[14].

Feedback mediation. Chapter 6 and Chapter 7 illustrated the lack of solution to visualize and interact with a tailored view of public health statistical data. Such visualizations would potentially provide individuals with specific information about themselves, where they stand, and where they might get to, possibly encouraging a behavior change [1]. As such, the amount of public health data might be perceived as overwhelming [15]. Moreover, the individuals may not be able to interpret the information appropriately [16]. Recent research has suggested that humans and algorithms could be better than the sum of their parts and might form a mutually dependent feedback loop [17]. To support individuals in their process of behavioral change, it is particularly interesting to investigate how digital communities can transcend the online realm to bring information into the physical space. Considering the potential and the complexities of the dynamic consumer–object interaction that is not yet fully understood, we believe there might be untapped potential in ambient objects. Furthermore, advanced computers might have the potential to aggregate human- and machine- generated data and make it concise (e.g., peer support comments in online forums). Brohman et al. [18] address this by proposing mediation of the feedback. In their work, an intermediate person filters and prioritizes the information created by a computer system and ensures that the information that reaches the feedback receiver is not cognitively taxing and is easy to act upon [18]. Building on this research, further research could investigate the role that ambient objects might play in smart personalized feedback interventions. Ambient objects provide a bridge between physical and digital realms through devices situated in the living space environment allowing people to passively receive information.

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Appendix A

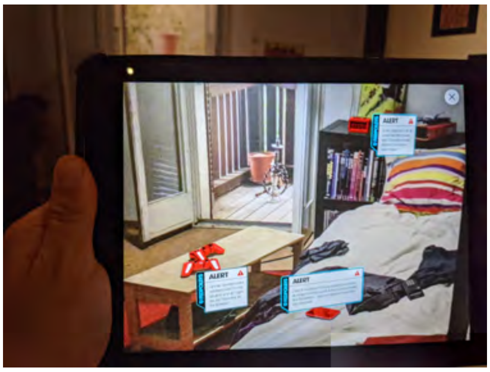
Escape Addict Complete Scenarios

Investigation 1 – Adrien This investigation tackles psychological dependencies such as that of video game addictions, sleep deprivation and energy drink consumption. The scenario indicates that the main character of the investigation, Adrien, a young teenager, has recently missed many days of school. Through the instructions transmitted through the tablet, the teams must search for objects that could relate to these strange absences. The teams search the objects using the tablet's camera. The pupils point to the different objects in the room illustrated in the standing banner (Figure A.1). The illustration contains, among other things, a computer, a game console, a smartphone, an alarm clock and some empty energy drink cans. These objects trigger informative augmented reality popups on the tablet screen (Figure A.1b). The alerts include information about video game addictions, sleep deprivation and energy drink consumption. After discovering all the suspect objects, a short quiz evaluates key information assimilation (Figure A.1c). Providing right answers allow pupils to earn some points. The investigation ends with a conclusion screen providing again all the essential information about the problematic areas tackled in the investigation.

Investigation 2 – Jordan This investigation aims to raise pupils' awareness of the risks of alcohol consumption, tobacco and cyber-bullying on social networks. When Jordan, the "suspect" of investigation 2, wakes up without memories of the previous night, he discovers some embarrassing pictures of himself on social networks. Players have to browse various videos of Jordan representing his blurry memories, to hopefully discover what happened to Jordan last night. In the first video, a 360° video, pupils have to look around them, making them aware of the many times Jordan was the target of tobacco advertising (Figure A.1d). In the following videos, pupils discover how Jordan went to a drunken party through peer pressure. At the party, Jordan abused alcohol and people at the party posted compromising photos of him on social media. Viewing snippets of memories, and thus videos, is interspersed with short quizzes that make pupils aware about their exposure to the tobacco industry, alcohol consumption risks and harassment on social networks. In the same vein as investigation 1, providing right answers to quizzes allow pupils to earn some points. This investigation also includes a digital investigation game as well a short enigma related to the content of the videos, allowing them to earn additional points.

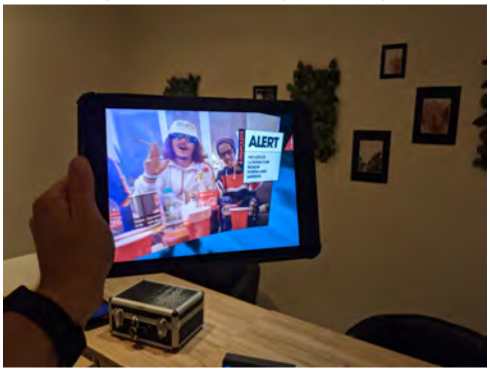
Investigation 3 – Lyse This investigation aims to raise pupils' awareness of the risks of excessive alcohol consumption, tobacco-derived products such as Shisha pipe and media manipulation specially targeting teenagers. In this investigation Lyse wakes up in the hospital after an alcoholic coma resulting from a party where she smoked a shisha pipe and indulged in excessive alcohol consumption. Pupils have to discover what has brought Lisa to the hospital by pointing and clicking on the various objects in the hospital room (Figure A.2a). Behind each objects, pupils find pieces of puzzle that will help them discover what happened to Lyse. Among the various elements, pupils' awareness is raised about data manipulation targeting teenagers, for instance edited photos in advertisements or on social media (Figure A.2b). Quizzes asking pupils to recognize edited photos or fake social media accounts allow pupils to earn points. The investigation finishes by discovering a video of Lyse's memories and quizzes about the potential risks of alcohol and tobacco-derived products.

(A) Investigations menu.



(B) Augmented reality pop-ups on the standing banner during investigation 1.

(C) Quiz during some investigation.

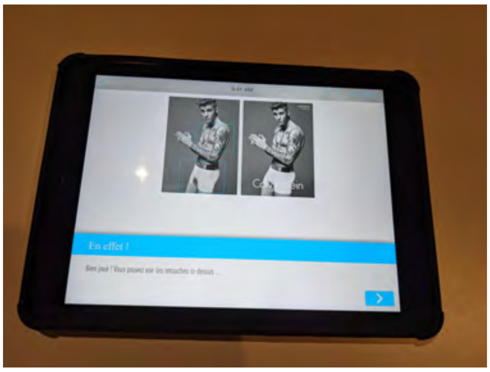


(D) 360 degrees video with popup information content.

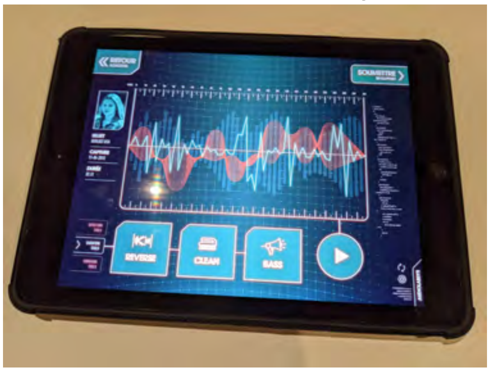
FIGURE A.1: Investigations screens capture.

Investigation 4 – Lisa This investigation aims to raise pupils' awareness of the risks of co-addiction. In this investigation pupils have to reassemble an audio message to discover why Lisa is missing so many classes (Figure A.2c). In that audio message, pupils learn that Lisa is living with an alcoholic mother which is the source of her absence. Pupils' awareness of existing services for kids suffering from the dependence of their parent is raised through various quizzes.

(A) Point and click investigation.



(B) Retouched photo targeting teenagers.



(C) Audio enigma.

(D) Final puzzle solving.

FIGURE A.2: Investigations screens capture.

Appendix B

Quantitative Survey

TABLE B.1: Survey measures and scales translated from French (*correct answers; **also accepted as correct answers as more protective from a health perspective)

type	question	answer scales	coding
Knowledge	How many packs of cigarettes does a shisha correspond to?	6-items (0: less than one, 1, 2*, 3, 4, 5 packs)	% correct answers
	Not counting internet ads, how many times a day on average is a young adult subconsciously influenced by the tobacco industry, for example through posters or ads?	5-items (1: 5 times, to 5*: 25 times)	
	Is it legal to post photos and/or videos of others on social networks?	1: no, in no case** 2: yes, but only with their prior consent* 3: yes, but only if the photo is taken in a public place 4: yes, but only if there are two or more on the picture 5: yes, in any case	
	Can social networking or video games be addictive?	1: no 2: yes, a psychological addiction* 3: yes, a physical addiction** 4: yes, a psychological and physical addiction**	
	Can a coma due to excess alcohol lead to death?	1: no 2: yes, but only with strong alcohol 3: yes, but only with the use of drugs 4: yes*	
Risk Eval.	How risky do you think it is for teenagers to do the following activities? The more boxes you check on the left, the less risky you think the activity is; the more boxes you check on the right, the more risky you think it is.	7x 11-items Likert scale (smoking, cannabis consumption, alcohol consumption, social network and internet related behaviours, video gaming) (1:low risk, 11:high risk)	1–11 7-items average scale
Behav.	In the past two weeks, have you discussed, even briefly, the topic of addictions (e.g., addiction to tobacco, alcohol, video games, or cannabis) with one or more of:	3x yes-no question (parents, friends, teachers)	0–3 diff. inter-locutors
	Have you activated the privacy settings in your various social network accounts?	1: yes 2: yes, for some networks 3: no 4: I don't know 5: I don't have an account on social networks	activated = 1
	In general, how many days a week do you play video games on a computer, console or smartphone?	8-items Likert scale (0: 0, 7: 7)	min./week
	During the days you play video games on your computer, console, or smartphone, how long on average do you play?	text input	
EA Exp.	How much did you enjoy Escape Addict?	7-items Likert scale (1: did not enjoy at all, to 7: enjoyed a lot)	1–7 scale
	Did the situations presented in Escape Addict seem realistic?	7-items Likert scale (1: no at all realistic, to 7: very realistic)	1–7 scale
	How involved did you feel in the discussions within your team during Escape Addict?	7-items Likert scale (1: no at all, to 7: a lot)	1–7 scale
	How much do you feel that Escape Addict has helped you gain new knowledge?	7-items Likert scale (1: very little, to 7: a lot)	1–7 scale
	Have you talked about Escape Addict with one or more of:	3x yes-no question (parents, friends, teachers)	0–3 diff. inter-locutors
Gender	You are?	1: a girl, or 2: a boy	girl=1, boy=2
Educ. Achiev.	What is your level in math?	0: basic, or 1: advanced	0-4 scale
	What is your level in French?	0: basic, or 1: advanced	
	What is your level in German?	0: basic, or 1: advanced	
	What is your level in science?	0: basic, or 1: advanced	

Appendix C

Qualitative Interview Guide translated from French

The questionnaire has evolved. This is the final version. The probing questions are in italic.

Introduction

I am evaluating Escape Addict (EA), the escape room you took part in last Thursday, to see if it is an interesting approach to talking about addiction. I am interested in learning about your EA experience. Did you take part last Thursday?

This interview is confidential. No-one except me will know what you have said in this interview; your name will not appear in my report and I will exclude anything that might identify you. You can speak completely freely. Once the project is finished, I will also delete the file with the names of the people who were interviewed.

May I record the conversation? This will allow me to listen to it again when I write the report. The audio file will be deleted as soon as the project is finished.

You are under no obligation to answer the questions, and you can always drop out of the interview and return to class.

Before Escape Addict

1. When did you know you were going to participate in EA?
    1.1 *Had you heard about it before? Where from?*

2. What did you know about EA before you took part?
3. Did you have any expectations? Or fears?

During Escape Addict

4. Can you describe your experience during Escape Addict?
   4.1 *How did you feel?*
   4.2 *Can you describe your involvement during EA?*
5. What did you think of the group dynamic?
   5.1 *How were decisions made within the team?*
      5.1.1 *How much did you discuss decisions before they were made?*
      5.1.2 *Was there a team leader?*
      5.1.3 *What was discussed in general?*
      5.1.4 *What topic did you discuss the most within the team?*
   5.2 *Did you feel left out of the group's decisions? Why?*
   5.3 *Did you get the impression that other people in the group were being left out? Why?*
   5.4 *What was the role of your team in shaping your experience and your understanding of the game and the messages?*
      5.4.1 *What was the size of your team?*
      5.4.2 *What do you think about the size of your team?*
      5.4.3 *How many boys/girls?*
6. What did you think about the facilitator's role?
7. What motivated you in the game?
   7.1 *The puzzles themselves? The content? Gamification elements (competition, rewards, etc.)?*
8. Did you have any difficulties? What were they?
   8.1 *Understanding the questions?*
9. What did you appreciate? And what did you appreciate less?

10. What was your experience of the debrief?

    10.1 *What was your state of mind and your motivation at that time?*

    10.2 *How useful was it?*

11. Do you have any particular events you would like to mention within your team or class during or after Escape Addict?

After Escape Addict

12. Did you talk about EA with your friends? Your parents? Your teachers?

    12.1 *What did you discuss?*

13. What key messages did you take from EA?

    13.1 *Which puzzle struck you the most? What was it talking about?*

    13.2 *Who had the tablet at that time?*

    13.3 *What did you do with the flyer you received? Did you show it to your parents?*

    13.4 *What is the best way of giving you lasting information which you can use in the future and will not just get rid of?*

14. Did EA change anything for you?

    14.1 *Consumption, beliefs, representations?*

15. Do you think EA could be useful? In what ways?

16. Would you like to suggest any improvements?

    16.1 *Animation*

    16.2 *Gameplay*

    16.3 *Debrief*

    16.4 *Questions (complexity vs simplicity)*

Pupil's behaviors and perceptions

17. Do your parents sometimes try to discuss the subject of addiction with you?

    17.1 *How does that go? How do you react?*

    17.2 *If it does not go well,, why not?*

18. What do you think about:
    18.1 Tobacco addiction?
        18.1.1 *Smokers*?
        18.1.2 *Why do you think young people start smoking?*
    18.2 Video games?
    18.3 Social media?
    18.4 Alcohol?
19. In your life so far, have you ever:
    19.1 Smoked a whole cigarette?
    19.2 Had one whole glass or more of alcohol on one occasion (e.g. in one evening)?
    19.3 Smoked cannabis?
20. During weekdays, how many hours per day do you play video games? How about at weekends?
21. How many times per day do you go online to post, like, comment, or just read social media posts?

End

22. Which class level are you in? maths, French, German, sciences
23. Do you have any other comments or feedback?

Thank you!