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Implementing data-driven systems for work and health: The role of incentives in the use of physiolytics

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Stefan Stepanovic

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1. Introduction

Digitalization is a prevalent aim amongst organizations, a key target for many managers in industries, a main focus for policymakers and a strong driver in scientific research (Erkut 2020; Hansen et al. 2018). New information and communication technologies represent assets that can improve organizational processes and performance, while transforming the environment in which they operate (Kuusisto 2017). Acquiring knowledge on how digitalization is facilitated in organizations is therefore a central (and recurring) objective for all these parties, because it offers possibilities to develop positive strategies that can translate to practice.

While the *first wave* of digitalization mainly entailed task automation and digital communication, the last two decades mark the emergence of a *second wave* of digitalization in organizations, with the introduction of technologies based on data analytics and internet of things (Meuer et al. 2019). Such digitalization is defined by the implementation of information systems (IS) that are able (1) to increase organizational capacities to gather, store, and analyze information, as well as (2) to provide an interconnected infrastructure to advance organizations' processes and services (Wortmann and Flüchter 2015). However, the implementation of these data-driven systems in organizations sets new challenges at all management levels. Typically, at an individual level, issues may arise regarding the capacity for employees to convert information into solutions. Likewise, at an organizational level, huge growth in personal data may amplify privacy concerns and impact organizational culture (McAfee et al. 2012). For these reasons, there is a need to further refine how digitalization is apprehended by organizations, policymakers and researchers to critically integrate practical and social issues associated with data-driven systems (Newell and Marabelli 2015).

This dissertation proposes the study of an IS - physiolytics - that is implemented by organizations for its promises in terms of data analytics, and the study of a new phenomenon - incentives - that appears with physiolytics' implementation. Physiolytics are wearable devices with sensors (e.g., smartwatches, connected wristbands) that collect physical and biological data to advise individuals about their physiological state (Wilson 2013). Originally designed for an individual use in leisure time, these systems have started to emerge in organizational settings, mainly as part of occupational health programs and data-driven health insurance plans. In fact, organizations have begun to include physiolytics in their business plans in order to offer a new model of health self-management to their employees/customers, while also creating a novel and unprecedented source of individual data collection (Neff and Nafus 2016; Soliño-Fernandez et al. 2019). Yet, the prerequisite for the implementation of physiolytics in organizational settings is that individuals voluntarily engage in the use and eventually share their information (Seiferth and Schaarschmidt 2020). Because collected data may be considered as sensitive and highly personal, individuals cannot be complied to use these systems in any non-clinical organizational context (Dinev et al. 2013; Yassaee and Mettler 2017a). In fact, data protection laws in most industrialized countries impede a unilateral collection of personal information (e.g., the *Federal Data Protection Legislation (2019)* in Switzerland or the *General Data Protection Regulation (2016)* for the European Union). They also provide strong frameworks when personal data can be collected, require a form of consent from individuals, and involve strict confidentiality rules whenever an entity has accessed personal data (Ajana 2020). Individual motivation regarding the use of physiolytics in organizational settings is therefore determinant: benefits for both individuals and organizations are dependent to the extent to which users adopt and use the systems.

In order to promote the use of such systems, organizations mostly rely on incentives. These incentives may take the form of enhanced feedback loops (Rabbi et al. 2015), badges (Hamari 2017), financial retributions (Henkel et al. 2018) or modifications of the environment (Gomez-Carmona and Casado-Mansilla 2017). Developed in parallel with the devices, incentives serve organizations' objectives by changing individual perceptions of the IS, but also by affecting individual practices and modifying workplace environments. Although it is a standard practice to incorporate incentives into physiolytics-centered organizational programs, there is little evidence of their overall role and influence. This is an important issue because these incentives may blunder the frontiers between what is voluntary and what is not (Ajana 2020). They may push individuals to consent to greater data sharing, coerce them to participate for other motives than individual health purposes or expose them to management/peer pressure. Put differently, incentives modify the relationship between organizations and individuals: individuals, that do not have inner motivation to participate in such programs, may engage due to proposed incentives. Incentives hence participate to increase an asymmetry in the *power relation* between organizations and individuals, giving organizations additional leverages to prompt individuals to do what they expect (following Foucault (1982), all the actions in the society have strategies and intents attached to them and institutions, by essence, aim to standardize individuals' behaviors with their interests, thus generating power relations). For these reasons, scholars call to critically engage in the study of physiolytics-centered organizational programs (Meyer et al. 2020; Miele and Tirabeni 2020).

Against this context, this dissertation raises the following overarching question:

RQ. How can incentives influence users in physiolytics-centered organizational programs?

To answer this question, this dissertation takes a critical realist perspective. The objective is to apprehend in which circumstances incentives are used and when they have an influence on individual behaviors. Therefore, this dissertation aims to consider incentives as a generative mechanism, rather than stick with only one particular instance of incentive (e.g., financial retribution) and theorize around it. In other words, this dissertation seeks to look at the properties of incentives that have an influence in the context of physiolytics in organizational settings. These properties are the qualities that an incentive has to possess to exert influence on individuals. Certainly, user characteristics, such as personality (e.g., technology-savvy versus technology skeptics) and demographics (e.g., age barrier) might have an outcome on the role of the incentives, but the objective is to adopt a higher perspective, to abstract elements and to isolate features that are observed in most incentives that are used by organizations (Kim 2020). In this line of thought, this dissertation serves as a qualitative theory development application and properties of incentives constitute a meta-framework. They form a knowledge base that structures problem-solving approaches (Armstrong 2019; Sayer 2004), and contributes to helping actors confronted with the complexity of affecting individual use (Bygstad et al. 2016). Through this approach, parties involved in digitalization may gain precise insights on how to deal with the implementation of data-driven systems such as physiolytics (which are emblematic of upcoming digital transformations in organizations). It may consequently help these actors to position themselves, increasingly, in anticipating challenges of digital evolution rather than reacting to them.

In practical terms, this dissertation is divided into two phases: an exploratory phase and an explanatory phase. The exploratory phase serves to detect and map out how incentives manifest in organizational settings. The explanatory phase seeks to focus on the main manifestations of incentives in organizational settings and analyze under what conditions they may influence individual motivation. After retroduction, the nature and the main properties of incentives in organizations are discussed. Then, derived implications for individuals, organizations, policymakers and scientific research are presented. Finally, limitations and opportunities for further research are provided.

2. Foundations

2.1 The emergence of physiolytics

It has become common for individuals in western societies to gather data and information to better understand their health levels (Lupton 2016). Sleep cycles, physical activities or vital signs can nowadays be monitored through systems that use machine-learning algorithms to gather behavioral, physical or environmental data and correspondingly generate feedback (Lee 2014; Patel et al. 2015; Swan 2013). Such pursuit of introspection through the collection of personal metrics is generally referred to as *the quantified self movement* (Sharon 2017). It builds upon the conviction that individual health progress can be obtained through an aggregation of individual data, as they may allow a new form of self-improvement, self-experimentation and growth of personal autonomy (Bode and Kristensen 2016). The development of this phenomenon is closely linked to the uprise of personal technology in the consumer market and, specifically, to the development of wearable health devices (Swan 2012). As displayed in *Figure 1*, wearable health devices have known a steady evolution since the 2010's. This has been mainly enabled by an improved accuracy of sensors, an efficient miniaturization of systems, an automatization in gathering and stocking collected data as well as an enhanced accessibility in terms of costs and use (Lavallière et al. 2016; Stepanovic et al. 2019a). Far from simple instruments which provide identifiable and single measurements (only accessible for the user), consumers have now access to newer generations of connected systems. These are able to measure numerous health variables and to process large amounts of data. Then, based on collected information, they manage to provide some automated analyses. Individual behaviors therefore become perceptible and visible through a series of indicators, numerical evidence and statistics (Ruckenstein 2014). A new type of personal information is then produced, which can be tailored and personalized to the needs of individuals, thus fueling the development of the quantified self movement (Lupton 2016).

These newer generations of complex wearable health systems can be referred to as *physiolytics* (for clarity purposes, this dissertation will essentially employ this term). Following Wilson (2013), physiolytics describe wearable health systems that are able to automatically gather personal data to provide quantified feedback and assist with algorithm decision-making.

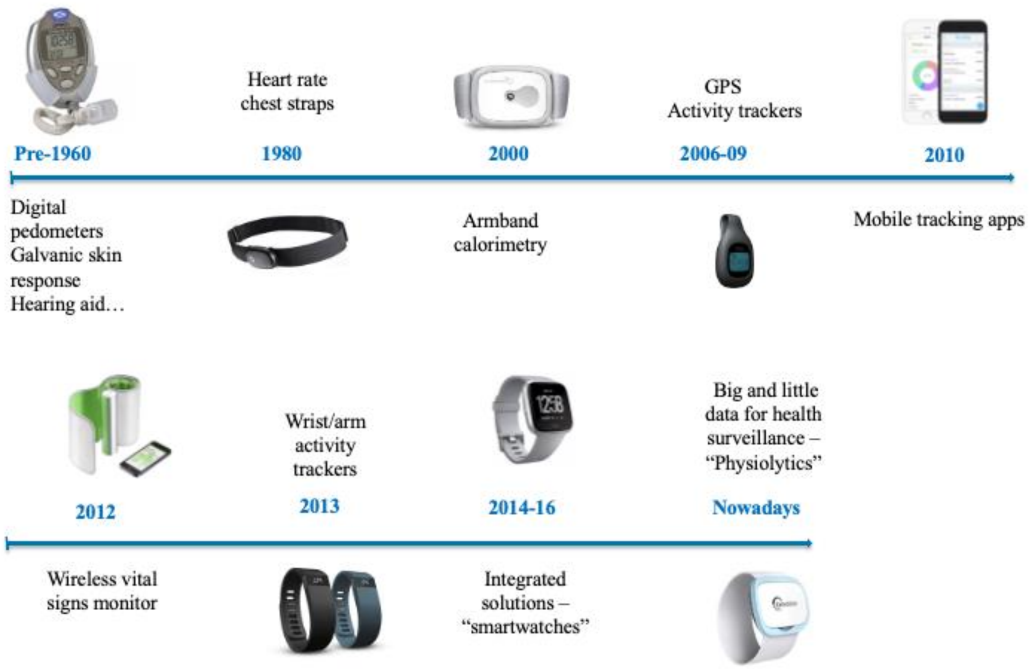

Figure 1. Evolution of wearable health devices, adapted from Kurzweil (2013); Valencell (2016) and Edwards (2018).

The practice of producing, aggregating and disseminating personal information via physiolytics has also drawn large interest from organizations (Swan 2013). Outside of traditional medical contexts, where physiolytics add up to the existent tools for disease management and assisted care (e.g. better monitoring of biological parameters (Brown et al. 2017), elaboration of treatment scenarios (Costa Figueiredo et al. 2017) or medication intake control (Goold 2019)); many other organizations have started to consider the implementation of these devices in non-clinical contexts. Private firms, health insurance companies, public services or the military are particularly taking a close look on the potential of these systems (Lupton 2014). They notably see value in the data that arises from these systems: collected information is considered as a means of appreciating, after aggregation, health characteristics of a population as well as its economic and productivity traits (Ajana 2017; Ajana 2020; Lupton and Michael 2017). Surely, for organizations, physiolytics devices also constitute a renewed potential of self-improvement for their employees or customers. Nonetheless, the real game changer lies in the novel opportunity for systematic monitoring approach (Ajana 2017; Tedesco et al. 2017). As a matter of fact, physiolytics offer new horizons in data collection: organizations may gather a high volume and high variety of information about individual lives that were formerly unapproachable (Neff and Nafus 2016; Soliño-Fernandez et al. 2019). This means that they are in position to create more tailored programs to fulfill their organizational objectives. For instance, firms are taking advantage of physiolytics to create digital occupational health programs centered around these systems. They see opportunities, through this technology, to handle some practical health-related challenges at the workplace, such as managing stress among employees or promoting physical activities (Buchwald et al. 2015; Gorm 2017; Mettler and Wulf 2019; Yassaee and Mettler 2017b). They also perceive potential benefits on an organizational level, notably in an effort to lower the cost of absenteeism due to sickness (Lupton 2014) and ensure better performance management (Swan 2013). Thus, many big corporations, such IBM or SAP, have already invested in this technology. Reports estimate that circa 75 million wearable health devices will be distributed by the end of 2020 within work settings (Swinhoe 2018).

On a similar note, health insurance companies are massively integrating physiolytics into their business plans. They are creating data-driven health plans, centered around physiolytics, with the assumption that individuals will be willing to subscribe under acceptable economic, data privacy and technical circumstances (Soliño-Fernandez et al. 2019). Benefits are typically given to users who connect physiolytics to companies' app and share their data. Even more than for firms, collected information could assist health insurance companies to realize most of their organizational goals, such as a general monitoring of health levels among their subscribers; the creation of more tailored insurance products or an expansion of their field of activity (Henkel et al. 2018; Lewalle 2006; Samuel and Connolly 2015; Stepanovic and Mettler 2020; Tedesco et al. 2017) [1].

2.2 Conceptualizing the use of physiolytics in organizations and the role of incentives

Engaging in a quantified-self practice within an organizational program certainly entails different dynamics than physiolytics use in private settings. Following Lupton (2014), the use of physiolytics in organizational settings can be considered as a *pushed quantified self practice*, since the engagement in the use of physiolytics is impulsed by a third entity. Even if the use is voluntary, individuals engage in the use because they are provided with this particular opportunity, in this particular context. It opposes private use, where the use of physiolytics is self-initiated and undertaken for purely personal reasons. Plus, for individuals, tensions may arise if they perceive that such programs engender a loss of privacy and control towards the

[1] In this dissertation, the phenomenon under research is *using physiolytics* and all the individuals have equal access to these systems, regardless of whether they own their device or not. In fact, in digital occupational health programs, these devices are often distributed while in data-driven health plans, they are already owned by clients.

organizational structure. In particular, there may be a fear that organizations start to classify individuals regarding their behavior and ultimately discriminate between elements that are considered as *good* and *bad* (Constantiou and Kallinikos 2015; Mettler and Wulf 2020).

IS research has started to shed some light on these issues, by notably investigating ethical and privacy concerns. In workplace settings, research has considered individual perception on the management of personal information (Spiller et al. 2018), privacy perceptions and mental burdens (Li et al. 2016; Marcengo and Rapp 2016; Yassaee and Mettler 2017b), acceptability and scalability of physiolytics interventions (Lavallière et al. 2016), mental models of employees who are faced with the introduction of physiolytics (Mettler and Wulf 2019) and the perception of barriers to the adoption of such technology at work (Schall Jr et al. 2018). A similar approach may be found for data-driven health plans, with some early work on the disposition to disclose health data to health insurance companies (Paluch and Tuzovic 2019; Patterson 2013; Von Entreß-Fürsteneck et al. 2019). In any case, the prevailing approach for organizations to lessen these eventual concerns and increase participation is to introduce incentives. These may take the form of monetary retributions (Henkel et al. 2018; Paluch and Tuzovic 2019; Tedesco et al. 2017), fun elements (Gorm and Shklovski 2016; Suh et al. 2017), symbolic rewards (Wu and Paluck 2018; Zuckerman and Gal-Oz 2014) or modifications of the work environment (Gomez-Carmona and Casado-Mansilla 2017). In this regard, incentives may be understood as mechanisms that seek to spur individual motivation to adopt a behavior that is line with organizational expectations and goals (Burton-Jones and Grange 2012; Chung et al. 2017; Stajkovic and Luthans 2001), by increasing satisfaction, inner interest (i.e. intrinsic motivation) and/or social approval, recognition or monetary benefits (i.e. extrinsic motivation) (Bandura 2004; Brinson 2017). They therefore serve to align interests of a collection of individuals with the interest of the structure that provides the incentive (Raduescu and Heales 2005).

Traditionally, in the IS field, influences on individual behavior regarding IS use are framed within behavioral theories, such as the *Technology Acceptance Model* (Davis 1989), the *Expectation-Confirmation Model* (Bhattacherjee 2001), or the *Unified Theory of Acceptance and Use of Technology (Venkatesh et al. 2003).* These frameworks propose rather static, technocentric and deterministic views of behavioral intention: few variables that relate to the design of the device (e.g. perceived usefulness, perceived ease of use) determine the degree of individual use (Awa et al. 2016). Although very valuable, it is essential to complement such views with more social and psychological perspectives in order to dissect incentive mechanisms, which may not necessarily rely on the IS artefact. For that matter, the *Social Cognitive Theory*

(Bandura 2001) and the *Self-Determination Theory* (Ryan and Deci 2000) offer theoretical frameworks that are less oriented toward technological artefacts (Carillo 2010), provide a strong focus on motivation and particularly emphasize the role of social and environmental factors in the influence of personal dispositions and use behavior (Ambrose and Chiravuri 2010; Hoffmann et al. 2015; Villalobos-Zúñiga and Cherubini 2020). First, Social Cognitive Theory can be defined as a conceptual structure that explores human motivation, thoughts and structure (Bandura 1986), with an accent on an interactive archetype of causation in which cognitive determinants, behavioral features and environmental factors all influence each other (Bandura 2001). When analyzing use behaviors regarding physiolytics, this theory largely emphasizes two internal concepts: *self-regulation* and *self-efficacy* (Zhang and Lowry 2015). Self-efficacy corresponds to the conviction of an individual in its capacity to execute a behavior and self-regulation to its capability in terms of self-control and decision making to sustain the behavior (Kooiman et al. 2020; Schunk and DiBenedetto 2020). Hence, following this approach, engaging in quantified self practices is a matter of individual expectations building on these different groups of factors. An individual subjectively develops an expectation of how he can succeed in being physically active, and for instance, a positive environment (e.g. social support from the family) promotes his positive expectation regarding his health behavior change (Anderson-Bill et al. 2011). While this is certainly appropriate for private settings; in organizational settings, with incentives, the use of physiolytics may obey to a reverse effect: environmental factors may mainly determine the response to the behavior and affect the likelihood of sustaining the behavior (Lamorte 2016). In that regard, Self-Determination Theory allows a more granulated view of what constitutes these environmental factors that influence individual behavioral intention. This approach precisely characterizes external conditions (i.e., extrinsic motivators) that regulate individual behavior. Specifically, Self-Determination Theory posits that individuals engage in action based on intrinsic motivation and extrinsic motivation (Ryan and Deci 2000). Intrinsic motivation is linked to the state in which an individual does an action for the joy or the satisfaction derived from the activity itself, while extrinsic motivation refers to the state in which a person primarily performs an action because of external outcomes, such as rewards or social pressure (Ryan and Deci 2000). Additionally, this theory posits that several types of extrinsic motivation exist, depending on the propensity of volition and choice linked to the behavior. These different types can be placed on a continuum (*see Figure 2)*, going from a high self-determined behavior to a low self-determined behavior and even a complete non-self-determined behavior (amotivation). Precisely, a high self-determined behavior is linked to integrated and identified regulations of behavior and appeal to the individual himself.

Integrated regulation implies that the individual is in complete synthesis with himself regarding the behavior and that this behavior is congruent with his beliefs. It is almost intrinsic motivation, with the difference being that internalized goals originate from an external source rather than the self. Identified regulations refer to an individual who has internally accepted the importance of a goal. He identifies that such behavior is important, valuable and beneficial. Introjected behavior is a behavior driven by external demand: it does not come from the individual and individuals comply because of sense of obligation, external standards of self-worth or social approval. Finally, external regulation is a behavior that is fundamentally motivated by a form of reward (social, material) or, conversely, driven to prevent punishment. This behavior is enacted, but the individual does not share an interest to engage in the behavior for the sake of the behavior.

Ryan and Deci (2000) consider that creating and sustaining intrinsic motivation should be the primary objective for every intervention, as intrinsic motivation corresponds to an inherent motivation that is believed to be more qualitative and thus sustainable. In that regard, extrinsic motivators such as incentives serve to prompt an initial action or behavior change, but, in the long run, a form of intrinsic motivation has to be generated (Gagné and Deci 2005; Lohmann et al. 2018). To do so, incentives should particularly aim to satisfy contextual conditions of three basic psychological needs that are related to intrinsic motivation: autonomy, competence and relatedness. Autonomy, as mentioned above, refers to the degree that the behavior comes from the individual himself. Competence constitutes the perceived capacity of an individual that he can do a behavior, with control, mastery and efficacy. Finally, relatedness is associated with the connection that an individual has by doing the behavior with others and community (Martela and Riekki 2018).

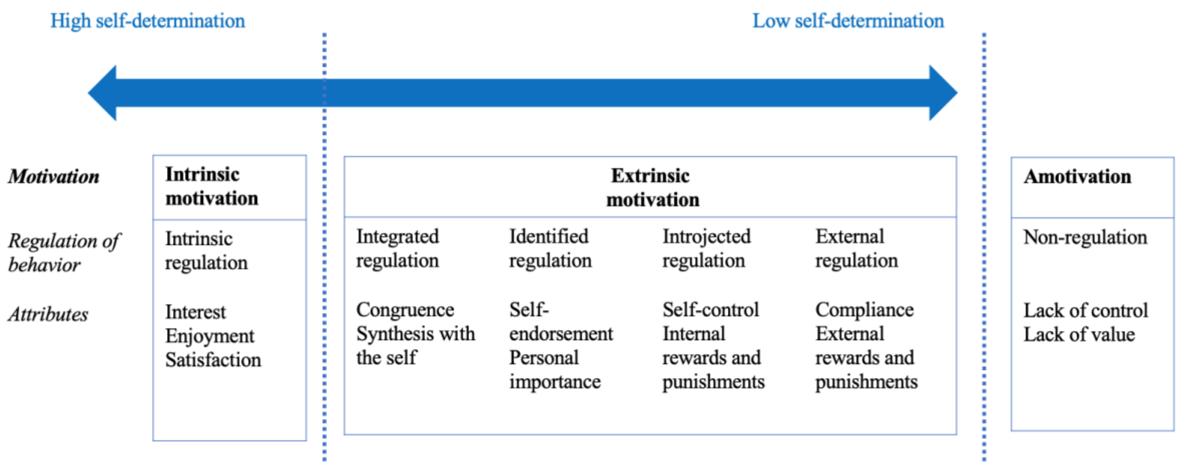

Figure 2. The self-determination continuum, adapted from (Ryan and Deci 2000).

3. Research approach

3.1 Research aim

This dissertation focuses on the role of incentives in a *pushed quantified self practice*. It aims to uncover how these incentives materialize as well as to better understand the conditions in which incentives might be accepted and integrated by individuals, thus influencing their use of physiolytics. In this respect, this research seeks to address a real-world problem that appears with the emergence of physiolytics-centered organizational programs: organizations attempt to promote participation in order to have a return on investment. This dissertation therefore aims to build a general knowledge regarding these incentives, in order to help individuals to recognize challenges linked to participation in physiolytics-centered organizational programs, assist organizations in creating incentives and guiding policymakers in identifying new social issues that appear with this form of digitalization in organizations. Regarding IS research, this dissertation seeks to illustrate how incentives position themselves in relation to individual IS use.

The following sections detail the research paradigm, the research questions and research context related to this dissertation.

3.2 Research paradigm

The focus of this research is a mechanism at the interplay of organizations and individuals, located in a particular context. Put differently, the challenge is not a technological issue per se. Therefore, defining the research paradigm is useful, as it helps to delineate the scope of both requirements and contributions of the study (Teddlie and Tashakkori 2010). In that regard, this dissertation follows a critical realist perspective, aiming to understand the generative mechanism behind incentives in physiolytics-centered organizational programs. In a critical research approach, reality exists independently of individual perception and cognition: it is a stratified reality (Vincent and O'Mahoney 2018; Wynn Jr and Williams 2012). Accordingly, there is first the *real domain,* composed of structures and entities that possess abilities to independently exert causal power (called generative mechanisms). Then, there is the *actual domain*, which is a division of the real domain, that involves an enactment of the structures and the entities (regardless of the fact that they are perceived or not by humans). Finally, the *empirical domain* consists of events, occurrences or outcomes that can be observable and measurable.

While positivist and interpretative approaches mostly concentrate on the empirical domain (and thus give a preponderant importance to events), critical realism is more focused on identifying and highlighting mechanisms that generate these events (Tsang 2014; Wynn Jr and Williams 2012). Therefore, a critical realist approach is particularly suitable for this dissertation because it allows a better conception of how user behaviors are part of relations between structures (*see Figure 3*). It notably underlines how an entity, such as an organization, has the power to activate a mechanism through incentives to influence participation in physiolytics-centered organizational programs. As a matter of fact, even if the event *participation in a physiolytics-centered program* does not occur (or does occur without the need for an incentive); organizations have nevertheless the power to generate such occurrences. Also, the absence of participation in programs centered physiolytics does not automatically mean that the underlying mechanism does not exist (Tsang 2014): it exists as a mechanism in the real domain and may, for some individuals, concretize and induce a participation in physiolytics-centered organizational programs. In sum, through this lens, this dissertation seeks to "zoom out" and not only focus on a particular expression of one particular incentive (e.g. badges or monetary contributions) to then describe it in theoretical terms. Rather, it seeks to gather a wider comprehension of how incentives take part in the organizational context and in what circumstances they exert power on individuals.

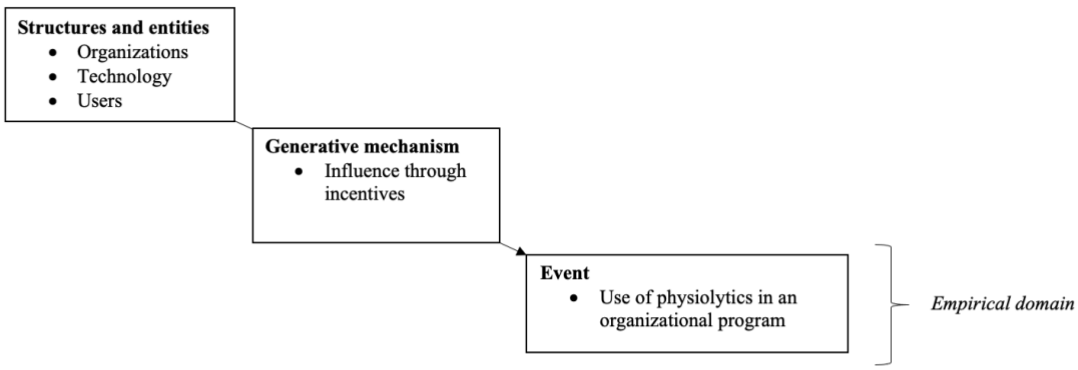

Figure 3. Conceptual schema of incentives.

Because a critical realist approach serves to distinguish mechanisms, there is no emphasis on prediction and cause-effect relations (Vincent and O'Mahoney 2018; Wynn Jr and Williams 2012). The idea is to identify the properties of a mechanism in a given context. This is typically done by means of explorations of empirically observable elements and case studies (Fletcher 2017; Tsang 2014; Williams and Wynn Jr 2018). They serve as a foundation from which the researcher seeks to derive appropriate explanations (i.e., retroduction). From an epistemological point of view, critical realism is thus flexible and there is no prioritization between quantitative and qualitative methods (*see Table 1*). The research question and the evolution in the research procedure suggest the appropriate methods to follow (Fletcher 2017; Sousa 2010). In the same vein, theory may serve as a starting point, but it should not lead the course of the research, as theory (from a critical realist perspective) is never totally proven in the social world (Keegan et al. 2014). Nonetheless, the framework of Self-Determination Theory and a critical realist stance align in the sense that they both emphasize environmental and contextual factors. Importance is given on how individuals create meaning from their experiences and how this meaning is influenced by the social environment (Braun and Clarke 2006; Yin 2013). It therefore supports the researcher in building a first critical investigation of how incentives deploy as a mechanism in physiolytics-centered organizational programs.

In sum, adopting a critical realist view indicates a will to critically analyze social challenges in order to build knowledge. This knowledge then serves to produce recommendations for action and policy guidance on the identified issues (Armstrong 2019; Fletcher 2017). These recommendations and guidelines may, per definition, also be fallible and not produce identical outcomes in other contexts, yet they assuredly contribute to illustrating the interplay of different tendencies and causal mechanisms (Fletcher 2017).

	Critical realist approach
Ontology	Stratified reality. Reality exists but is only partially apprehended. Influence of incentives as a mechanism.
Epistemology	Modified subjectivity. Emphasis on description and explanation.
Methodology	Both qualitative and quantitative. Linking empirical evidence and abstract conceptualization. Relevant incentives are identified, analyzed and properties are revealed through retroduction.
Goal	Explaining a phenomenon (influence of incentives) that arises in a context (organizational settings).

Table 1. Outline of the research paradigm, adapted from (Sorrell 2018; Sousa 2010).

3.3 Research questions

In accordance with the development above, the following overarching question is formulated:

RQ. How incentives can influence users in physiolytics-centered organizational programs?

To accurately investigate this phenomenon, this dissertation seeks, in a first phase, to specify incentives in physiolytics-centered organizational programs (exploratory phase). In a second phase, this dissertation aims to consider what makes incentives work in physiolytics-centered organizational programs (explanatory phase). Put differently, it aims to identify relevant cases that provide information on the qualitative nature of incentives (Sayer 2004). Further details are provided in the following segments. The research design is illustrated in *Figure 4.*

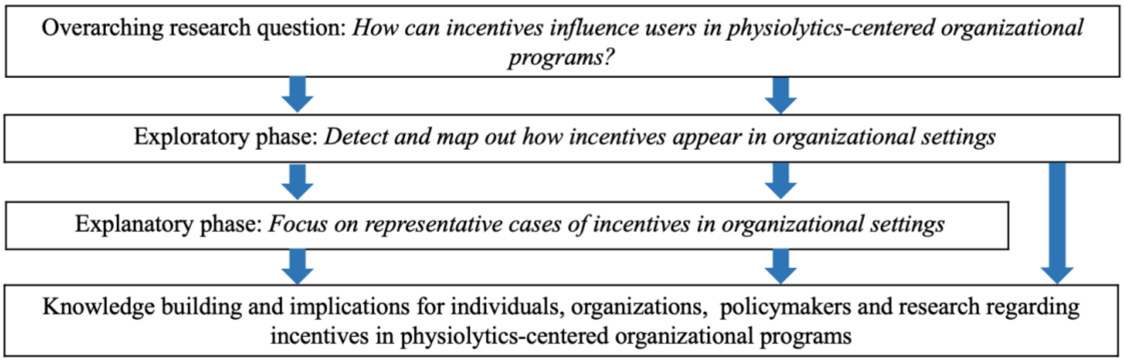

Figure 4. Outline of the research design.

The first exploratory phase consists of detecting incentives and the contexts in which they deploy. As indicated in the previous sections, there is, to the best of found knowledge, no structured appreciation of how organizations influence participation in physiolytics-centered organizational programs. Hence, the following sub-question addresses this issue:

RQ1. What forms of incentives are implemented in physiolytics-centered organizational programs?

The objective is therefore to generate, with scientific rigor, a starting point for further research. Such work could support a more systematic view of the notion of incentives in physiolytics-centered programs, in an effort to increase its potential contribution to practice and theory. This phase characteristically relies on an exploration of empirically observable occurrences of the chosen phenomenon (i.e., incentives); mainly through academic literature reviews and in-depth study of actual practices (e.g., existing incentives proposed as part of data-driven health plans). Building on the first phase, the second explanatory phase consists of assessing the organizations' ability to influence individual use of physiolytics in organizational environments. Consequently. the goal is to describe the forces in question and how they result in a phenomenon (Levy and Henry 2003). This leads to the ensuing sub-question:

RQ2. Under what conditions incentives influence users in physiolytics-centered organizational programs?

The objective is to review particular occurrences of incentives in physiolytics-centered programs. Representative cases are typically useful to offer original insights and interpretations regarding certain characteristics of the domain to which the case belongs (Tsang 2014). Events, beliefs and attitudes that participate in shaping a phenomenon can therefore be identified and analyzed. Both quantitative and more interpretative and qualitative methods can be employed, as they all portray, in their own way, a facet of the eventual influence of incentives in physiolytics-centered organizational programs.

In the direct continuity of this stage, main properties of incentives are defined to specify recommendations and guidelines for participants in physiolytics-centered organizational programs, organizations, policymakers and researchers.

3.4 Research context

Given that every research on social matters is rooted in a context, it is challenging to implicitly suggest a universalism of results (Davison and Martinsons 2016). This segment therefore situates the cultural and institutional background in which this dissertation has been developed. As part of a project supported by the Swiss National Science Foundation[2], this work primarily draws its impulse and data from Switzerland. Switzerland is an innovative and open economy, where digital initiatives are highly supported by governmental agencies, as they are seen as key aspects for economic growth and competitiveness at the international level. Various resources, platforms and associations are proposed by the federal state and cantons to assist public and private organizations in digital transformation. For instance, *DigitalSwitzerland* is a multi-stakeholder national-wide initiative that brings together leading public and private organizations, research institutes (e.g., Swiss Federal Institutes of Technology in Zurich and Lausanne) and several cantons (e.g., Canton du Valais, canton de Vaud) to promote policies and regulatory frameworks. In the same vein, umbrella associations play a strategic role for digitalization in organizations: *Swissmem*, which is the leading professional association for firms in machinery, electric equipment and metals industry, has for key objective to boost digitalization in the industry by providing education, formation courses and strong networks to its members. As a result, by 2016, 10% of small and medium enterprises had already incorporated internet of things in their organizational structure. This number attained 20% for firms with more than 250 employees (Balsmeier and Woerter 2019). Four years later, in 2020,

[2] Swiss National Science Foundation grant number: 172740. *Physiolytics at the workplace*. www.unil.ch/physiolytics/

this number has gone up to 73 % of large firms that have invested in internet of things, valuing this technology as a significant aspect in future operations (PwC 2020).

It is in this context that physiolytics have started to spread across the Swiss organizational landscape. Swiss health insurance companies have particularly been proactive into integrating physiolytics in their strategy, so that they are able to access growing flows of personal data (Martani et al. 2019). Specifically, they have started to propose data-driven health plans that allow customers to connect their physiolytics device with a specific insurance app, so as to participate in a financial incentive scheme. For instance, CSS, one of the most prominent Swiss insurance companies (in terms of subscribers), proposes through its application *Mystep* a credit of CHF 0.20 (¢20) each day participants do between 7500 steps and 9999 steps, and CHF 0.40 (¢40) when participants perform more than 10’000 steps per day. Credits can then be converted into cashback (CSS 2020).

Such practices are possible because Switzerland has a liberal healthcare market. Private health insurance companies are providing, under regulations from the Federal Health Insurance Act (HIA), coverage options for every permanent resident (Swiss Office of Public Health, 2020). Permanent residents can freely select among health insurance companies the insurance model that fits them the most. Still, they are mandated by law to at least subscribe to a basic insurance plan that covers illness and accidents. In practice, monthly premiums considerably vary from health insurance companies depending on the location, age group, insurance deductibles and the degree of supplementary health plans (e.g., dental care, complementary medicine or data-driven health plans). In consequence, permanents residents often supplement the basic coverage with particular insurance plans, as more than 70% of permanent residents contract a form of extra plan (Laske-Aldershof et al. 2004; Schoen et al. 2010). Health insurance companies have therefore to be competitive because permanent residents may change for better offers (possible up to two times a year), considering that the switching rate may attain 15% per year (Daley et al. 2007; Thomson 2015).

On another note, physiolytics have also penetrated workspaces, as pillars of occupational health programs. Organizations are required by the Swiss Labor Act (art. 6, 35 et 36a) to care for employees’ health and safety at the workplace. In such context, physiolytics typically appear as fairly affordable, undemanding and innovative ways to develop digital occupational health programs. As illustrated, they are off-the-shelf products that push employees to self-improve, while also gathering data and potentially helping organizations to diminish charges (Marquard and Zayas-Cabán 2011).

The rise of physiolytics in Swiss workspaces is also particularly correlated to the use of physiolytics in white collar environments (Moore and Robinson 2016). As a matter of fact, work-related stress has supplemented safety hazards as the primary health concern for Swiss organizations. In 2018, it was estimated that 27.1% of active population in Switzerland was in a red zone regarding stress (Promotion Santé Suisse 2018), meaning that employees had the impression that the constraints at work were bigger than the resources they had. This inevitably (and substantially) affects organizations. Repercussions are notably materialized by high turnovers of middle/high management that appears difficult to replace, reallocations of duties as well as additional costs due to work absenteeism (Stepanovic et al. 2019b). In numbers, stress-related productivity loss for organizations may be estimated up to CHF 5.7 billion ($5.7 billion) per year. In light of this, physiolytics offer the advantage of providing tangible metrics for a phenomenon like stress. Collected data can be used, analyzed and even employed, in an anonymous and aggregated manner, to produce dashboards. These may then serve to signal to all employees collective levels of physical activity or different peaks of stress (Stepanovic et al. 2019b).

4. Research procedure and article summary

Built on the overriding question and sub-questions, this dissertation contains four articles that combine to achieve the indicated research goals. This section introduces their logical and structural connections *(see Figure 4*) and briefly summarizes their content.

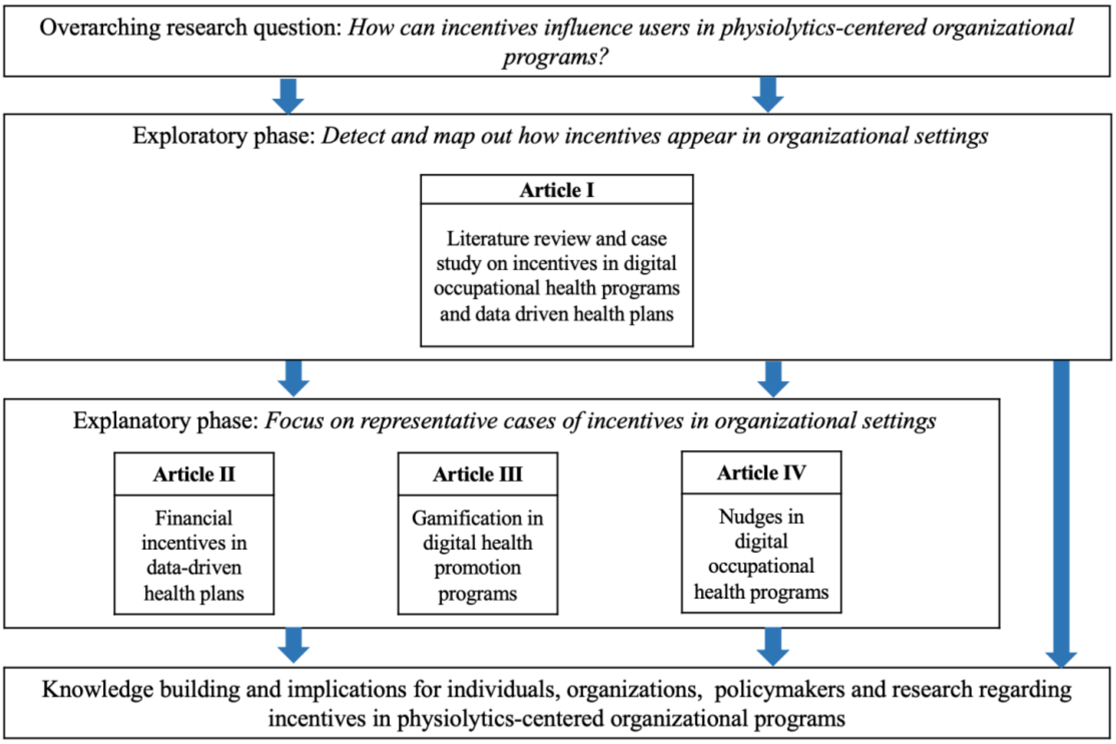

Figure 5. Outline of the research procedure.

The motive of this dissertation (and **Article I)** is the emerging phenomenon of incentives implemented in physiolytics-centered organizational programs to induce participation. Firms and health insurance companies, in particular, are creating physiolytics-centered *digital occupational health programs* (e.g. Gorm and Shklovski 2016; Olson 2015; Vyas et al. 2015) and *data-driven health insurance plans* (e.g. Mettler and Wulf 2020; Paluch and Tuzovic 2019; Tedesco et al. 2017). By doing so, these entities expect to improve individual health management, but also to gather large quantities of personal data. To prompt engagement and eventually diminish privacy/security concerns (e.g., fear of documentation of high risk profiles to determine individualized pricing for health premiums, or an institutionalization of syndromic surveillance for work productivity (Lupton 2016)), organizations often rely on incentives (e.g. rewards or bonuses). Because little is known about the procedures that are put in place by these structures (Ajana 2017), Article I serves as an exploratory study. It strives to offer an initial appraisal to provide direction for future research and help to elaborate study designs (Singh 2007). Specifically, incentives and their use in the IS field are presented, and then two particular situations (1) *digital occupational health programs* and (2) *data-driven health insurance plans* are considered. Following De Ridder et al. (2017), this paper first formulates a typology of incentives for physiolytics in organizational settings. Relying on the characteristics of physiolytics (i.e., portability, connectivity, real-time reporting), these incentives aim to deliver inputs (*feedback*), notify to users (*reminders* or *alerts*), connect individuals (*social*), provide educational content (*education*), add fun elements (*gamification*) or offer monetary compensation (financial).

Because firms are considered to be very early adopters of physiolytics for organizational objectives (Lupton 2016), the chosen research design for *digital occupational health programs* was based on a methodical search of academic articles in relevant electronic databases, i.e. the principal database for IS literature (*AISeL*), the main platform for computing and information technology (*ACM*), as well as the principal cross-disciplinary database (*Web of knowledge)*. Results show that all of the identified occupational programs propose a feedback incentive, by way of interactive feedback (e.g. Gomez-Carmona and Casado-Mansilla 2017) or specific individual counselling sessions (e.g. Jelsma et al. 2019). These are commonly associated with other incentives, primarily with financial remuneration or gamification, but also with education (to support the communication, advices and problem-solving).

For data-driven health plans, as there is not much academic evidence which can be assessed based on a literature analysis, a methodical review of offerings from major health insurance companies was done in Switzerland. Results show that most of the leading Swiss health insurance companies propose data-driven health plans and that they all rely on financial incentives (e.g., cashback, reductions in premiums obtained in function of physical achievements) with the ambition to enhance participation.

Overall, findings from Article I demonstrate that similarities exist between digital occupational health programs and data-driven health plans in how they encourage users to participate in their respective programs (e.g., feedback loops). It also shows that there is an overrepresentation of financial incentives for data-health plans, indicating that health insurance companies are building their strategy on external motivators (and external regulation of behavior).

Article II furthers the inquiry on the role of financial incentives in data-driven health plans. To assess their weight, a survey was conducted with a representative sample of Swiss permanent residents regarding their intention to participate in data-driven health plans. As seen in *Section 3.4*, Swiss permanent residents are required to subscribe to a basic health insurance plan (of their choice). They also commonly enroll in various forms of additional health plans (going from dental coverage to data-driven health plans). To correctly interpret the power of financial incentives on the intention to participate in data-driven health plans, constructs *health status* and *income* were added, as they were identified in the literature as major factors in choosing additional health insurance plans (Daley et al. 2007; Schoen et al. 2010). The survey sample consisted of two different settings: within the first, the survey included a discount offer in case of subscription to a data-driven health plan while, in the second setting, no discount offer was proposed. Participants were randomly assigned to one of the two groups, with a sample of 223 valid responses for the survey with the discount offer and 218 valid responses for the survey without discount.

Results notably unveil that financial incentives impact intention to use physiolytics provided by health insurance companies. The intention to use physiolytics is significantly associated with the presence of discounts, while there are no significant effects when single factors *health status* or *income* are tested alone. Even if the increase of intention due to the discount offer is relative, financial incentives exert a determinant influence for some individuals. Financial incentives especially drive more interest from individuals with a high income and a perceived poor health status. This sheds light on the importance of the opportunity that these plans represent for consumers. Article II argues that financial incentives increase the perception of an opportunity to grasp (either to gain some monetary retribution or to improve poor health levels) with a plan that is otherwise (i.e., without discount) not particularly appealing for the wider population.

Article III focuses on gamification, an incentive that was identified in Article I as a common incentive in digital occupational health plans. As for financial incentives for data-driven health plans, this dissertation aims to analyze the capacity of gamification to exert an effect on individuals. Gamification has become a very popular approach in the IS field and is notably applied for promoting healthier life choices (Alahäivälä and Oinas-Kukkonen 2016; Sardi et al. 2017). Capitalizing on its presumed ability to make humans positively react to game-based features (Hamari et al. 2014), gamification is used to facilitate and promote the use of IS devices for health promotion purposes (Alahäivälä and Oinas-Kukkonen 2016). Yet, a research gap was identified in the form of a scarcity of evidence regarding gamification and its faculty to sustain effects on health behavior change, although these are specifically implemented to support user engagement over time. Therefore, Article III takes the shape of a scoping literature review with a systematic search of scholarly articles that explicitly deal with digital health promotion and gamification. The objective was to account for empirical studies that presented a longitudinal design (>4 weeks of intervention) or comported at least one follow-up. An electronic database search was performed on the subsequent platforms: *Scopus, EBSCOHost, Web of Science* and *ACM Digital library,* which reference key cross-disciplinary research. Results indicate a lack of evidence (reported in academic studies) concerning continuous engagement and/or long-term effects of gamification interventions applied to physiolytics. Furthermore, the only longitudinal study that met the highest criteria (+20 weeks of intervention) reported no significant effects of gamification for digital health behavior change over time (Coombes and Jones 2016). The impact on individual motivation is therefore difficult to dis

Article IV is a continuation of article III, as it generates a research interest to consider an alternative form of incentive within organizational settings. The chosen approach is nudging, which may be similar to gamification through its inclination to recognize and reward effort (AlMarshedi et al. 2017). In IS spheres, nudging starts to be considered as a strong procedure to impact on individual behaviors so as to better align organizational objectives and employee attitudes (often named the *person-organization fit*), as the compatibility between people and organizations (regarding attitudes, beliefs or behaviors) is important for the success of an IS implementation. Nudging can be defined as an attempt to support individuals for their own good, by subtly (and non-coercively) modifying the environments in which they evolve, i.e., altering the environment without forbidding any options or considerably shifting any economic configurations (Hausman and Welch 2010; Leonard 2008; Sunstein 2014). The main assumption is that individuals do not make choices in a vacuum, and that a cautious design of cues in the environment can influence these choices (Balebako et al. 2011; Coventry et al. 2014; Sunstein 2014). Also, this appears to be particularly relevant with systems that aims to change health behaviors, as users get involved in time lasting processes to improve their health levels and often need additional support when using physiolytics (Hansen et al. 2016; Keselman et al. 2008; Zayas-Cabán and Marquard 2009). In fact, as expressed by Patel et al. (2015), physiolytics are not drivers of health behavior change, but facilitators that particularly connect with human behavior only when they are implemented with engagement strategies, especially in complex and dynamic environments such as the workplace (Mashhadi et al. 2016; Weeger et al. 2014). To determine if nudges can motivate employees to engage with the use of physiolytics, Article IV provides insights on employees attitudes on this matter by employing a mixed research approach called Q-methodology (Stephenson 1986). This method offers a robust procedure to systematically explore subjectivity by measuring individuals' mindsets and opinions (Brown 1993). Participants who took part in the whole procedure consisted of employees of a medium-sized public administration in Switzerland that wore a physiolytics device as part of an occupational health program initiative, and employees from another comparable public administration in Switzerland who did not have contact with such technology. Results yield five main attitudinal groups that represent the five major perspectives on which types of nudges are positively perceived by employees. The use of physiolytics may subsequently be enhanced through (1) positive reinforcement and fun elements; (2) controlling the organizational environment; (3) expanding personal commitment and self-responsibility; (4)

increasing group efforts and collective responsibility; (4) or by allowing users to adapt their individual environment as much as possible. In terms of specific nudges, only the nudge *increase access to information* (that advocates for more metrics and/or more communication on quantified self practice) has gathered a majority of positive opinions across the five identified altitudinal groups.

		Title	Publication outlet	Research question	Research design	Main findings
Exploratory phase	Article I	Incentivizing the Use of Quantified Self Devices: The Cases of Digital Occupational Health Programs and Data-Driven Health Insurance Plans	Well-being in the Information Society	What are the mechanisms implemented by organizations to motivate individuals to participate in programs with physiolytics?	Scoping literature review and case study	Feedback, gamification features and financial incentives are the most implemented incentives. Financial incentives are particularly widespread for data-driven health plans.
Explanatory phase	Article II	Financial Incentives and Intention to Subscribe to Data-Driven Health Plans	International Conference on Information Systems	What are the effects of financial incentives on the intention to subscribe to data-driven health plans?	Survey research	Financial incentives impact intention to use physiolytics provided by health insurance companies. They especially drive more interest from individuals with a high income and a perceived poor health status.
	Article III	Gamification applied for health promotion: Does it really foster long-term engagement? A scoping review	European Conference on Information Systems	How do studies on health promotion through gamified systems account for the long-term aspects?	Scoping literature review	Results underline a deficit of consideration from a long-term perspective as well as a lack of measurement related to the lasting effects of gamification.
	Article IV	Which nudges are acceptable in connected workplaces? A Q-methodology study	Information Systems Journal	Which forms of nudging would be perceived as acceptable by employees in a connected workplace?	Mixed methods research	Findings display five types of nudges that employees consider advantageous and ethically acceptable: (1) positive reinforcement and fun, (2) controlling the organizational environment, (3) self-responsibility, (4) collective responsibility, and (5) adapting the individual environment.

Table 2. Summary of the articles.

5. Discussion

The overall goal of this dissertation is to consider the influence of incentives in the context of physiolytics-centered programs. This dissertation fundamentally addresses this goal in two phases. First, a structured overview of incentives is provided through an exploratory study (Article I). Second, an explanatory phase is done with the consideration of three relevant implementations of incentives to apprehend their influence on individuals. This is respectively done in the context of financial incentives for data-driven health plans (Article II), gamification for digital health programs (Article III), and users' perception of nudges in occupational health programs (Article IV). Altogether, these articles give insights on the role of incentives and how this mechanism positions itself between organizations and individuals. The following parts detail these elements.

First, this set of articles shows that incentives are inherent to organizational programs with physiolytics (*see Figure 6*). Feedback-based incentives, financial incentives and gamification are the most observable forms in practice (Article I). In a sense, organizations emphasize extrinsic motivators (financial incentives, game elements) because these are simple to operate. In contrast, generating genuine interest (i.e. intrinsic motivation) among individuals during organizational-related implementations is a difficult and uncertain task (Yoo et al. 2012). Such observation is especially true for physiolytics, whose perception vary depending on personal sensitives. In this respect, physiolytics possess high barriers to participation in organizations (due to collection of health data), that can instantly discourage a fraction of population, such as technology skeptics (Mettler and Wulf 2019).

The prevalence of feedback to motivate physiolytics use is, in a way, in line with the essence of quantified-self practices: participants that engage with such systems are searching to gather more data and information about themselves and their environment. Thus, feedback incentives often serve as supplements to assist users (e.g., counselling meetings). Such phenomenon demonstrates the importance for organizations to connect with users. They must reassure participants regarding their commitment to support users' health and lifestyle progress (Article I). This is reinforced by the fact that individuals clearly favor nudges that increase their information level (Article IV). Although physiolytics function through self-management, participants are eager to gather additional support to help them navigate through occupational health programs. This follows existing scientific evidence from web-based health promotion in work settings, which show that dropouts are significantly bigger when there is no additional support apart from the automated health initiative (Donker et al. 2009; Dunkl and Jiménez 2017; Proudfoot et al. 2011; Spek et al. 2007). In this sense, providing information in such occupational health programs may serve to maintain momentum. It may help to bypass eventual ethical challenges, negative side-effects, failed usages, or even misinterpretation of on-screen displays, which may appear with unguided digital health initiatives (Donker et al. 2009; Dunkl and Jiménez 2017). Feedback accordingly serves to augment the sense of competence and autonomy of individuals, thus affecting more intrinsic forms of motivation (Burgers et al. 2015). In the same vein, firms often resort to game elements in occupational health programs (Article I and III). These aim to stimulate interest and playfulness with relation to the use of physiolytics, to, once again, appeal to internal regulations of behavior. Even if there is evidence that gamification enhances individual participation (e.g. Wortley 2015), Article III shows that there is little ground that allows to gauge whether this motivation is then internalized. Furthermore, some recent works tend to show that gamification only exists because of the sense of novelty (Bamidis et al. 2016) and that it may cause adverse and detrimental effects to sustained motivation (Schmidt-Kraepelin et al. 2019).

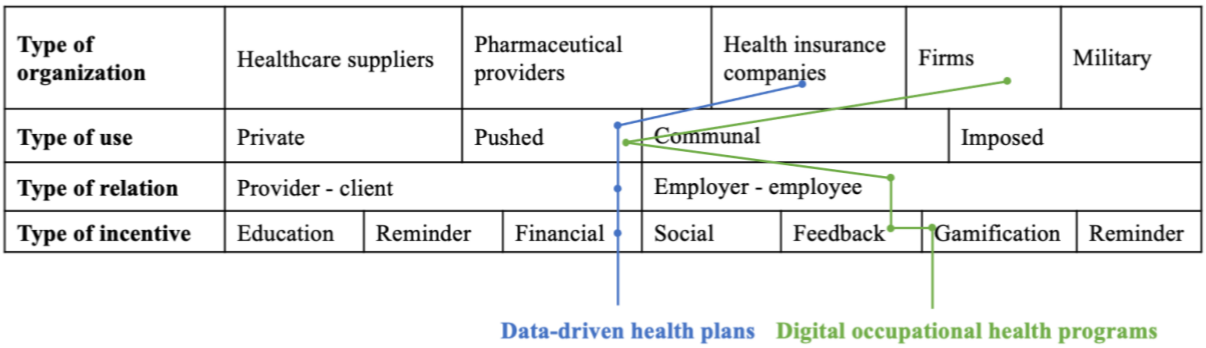

Figure 6. Common designs in organizational programs with physiolytics.

The last key takeaway on the occurrences of incentives is the systematic use of financial incentives for data-driven health plans. This shows that health insurance companies are directing their engagement strategy on removing adoption costs through external rewards (Article I and II). This is a common procedure when barriers to adoption are perceived as high, or when defined objectives are considered difficult to achieve (Norman et al. 2016). The use of financial incentives always triggers a persistent debate concerning the degree to which this low self-determined and external motivator can enable action over time. While many studies tend to show that financial incentives are prejudicial for intrinsic motivation in the long run because individuals perform the activity without compliance (Cherubini et al. 2020; Ryan and Deci 2000), some research, in organizational settings, suggests that the effect of financial incentives is contextual. Compensation plans using financial incentives and bonuses can be effective when these are integrated in a parsimonious and punctual manner, so that individuals do not develop expectations based on external rewards (Landry et al. 2017). In any event, as indicated by Canhoto and Arp (2017), most individuals are at least receptive to financial incentives when these are proposed as part of physiolytics-centered organizational programs.

After identifying the main incentives in physiolytics-centered organizational programs, properties of incentives that exert influence can be defined through a retroductive process. In such situations, when the context is known but the mechanism is unknown, representative cases are useful to identify properties that make an event occur (Vincent and O'Mahoney 2018). Knowledge is thus obtained through a set of regularities in a given process (Khazanchi and Munkvold 2003). Put differently, the four articles in this dissertation serve as a foundation to appreciate in what precise circumstances incentives influence user behavior. It notably helps to take a higher perspective than normative views, so that it is possible to build alternative managerial and policy viewpoints (Sayer 2004). Complexity is thus less reduced and there is therefore less chance to create inadequate solutions and incomplete explanations (Armstrong 2019). The objective is therefore to transcend the type of incentive (gamification, nudge, financial incentive) and other contextual factors, such as socio-economic considerations (article II) or personality (Article IV), to offer a novel perspective on incentives. Based on these observations, the following properties on the influence of incentive on individual use can be extracted.

Transparency. Incentives tend to have a power on individuals when their occurrence and purpose is clear and manifest. Whether it is the high representation of feedback incentives, financial retributions or educational content (Article I), the influence of financial incentives on use intention (Article II) or nudges that promote more information (Article IV), all these incentives are straightforward in their intention and understandable by individuals. They consequently enable an information flow between entities (organizations and individuals) and give opportunities to individuals to better make decisions and engage in actions regarding physiolytics (Hosseini et al. 2018). In short, they eliminate uncertainty around physiolytics-centered organizational programs. As described in other health IS domains (e.g., electronic patient records), less uncertainty and better flow information specifically increases trust. And trust, in turn, increases adoption rates of the systems (Gajanayake et al. 2011). Individuals are accordingly in position, following van der Werff et al. (2019), to open their a black box of "willingness to be vulnerable" and to develop a self-motivated, volitional trust in the organization. A typical illustration of transparency for incentives is well-defined boundaries in collected data. For instance, in an incentive based on financial bonuses, organizations might take only one metric, such as steps taken during the day, and clearly explain how it translates into a financial benefit (e.g., 10’000 steps equal 1CHF9. Likewise, enabling a total access to the data (e.g., steps count) allows participants to easier adhere to the incentive scheme.

Individual empowerment. Similar to transparency, incentives gain influence on individuals when they convince individuals that using physiolytics systems in organizational context empower them. This empowerment may relate to knowledge (Article I and IV) or financial capabilities (Article II). Empowerment through knowledge directly pertains to the notion of autonomy and competence of individuals, but also with the notion of self-efficacy and the use of physiolytics in private settings. By strengthening individual conviction and expectations regarding the benefits of physiolytics-centered programs, individuals are more likely to engage in a behavior. They perceive themselves as prepared to mobilize resources (e.g. cognitive resources) to perform the behavior and sustain it over time (Bandura 1986). In other words, it gives them the resources to enhance their motivation by having the impression to be more adaptive and receptive to their environment (Ahearne et al. 2005). For instance, detailed data on performance (i.e., concrete indicators such as calories burned) or information about the benefits of using stress management tools are time typically instances of complementary information that may empower the user (Article IV). With regard to financial incentives, the degree of empowerment remains debatable. In any case, it is certain that empowerment through financial incentives appears to be particularly important in contexts when the confidence level is really low due to perceptible obstacles (e.g., privacy concerns regarding data-driven health plans). And, privacy and security concerns are the elements that hinder the most the determination and the perseverance to engage in a behavior with an IS (Stajkovic and Luthans 2001).

Defined benefits. There are more probabilities that individuals react to incentives when the outcomes are noticeable. Financial incentives (Article II) and increased data loops (Article IV) create conditions where individuals may easily appreciate their effort, as well as the reward to which the effort corresponds. In other words, such rewards provide either a monetary or a functional value for individuals (Tedesco et al. 2017). In contrast, at the other end of the spectrum, incentives that rely on social components or playful principles appear to be less unanimous (Article IV); and their impact on systems use is also less evident among participants (Article II and IV). As an illustration, providing a support through individual counselling sessions with health specialists is a form of tangible benefits that make an incentive more appealing.

5.1 Implications for individuals

By characterizing incentives and their properties, individuals may recognize organizational attempts to influence their behavior. The creation of volumes of personal data irremediably attracts entities, such as private firms. These may seek to harness personal information to either manage their workforce, create new customer products or expand their business reach (Cooper and LaSalle 2016). Gathering some knowledge on the mechanisms that such organizations may employ is beneficial for individuals, as they may get a comprehensive view of the power relation (and consequently, not being automatically subject to it). Critical realism possesses in this regard a transformative nature. It allows a specification of relationships between entities in order to, if necessary, change the status quo and create an emancipation for individuals (Khazanchi and Munkvold 2003). In this respect, Article II unveils how different socio-economic determinants may play a role in the decision to participate in a data-driven health plan (i.e., more interest is drawn from individuals with a high income and a perceived poor health status). Likewise, Article IV indicates how individuals have different mindsets regarding physiolytics and regarding incentives that are associated with (i.e., some individuals see that as a game, others as a commitment while another group is little receptive). This may help individuals to evaluate how their autonomy and integrity is impacted by such incentives, which may reduce eventual apprehensions and dilemmas regarding the organization. In other words, this dissertation participates in the creation of a big picture for individuals regarding data-driven digitalization in organizations.

In theory, individuals dispose of the tools to enhance their decision-making, but in practice, individuals often have difficulties in qualifying the relationship they have with an organization through data-driven systems. The lack of transparency in how organizations value collected personal data makes it difficult for employees or customers to gauge the worth of their information and meaningfully participate in programs centered around such devices (Sabin 2019). By characterizing incentives that are used (and providing guidelines for their design), individuals may make more enlightened choices regarding their participation in such programs. Shedding the light on these matter is particularly important as the practice indicate that there is significant mismatch between how managers and individuals perceive data-driven systems: surveys show that 73% of organizations assume that their employees are open to data-driven approaches, while, in the same time, 65% of surveyed organizations indicates that they have experienced resistance from their employees when implementing data-driven systems (Exasol 2020).

5.2 Implications for organizations

For organizations, incentives represent the main way to make motivation concepts tangible. As seen, incentives are implemented to specifically trigger a predictive response from individuals in order to align their interests with those from organizations (Jenkins Jr et al. 1998; Scekic et al. 2013). Overall, this dissertation outlines the necessity for organizations to invest time and resources to construct viable programs around data-driven systems such as physiolytics. In this regard, the design of incentives should be carefully considered and in line with organizations' strategic objectives. Typically, for digital occupational health programs, implementing a single incentive instrument may be challenging, as employees think and react differently (Article IV). In fact, incentivizing is subjective approach: appealing only to a specific group of people or a specific behavior may either generate resistance from some employees (Article II and IV) or create some unwanted responses from others (Laffont and Tirole 1993). Gamification in organizations perfectly embodies this phenomenon: game features may, for some employees, create a positive and ludic activity sharing environment, while, for others, it may look like an attempt (under the disguise of fun) to subtly push employees to compliance (Deterding 2014; Stepanovic et al. 2019a; Vyas et al. 2015). In the same vein, Article IV shows that there is hardly any consensus on how to proceed in developing an incentive. As consequence, organizations have to know their audience well. Involving individuals in the creation of physiolytics-centered organizational programs may be a suitable approach to overcome such hurdles. For health insurance companies, this may go through a representative sample of customers to adapt their incentive strategy. For firms, appraisals such as questionnaires, surveys or small focus-groups may help organizations to gauge the number of potential participants, evaluate from the beginning individuals' preferences and measure their expectations regarding physiolytics (Article IV; Miele and Tirabeni 2020; Santos et al. 2013). Such elements typically resonate with the notions of individual empowerment and transparency that are significant for incentives to support the use of physiolytics. By the same token, organizations have to be precise and transparent about the boundaries of physiolytics-centered organizational programs. Well-defined protocols, clear limits in the organizational use of collected data (Miele and Tirabeni 2020) and frequent communications participate in the empowerment and transparency, so that the trust relationship between employers and employees may be strengthen (Article I and IV). In fact, incentives act as symbols: the ways organizations are implementing such mechanisms provide a message to employees or customers. And, evidence shows that organizations largely benefit when they make sure that the *rules of the game* are understood by participants (Weston 2015).

Incentives can also be gradually introduced (or revoked) by organizations. Article III points out that a loss of interest may appear after a certain time with gamification features. To bypass such issues, organizations may progressively integrate incentives, but also use incentives on punctual occasions. Simple variations between means may additionally lead to sustained individual motivation and engagement. Organizations may accordingly propose different options for participants (monetary rewards, gifts, counselling session) in order to appeal to different sensibilities.

Training managers is also an important element to increase the influence of incentives: Articles III and IV show that individuals do not adhere in the long run with physiolytics when there are no appropriate follow-ups from the organizational structure. Increasing literacy in management is therefore part of this general empowerment of individuals that programs centered around physiolytics should tend to reach. The idea is to create an environment where physiolytics can function soundly and smoothly, and where managers, employees or customers can internalize information that is provided. As Ryan and Deci (2000) indicate, creating an environment where individuals can actually sense that they are able do something, and that they are good at doing this thing is by itself motivating. It consequently constitutes the most fertile ground to inspire intrinsic motivation. In sum, the challenge for organizations is to create an organizational culture that is conducive to the integration of physiolytics. This dissertation shows that making information visible, democratizing access to data, tailoring organizational approach to individual ethos (Weston 2015) and proactively adjusting organizational environment are essential conditions for this to happen. Therefore, by following such guidelines, organizations may increase the odds of successful implementations and the success of physiolytics, which is inherently critical for organizations as they invest financial resources, time, and efforts (Dunkl and Jiménez 2017; Nurhas et al. 2019).

5.3 Implications for policymakers

Creating physiolytics-centered organizational programs can be a winning formula to improve public health while solving a number of organizational challenges (e.g., fighting stress-related issues, creating better insurance products). Such programs are innovative and creative in the way that they promote individual self-regulation and increase individual health consciousness. However, the use of incentives by organizations inevitably raises questions about the balance and equity in the relationship between organizations and individuals. Akhtar and Moore (2016) ask for a thorough reflection on the notion of consensus between organizations and individuals. In fact, incentives are a form of soft power, which may participate in structural pressure on employees (or customers) to sacrifice some autonomy or privacy (Akhtar and Moore 2016; Maturo 2015). In certain cases, they may create *an erosion of choice* for individuals (Baker 2020) by persuading individuals that physiolytics are necessary, oversimplifying challenges related to data-sharing or creating short-cuts to decision-making. Article II illustrates such concerns by discussing how financial incentives may be framed as opportunities that should not be wasted to save money on health premiums.

Policymakers have therefore to take into account these potential negative side-effects and thus be proactive in considering how organizations implement such incentives. In connection with the identified properties of transparency, individual empowerment and defined benefits, regulations must be designed to ensure (1) clear consent of participants, (2) guarantees regarding the proportionality of incentives and (3) involvement of entities that can guide individuals through data-sharing. Swiss labor laws (Ordinance 1 on the Labor act) require organizations to have a proportional use of data-driven systems: performance monitoring is possible, but control of employers' behavior is prohibited. Incentives consequently have to fall within this line, namely to serve a legitimate aim and not damage individuals' autonomy and privacy (Akhtar and Moore 2016). Ensuring transparency is particularly important, so that incentives do not increase the perception of physiolytics as social control tools in the service of an organizational process (Baker 2020). Moreover, Article IV shows that individuals mainly value information regarding such programs, so any hidden incentive or any hidden use of data may deteriorate trust relations in the workplace. In this regard, labor unions and other regulatory structures have a major role to play. If they are sensitized to such issues and informed about good practices regarding incentives, they may critically evaluate incentives that are put in place to enhance physiolytics' use. They may also guide employees during digital occupational health programs and answer eventual privacy questions regarding physiolytics. By doing so, these entities contribute to lessening potential power asymmetries that incentives may create between organizations and individuals. As a matter of fact, the risk with incentives is that they exacerbate a neoliberal perspective of individual health (Dickenson 2013). Article II and IV precisely reveal that physiolytics may increase inequalities at the workplace: managers may engage more easily in the use of physiolytics and take the incentives, because they have more autonomy and flexibility in their workplaces. Thus, they might be in a better position to actively use physiolytics and benefit from physiolytics-centered organizational plans (Charitsis 2019; Esmonde and Jette 2018). Even more than that, without regulations, greater incentives may become part of a *new normal* in the workplace, where pressures to adopt physiolytics become higher along with the stigma for opting out (Calvard 2019; Moore and Piwek 2017). The same goes for data-driven health plans: Hart (2018) argues that if consumers are not cautious about the way they engage in the use with physiolytics and how they consider incentives, data-sharing might become the default. This might thus leave others with few alternatives but to conform and share information, or potentially be forced to pay higher rates elsewhere.

5.4 Implications for research

Data-driven systems, such as physiolytics, are complex systems that bring on the table new challenges in organizations (especially regarding data collection and individual privacy). It is therefore important for IS research to consider relationships between organizations and individuals. Incentives are in that way a phenomenon that can partake in a new form of distortion in this relationship, by blurring boundaries between voluntary and imposed use (Ajana 2020). This dissertation therefore particularly focuses on incentives and IS use. Article I tackles the lack of structured review regarding the types of incentives that are employed in pushed quantified-self practices. As an exploratory work, it aims to build knowledge that is necessary for the construction of further study designs (Singh 2007). It thus typically answers the question *what is* (Gregor 2006), underlining what are the salient occurrences of incentives in physiolytics-centered organizational programs (i.e., financial incentives, feedback loops and gamification). It therefore helps to situate the role of incentives regarding individual IS use. Plus, incentives often have to be comprehended as part of a context: it is difficult to transpose incentives from different environments because incentives highly depend on the overall objective, participators' preferences and individual characteristics (Harari et al. 2017). Put differently, incentives that are used for employees in a public administration cannot necessarily be transposed for university students.

As a second step, this dissertation seeks to answer the question *how is* (Gregor 2006). Scekic et al. (2013) express that incentives bring elements from other fields to IS matters. With Articles II, III and IV, this dissertation combines insights from economics (financial incentives), game theory (gamification) and behavioral economics (nudge) to explain the role of incentives, and then root this concept in the context of physiolytics in organizational settings. Beyond the single contributions of each paper, this dissertation shows that transparency, individual empowerment and defined benefits are properties that increase the power of incentives on users in a physiolytics in organizational settings. These inputs can be put in parallel with contextual conditions of basic psychological needs - autonomy, competence and relatedness - that are related to intrinsic motivation and individual IS use. Transparency and individual empowerment are elements that participate to enhance an internal regulation of behavior. They are thus absolutely in line with the concepts of autonomy, competence and relatedness. Clear and transparent communication between the organization and the employee/customer increases individual perception of independence, partnership and inner competence. Individual empowerment may allow individuals to better express and follow their needs and values. In fact, individual empowerment embodies in itself a form of self-determined and autonomous motivation (Gagné and Deci 2005; Sun et al. 2012). Empowered individuals thus connect more meaningfully to the organization (Ryan and Deci 2000) and may adhere to the use of physiolytics in organizational settings.

In contrast, defined benefits may not necessarily go in the sense of an internal regulation of behavior. When these benefits correspond to tangible rewards, intrinsic motivation is a priori not solicited. This signifies that, for physiolytics-centered programs, individuals may follow purely utilitarian motives to perform an action. In addition, it also implies that incentive schemes that associate extrinsic and intrinsic motivators may be particularly suitable for physiolytics-centered programs.

Finally, this dissertation offers possibilities to reflect on the notion of power in organizational settings. It notably offers perspectives on how organizations can develop appropriate and desirable environments, so that individuals may enhance their decision-making processes (Meske and Amojo 2019) and organizations succeed in their implementation (Article IV). This is fundamentally in line with recent developments in IS use calling for a strong focus on the environmental cues that may trigger IS effective use (Burton-Jones and Grange 2012; De Guinea and Markus 2009).

6. Closing remarks

6.1 Limitations

Using critical realism as an angle of approach entails some limitations. Although this worldview offers a new perspective and has a highly explicative capacity, it has relatively little predictive power (Fletcher 2017; Sousa 2010). Identified properties and mechanisms (i.e., causal powers) operate under certain conditions and it is challenging to specifically predict outcomes in each case (Bhaskar and Danermark 2006). Will transparent incentives based on information always motivate more individuals to use physiolytics in organizational settings? Some critical realist researchers would argue that it is tough to say in a social world full of diverse other mechanisms.

In this dissertation, a less radical point of view is adopted: identifying several regularities, which are valid within a certain temporal and spatial context (Næss 2004), offer possibilities qualitative and upper level predictions. They open the way for further validation, with novel perspectives on the hypothesized mechanism and its properties. As Aaltonen and Tempini (2014) indicate, validation ultimately happens, when other academic studies work on the same phenomenon and support with independent investigation the presented theoretical findings and explanations. The objective of this dissertation is therefore - not to offer a one-size-fits-all strategy - but to put in place safeguards and reconceptualize incentives for physiolytics. In fact, this dissertation exposes (1) major types of incentives (e.g., financial incentives, gamification), (2) indicates to entities such as organizations and researchers the properties that incentives have to possess to influence individuals (i.e., transparency, individual empowerment and defined benefits) and, finally, (3) shows what all of this implies for organizations (e.g., know their audience, implement different forms of incentives, train their staff), for policymakers (e.g., developing means to ensure a clear consent of participants, a proportionality of incentives and an involvement of support groups) or for scholars (influence on IS individual use).
Moreover, as research is inevitably rooted in a context, researchers and practitioners have to be conscious of different organizational cultures and other environmental aspects. Relations between an organization and individuals and the weight of incentives reflect some value systems and common beliefs. The notion of engagement and commitment in the workplace, the role of organizations in employees' health management, or the presence of ludic components in corporate settings may vary across nations. The same goes for data-driven health plans that apprehend incentives in the context of a liberal healthcare market (a type of healthcare governance that is certainly common to many industrialized countries), that obviously gives more depth to the notion of incentives. Ultimately, values of high individualism and high uncertainty avoidance are reflected through this work, which, as Meier et al. (2020) illustrate, may differ for a Chinese context, where physiolytics and incentives are set in a society that is more collectivist and has a higher power distance (i.e. higher acceptance of power relations and hierarchy in the society).

6.2 Future work and outlook

This dissertation helps lay the foundation for how organizations and individuals connect through incentives. The ensuing question is to understand how this relationship is further considered, particularly by users. For instance, as shown in Article II, the fact that financial incentives push some individuals to subscribe to data-driven health plans (because of the monetary compensation) may ask the question on an eventual *indirect coercion* on individuals (Rieder 2015; Stepanchuk 2017). In fact, individuals face a situation where a non-participation may give the impression that they are losing an occasion to save money; that they are charging more on health premiums than other people or that their eventual lack of physical activity is instating unfair treatment compared to healthier individuals (Paluch and Tuzovic 2019; Rieder 2015). As a consequence, it would be interesting to appreciate how many individuals subscribe to data-driven health plans for economic necessities in order to "monetarize" their personal data (Veale 2018).

On a similar note, it is important to consider social consequences of incentivizing individuals. Incentives may create a bigger digital division between individuals, increase technostress (i.e., negative psychological state provoked by an increasing presence of information and computer technology) or promote cheating schemes regarding system use. For instance, in Article IV, the discussion is centered on the capacity of nudges to make physiolytics fit within organizational settings (with the 5 identified potential types of nudging). Further studies might follow this line and understand if and how other incentives (e.g., gamification) assist data-driven systems in creating spaces where individuals' beliefs or behaviors are integrated. A perceived absence of fit from individuals might be the signal that the incentive engenders strain and stress for the participants (Ayyagari et al. 2011). Likewise, cheating is another element that have appeared with presence of incentives in programs with physiolytics (in particular financial incentives). By creating a remuneration based on data collection, organizations expose themselves to individuals that attempt to retrieve the bonus without changing their health behavior. As Mettler and Wulf (2020) show, such social cheating, that exists in insurance industry due to self-interest behaviors, negatively impacts intention to subscribe to data-driven health plans because clients are well aware that some individuals are willing of or susceptible to take advantage of the system. Thus, additional studies could consider the frequency of cheating in digital occupational health programs and how this phenomenon is perceived by employees in the workspace.

Next, while incentives may be necessary for organizations to increase adoption rates of physiolytics-centered programs, the question still remains if these incentives really help individuals to attain their personal objectives and benefit in terms of individual health levels. This is perhaps the most important question from an individual perspective, as the use of physiolytics is mainly valuable for individuals when it initiates a positive health behavior change. As a matter of fact, the evidence gathered on gamification (article III) shows that such incentive has a purely speculative long-term effect on individual health behavior change. More academic attention is therefore needed on the capacities of incentives, such as gamification, to induce worthwhile outcomes for individuals (which characteristically calls for more research with longitudinal research designs).

With regard to an organizational perspective, this dissertation paves the way for further investigation into organizations' roles in physiolytics-centered organizational programs. For instance, the question of an eventual calculation behind the distribution of these devices may appear. It is reasonable to imagine two scenarios with more accurate and expensive physiolytics devices being distributed first among managers or specialists, who are key human resources in a company, and possibly less developed, cheaper devices to all employees. Because firms do not want to lose their key human resources owing to burnout, their focus may shift to this part of their workforce, generating a lopsided health initiative. In these settings, incentives destined for high-profile managers or specialists might be more *qualitative*, because oriented to enhance intrinsic motivation by inspiring individuals and generating creativity (Laske and Schroeder 2017). It would be interesting, by extension, to further investigate the inner motives of organizations when they implement physiolytics-centered programs and when they design incentives. Typically, question arises if the rationale for using financial incentives in data-driven health plans reflects more a willingness to attain the greatest number of individuals possible, rather than a willingness to generate sustained motivation.

Altogether, this dissertation strives to open perspectives on new dynamics and challenges that appear in organizational settings with the introduction of physiolytics, and data-driven systems in general. These challenges may be, at the same time, of psychological, social, economic and technical nature, which illustrates the growing complexity and entanglement of the relations between organizations and individuals. This means that IS researchers should aspire to draw on different disciplines (e.g., psychology, sociology, behavioral economics), epistemological perspectives and methodological procedures. Such multi-disciplinary approach may unveil new facets of digitalization in organizations. It may also enrich the comprehension of how digitalization is currently developing. What is certain is that organizations are integrating at a fast pace data-driven systems in their strategies (Beane 2020). It is therefore the duty of every party involved (i.e., employees/customers, organizations, policymakers, researchers) to consider power relations that come with these ubiquitous systems, but also to investigate other related concerns such as ethical issues, security problems and technostress. In this way, current digital transformation in organizations may be directed to a balanced, harmonious and lasting progress.

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Article I

Article I: Incentives in digital occupational health programs and data-driven health insurance plans

Title: Incentivizing the use of quantified self devices: The cases of digital occupational health programs and data-driven health insurance plans

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Abstract: Initially designed for a use in private settings, smartwatches, activity trackers and other quantified self devices are receiving a growing attention from the organizational environment. Firms and health insurance companies, in particular, are developing digital occupational health programs and data-driven health insurance plans centered around these systems, in the hope of exploiting their potential to improve individual health management, but also to gather large quantities of data. As individual participation in such organizational programs is voluntary, organizations often rely on motivational incentives to prompt engagement. Yet, little is known about the mechanisms employed in organizational settings to incentivize the use of quantified self devices. We therefore seek, in this exploratory paper, to offer a first structured overview of this topic and identify the main motivational incentives in two emblematical cases: digital occupational health programs and data-driven health insurance plans. By doing so, we aim to specify the nature of this new dynamic around the use of quantified self devices and define some of the key lines for further investigation.

Article I

1. Introduction

The use of wearable devices that allow individuals to track and monitor their personal health data is starting to become mainstream in industrialized countries (Kunze et al. 2013; Starner 2014). For purposes of individual health, fitness, or well-being (Lupton 2014; Pfeiffer et al. 2016), interested parties can obtain a myriad of dedicated devices, ranging from low-cost activity trackers to wristbands, smartwatches and more complex biosensors (Patel et al. 2015). These provide precise information about one's physical activity (e.g. calories burned, distance covered), health levels (e.g. quality of sleep, blood oxygenation) or personal performance (e.g. evolution in numbers of steps taken).

Engaging in the practice of automatically collecting personal data is generally referred to as *quantified self*; but also known under analogous terms such as *self-tracking*, *lifelogging* or *life-hacking* (Calvard 2019; Pfeiffer et al. 2016). This practice builds upon the assumption that human bodies can be measured and understood through numbers (Whitson 2013) and that the knowledge of these numbers can enable each individual to discover, learn and act upon its attitudes and behaviors (Choe et al. 2014). In the common understanding, quantified self practices are related to an individual use of systems in private settings: lifestyle gadgets and health products are designed for the consumer market and collected data is destined for private use only (Gabriels and Moerenhout 2018). Yet, we are witnessing an emergence of third-party entities, such as government bodies, pharmaceutical industries, health insurance companies, healthcare suppliers or employers, that are integrating the relationship between the technology provider and the consumer (Ajana 2017; Paluch and Tuzovic 2019; Tedesco et al. 2017). They start to distribute these systems as part of their own programs; so more and more quantified self devices are embedded into medical programs supporting rehabilitation processes (Appelboom et al. 2014), chronic disease management (Chiauzzi et al. 2015), integrated into occupational health programs (Gorm and Shklovski 2016; Olson 2015; Vyas et al. 2015), or health insurance plans (Mettler and Wulf 2020; Paluch and Tuzovic 2019; Tedesco et al. 2017). These new actors are particularly attracted by the potential of quantified self devices in terms of self-care and positive impact on behavior. But they are also interested in the massive amount of detailed data that is generated by this technology (Silvello and Procaccini 2019). Whereas in healthcare settings, it can be argued that enabling access to such a source of personal health information may be beneficial for the community (Lupton 2016) – as it allows, for example, a better monitoring of diseases or further research on new therapies – in other contexts, the use of quantified self devices may raise questions among users concerning the repurposing of the collected data for commercial or organizational goals. These potential exposures may concern a categorization of habits for marketing purposes (Tedesco et al. 2017), an identification of high risk profiles to determine individualized pricings health premiums (Constantiou and Kallinikos 2015), or an institutionalization of syndromic surveillance for work productivity (Lupton 2016). In order to mitigate these concerns, organizations often use motivational incentives, such as bonuses or rewards to motivate people to participate in programs with quantified self devices (Tedesco et al. 2017). Since participation in such organizational programs relies on a voluntary basis (given that these systems gather information that is potentially sensitive), organizations distributing quantified self devices to their employees and clients seek, through the implementation of incentives, to overcome resistance and increase adoption. Yet, little is known about the procedures that are put in place by these structures, as this represents a new and developing phenomena, both within practice and research (Ajana 2017).

Therefore, in this paper, we present an exploratory study on the mechanisms implemented by organizations to motivate individuals to participate in programs with quantified self devices. In contrast to conclusive studies, exploratory research is typically used as an initial appraisal, to provide a direction for future research and help to elaborate study designs (Singh 2007). Concretely, after introducing motivational incentives and their use in the Information Systems (IS) field, we particularly consider two practical cases (1) *digital occupational health programs* and (2) *data-driven health insurance plans*. These record a steady increase in use of quantified self devices, as reports indicate that (1) 13 million quantified self devices have been used in occupational health programs by 2018 and that up to 27,5 million are planned to be distributed by 2020 (Giddens et al. 2016; Olson 2015); and that (2) among 221 health insurance companies in the world in 2015 (Accenture 2015), a majority of 60% had the intention to rapidly integrate this technology in their business plan (if not already done). For each case, we present our exploratory research design and provide the main results. We conclude by discussing these results, outlining the main learnings and proposing avenues for further research.

2. Related papers

Since the early days of Taylorism at the beginning of the 20th century, incentives have been acknowledged as means to motivate individuals to perform tasks (Harunavamwe and Kanengoni 2013). From the first monetary and financial remunerations, whole segments of research in psychology, organizational studies and behavioral economics have specialized into mechanisms that act on individual motivation. Most of this research builds upon the common division between *intrinsic* and *extrinsic* motivation, that refers to the nature of the motivation behind an action. Intrinsic motivation is linked to something inherently interesting or enjoyable, while extrinsic motivation refers to doing something because it leads to a separable outcome (Ryan and Deci 2000), The latter has particularly led to *incentive theory*, which is one of the main theories of motivation (Bretschneider and Leimeister 2017). It stipulates that individual behavior can be guided by external goals, such as recognition, rewards or money (Hockenbury and Hockenbury 2010). In the IS field, this theory has notably been apprehended through the lens of *technology adoption*, with Rogers (2010) defining a typology of incentives that help individuals to embrace a new technology (and then eventually stick with it). He has notably classified incentives between monetary and non-monetary; immediate versus delayed (i.e. performing a task knowing that a reward will be given later) or positive or negative (i.e. praises, gratifications and rewards or, on the other end, punishments). Number of works have followed this path, with investigations on incentives applied to various fields, such as privacy and security information management (e.g. Gal-Or and Ghose (2005)), corporate performance (e.g. O'Byrne and Young (2005)), but also for health improvement (e.g. Doolan and Bates (2002)).

Precisely, within the domain of quantified self devices, De Ridder et al. (2017) have conducted a systematic review of incentives for motivating people to use quantified self devices in the context of chronic disease self-management. Even though this work is rooted in a medical perspective (i.e. the user chose to use the device as part of a disease self-management), it offers a good basis for an examination of incentives offered by some types of organizations/institutions. In particular, it shows how organizations can build on the characteristics of quantified self devices (i.e. portability, connectivity, real-time reporting) to provide dialogue support to their users, i.e. evaluation of the use/performance (*feedback*); notice to engage with the use (*reminder*) or warning if there is a problematic element during the process (*alert*). Similarly, it associates social elements to connect users (*social*) as well as educational principles to provide information/training to prompt the use (*education*). Also, based on assumption that humans are attracted by playfulness and games in general (Hamari 2013), it can include fun components to make the use more enjoyable and entertaining (*gamification*). Finally, financial rewards can be added to provide an external source of motivation to engage in the use of quantified self devices (*financial*). Table 1 details these motivational incentives, as well as their general mechanisms and some concrete examples of application.

Motivational incentives	Incentive mechanisms	Application examples
Feedback	Informing the user about his quantified self practice	Personalized messages, individual counselling sessions
Reminder	Systematically notifying the user to engage in the quantified self practice	SMS, push notifications
Alert	Warning the user about possible issues related to his quantified self practice	SMS, notices
Social	Connecting users between them	Forums, peer support networks, peer messages
Education	Providing the user with instructions, information and training	Online notes, leaflets, process guidelines
Gamification	Adding a fun component to the quantified self practice	Leaderboards, badges, avatars
Financial	Providing a financial remuneration to the quantified self practice	Cashback, value points, vouchers

Table 1. Typology of motivational incentives for quantified self devices, derived from (De Ridder et al. 2017).

3. Case 1: Incentives in digital occupational health programs

3.1 Research design

Firms are considered to be very early adopters of quantified self devices in the organizational environment: they have started since the 2010s to examine the capacity of quantified self devices to tackle one their largest cost factor, employees' health and safety, while providing an opportunity to gather information on their workforce (Lupton 2016). Accordingly, we decided to look at the published academic literature to gain some insights on the current state of research. We thus conducted a scoping literature review of the incentives that are employed by firms to motivate individuals to participate in programs with quantified self devices. This form of literature review serves as a preliminary assessment of the state-of-the-art, while remaining transparent, methodical and replicable (Munn et al. 2018). The mechanisms are similar to systematic reviews, as we methodically searched academic articles in relevant electronic databases. In our case, we determined the following search string "*quantified self" OR "self-tracking" OR physiolytics OR lifelogging OR wearable health device OR fitness tracker OR activity tracker AND corporat* OR work* OR organization* AND incentiv* OR motivation* OR reward* and applied it to *title, abstract and keywords* screening in the principal databases for IS literature (*AISeL*), computing and information technology (*ACM*), as well as in one of the main cross-disciplinary databases (*Web of knowledge*).We specifically targeted empirical papers (journal and full conference papers) and limited our research to publications which were published in English. Finally, we excluded studies that had no direct link with quantified self devices and digital occupational health programs. By means of our database search, we identified 86 records from AISeL, 17 from ACM, and 80 from Web of knowledge. After removing duplicates, screening titles, abstracts and keywords, and applying our inclusion/exclusion criteria, we obtained a list of 12 publications which met our above-mentioned requirements (cf. Table 2).

3.2 Results

One of the striking elements is the prevalence of feedback incentives in our selected studies. Arguably, due to the design of quantified self devices, a form of feedback incentive is essentially present in every program based on these systems (i.e. the user can see the data provided by the device), yet all of the identified occupational programs also propose a form of interactive feedback (e.g. Gomez-Carmona and Casado-Mansilla 2017) or individual counselling sessions (e.g. Jelsma et al. 2019). These are commonly associated with other motivational incentives, primarily with financial remuneration or gamification, but also education (to support the communication, advices and problem-solving). In fact, out of these 12 selected studies, 6 included a form of financial incentive that provides cash rewards or vouchers (if defined goals regarding physical activity are attained). These goals generally take the form of daily objectives (e.g. averaging a certain number of steps a day) or improved biometric levels (e.g. Body Mass Index under a certain figure). Also, such incentive schemes are often associated to virtual value points, creating an intermediary currency between physical activity and its economic value. Their aim is to make it easier for participants to understand, follow and measure their progress and achievements. In terms of effectiveness, all studies reported positive results for financial incentives in promoting a participation in the beginning of the digital occupational health program, although this effect is sometimes marginal (e.g. Yu et al. 2019). Yet, two studies (Chung et al. 2017; Hunter et al. 2016) questioned the effects of financial incentives on the individual long-term participation (more than 6 months) as well as the durability of this approach in a digital occupational health program. Another popular motivational incentive consisted in relying on gamification, with a third of our selected publications applying such a mechanism. Virtual points also constituted a key element in the structure of these incentives: they translate users' physical activity into a metric, that is used, in this case, for leaderboards and classifications. Building on a competitive spirit of participants, these leaderboards aim to increase users' appeal to play and leverage a dynamic participation. As for incentives, gamification is found to have a positive effect on the engagement in the first phases, but there are still interrogations about the sustainability of this approach (e.g. Kim et al. 2016). A brief review of the retained studies can be found in Table 2.

Publications	**Study sample and duration**	**Motivational incentives**	**Incentive mechanisms**	**Incentive evaluations**
Chung et al. (2017)	504 participants, 12 months	Feedback, Financial	Virtual points are given according to users' physical activity levels (1 step = 1 point) or if activity goals are attained in a given time (e.g. averaging 7,000 steps per day). These virtual points can be exchanged for cash rewards, gift cards or insurance discounts.	Effectively motivate users in the first phases to motivate users, sustainability has to be investigated.
Coffeng et al. (2017)	750 participants, 30 months	Education, Feedback	Coaching feedback sessions	To be determined
Gilson et al. (2016)	19 participants, 20 weeks	Feedback, Financial	Virtual points are given if physical activity goals are attained (e.g. averaging a number of steps per day). These virtual points can be transformed in vouchers.	Small positive changes for a majority of users
Gomez-Carmona and Casado-Mansilla (2017)	4 participants, 1 week.	Feedback, Gamification.	Motivational advice related to physical performance, leaderboards.	Effectively motivate users in the first phases
Hunter et al. (2016)	853 participants, 13 months.	Feedback, Financial	Virtual points are given according minutes of physical activity (1 min of activity recorded= 1 point). These virtual points can be exchanged for vouchers.	Effective after 4 weeks, after 6 months no significant differences with the control group
Jelsma et al. (2019)	250 participants, 12 months	Feedback, Education	Face to face sessions, individual counselling, self-help program leaflet	To be determined
Kim et al. (2016)	455341 participants, 12 months	Feedback, Financial, Gamification	Various challenges regarding physical activity, rewards platform where gains can be collected	Difficult to prove the role of incentives, although participation is enhanced
Lin et al. (2006)	19 participants, 14 weeks	Feedback, Gamification, Social	Daily users' steps are related to the growth of an animated virtual character	Effective as users have established new routines with positive impact on their physical activity and health levels

Publications	Study sample and duration	Motivational incentives	Incentive mechanisms	Incentive evaluations
Lee et al. (2019)	79 participants, 12 weeks	Feedback, Reminder	Daily motivational text messaging, biweekly counseling and a specifically designed workbook for 12 weeks	Counseling and tailored text messaging are effective for physically inactive users
Patel et al. (2016)	304 participants, 26 weeks	Financial	Various challenges regarding physical activity. Individual and team performance are rewarded by cash prizes	Effective in increasing physical activity
Vyas et al. (2015)	17 participants, 100 days	Feedback Gamification	Through a step counting mechanisms, participants can unlock trophies, leaderboards	Positive results, motivation enhanced
Yu et al. (2019)	1,436 participants, between 2011 and 2014	Feedback, Financial	Achieving certain health standards based on biometric screening values (e.g., Body Mass Index of 18.5–27.5) is rewarded by cash prizes	Statistically little impact

Table 2. Selected studies for review.

4. Case 2: Incentives in data-driven health insurance plans

4.1 Research design

In liberal healthcare markets such as Germany, the Netherlands or Australia, health insurance companies have just begun to propose additional health plans that include quantified self devices (Henkel et al. 2018). Consequently, there is no much academic evidence which can be assessed based on a literature analysis. Therefore, we decided to review offerings from major health insurance companies. The idea was to explore if plans with quantified self devices are proposed and if so, reference what kind of incentives are included. We decided to focus on Switzerland, as it is a liberal market with a high competition between health insurance companies: permanent residents can enroll in extra health insurance plans (such as data-driven health plans) in addition to a standard insurance plan that covers basic healthcare costs, i.e. examination and treatment of a medical condition and its consequences. There are therefore expectations with respect to choice options for the side of consumers, particularly as Swiss are often well-equipped in terms of Information Technology, financially well-off and generally early adopter of consumer technology. To review offerings, we based our research on the official directory of health insurance companies made by the Federal Office of Public Health[1]. We concentrate on the five biggest health insurance companies (> 500'000 clients), which account for two thirds of the Swiss market share and therefore offer a representative picture of what type of data-driven insurance plans individuals may obtain in Switzerland.

4.2 Results

Out of the 5 major Swiss health insurance companies (*Assura, CSS, Helsana, Swica, Concordia*), 3 offer plans with quantified self devices (i.e. CSS, Helsana, Swica). They display similar practices by offering to participants to link a quantified self device to their dedicated app and therefore open the possibility for a financial gain on healthcare costs and premiums. Concretely, through its program *myStep,* CSS compensates with CHF 0.20 (¢20) each day when users do between 7500 steps and 9999 steps, and with CHF 0.40 (¢40) each day when they do more than 10000 steps (CSS 2020). Similarly, Helsana offers to consumers to connect with a Garmin or a Fitbit to their app *Helsana+* in order to collect so-called *Plus points*. A plus point is commonly obtained if users attain during the day one of the following values: 10000 steps, a pulse rate of 110 per minute for 30 minutes or 150 calories burned in 30 minutes (Helsana 2020). These points may then be converted into cashback, reductions or gifts, allowing consumers to earn/save up to CHF 300 ($300) a year. Finally, Swica offers through its *Benevita* program a possibility to automatically gather quantified self data and complete an online form with health/lifestyle related questions to gather bonus points in order to save up to 15% of the premium (Swica 2020). It also proposes lifestyle challenges and fun games that users can share with other users, as well as possibilities to retrieve educational content (regarding, for instance, physical exercises or nutrition).

[1] Statistique de l’assurance maladie 2019, URL : https://www.bag.admin.ch/bag/fr/home/zahlen-und-statistiken/statistiken-zur-krankenversicherung.html

Health insurance	Motivational incentives	Incentive mechanisms
CSS (2020)	Financial	Amount of money is credited each time a defined goal is achieved.
Helsana (2020)	Feedback, Financial, Gamification	Points are collected each time a defined goal/challenge is achieved. Points can be transformed into discounts or vouchers.
Swica (2020)	Education, Financial, Gamification, Social	Points are collected each time a defined goal/challenge is achieved. Challenges can be shared with other participants. Through the app, clients can retrieve informative leaflets on nutrition or physical activity. Points can be transformed into discounts or vouchers.

Table 3. Selected plans for review.

5. Discussion and key implications for future research

The starting point of this explorative study is that organizations, such as firms and health insurance companies, increasingly include quantified self devices in their operations and often resort to motivational incentives to incite individuals to adopt and return to their quantified self solution (De Ridder et al. 2017). Our findings show that similarities exist between digital occupational health programs and data-driven health plans in how they encourage users to participate in their respective programs. First, drawing on the design and capabilities of quantified self devices (i.e. enabling automatic flows of information about one's health levels), organizations commonly provide a feedback loop to assist participants in their tracking. This is particularly prevalent in workplace settings where firms often propose individual counselling or personalized messages as part of their digital occupational health program. This may be explained by the necessity for firms to communicate through the whole process: they need to reassure employees or clients regarding their engagement to improve their health behavior. As we have seen, quantified self devices may create a tension between leisure and work contexts as they gather, independently of context, data about one's physical activity and lifestyle (Whitson 2013); so it is essential for firms to show to their employees the added value such devices provide as well as offer help in interpreting and understanding the collected data and what is further done with it. Simultaneously, it offers to firms a way to monitor the effectiveness of the occupational program and refine the global picture regarding workforce health levels.

Our results also indicate that feedback mechanisms are commonly associated with other incentives, especially financial incentives and gamification. The extensive use of financial incentives reveals that organizations consider that existing benefits (promises that the user may improve his health levels) are still not sufficient to prompt individuals to use quantified self devices in organizational programs (Tedesco et al. 2017). They therefore build their motivational strategies on external rewards, which are typically used when the barriers to adoption are perceived as high, or when the defined objectives are considered difficult to be achieved (Norman et al. 2016). Our exploratory study suggests that, in workplace settings, financial incentives have a positive effect in the first phases of engagement with quantified self devices, although the sustainability of this approach remains questionable on the long run. This is in line with reports (e.g. Promberger and Marteau 2013) that showed that financial incentives potentially reduce intrinsic motivation (even if the interest is initially high) and undermine performance once the incentive is removed or lowered. Yet, a long-term use of quantified self devices is crucial in organizational programs, both for organizations than for participants. It ensures that enough data is gathered and that this data can be used for meaningful analyses and feedback. In this way, it may raise awareness regarding health levels and potentially support an individual behavior change (which is generally a lasting process). In consequence, for digital occupational health programs, further research may focus on unveiling the long-term effectiveness of financial incentives, in order to clearly assess the scope of (positive) impact of this incentive. For data-driven health plans, the systematic use of financial incentives demonstrates the high importance given by health insurance companies to this particular mechanism. Further analysis may therefore be oriented to thoughtfully consider the ramifications of this motivational incentive: does it increase individuals' participation? If so, is there a population group that is more prone to subscribe to such plan? What are the implications in terms of participants' privacy? And, as for digital occupational health programs, do financial incentives foster a long-term engagement in data-driven health plans?

Finally, our review indicates that gamification also represents a frequent motivational incentive. This is in line with the popularity of gamification as a design approach to address motivational issues for commercial and medical purposes (Hamari 2013). Its implementation in organizations mainly consists in easing the execution of actions that are associated with a positive lifestyle (e.g. points-based scheme that translate the number of steps per day) and promoting the consistent of quantified-devices (e.g. extra points if performed on consecutive days) (Alahäivälä and Oinas-Kukkonen 2016). Nonetheless, gamification, as a motivational incentive, encounters similar challenges as financial incentives: evidence shows that it may have a positive impact on the use of quantified self devices in the first weeks, but its long-term impact is still not evident. In fact, some figures and numbers suggest that gamified interactive systems for health behavior change are considered as successful in merely 50% of the cases (Hamari et al. 2014). It seems therefore important to further assess the capacity of gamification to foster long-term engagement with quantified self devices, and then consider its application in organizational environments.

In sum, quantified self devices are emerging in organizational environments and lots of opportunities for research are arising with them. Various perspectives (e.g., organizational vs. individual) and approaches (e.g. utilitarian vs. hedonic) can be adopted and developed. So, we hope that, through this explorative study, we have indicated some of the paths worth investigating; and that these paths may ultimately lead to the development of effective digital programs for organizations as well as harmonious environments for individual health improvement.

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Article II

Article II: Financial incentives in data-driven health plans

Title: Financial incentives and intention to subscribe to data-driven health plans

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Abstract: Over the last years, health insurance companies have displayed considerable dynamism in integrating quantified-self-devices (such as smartwatches and activity trackers) in their business models to create data-driven health plans built around these systems. In order to motivate consumers to participate in these programs — and share their data — health insurance companies often make use of financial incentives. Yet, there is little evidence on the effects of discounts or rewards on individual intention to subscribe to data-driven health plans. In particular, little is known about the type of consumers for which financial incentives serve as a trigger for participation. In this paper, we thus report results from a survey made in Switzerland, which constitutes a representative context of consumers' choice in a liberal health insurance market, about consumers' intention to participate in (incentivized) data-driven health plans. By doing so, we seek to lay the foundations for a better comprehension of individuals' aspirations and drivers to engage into these programs.

Article II

1 Introduction

The way the wider masses perceive their health levels has evolved since the 2000's: information based on data and numbers have penetrated the collective awareness and many have become reliant on data analytics and algorithms to find out whether they have done enough physical activity; they have slept well or their diet is appropriate (Ajana 2017; Lupton 2016). This was made possible by the rapid development and the large commercialization of wearable systems that track individual behaviors, physical capacities, psychological wellness or environment parameters, in order to offer a quantified feedback to improve individual condition and performance (Wilson 2013). This new paradigm of individual empowerment and self-management through health data (commonly referred to as the *quantified self* movement) has also spread across the healthcare sector (Lupton 2016; Ruckenstein and Pantzar 2017; Swan 2013). We find today quantified self devices as cornerstones of many programs for physical therapy, patient monitoring, chronic disease management and preventive care (Appelboom et al. 2014; Marakhimov and Joo 2017). In particular, one key healthcare actor is showing a high interest in quantified self devices: health insurance companies. According to an industry report made in 2015 across 221 insurance companies in the world, 31% of the respondents have adopted this technology in one of their programs, while 61% were considering to incorporate quantified self practices in a foreseeable future (Accenture 2015). In fact, accessing to a constant tracking of physical or behavioral levels may allow health insurance companies to meet most of their commercial and organizational objectives, such as supervising the evolution of chronic conditions among the population, strengthening the range of provided health services, offering new insurance products and fostering consumers' engagement (Henkel et al. 2018; Lewalle 2006; Samuel and Connolly 2015; Tedesco et al. 2017). Yet, such health data tracking may also allow to identify potential health risk behaviors among users (which could impact how health insurance companies determine premiums) or characterize individual behaviors for further marketing and commercialization considerations (Constantiou and Kallinikos 2015; Tedesco et al. 2017).

In order to motivate data sharing from consumers, health insurance companies often resort to financial incentives, as motivational mechanisms to increase adoption rates and reduce resistance (Henkel et al. 2018; Paluch and Tuzovic 2019). Discounts or rewards are offered to consumers that link a quantified self device to company's dedicated app and, then, attain some objectives or challenges (e.g. averaging 7,000 steps per day). However, little is known about the effects of financial incentives on individual intention to subscribe to data-driven health plans and, specifically, if financial incentives act as a trigger for some types of consumers to engage in such programs. In fact, as academic attention directed towards data-driven health plans have started to grow, the main foci were either (1) privacy challenges (e.g. Patterson 2013); (2) individual willingness to disclose health data (e.g. Von Entreß-Fürsteneck et al. 2019) or (3) concrete applications of quantified self devices in these plans (e.g. Henkel et al. 2018; Tedesco et al. 2017). Thus, despite an emerging interest, there is little evidence on the effects of financial incentives, which may be determining in consumers' choice to subscribe to data-driven health plans. Such knowledge is not only essential to better understand individuals' aspirations and drivers to engage into these programs, but may also help health insurance companies, technology providers, and healthcare professionals to get insights about health-related behaviors of consumers who are willing to share health data, in order to ensure a successful integration of quantified self devices in their respective programs (Paré et al. 2018). This is particularly essential in the context of a market-oriented health insurance system, as the viability of a complimentary plan depends on the understanding of consumers' demands, preferences and level of access (Uschold et al. 2005).

Accordingly, we set out the following research question: *What are the effects of financial incentives in the intention to subscribe to data-driven health plans?*

To adequately explore this issue, our investigation has to be carried in a liberal healthcare system, where residents have choice options. This is the case of Switzerland, as permanent residents have to enroll in a basic insurance plan (individual free choice among state recognized private insurance providers) that supports elementary healthcare needs (i.e. covers the costs of the examination and treatment of a medical condition and its consequences). Additionally, permanent residents can contract any type of supplementary coverage (such as data-driven health plans), which is a standard practice in Switzerland, as more than 70% of permanent residents subscribe to some extra plans (Laske-Aldershof et al. 2004; Schoen et al. 2010). In all cases, the Swiss health insurance system shares numerous similarities (as regards health needs, economic opportunities and political context) with other healthcare systems across Europe (e.g. Germany, the Netherlands) and North America (Schoen et al. 2010; Thomson et al. 2014). This is why we believe that our paper provides evidence and reflection that can be generalizable for a multitude of contexts. We thus present findings which are based on a survey conducted with a representative sample of Swiss permanent residents regarding their intention to participate in data-driven health plans.

The remainder of this paper is structured as follows: we first introduce the notion of quantified self and then detail their connection to data-driven health plans. With reference to the literature, we next investigate the main dynamics and factors in the individual rationale of subscribing to data-driven health plans and accordingly develop our survey. We then test the effects of financial incentives and their interaction with other key factors, using a sample of 441 people, who were randomly selected to participate in our study. We conclude by discussing the results, the limitations of our analysis as well as the opportunities for future research.

2 Background

In the quantified self movement, there is a deep conviction that self-knowledge can be enhanced through numbers by regularly gathering data on oneself to better apprehend routines, behaviors and feelings (Choe et al. 2014; Lupton 2014b; Swan 2012b). The body is seen and framed as something that can be measured and quantified. The corresponding data is then automatically analyzed, plotted and even evaluated, so that individuals are provided with information that may guide them in a course of action (Heyen 2016; Whitson 2013). There is therefore a proactive stance that individuals themselves may be the focus and the center of action taking (Swan 2012a), as they are in position to collect health information and act based on it (Li et al. 2011; Whooley et al. 2014). For this reason, the notion of transparency is a key element of the quantified self movement: *self-quantifiers* are eager to unveil performance and "make existence knowable" (Didžiokaitė et al. 2018; Ruckenstein and Pantzar 2017). This ensures an optimization of their health levels by unlocking realizable, although initially vague, opportunities (Meißner 2016; Ruckenstein and Pantzar 2017). Eventually, communication also constitutes a fundamental pillar of the quantified self movement, because individuals acquire benchmarks (due to standardized measurements and visualizations) that allow them to share, compare and discuss health data. This can be done according to user's own data history but also compared to others, which explains why quantified self devices are often accompanied by web platforms or applications that enable resource-sharing (Heyen 2016; Meißner 2016).

In practice, quantified self-devices are wearable self-reliant systems that allow the monitoring of a wide range of vital parameters (e.g. blood pulse rate, oxygen saturation, body temperature), physical and behavioral activity (body movement calories used), mental status (e.g. mood, attention, stress), and environmental variables (e.g. noise, pollution, distance covered). They aim to better apprehend individuals' behaviors, enhance wellness and act on health levels (Choe and Fesenmaier 2017; Glaros and Fotiadis 2005; Gorm 2017; Lavallière et al. 2016). Considerable amounts of quantified self devices have been developed in the past years for the consumer market, going from activity trackers to complex systems derived from medical contexts (Mettler and Wulf 2020). Such diversity is due to the involvement of a large panel of new actors (West et al. 2016) that are coming from various sectors, such as the sport industry (e.g. *Under Armour, Nike*), consumer IT (e.g. *Garmin, Apple, Samsung*) or fashion (e.g. *Fossil*). With their active presence in the consumer market, these kinds of companies have constantly improved quantified self devices in terms of affordability, miniaturization, capacity to store data, and accuracy of health sensors (Heyen 2016; Lavallière et al. 2016; Stepanovic et al. 2019) making them accessible to a large number of people.

As a consequence of the wide dissemination of low-pricing quantified self devices such as activity trackers or smart wristbands in the consumer market, prior research has primarily concentrated on the study of quantified self devices for private use (Mettler and Wulf 2020). In fact, the research effort has been rather prolific (De Moya and Pallud 2017). The most recurring themes and discussions have covered adoption factors (e.g. Canhoto and Arp 2017; Li et al. 2016), privacy challenges (e.g. Mills et al. 2016; Piwek et al. 2016), use experiences (e.g. Kim 2014; Shin and Biocca 2017), self-experimentation (Karkar et al. 2015), styles of tracking (Rooksby et al. 2014), post-adoptive use (e.g. Buchwald et al. 2015; Marakhimov and Joo 2017), design (e.g. Epstein et al. 2015; Rapp and Cena 2014), and quantified self as a cultural and societal phenomenon (Choe et al. 2014; Lupton 2014c; Ruckenstein and Pantzar 2017; Swan 2013). In contrast, the attention on quantified self devices provided by third parties is starting to grow, as more and more investments are made by government agencies and businesses in order to harness health-related information obtained from quantified self devices (Lupton 2014a; Paluch and Tuzovic 2019). As outlined, health insurance companies are particularly active in this regard, because quantified self devices are seen as new opportunities to gain control on health expenditure and improve health service delivery (Mettler and Wulf 2020; Patterson 2013; Tedesco et al. 2017). As opposed to passive forms of information provision, the information collected by sensors may provide with more accurate and contextualized health advice (King et al. 2015; Mettler and Wulf 2020). Such companies are therefore attracted by the promises of accuracy, precision and efficiency in collecting information that quantified self devices offer (Dargazany et al. 2018). This may generate favorable conditions to reduce health costs, create new insurance products and services, or enhance engagement of consumers (Henkel et al. 2018; Samuel and Connolly 2015; Tedesco et al. 2017). For academics, privacy challenges and individual adoption remain the main focal points. In particular, scholars have acknowledged that potential security breaches, disruption of private life, fear of a discrimination based on health levels and unwanted targeted marketing have been the key individual concerns regarding the use of quantified self devices in a data-driven health plan (Cheung et al. 2016; Paluch and Tuzovic 2019; Patterson 2013; Von Entreß-Fürsteneck et al. 2019). Likewise, perceived data sensitivity has been found to exercise a moderating effect on this risk-benefits analysis, with a willingness to share data being more predominant for data such as steps or distance walked, and less for information such as heart rate or rhythm, blood pressure or weight (Von Entreß-Fürsteneck et al. 2019). In any case, evidence shows that data-driven health plans are starting to be proposed by health insurance companies across most industrialized countries (Dargazany et al. 2018). This is particularly perceivable in settings where the employer constitutes the link between quantified self devices and health insurance companies (Olson 2014). For instance, within the oil corporation *BP*, approximately 14.000 employees opted to wear a free wearable device to monitor their steps in order to reach a predefined objective (i.e. one million steps over the year) in order to obtain a lower insurance premium (Olson 2014).

Lastly, financial incentives appear to be a central element in data-driven health plans: studies which have investigated the application of such programs (e.g. Henkel et al. 2018) have found a prevalence of the use of direct and undirected financial rewards to motivate consumers to subscribe to data-driven health plans (Henkel et al. 2018). These discounts and rewards may take the form of vouchers, cashback, fidelity points, service upgrades or free gifts (Henkel et al. 2018; Hui et al. 2006; Von Entreß-Fürsteneck et al. 2019). Third-party providers may also be involved, with reductions on their products and services (e.g. miles in exchange to airline tickets). Either way, this indicates that health insurance companies often opt for a motivation approach based on external features, which is typically employed when barriers to adoption are perceived as high or when the established goals to achieve are considered as difficult (Norman et al. 2016). This also suggests that the current advantages are still not sufficient to motivate people in using quantified self devices, inducing low opt-in rates (Tedesco et al. 2017). Nonetheless, what is certain is that the use of financial remunerations makes data-driven health plans distinct from any regular complementary coverage or any other health promotion program (Henkel et al. 2018; Martani et al. 2019).

3 Research framework

3.1 Research context

In Switzerland health insurance companies are part of a heavily regulated market, where it is made mandatory to every permanent resident to acquire a standard health package from a private health insurer (Swiss Federal Office of Public Health 2019). Individuals are nevertheless free to choose the provider they find appropriate, and fund any additional health care packages (such as data-driven health plans) they find suitable. The whole idea is to maintain a competitive system which assures that the costs of premiums are staying relatively low and that health standards are driving up (Daley et al. 2007). Policies are promoting individual responsibility, consumer control and transparency between all the actors, i.e. health insurance companies, healthcare providers and consumers (Brown 2013; Herzlinger and Parsa-Parsi 2004). It consequently creates space for programs based on quantified self devices. In fact, while health data protection regulation has inhibited these organizations to directly collect highly detailed, health-specific data about their customers (Rosenblat et al. 2014), individuals still have the possibility to upload their biometric information through quantified self devices and share their health reports (Salamati and Pasek 2014). Hence, several Swiss health insurance companies have established data-driven health plans including some sort of quantified self devices device and software for incentivizing a healthier lifestyle, sometimes operating in a grey zone regarding collected health data.

Financial incentives are also largely used as mediums to motivate Swiss consumers to participate in data-driven health plans. Among the five main insurance companies in the country – in terms of insured individuals in 2019 (Swiss Federal Office of Public Health, 2020) – all of them offer a form of financial remuneration to their clients when proposing such programs. Practices vary from reverberating financial gains on healthcare costs, such as a reduction on premiums (e.g. *Helsana)* to delivering vouchers to be spent with one of their partner companies (e.g. *Sanitas*), or providing cashback to clients (e.g. *CSS*, *Visana*). Table 1 details some of these financial incentives scheme implemented in data-driven health plans in Switzerland.

Health insurance companies	**Data-Driven Health Plans**	**Financial Incentive Schemes**
CSS	Mystep	7500 steps to 9999 steps each day enable a credit of CHF 0.20 (¢20); more than 10’000 steps equal to CHF 0.40 (¢40). Credits can be transformed into cashback (CSS 2020).
Helsana	Helsana+	Points are obtained each time the client attain 10000 steps, a pulse rate of 110 per minute for 30 minutes as well as 150 calories burned in 30 minutes. These points can be transformed into discounts or vouchers (Helsana 2020).
Sanitas	Sanitas Active	A daily activity indicator maps the amount of activity done through the day (e.g. steps, natation and biking). Points are collected the daily objective is attained. These points can be transformed into discounts or vouchers (Sanitas 2020).
Swica	Benevita	Points are collected each time a defined goal/challenge is achieved. These points can be transformed into discounts on premium (up to 15%) or vouchers (Swica 2020).
Visana	Mypoints	Points are accounted as soon as the client attain 5000 steps 200 calories burned during the day. These points can be transformed into cashback (Visana 2020).

Table 1. Data-driven health plans in Switzerland

3.2 Hypotheses and constructs development

To adequately investigate what the effects of financial incentives are regarding the subscription of data-driven health plans, we first review the literature to define how we capture the intention to subscribe to data-driven health plans. We consider this aspect through *use intention*, referring to individual conscious decisions to use a system (De Guinea and Markus 2009). This corresponds to a notion that is systematically used in the Information Systems (IS) literature for approaching the use of a system (De Guinea and Markus 2009; Venkatesh et al. 2003). In fact, following Delone and McLean (2003), use intention communicates an attitude (while use refers more to a behavior, that is often arduous to measure) and thus informs on the likelihood that people use a system. It is therefore considered as an adequate predictive variable for system use (Chen and Cheng 2009).

Next, following our research objective, we assume that financial incentives (e.g. a discount on premiums) increase the proportion of individuals who intend to subscribe to data-driven health plans. As a matter of fact, in a market-oriented health insurance (such as Switzerland, but also Germany or the United States), costs and expenses have a significant impact on choosing and switching between a large panel of private companies (Laske-Aldershof et al. 2004; Thomson et al. 2014). Switzerland notably presents relatively high discrepancies between premiums (even for standard coverage) with health insurance providers distinguishing themselves through discounts, deductibles and particular insurance plans (Daley et al. 2007; Schoen et al. 2010; Thomson et al. 2014). Switching for better offers or preferred care networks is therefore something relatively common: it can be done up to two times a year (Daley et al. 2007) and may attain a rate of 15.4% (2009-2010) among all permanent residents (Thomson et al. 2014). Consistent with this, we posit the following hypothesis:

H1. Financial incentives positively relate to the intention to subscribe to data-driven health plans. The presence of financial incentives increases the intention to subscribe to data-driven health plans.

3.3 Moderating factors

To prevent an over-interpretation of the weight of financial incentives as a single factor in the choice of subscribing (or not) to data-driven health plans, we also examine the current literature to uncover the most salient dynamics (alongside financial incentives) that an individual face into subscribing a data-driven health plan in a liberal health insurance market (as in Switzerland). It therefore opens the way to eventual moderating variables that may better explain intention to subscribe to data-driven health plans. It also enables an investigation on eventual significant interactions between financial incentives and other factors.

The literature particularly underlines two dimensions that are dominant in the rationale of choosing a private health insurance company, i.e. consumers' financial capacity and their overall health status (Daley et al. 2007; Schoen et al. 2010).

Earnings and revenue tend to play a big role in consumers' choice regarding insurance scheme, even though Swiss health insurance companies cannot discriminate individuals based on their income (Martani et al. 2019). High income individuals have more opportunities to opt for extra insurance packages and navigate among health insurance companies to target their preferred ones (e.g. health insurance companies that provide data-driven health plans). Further, it is shown that in the consumer market, individuals owning a quantified self device for health promotion are, as a share, persons with higher income, and that they tend to be more active into digital communities (Abril 2016; Ertiö and Räsänen 2019; Régnier and Chauvel 2018). Conversely, individuals with lower income are more cautious in connecting with quantified self devices and engaging in quantified self practices. Early evidence also suggests that white-collar workers (usually individuals with higher incomes) have more possibilities to engage in physical activities than blue-collar workers, because they have more autonomy and flexibility in their workplaces. Thus, they might be in a better position to use quantified self devices effectively and embark onto data-driven health plans (Charitsis 2019; Esmonde and Jette 2018). Hence, we set out to investigate this relation and formulate the hypothesis that individuals with a higher income profile tend to participate more in data-driven health plans.

H2: Income positively relates to the intention to subscribe to data-driven health plans. As income increases, the impact of financial incentives on intention to subscribe to data-driven health plans decreases.

Alongside economic opportunities and financial capacity, the other main factor in the intention of subscribing to health insurance coverages is the perceived health benefits that can be achieved through it. Following the essence of the quantified self-movement, individuals may view quantified self devices as opportunities to scale their physical activity, manage their health levels, and, on the top of that, earn advantages from their health insurer (Paluch and Tuzovic 2019). It may therefore be a way to demonstrate healthy lifestyles (Von Entreß-Fürsteneck et al. 2019); leverage own's low-risk behaviors (Cheung et al. 2016; Paluch and Tuzovic 2019); fix objectives to remain motivated during a long period of time, and even contribute to the "community" with personal data (Cheung et al. 2016). Yet, following Paluch and Tuzovic (2019), individuals that are interested in participating in data-driven health plans express the importance of self-determination: they want to remain in control regarding when to exercise, which information to share and how long to take part in the program. Therefore, we assume that individuals with better health status are more likely to subscribe to data-driven health plans. This idea is further reinforced by the fact that, in a consumer market, individuals that report better health levels (or who do not suffer from chronic illnesses) are also investing more in quantified self devices and quantified self behaviors (Abril 2016). Likewise, individuals with healthy lifestyle patterns frequently perceive and behave in an affirmative way towards new health initiatives (Coulson et al. 1997). Accordingly, we postulate that a better health status is determining for the intention to subscribe to data-driven health plans.

H3: Health status positively relates to the intention to subscribe to data-driven health plans. As the health status increases, the impact of financial incentives on intention to subscribe to data-driven health plans decreases.

In sum, because data-driven health plans are distinctive form any other health insurance coverage plans due to the presence of financial incentives, we get three main factors that presumably influence intention to subscribe to data-driven health plans (i.e. financial incentives, economic conditions and health considerations).

3.4 Measurement development

Investigations on use intention have generally been conducted through quantitative surveys (Delone and McLean 2003), which are considered as appropriate research designs to assure a high generalizability of results (Johnson and Duberley 2000). Accordingly, we opted for a survey in order to gather empirical data and test our research design. More precisely, we conducted a survey in which Swiss permanent residents were asked to explore their intention to subscribe to a data-driven health plan.

To ensure robustness, several iterations of psychometric assessments were done, which resulted in the re-wording or discarding of questions following the discriminant, convergent, and nomological validity of items (see Table 2). All items were asked by means of sliding scales from 0 to 7, with the anchors for all items being 0 = strongly disagree to 7 = strongly agree.

Construct	Item	Description	Based on
Use Intention (UI)	UI1	I wouldn't mind wearing a quantified self device as part of my health plan.	Delone and McLean (2003); Bélanger and Carter (2008); Chen and Cheng (2009) and Pfeiffer et al. (2016)
	UI2	I have no problems in sharing the collected health data of my quantified self device with my health plan provider.	
	UI3	I'm open to using a quantified self device as part of a data-driven health plan.	

Table 2. Measurement instruments

To assess the weight of financial incentives, two different settings were generated. Within the first, the survey included a discount offer in case of subscription to a data-driven health plan while, in the second setting, no discount offer was proposed. In line with what is being done in Switzerland, the discount proposed in the setting with a financial incentive was a *money per step* scheme, where participants would earn credits (to lower their insurance premium) according to their physical activities.

With regard to previously identified moderating factors that may influence an individual's tendency to subscribe to a data-driven health plan, *income* is corresponding to *available household net income per month*, as it is a standard measure to consider relations with insurance subscriptions (e.g. Schoen et al. 2010). In this study, it was measured on an ordinal scale (1 corresponds to a monthly income < 3000 CHF; 2 a monthly income between 3000 and 6000 CHF; 3 a monthly income of >6000 CHF). For *health status*, a self-rated, ordinal scale was used (1 means that a person has estimated his or her health to be poor; 2 to be neutral; and 3 to be good). As a matter of fact, it is challenging to determine if an individual is in good health, given that it reflects a relative concept which experts continuously redefine and adjust in view of current societal transformations and new medical evidence (Mettler and Wulf 2020). Therefore, self-reported health is a valid and consensually accepted way to overcome this hurdle and measure overall health statuses (Abril 2016; Bowling 2005), being used both in surveys in academic spheres and international organizations (e.g. World Health Organization). For further refinement of the analysis, we also included two control variables: *age* and *gender*. Age was measured on a 3-point ordinal scale with ranges < 25 years, 25 to 55 years, > 55 years and is assumed to have a moderating effect on the intention to subscribe to a data-driven health plan (Morris et al. 2005) as may have gender (Abril 2016), which we measured as a dummy variable (1 referring to female respondents and 0 to male respondents).

The necessary data for testing our hypotheses was obtained by means of an online survey. Respondents for this study were recruited through social media, announcements on our website, as well as by face-to-face recruitment. For reasons of privacy and confidentiality, participants were informed that their answers would remain anonymous and only employed in an academic perspective.

3.5 Profile of the sample

Participants were randomly assigned to one of the two groups, with a sample of 223 valid responses for the survey with the discount offer and 218 valid responses for the survey without discount (see Table 3). Note that only full records (without missing data) were included into analysis. Out of the sample with a discount offer, 48.8% were male and 51.1% female. As regards the age of the respondents, 53.4% were below 25 years, 30.9% between 25 and 55, and 15.7% older than 55 years. 43.1% declared themselves to be in excellent health, 11.9% in reasonable health, and 9.4% expressed to be in rather poor health conditions. From a financial perspective, 54.7% had less than 3,000 CHF a month in disposable income, 39.0% between 3,000 and 6,000 CHF, and 6.3% a monthly budget of more than 6,000 CHF. For the sample without discount, relatively similar numbers were obtained: 51.8% were female, 48.2% male; 44.0% were younger than 25 years, 33.0% were between 25 and 55 and 23.0% were more than 55 years old. 16.1% declared having a rather poor health, 39.0% reasonable health conditions and 45.9% good health levels. Lastly, 42.2% expressed having a household net income below 3000 CHF, 36.2% between 3,000 and 6,000 CHF, and 21.6% a monthly budget of more than 6,000 CHF.

	With discount (n=223)	**Without discount (n=218)**
Gender	109F (48.8%), 114M (51.1%)	113F (51.8%), 105M (48.2%)
Age (<25|25-55|>55)	119 (53.4%), 69 (30.9%), 35 (15.7%)	96 (44.0%), 72 (33.0%), 50 (23.0%)
Income (<3k|3k-6k|>6k CHF)	122 (54.7%), 87 (39.0%), 14 (6.3%)	92 (42.2%), 79 (36.2%), 47 (21.6%)
Health (poor|neutral|good)	21 (9.4%), 106 (47.5%), 96 (43.1%)	35 (16.1%), 85 (39.0%), 98 (45.9%)

Table 3. Descriptive statistics of survey experiment

3.6 Data analysis

An analysis of variance (ANOVA) was performed to test the main between-subjects effects, using *Stata version 14.2*. Results of the analysis can be found in Table 4.

First, from the F-statistic, we identified that the main effect *discount* reached a significant level (F=13.37, Sig. 0.0). Main effects *income* (Sig. 0.10) and *health* (Sig. o.24) are not found to be statistically significant, as probabilities for both are more than the standard significance level of 0.05. Second, as regards interaction effects, only the crossover *interaction* *discount×income×health* is found to be statistically significative (Sig.0.05). The effects of *income* and *health* only exist over levels of *discount*.

It therefore means that only H1 is supported, whereas H2 and H3 are rejected.

Source	**df**	**Mean square**	**F**	**Sig.**
Discount	1	15.86	13.73	0.00
Income	2	2.63	2.28	0.10
Health	2	1.65	1.43	0.24
Discount×income	2	0.58	0.50	0.61
Income×health	4	1.32	1.14	0.33
Discount×health	2	1.66	1.44	0.24
Discount×income×health	4	2.69	2.33	0.05

Table 4. ANOVA test –main and interaction effects

To better visualize the interplay between *discount*, *income* and *health*, we graphed in Figure 1 the relationships between these 3 factors. In accordance with our sliding scale employed for use intention, we also delineated into thirds areas regarding individual intention to use data-driven health plans (i.e. *no-go area*, from 0 to 2.33; *reflection area*, from 2.34 to 4.66 and *definitive use area*, from 4.67 to 7).

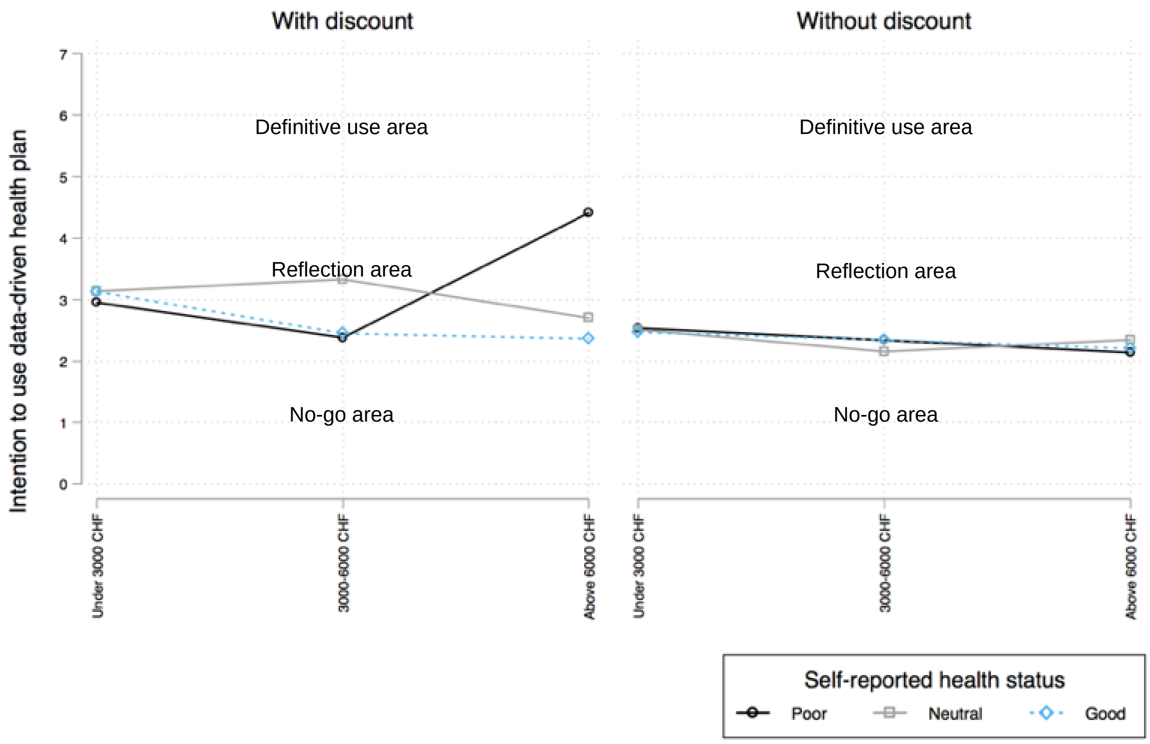

Figure 1. Interaction effects discount×income×health on intention to use data-driven health plans

4. Discussion

First, the findings of the present study underline the importance of financial incentives to motivate consumers to subscribe to data-driven health plans, as the intention to use quantified self devices is significantly associated with the presence of discounts. Data-driven health plans that include such bonuses, which are often emphasized by the institution (Henkel et al. 2018; Von Entreß-Fürsteneck et al. 2019), have an increased likelihood of consumers' participation compared to data-driven health plans with no discount. Some individuals are consequently perceiving the use of quantified self devices under a utilitarian and functional perspective: the discount acts as an extrinsic factor that triggers the motivation (Ryan and Deci 2000). This is in line with conclusions drawn by the literature about the use quantified self devices in consumer settings, as the role of external factors (e.g. discounts, rewards) is acknowledged to prompt adoption (Mekler et al. 2017; Shin et al. 2015). These external motivators therefore serve as proxies to reduce the costs of engaging into the early stage of use of quantified self devices (Attig et al. 2018; Munson 2017; Rapp and Cena 2014). The same phenomena can be also found in organizational settings, especially in contexts where the employer is providing health insurance to employees (Olson 2015; Suh et al. 2017). For instance, within the oil corporation *BP*, approximately 14.000 employees have opted to wear a free wearable device to monitor their steps in order to reach a predefined objective (i.e. one million steps over the year) in order to obtain a lower insurance premium (Olson 2014).

Second, in the scenario where discounts are not included, income or perceived health levels do not exercise a particular effect on the intention to subscribe to data-driven health plans. In this regard, our findings do not resonate with evidence from commercial use, as (1) Ertiö and Räsänen (2019) found that the most salient contextual factor in purchasing quantified self devices was income; while (2) Abril (2016) indicated that consumers with better health levels tended to invest more in quantified self devices. Moreover, without the presence of a discount, use intention remains low among the wider audience (even reaching the *no-go area*). This confirms that the promises of health improvement are still not sufficient to motivate people to use quantified self devices provided by health insurance companies. It may also illustrate that concerns about these programs are still very prevalent. As mentioned earlier, first studies on data-driven health plans have mainly assessed privacy challenges regarding individual adoption. In particular, they have determined that potential security breaches, disruption of private life, fear of a discrimination based on health levels and unwanted targeted marketing have been the key individual concerns regarding the use of quantified self devices in data-driven health plans

(Cheung et al. 2016; Paluch and Tuzovic 2019; Patterson 2013; Von Entreß-Fürsteneck et al. 2019). Likewise, perceived data sensitivity has been found to exercise a moderating effect on this risk-benefits analysis, with a willingness to share data being more predominant for data such as steps or distance walked, and less for information such as heart rate or rhythm, blood pressure or weight (Von Entreß-Fürsteneck et al. 2019). Hence, the role of financial incentives are still fundamental for health insurance companies to overcome these barriers and attract more than a small proportion of early adopters, which are found to be more risk-tolerant (Cheung et al. 2016). These are usually highly motivated, computer literate and tech savvy individuals that are moved by a determined wish for self-improvement and a curiosity for detailed personal information (Ancker et al. 2015; Whooley et al. 2014), but that do not represent in any way the rest of the population.

This naturally brings us to take a more precise look on the proportion of increase in use intention that financial incentives induce and, then, eventually define typical profiles where this increase is more perceptible. The existence of a discount mechanism overall increases intention to subscribe to data-driven health plans among all types of profiles (notably moving all patterns outside the *no-go area*). Still, for a majority of cases, this represents a marginal growth in intention, showing that a certain amount of skepticism remains towards institutions providing data-tracking technologies (Cheung et al. 2016; Mettler and Wulf 2019; Patterson 2013).

In two combinations, however, this increase in use intention is more pronounced. First, individuals with lower income, regardless of their health status, are more inclined to subscribe to data-driven health plans with discounts. This may be the expression of an engagement out of financial need: the incentive acts as a trigger and engenders a trade-off between data sharing and financial benefit (Veale 2018). Second, consumers with a high income and a perceived poor health status show a noticeable increase in use intention. Such a result might appear surprising at first, as the general comprehension is that individuals with good perceived health status may be driven by a need to demonstrate their good health habits and gain recognition for their capabilities in self-management (Hardey 2019). However, providing access to quantified self practices might also be apprehended by some as an occasion to improve their health levels (Patterson 2013; Spender et al. 2019). This dichotomy truly illustrates the ambivalent nature of quantified self practices: at the same time, they may represent opportunities and challenges in terms of health promotion; thus it is often according to a particular situation that one of these dimensions emerges (Lavallière et al. 2016; Majmudar et al. 2015; West et al. 2016). For our particular case, we can argue that high income individuals have, in theory, more flexibility into contracting additional coverages, which means that they are primarily interested into enhancing their health levels. In fact, some studies suggest that a considerable share of individuals with perceived poor health status are willing to make their information visible. They do so to either motivate themselves (Nelson et al. 2016) and/or receive quality healthcare (Kordzadeh and Warren 2014). Put differently, they are often the ones that value the most the accessibility and availability of health data (Lafky and Horan 2011).

Finally, the fact that financial incentives have a significant impact on use intention might raise questions about the role of this reward in the relation between health insurance companies and consumers. For instance, some may argue that it creates an environment of *indirect coercion* on consumers (Rieder 2015; Stepanchuk 2017), as it may give the impression to individuals that they are high downsides on refusing the discount and the subscription. It may notably induce the feeling that they are missing an opportunity to spare money, that they are putting themselves in position to pay a higher health premiums than others, that they do not have the same opportunities as people that exercise often or that they are discriminated based on their health condition (Paluch and Tuzovic 2019; Rieder 2015). As a result, offering financial incentives in data-driven health plans may call for a new form of regulation of the health system in order to maintain social solidarity among consumers (Martani et al. 2019; Paluch and Tuzovic 2019; Rieder 2015). It may thus generate a source of tension between individual responsibility and solidarity, distorting the perception of individual duty, consumer control and transparency between all the actors, i.e. health insurance companies, healthcare providers and consumers (Brown 2013; Herzlinger and Parsa-Parsi 2004; Martani et al. 2019).

5. Limitations and future research

Certainly, this study has several limitations. First, it is based on hypothetical scenarios that are necessarily rooted in a context. In Switzerland, people are considerably vigilant and regardful of healthcare costs and means of diminishing these costs (Schindler et al. 2018), because it represents for most Swiss residents the greatest share of household expenditure (i.e. compulsory health insurance and extra coverages). Therefore, individuals are rather proactive in migrating between health insurance companies, which might be different than in other cultural contexts or societies. Similarly, we have developed our research framework (and independent variables) on the basis of the assumption of a liberal market with choice options. Although this form of healthcare system is common in industrialized countries, researchers and practitioners should always be aware of their particular context to assess the applicability of our outline and accordingly adapt to the specificities of their situation.

Next, we intend, through this work, to lay the foundations for better understanding the role of financial incentives in consumers' choice regarding subscription to data-driven health plans. While we provide a precise direction, future work could use more granularity in the level of analysis. For instance, we have unveiled that perceived health levels might influence intention to subscribe to data-driven health plans (for individuals with high income and in the presence of discount): yet, we presume that it might the case for individuals that perceive their health as poor but do not suffer from a chronic disease. In fact, we base such assumption upon evidence from commercial use: Paré et al. (2018) reveal that there is no statistically significant difference between groups in perceived health levels in the use of quantified self devices, whereas individuals suffering from a chronic condition have less chance to engage with the use of quantified self devices.

Nonetheless, this also illustrates the large possible avenues and opportunities for further research. In particular, qualitative studies may help to complete the profile of individuals that participate in data-driven health plans, providing a more nuanced view of the overall population (Levine et al. 2017). As use is a behavior, it is often more complex than a an intention, which is driven by a small number of independent and defined variables (Lippke et al. 2015). Thus, use experiences, familiarity with technology, habits, emotions have also an important effect of observed IS use (Beaudry and Pinsonneault 2010; Polites and Karahanna 2013; Stepanovic et al. 2019; Van der Heijden 2004). In particular, they allow to expose different patterns than demographic characteristics, since they are not detected with typical survey-based studies (Mettler and Wulf 2019; Zabala and Pascual 2016).

Furthermore, investigating continuation patterns and long-term engagement with quantified self devices sponsored by health insurance companies is crucial. Quantified self instruments have to be, in principle, used in a continuous manner to generate records and information to both support individuals' health empowerment and provide health insurance companies with relevant data. The following step subsequently lies in understanding if financial incentives also engender a long-term participation. Early evidence in consumer or organizational settings tend to show that involvement in quantified self practices is not necessarily assured with the presence of discounts or rewards. For example, Hunter et al. (2016) report that there they did not found any significant difference between control and intervention groups in terms of minutes of physical activity recorded (after 3 months and 6 months) in a workplace health program. Similarly, Spender et al. (2019) indicate that they had no confirmations of change in long-term health behavior, even in clinician-led health intervention plans.

Finally, another interesting opportunity to continue this reflection is to examine how consumers perceive financial incentives provided by third-party entities. While we have mentioned the general distrust among the population regarding data-driven health plans, some researchers argue that the presence of a financial reward is a form of confession on the uselessness and unpleasantness for the consumers (Maturo and Setiffi 2016; Morozov 2013) and that the use quantified self devices in these plans is directly conflicting with consumers interests. There is therefore a high potential to consider their use in other settings (e.g. at the workplace) as well as explore ethical sides regarding such ubiquitous technology and the potential economization of data. In particular, investigations regarding the fairness in offering financial retribution in exchange of access to individual data or the moral obligation for individuals to participate in data-driven programs sponsored by third-party entities may be interesting avenues for research.

6. Conclusion

Some scholars indicate that quantified self devices are becoming a new paradigm for many health insurance companies around the globe (Martani et al. 2019). While there is a general buzz and interest among these companies, as well as among researchers, public institutions and mass media (Silvello and Procaccini 2019), very little is known about mechanisms, such as financial incentives, that drive individuals to subscribe to data-driven health plans. To address this lack of generalizable findings, we report results from a survey made in Switzerland, which represents a context of typical consumers' choice in a liberal health insurance market.

Our results notably unveil that financial incentives significantly impact intention to use quantified self devices provided by health insurance companies. They especially drive more interest from individuals with a high income and a perceived poor health status. This shed light on the importance of opportunity that these plans correspond for consumers. We argue that financial incentives increase the perception of a chance to gain financial retribution or improve a poor health level with a plan that is otherwise (without discount) not particularly appealing for the wider population. Likewise, we identify elements that allow to continue the reflection on individual characteristics, mindsets and motivations to participate in data-driven health plans and propose potential avenues for further research. We accordingly hope to provide a solid basis on which researchers might continue investigating a topic that is gaining a high relevance.

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Article III

Article III: Gamification in health promotion programs

Title: Gamification applied for health promotion: Does it really foster long-term engagement?

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Abstract: Gamification is a popular design approach with the purpose to increase engagement and continuous use of Health Behaviour Change Support Systems (HBCSS) with the purpose to establish health and well-being. It is widely employed for promoting healthier life choices or for supporting people with chronic diseases in their daily activities. Yet, there is a lack of evidence concerning gamification and its ability to sustain favourable effects on health behaviour change. This paper presents a scoping review about the long-term perspective in gamified HBCSS, focusing primarily on IT-reliant systems that treat individual lifestyle habits like healthy nutrition, exercise or smoking cessation. We systematically selected studies that consider gamified HBCSS for health promotion and discuss to what extent long-term engagement is explicitly included in their design. Our results underline a deficit of consideration of the long-term perspective as well as a lack of measurement related to the lasting effects of gamification. We therefore propose to intensify the use of longitudinal and prospective observational studies in the context of HBCSS, in order to increase the level of evidence of gamification interventions.

Article III

1. Introduction

Gamification transposes game mechanisms and elements to non-game contexts as a way to motivate people, initiate participating processes and improve user experiences (Deterding et al. 2011a). Badges, rewards or social competitions are thereby employed to orient and positively influence individuals' motivation, behaviour and/or productivity (Blohm and Leimeister 2013; Deterding et al. 2011a; Huotari and Hamari 2012).

Popular among marketing, production, and learning environments (Deterding et al. 2011a; Nacke and Deterding 2017; Seaborn and Fels 2015), gamification is obtaining great attention in the area of healthcare as well (Johnson et al. 2016; King et al. 2013; Pereira et al. 2014). Evidence suggests that gamification rises enjoyment, engagement and compliance of health-related activities, while positively impacting health outcomes and cost of service delivery (Lenihan 2012; Pereira et al. 2014). Its implementation is reinforced by the development of advanced digital health platforms, built around ecosystems of wearable and mobile devices, such as fitness trackers or other sensing devices like smartphones (Rapp 2017; Thiebes et al. 2014). Whether these digital services are conceived to enhance individuals' well-being, guide rehabilitation periods or assist patients in their disease management, gamification holds great potential for adding further positive experiences to their primary health-related goals (Alahäivälä and Oinas-Kukkonen 2016; Sardi et al. 2017).

These digital services can be referred to as *Health behaviour change support systems (HBCSS)* when their aim is to alter individuals' attitude and behaviour toward wellbeing and healthier lifestyles (Alahäivälä and Oinas-Kukkonen 2016; Mettler 2015). In such cases, gamification is mostly applied for encouraging individuals to continue using the service in a more regular manner, or facilitating and promoting the completion of certain health-related activities which are associated with a positive behaviour (Alahäivälä and Oinas-Kukkonen 2016). A major assumption of gamification in HBCSS is therefore that human behaviour and attitudes can be positively influenced through technological interventions (Hamari et al. 2014a). That said, these attitudes and behaviours need to be maintained over time in order to lead (if at all) to *concrete* and *positive* outcomes in terms of health and well-being (Bandura 2004; Klasnja et al. 2009; Mettler 2015). In this sense, the temporal dimension inside gamification is of utmost importance. Yet, long-term effects induced by gamification for digital health and, specifically, HBCSS are insufficiently explored and understood. Johnson, et al. (2016) and Sardi et al. (2017) identified the long-term viability of gamified health services to be a major challenge. Likewise, Cugelman

(2013) showed that scholars frequently report difficulties to express if outcomes represent sustainable long-term impacts on health, or just elusive short-term effects. Accordingly, this paper aims to develop an exploratory study regarding the long-term engagement in digital health behaviour change interventions, and concentrate, as an initial approach, on systems designed for health promotion. To this end, we set out to investigate the following research question:

RQ: How do studies on health promotion through gamified systems account for the long-term aspects?

The remainder of this paper is structured as follows. After explaining *gamification* in more detail, we then describe our methodological approach in reviewing the extant research. This is followed by the examination of gamification approaches in HBCSS together with the investigation of how long-term engagement and temporal considerations are included in the identified literature. We conclude with a reflection on the practical and theoretical implications of our study, as well as an indication of the limits of our work and some propositions to guide future research.

2. Conceptualizing gamification in HBCSS

Gamification is frequently understood as the use of game design elements in non-game contexts (Deterding et al. 2011a) or as the process of enhancing services with motivational affordances for "gameful" experiences (Alahäivälä and Oinas-Kukkonen 2016; Hamari 2013; Hamari et al. 2014b; Schmidt-Kraepelin et al. 2018). Gamification therefore corresponds to a mechanism with game characteristics that tries to positively influence one's personal motivation and/or perception about a selected action so that it is more engaging. It notably involves supporting user engagement and enhancing positive patterns in service use, such as increasing user activity, boosting social interaction, or raising quality and productivity of actions (Hamari 2013; Hamari et al. 2014b).

In order to appreciate how these gamification mechanisms are deployed, it is first of all necessary to understand that the notion of game is not the main object of the system: it is only a means to support and lead to a certain behaviour (Darejeh and Salim 2016; Deterding et al. 2011a; Ryan and Deci 2000). That also grants the differentiation between gamification and serious games (Deterding et al. 2011b; Sailer et al. 2017). In fact, serious games utilize gaming as a central and primary medium (Fleming et al. 2017): they are fully-developed games serving a specific and non-entertainment purpose (Deterding et al. 2011a; Mettler and Pinto 2015; Sailer et al. 2017; Xu et al. 2013). Gamification, on other hand, contains some game components but does not present a fully virtual game environment nor fulfil a game experience where the user can completely immerge himself (Fleming et al. 2017). Furthermore, in contrast to game-based technologies that include engines or controllers, gamification designs typically only involve game references. Hence, game design elements (or gamification elements) are defined as those elements that are characteristic of games, that can be found in most (but not necessarily all) games, and that are meaningful to the sense of the game and the gameplay (Deterding et al. 2011a; Deterding et al. 2011b; Sailer et al. 2017). Put in other words, they constitute features implemented to add some hedonic element(s), in order to support the completion of an utilitarian purpose (Hamari et al. 2014b).

Gamification elements are diverse and materialize in different forms (e.g. points, badges, levels, leaderboards etc.). However, only reasoning in terms of gamification elements (without context attention) and presuming their effects on motivation seems rather speculative (Alahäivälä and Oinas-Kukkonen 2016; Cugelman 2013). We shall not, for instance, simply suppose that *points* motivate users. In fact, we also have to consider the persuasive strategies that the *point* fulfils; take in account the value that a community places on that *point* and weighing the value that the individual himself bases on the *point* (Cugelman 2013). Hence, calling on (successful) gamification requires a deep comprehension of the contextual factors, and the same goes for any analysis of gamification mechanisms. Gamification elements therefore relate to gamification strategies. Hence, an element is implemented with regard to a plan of action, especially when it targets a behaviour change. For instance, a popular gamification strategy is enhancing motivation by indicating success (Sardi et al. 2017). *Points, badges, achievements*, or *statuses* typically provide the path to its application. Adding a feedback to increase interest and/or positive attitudes in completing a given action forms another common strategy. Gamification may also refer to a form of competition, by setting challenges, creating confrontations and making the effort visible to other users (e.g. via *leaderboards, performance graphs* or *rankings*) (Lister et al. 2014; Park and Bae 2014; Sailer et al. 2017; Sardi et al. 2017). Likewise, gamification can rely on social dimensions: the design therefore consists in enhancing participation (while completing the task) by group dynamics, interactions through a social network and exchanges with a given community (Pereira et al. 2014). *Narrative storylines, avatar-based self-representation, onboarding tutorials* (Cugelman 2013; Sardi et al. 2017; Yassaee and Mettler 2017), as well as *theme* and *clear goals* (Hamari et al. 2014b; Johnson et al. 2016) serve as additional gamification design elements. These latter also bring up the importance of the game design experience. Aesthetics are critical and might be the guarantor of the success of a gamified process (e.g. the quality of the technological depiction is essential in a virtual representation of a character). Plus, in everyday life, individuals are more and more accustomed to a certain quality of digital products and services: adoption of high quality gamified schemes is therefore crucial (Pereira et al. 2014).

When used for developing HBCSS, gamification strategies are similar to approaches and purposes of persuasive technologies: they aim, throughout artefacts, to induce behaviour change (Kappen and Orji 2017). In order to characterize them, we adopt Cugelman's taxonomy for digital health behaviour change (2013). It is, to our knowledge, the first research that provides a tested framework in the area of gamification for digital health behaviour change interventions. *Table 1* illustrates the retained gamification strategies and game design elements. By the same token, it summarizes the development presented in this section.

<table>
<tr><td colspan="4">Gamification strategies</td></tr>
<tr><td colspan="2">1. Goal setting</td><td colspan="2">5. Capacity to overcome challenges</td></tr>
<tr><td colspan="2">2. Providing feedback on performance</td><td colspan="2">6. Reinforcement</td></tr>
<tr><td colspan="2">3. Compare progress</td><td colspan="2">7. Social connectivity</td></tr>
<tr><td colspan="2">4. Fun and playfulness</td><td colspan="2"></td></tr>
<tr><td colspan="4">Game design elements</td></tr>
<tr><td>1. Points</td><td>4. Rewards</td><td>7. Achievements/Badges</td><td>9. Levels</td></tr>
<tr><td>2. Story/Themes</td><td>5. Clear goals</td><td>8. Feedback</td><td>10. Leaderboards</td></tr>
<tr><td>3. Progress</td><td>6. Challenge</td><td></td><td></td></tr>
</table>

Table 1. Framework explaining gamification strategies and game design elements for digital health behaviour change

Principal application areas of gamified HBCSS are the promotion of physical activity, guidance in nutrition, as well as supporting chronic disease management and rehabilitation (Johnson et al. 2016; Sardi et al. 2017). In fact, three major groups of use contexts can be differentiated:

A. *Individual lifestyle habits*. Operating on weight control, food consumption, eating habits, exercise, physical activity, unhealthy habits (e.g. smoking) and hand hygiene can be labelled as a function on lifestyle habits, where advanced gamified systems reinforce positive experiences and support individuals to adopt beneficial health behaviours (Alahäivälä and Oinas-Kukkonen 2016; Pereira et al. 2014). Pereira et al. (2014) thereby mention that gamification contains the ability to transform the obstacles (that may lead to behavioural changes, such as failure) into engaging, positively reinforcing and perhaps even fun experiences that encourage users to make sound decisions and activate the desired behaviour for the benefit of their health and wellness.

B. *Chronic disease management and rehabilitation.* Chronic disease management (e.g. diabetes, cancer, Alzheimer's disease, stroke and obesity) and rehabilitation respond to the presence of a given condition. Thus, gamification offers great opportunities in guiding patients through their treatment, making the procedure more engaging and facilitating new forms of self-management. The objective is therefore to establish an effective chronic disease management, in the interest of improving positive health outcomes (Cafazzo et al. 2012; Miller et al. 2014).

C. *Support of health professionals*. Lastly, gamified digital systems are also developed in order to support health professionals in their education and their daily tasks. The goal is to enhance their engagement and cooperation, notably by easing (or making more enjoyable) the practice of medicine, which often involves tedious, repetitive, boring, and/or painful routines for both the practitioner and patient (Alahäivälä and Oinas-Kukkonen 2016; Pereira et al. 2014).

That being said, Alahäivälä and Oinas-Kukkonen (2016) additionally stress the importance of reflecting about the user context (*Is there a targeted group of users? Who composes the majority of potential users?*), the technological context (*What is the technological support or modality that is being employed?*) or other contextual factors that practitioners, designers, and scholars need take into consideration in order to (successfully) design or analyse gamified systems for health behaviour change.

In sum, we presented a description of gamification and stressed the importance to apprehend game design elements, gamification strategies, as well as contexts all together to evaluate gamified HBCSS and put them on the challenge of time.

3. Opening the way to conceptualize a long-term perspective in gamified HBCSS

As mentioned before, HBCSS inherently ask for long-term engagement in order to act on behavioural intentions and attitudes that potentially lead to positive health outcomes (Bandura 2004; Klasnja et al. 2009; Mettler 2015). In view of the lack of theoretical evidence about long-term engagement in digital health, a *scoping review* of literature is necessary to explore the extent situation. This form of review provides the opportunity to map a body of literature that might be composite and understudied, as well as determine potential research possibilities (Grant and Booth 2009). However, as we have seen, gamification for digital health can be employed in several contexts, i.e. (1) maximising wellness, well-being and quality of life (health promotion), (2) restraining and managing an existent disease (rehabilitations processes and disease management) or (3) providing education for health professionals (Stuifbergen et al. 2010). For our scoping review we chose to concentrate on gamified systems for individual lifestyles habits (1), given that the situational context and end-user in the other two cases are much different. To be more precise, we excluded (3) because the use of IT-reliant systems in a professional setting is very different from a private setting (e.g. it could be mandated by management). Although relating to individual users in private settings, we excluded (2) because use intention and expectation of users could significantly differ and as such the long-term mechanisms. For gamified systems designed for health promotion, *wellness* appears to be the first focus, whereas *illness* serves as frame of reference and finds itself in the background. Gamified systems for rehabilitation or chronic disease management function the other way around: the primary target is *illness*, and *wellness* is a perspective in the background (Stuifbergen et al. 2010). Motivation and long-term engagement are in both cases challenges to address; however, it may appear much harder to motivate people that only have a perspective of *illness*, than patients that face the *illness* and are in treatment or rehabilitation. For these reasons, and in order to ensure coherence, we only selected a single stream of research for this paper, namely health promotion.

Additionally, long-term engagement and continuous use can surely be considered as relative concepts. What are, for instance, the frontiers when considering that gamification has achieved a long-term use and, therefore, that a health behaviour is adopted? Can it be rightfully claimed that the long-term use starts at one point and finishes at another? What is certain is that this subject seems insufficiently investigated. Again, regarding the lack of theoretical evidence, we decide to draw on our retained papers to see how they apprehended concepts like *long-time use* or *continuous engagement*. We therefore expand on the research methods applied in gamification for HBCSS: we formulate the assumption that longitudinal studies (frequent and continuous measurements to observe a particular cohort) and follow-up interventions provide reliable data about continuous use. As a matter of fact, longitudinal studies employ frequent and continuous measurements to observe a particular cohort over a long period of time (Caruana et al. 2015). Besides, we argue that any follow-up that is distinctly detached from the initial/main intervention, assures to capture some actual post-intervention effects. Our hypothesis is that these constitute the best approaches to evidence a long-term perspective, at least at this scoping phase of research. In our view, cross-sectional study designs (i.e. measuring engagement only once) offer weak evidence to explain long-term engagement, as it simply does not allow for causal inferences. Given the number of identified studies, we will still take this type of studies into account (although their contributions will be considered with caution) in order to provide a categorization and to investigate the evidence level of extant research. The purpose of this paper is to deepen the reflection about the temporal ("long-term") perspective and engagement.

4. Methods

To address our research goal, we first perform a systematic search of scholarly articles that explicitly dealt with digital health promotion and gamification. We then categorize the retained literature using our previously described framework (cf. Table 1), evaluate how gamification (or the gamification mechanisms employed) cope with long-term engagement and summarize our findings with a promising value proposition with respect to motivation and participation on the long run. Figure 1 depicts the study selection process in the form of a PRISMA flow diagram (Moher et al. 2009).

In concrete terms, we determine, as a first step, keywords that are directly related to gamification. The selected terms *gamification OR gamif* OR gameful* intuitively refer to gamification and ensure inclusion of multiple variations of the term, like (to) gamify or (being) gamified (Deterding et al. 2011a; Johnson et al. 2016). They also utterly align with the recent systematic literature reviews linked to gamification and health (Alahäivälä and Oinas-Kukkonen 2016; Johnson et al. 2016; Sardi et al. 2017). In addition, we take into consideration the following terms: *health* OR wellbeing OR well-being* to potentially include relevant studies associated to health, well-being and behaviour change. Our search is performed in the following abstract and citation databases: *Scopus, EBSCOHost, Web of Science* and *ACM Digital library*. These platforms offer electronic access to multiple databases that reference cross-disciplinary research. The prior mentioned search terms are employed for all fields (including title, abstract, keywords and full text), and all result types were reviewed.

Inclusion criteria for studies are: (1) written in English; (2) published on a peer-reviewed venue; (3) available in its full form; (4) clearly defines methodology of the study; (5) clearly refers to gamification; (6) clearly refers to health digital devices and services. Papers excluded from the review belong to at least one of the following categories: (1) only reports specific chronic condition management; (2) briefly mentions gamification but the actual substance is not gamification-related; (3) mentions health digital services and devices but the core is not related to them; (4) mentions persuasive technologies but does not actually study a topic connected with such technologies; (5) work-in-progress papers, study protocols and study prototypes. Accordingly, our review retains all the articles that explicitly refer to gamification (as defined in *Section 2*), automatically excluding serious games, video games and other applied games. In the same vein, papers that do not clearly relate to some sort of digital intervention (e.g. using mobile or wearable devices) are not considered, given that we are evaluating the use of gamification in digital health devices and services.

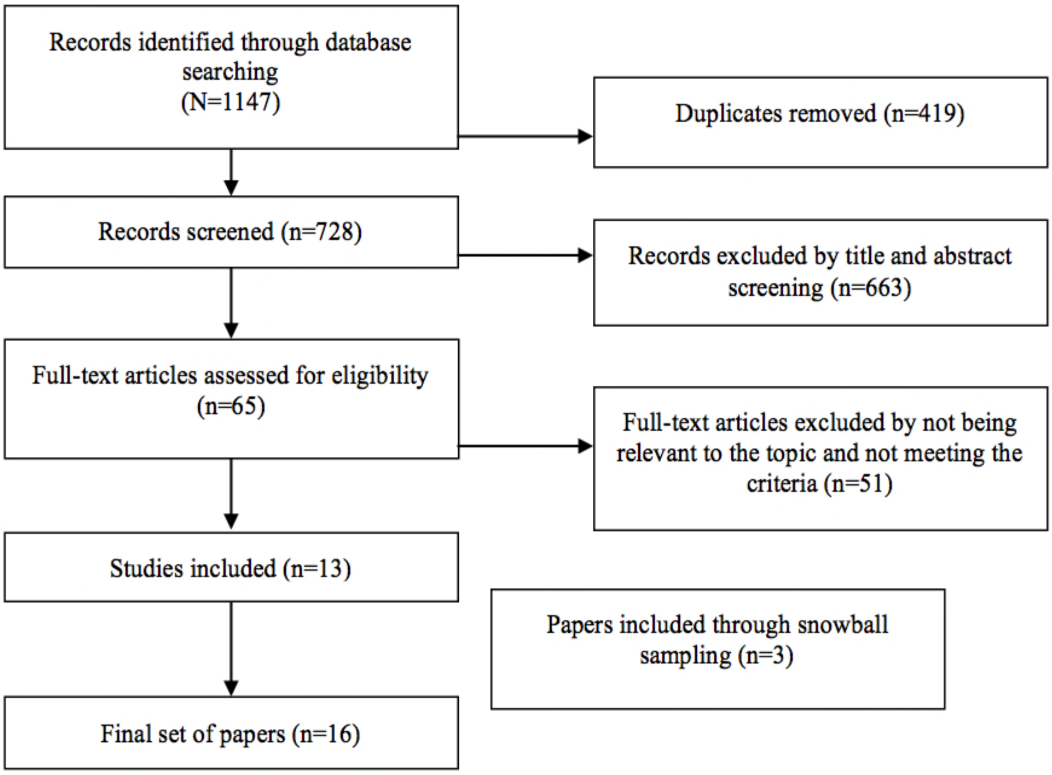

Figure 1. PRISMA flow chart for the selection of studies.

We qualitatively analysed our final set of papers with regard to the meaning of "*long-time use*" and "*continuous engagement*", as well as in relation to research methods applied for studying longitudinal or future effects. The research methods applied in the studies are presented in the *Results* section *(See Section 5)* and the approaches regarding the long-term perspective are presented in the *Discussion (See Section 6).*

5. Results

Our initial database search identified a large number of papers (N=1147), out of which 419 were duplicates. After removing those, we screened the remaining 728 papers by title and abstract. After excluding another 663 papers, a total of 65 papers were considered for a full text evaluation. Among these, 13 were found to meet our criteria. The most frequent reasons not to include papers were notably the use of gamification for managing a particular health condition, as well as the strong presence of studies that did not provide any empirical evidence (but rather only conceptual considerations or technical design recommendations). Following the guidelines provided by Wohlin (2014), we added three more articles to our analysis by using the snowballing technique. In consequence, a total of 16 papers were retained for comprehensive analysis. The selected papers are detailed in *Table 2*, along with the reported gamification approach (see *Section 2* for our classification modalities) and research design.

A vast majority of the retained papers (9 out of 16) focus on rising physical activity through gamification. Interventions, within this categorization, range from encouraging children to adopt an active travel to school (Coombes and Jones 2016), to improving commitment in sports tracking software (Giannakis et al. 2013). The second most common context of use can be labelled as *enhancing eating habits*, i.e. acting on school kids' fruit and vegetable consumption (Jones et al. 2014). Such a distribution is not really surprising, if we consider studies that report gamification for health and well-being: in that respect, gamification for behaviour change toward healthier habits is essentially linked with increasing physical activities and, to a lesser extent, improving nutrition (Alahäivälä and Oinas-Kukkonen 2016; Johnson et al. 2016; Sardi et al. 2017). The remaining four papers related to smoking cessation (El-Hilly et al. 2016), sleeping habits (Ilhan et al. 2016), health consciousness (Ogi et al. 2015), or stretching exercises (Kim et al. 2017).

The systems reported in the literature often make use of several gamification elements and strategies in parallel (cf. *Table 1*) Only one of them (Giannakis et al. 2013) exclusively relies upon one single element (*feedback*) and subsequently activate one particular strategy (*providing feedback on performance*). In this precise case, gamification is used to provide some visual data, in order to stimulate and motivate users to optimize their performance. Still, as our results show, gamification predominantly inserts itself in the design through a variety of modalities giving rise to a certain level of complexity as it activates different persuasive strategies and calls on diverse elements. The addition of those enables the creation of a particular incentive that aim to alter a behaviour in a specific manner. The distribution of gamification strategies in HBCSS reveals that (on 16 selected papers) the *goal setting* strategy is the most employed (12 out of 16) followed by *compare progress* (9 out of 16) and *providing feedback on performance* (9 out of 16). This concretely means that the most preferred gamification approach is to commit users to achieve a goal, which is often coupled with an monitoring of these goals with others (Cugelman 2013). The implementation is mostly done by *feedback* (9 out of 16), *leaderboards* (8 out of 16), and *points* (7 out of 16) which is obviously in line with the previous mentioned strategies. Hence, gamified HBCSS for healthier lifestyles commonly construct on three prevailing aspects: a definition of target(s), a feedback loop and a social component.

As a matter of principle, all of these gamified HBCSS aim to create a long-term engagement. In order to have a better picture of which gamification strategies (and elements) effectively foster long-term use, we need to appreciate how these studies report it. However, an overwhelming majority of the papers use cross-sectional study designs (14 out of 16) to gather data on gamified HBCSS. According to our procedure presented above, it already underlines a serious lack of consideration regarding long-term perspective and lasting effects of gamification. The consequences of such results are further commented in the next section *(See Section 6).*

Publication	***Use context***	***User context (sample size)***	***Technology context***	***Gamification strategy***	***Gamification element***	***Study design (duration of intervention)***
(Buchem et al. 2015)	Rising physical activity	Senior users (n=10)	Wearable device, Computer software	Goal setting, Social connectivity, Capacity to overcome challenges	Badges, Progress, Challenge	Cross-sectional (4 weeks)
(Chen and Pu 2014)	Rising physical activity	Students and lab workers (n= 36)	Wearable device, Mobile application	Compare progress, Social connectivity, Capacity to overcome challenges	Points, Badges, Leaderboards	Cross-sectional (2 weeks)
(Coombes and Jones 2016)	Rising physical activity	Children age 8–10 (n=80)	Wearable device	Goal setting, Providing feedback, Compare progress	Points, Feedback, Challenge	Intervention (9 weeks) + follow up (20 weeks after)
(El-Hilly et al. 2016)	Smoking cessation	Smokers (n=16)	Mobile application	Goal setting, Capacity to overcome challenges, Reinforcement	Achievements, Levels	Cross-sectional (5 weeks)
(Giannakis et al. 2013)	Rising physical activity	Young adults (n=5)	Mobile device, Mobile application	Providing feedback	Feedback	Cross-sectional (4 weeks)
(Ilhan et al. 2016)	Enhancing sleeping habits	Recruited participants (n=26)	Mobile application	Goal setting, Capacity to overcome challenges, Providing feedback, Reinforcement, Compare progress	Points, Feedback, Leaderboards, Story/Theme	Cross-sectional (2 weeks)

Publication	***Use context***	***User context (sample size)***	***Technology context***	***Gamification strategy***	***Gamification element***	***Study design (duration of intervention)***
(Jones et al. 2014)	Enhancing eating habits	Elementary school students (n=251)	Ambient display	Goal setting, Reinforcement, Capacity to overcome challenges, Fun and playfulness	Rewards, Levels, Story/Theme	Cross-sectional (2 weeks)
(Kadomura et al. 2014)	Enhancing eating habits	Children (n=5)	Mobile device, Mobile application	Providing feedback, Fun and playfulness	Feedback, Theme	Cross-sectional (9 days)
(Katule et al. 2016b)	Monitoring nutrition and physical activity	Households (n=14)	Mobile application	Goal setting, Capacity to overcome challenge, Reinforcement, Compare progress, Social connectivity	Points, Badges, Theme, Leaderboards, Challenge	Cross-sectional (6 weeks)
(Kim et al. 2017)	Stretching exercises	Students (n=42)	Wearable device	Goal setting, Providing feedback, Reinforcement	Rewards, Feedback, Clear goals	Cross-sectional (5 days)
(Ogi et al. 2015)	Improving health consciousness	Students (n=41)	Mobile device, Mobile application and Digital signage	Goal setting, Providing feedback, Reinforcement, Compare progress, Social connectivity	Levels, Feedback, Leaderboards,	Cross-sectional (14 weeks)
(Shameli et al. 2017)	Rising physical activity	Users of the selected application (n=800000)	Mobile application	Goal setting, Compare progress	Challenge, Leaderboards	Cross-sectional (1 week)

Publication	***Use context***	***User context (sample size)***	***Technology context***	***Gamification strategy***	***Gamification element***	***Study design (duration of intervention)***
(Thorsteinsen et al. 2014)	Rising physical activity	Recruited participants (n=21)	Website, SMS	Providing feedback, Reinforcement, Compare progress	Points, Feedback, Leaderboards	Cross-sectional (12 weeks)
(Wortley 2015)	Rising physical activity	Case study	Wearable device, Mobile application	Goal setting Providing feedback, Reinforcement	Feedback	Case study (2 years)
(Zhao et al. 2016)	Rising physical activity	Recruited participants (n=36)	Wearable device, Mobile application	Goal setting, Capacity to overcome challenge, Reinforcement, Compare progress, Social connectivity	Points, Levels, Leaderboards, Theme, Challenge	Cross-sectional (70 days)
(Zuckerman and Gal-Oz 2014)	Rising physical activity	Recruited participants (n=40)	Mobile application	Goal setting, Providing feedback, Compare Progress	Points, Feedback, Leaderboards	Cross-sectional (2 weeks)

Table 2. Selected studies for review

6. Discussion

The main objective of this paper was to study how extant research treated the link between long-term use and engagement in gamified, IT-reliant systems. We argue that gamification for digital health promotion should be apprehended as a process which effects have to be analysed on the long term. The research designs found in our selected studies already suggest that there is room for improvement regarding the significance of the reported outcomes, notably in terms of health behaviour change. Nevertheless, the manner these papers consider long-term engagement (if at all) is still particularly informative about the current state of discussions on this matter. To that end, and as stated above, we realize a categorization of the retained papers, following the extent they really discuss long-term usage.

Four papers do not devote any part of their work to develop a long-term perspective. Interestingly, among these, the gamified intervention for digital health behaviour change is rather short-timed: 5 days (Kim et al. 2017), 9 days (Kadomura et al. 2014), 14 days (Chen et al. 2014) or 4 weeks (Giannakis et al. 2013). The mechanisms employed in these papers can be classified as short-term actions, which aim at responding to small-timescale behavioural trends (Carrino et al. 2014). We cannot subsequently take them into account for further analysis, as we cannot fully ascertain if the described design really induces a sustainable behaviour change in the long run or not. A second group of studies only mentions this issue in the limits of their work or as a future research. Buchem et al. (2015) call for a longitudinal study in order to confirm the positive impact that has been measured. In the same vein, El-Hilly et al. (2016) express that it is required to evaluate the effectiveness of their proposed framework by assessing their relation to long-term effects of gamification. The third group is composed of papers that identify this issue, include it in their reflection, but do not provide enough follow-up data to prove the viability of the effects on behaviour change (produced by their gamified system). We also included the narrative case study made by Wortley (2015) in this group, given that the data (observations and measures) do not come from different (at least two) moments in time. However, all these studies can contribute with a first insight about how to consider and evaluate continuous use. Here are our main observations.

The post use questionnaire/post intervention survey. This represents a medium to appreciate if gamification has provided beneficial effects. However, in the cases of Ilhan et al. (2015) and Ogi et al. (2015), there is no indication about the modalities in terms of *follow-up*, except that users fulfilled the survey at the completion of the intervention. In consequence, we cannot affirm with certitude that the reported effects are sustainable on the long run, especially as the duration of the involvements (respectively two weeks and one month) are probably not sufficient to undoubtedly generate a behaviour change. For the record, both observe rather positive outcomes in relation to health behaviour change: Ilhan et al. indicate that 65 % of the recruited participants state that a gamified app would change sleep-wake behaviours in the long term. Ogi et al. (2015) question if the gamified systems have improved users' health consciousness: 57% moderately agree and 26% agree.

The novelty effect. Another interesting point is brought by Katule et al. (2016a) and Thorsteinsen et al. (2014): effects of novelty carried by gamification. The introduction of a technology often leads to a high usage in the beginning of the intervention, due to the interest in the new implemented technology. In that respect, a significant use might not correspond to an achievement, but might be driven by curiosity and attractiveness. In consequence, it can fade along the user getting accustomed and familiar with service/device. Both studies suggest that gamification is a viable tool (in a short term) that need further investigation to observe if the effects are sustainable.

At the end of the day, gamification interventions lower the interest. Implementation of game design elements can lead to a potential negative impact, given that some selected gamification elements might, as the time passes, reduce the implication and interest in using the digital service or device (Jones et al. 2014; Zuckerman and Gal-Oz 2014). Gamification, in that respect, might annoy users and lose all value and potency on the long run. Comparatively, such research has been undertaken about primarily utilitarian smartphone applications with hedonic or game design features (Mettler et al. 2014). The results show that gamification did not allow for a stabilized long-term usage scenario and negatively impacted the usage duration of the apps.

Intrinsic and extrinsic motivation. Well-established and a common matter in incentive theories, intrinsic and extrinsic motivation play a key role regarding continuous use of gamified systems. Intrinsic motivation corresponds to a self-determined motivation (e.g. interest, enjoyment) while extrinsic motivation relates to an external factor that drives the motivation (Ryan and Deci 2000). This may, for instance, be an external element (e.g. rewards or punishment) but also an internal motivation conditioned by an external factor such as congruence, social norms or external obligations. Wortley (2015) denotes that gamification potentially engenders an increase of intrinsic motivation (e.g. pleasure) and is more likely to provide sustainable outcomes. He develops the idea that the effects of intrinsic motivators mediate the effect of extrinsic motivators. As a consequence, intrinsic motivators are the principle vectors that contribute to the adoption of a healthier lifestyle.

Gradual addition of features. Zhao et al. (2016) express that applying a gradual addition of features/means (or substitute them on occasion) helps to sustain participants' interest and use. Thus, (consistent) updates of gamified systems might increase, to a certain extent, usage of the digital service or device. However, Zhao et al. (2016) precise that these findings only relate to data taken during their intervention and that there is a requisite for future analysis.

At last, one single paper (Coombes and Jones 2016) has done a follow-up research regarding gamification for HBCSS. The data has been gathered through a (+20 weeks) post-intervention measurement (using a wearable device) and a self-reported record (via a diary). Physical activity overall did not appear to be significantly higher at the follow-up between intervention participants and controls. There is consequently no evidence of a large intervention impact by the gamified system, even if the self-reported physical activity has been increased since the end of the intervention. Thus, the only study that meets our highest criteria, reports no significant effects of gamification for digital health behaviour change in the long term.

To conclude, the few identified studies show that there is a lack of evidence concerning continuous engagement and/or long-term effects of gamification interventions applied to HBCSS toward healthier lifestyles. This generates another implication: we cannot reasonably determine and label some gamification strategies/elements as more effective than others on the long run. At this point, gamification for healthier lifestyles is simply not proven to be effective in a long-term perspective. Considering which gamification approach is more suitable consequently becomes a pointless quest. As shown above, research suggests that gamification might induce behaviour change toward healthier lifestyles. Even if the long-term is insufficiently addressed (and that we do not possess enough evidence); it does not mean that gamification in HBCSS is ineffective on the long run. Maintaining long-term user commitment through gamification is surely a challenge (El-Hilly et al. 2016). Likewise, altering a lifestyle habit is proven to be difficult, notably in relation to health. This is precisely why gamification for HBCSS needs further longitudinal (or prospective observational study) research, in order to better comprehend the long-term perspective, and offer solutions that can tackle these challenges.

Engaging in longitudinal studies can be demanding as well: it requires time to develop an effective research design. We do not intend to enter into any judgements of intentions, we pertinently understand how difficult it is to undertake research in an environment that pressures for constant publication. Not to mention that a longitudinal approach may rise financial demands and request a higher involvement from the study participants (Caruana et al. 2015). Still, there is potential to overcome these hurdles. For instance, further longitudinal studies might build on secondary data and take advantage of existing data sets (Doolan et al. 2017). Likewise, existing cross-sectional studies can be employed as preliminary assessments, already providing a theoretical/practical groundwork upon which a new prospective observational study may develop (Caruana et al. 2015). Even planning a single follow-up after the main intervention is valuable in the context of HBCSS: it provides an early consideration of the degree of behaviour change over time and informs about how technology systems are integrated in situ (Anders et al. 2012; Caruana et al. 2015).

6.1 Implications

From a theoretical viewpoint, our study adds a first understanding of the long-term engagement to the existing research in gamification for digital health behaviour change. We address this particular issue, which is too often neglected, and propose an approach to measure and evidence long-term engagement in gamified HBCSS toward healthier lifestyles. Our work especially demonstrates that there is a clear gap regarding proved continuous perspective in these systems, which seriously challenges the effectiveness of gamification for digital health behaviour change. At this point, the longstanding effects induced in terms of health behaviour change are fairly speculative, which goes against the fundamental purpose of these services: to constantly change a behaviour towards a healthier lifestyle. Additionally, we compile and discuss all the indications found in our selected literature about long-term engagement, in order to summarize and evaluate what is already known.

From a methodological perspective, we call for the application of longitudinal and prospective observational studies or follow-ups after the initial or main intervention. Only through these procedures, we will be able to better understand the effects of gamification for digital health behaviour change. We also believe that users need to feel a constructive and positive game-based experience that is linked to the underlying non-game setting (Nicholson 2012). In fact, as we stated above, gamification should be a matter of specific association between strategies and elements regarding a particular context. In order that gamification in HBCSS become meaningful on the long run, practitioners, scholars and designers ought to consider the novelty effects that gamification may drive (and how to overcome it). Alongside they should be aware of the loss of interest and the annoyance that (too much) gamification potentially entails as time passes. An answer to this hurdle might be the gradual addition of features or, in the same manner, a change of means to sustain users' interest and engagement. Finally, leaning toward users' internal satisfaction and enjoyment regarding the gamified systems is critical. Users creating and controlling their own goals are more likely to find internal meaningful connections to the underlying activity and thus continue performing it over time (Zuckerman and Gal-Oz 2014).

6.2 Limitations and future work

Our effort to select an appropriate sample that allows comparison drastically reduces the sample size for analysis. As we have seen, gamification for HBCSS can be employed in several contexts. We decided to target gamified interventions on individual lifestyle habits in order to avoid, for instance, the presence and the interference of a contextual condition (e.g. diabetes). We assume that the continuous engagement in gamified HBCSS for rehabilitation or disease management relies on distinct mechanisms and motivations which primarily relate to the given condition. That restriction, however, provides the opportunity for further research studies. An investigation on disease management could complete the research on the long-term perspective in gamified HBCSS and potentially highlight a better representation of this concern.

Considering that we aimed to conduct a first scoping review on the long-term engagement in the literature of gamification for digital health behaviour change, we made the decision to completely rely on our selected studies to define concepts like *long-term engagement* or *continuous use*. Given that we did not find much evidence or empirical material to do so, the presented notions may have remained relatively vague. As a consequence, there might be the need for a better conceptualization. A potential approach to tackle this issue might be to consider how long-term engagement of gamified systems has been investigated in other fields. It could certainly constitute a valuable input to better understand all the challenges that the long-term engagement represents.

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Article IV

Article IV: Nudges in digital occupational health plans

Title: Which nudges are acceptable in connected workplaces? A Q-methodology study

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Under review

Abstract: Data-driven systems are increasingly being implemented in the workplace, with such decentralised and connected systems playing greater roles in organisations' decision-making and action planning. Yet, employees may not systematically adhere to and comply with the use of data-driven systems, questioning the person-organisation fit in such connected workplaces. In this context, the notion of nudging is emerging in Information Systems as a powerful approach to impact on individual behaviours so as to better align organisational objectives and employee attitudes. To capture the ability of nudging to increase such fit and consequently support data-driven system use, we take the perspective of users and ask: *Which forms of nudging are acceptable to employees?* Through the example of physiolytics, which are wearable sensors paired with data analytics and machine learning algorithms that are increasingly used in workplace health initiatives and by means of Q-methodology, a mixed methods approach specifically designed for studying subjective thought patterns, we map out five types of nudge strategies that employees consider advantageous and ethically admissible: (a) positive reinforcement and fun, (b) controlling the organisational environment, (c) self-responsibility, (d) collective responsibility, and (e) adapting the individual environment. Our findings delineate the boundaries of nudging in the context of connected workplaces and demonstrate the importance of a multi-level and participatory process in developing nudges.

Article IV

1. Introduction

Information-sharing, collaboration, planning, and communication tools are spreading in workplaces, allowing for a more flexible, connected and adaptable management of work (Ahlers, 2016; Harteis, 2018). More decisions and actions are supported by data-driven systems that quantify work performance and behavioural patterns of employees (Levchuk, 2019). Therefore, it is becoming all the more important for organisations that employees use such systems accurately, consistently and reliably (Burton-Jones & Grange, 2012; Eden *et al.*, 2018). However, employees may not always recognise the benefits of data-driven systems or even worse, perceive them to be intrusive or worrisome (Putzier & Cutter, 2020). Microsoft, after facing severe public criticism over its Productivity Score – a tool supposed to help organisations to measure and manage the use of its Microsoft 365 suite of applications – had to back down and remove all user names and all measures that quantifies individual user behaviour (Spataro, 2020). Likewise, Amazon is confronted with the largest, most viable unionization effort of its warehouse workforce, amongst other things, because of the introduction of a new employee tracking technology (Corkery & Weise, 2021). The enhanced capacity of new data-driven workplace applications to store, create, and analyse data raises concerns because employees do not exactly know what and how data is processed or get stunned by the sheer amount of information and complicated workflows that they have to deal with (Oinas-Kukkonen & Harjumaa, 2018). This might not only lead to increased frustration, resistance, or technostress (Tarafdar *et al.*, 2019) among non-tech savvy employees struggling to adapt their behaviour to the algorithmically suggested work routines (Deng & Chi, 2012; Kellogg *et al.*, 2020; Klaus *et al.*, 2010), but also to a possible, more general under-utilisation of such systems due to privacy and self-determination concerns (Kim *et al.*, 2016; Po-An Hsieh & Wang, 2007).

Therefore, to ensure the viability of data-driven systems in organisations – and the efficiency of their investments – organisations often seek to get their employees in the *right* mindset regarding system use (Kotarba, 2017; Tabrizi *et al.*, 2019). They rely on an agile forms of management (Bammert *et al.*, 2020) and attempt to modify work routines, norms and environments in which employees use data-driven systems. By doing so, they look to influence employees' perception of the system and how it integrates in this new *connected workplace*, for the purpose of aligning employees' attitudes with organisations' interests. Such pursuit of the compatibility between employees' attitudes and their work environment is generally referred to as the *person-organisation fit* (Kristof-Brown *et al.*, 2005; van Vianen, 2018). The underlying assumption behind this concept is that a congruence between employees' values and their work environments is likely to produce positive attitudes and behaviours from employees (Kristof-Brown *et al.*, 2005; Pee, 2012). Reaching a certain degree of congruence between employees' attitudes and organisations' missions is certainly crucial in connected workplaces. The more employees feel that their values (e.g. personal attitudes towards work surveillance) are in adequation with their work environment (e.g. the actual monitoring and performance appraisal practices of the organisation), the more they will be prone to comply with organisational norms and expectations (Andersson *et al.*, 2017). By the same logic, if there is a misfit between employees' values and organisational practices, employees are expected to develop dysfunctional attitudes which may be detrimental for both employees and organisations (Ayyagari *et al.*, 2011; Pee, 2012).

A popular – but also controversial – concept that holds the promise to act on person-organisation fit and better adjust employee behaviours to organisational goals is *nudging*. Scholars generally define nudging as planned modifications of environments to non-coercively act on individuals' behaviours and without affecting the range of available choices (Hausman & Welch, 2010; Sunstein, 2014). This approach, considered as *soft paternalism*, seeks to support individuals in their decision processes, purportedly for their own good (Menard, 2010). The main assumption is that individuals do not make choices in a vacuum, and that a cautious design of cues in an environment can influence these choices (Balebako *et al.*, 2011; Coventry *et al.*, 2014; Sunstein, 2014). In Information Systems (IS) research, nudging is also drawing strong interest because it is seen as a way to assist users in their interactions and decision processes with IS (Meske & Amojo, 2019; Weinmann *et al.*, 2016). Nudges are predominantly employed for consumer research in online environments, for instance, to prompt individuals to purchase an additional travel insurance or recommend certain products via presentation framings. Still, in workplace settings, there is little evidence of how employees respond to nudging and how it may be implemented as a management strategy (Meske *et al.*, 2020; Weinmann *et al.*, 2016).

In this paper, we therefore address the feasibility of introducing nudging to enhance the person-organisation fit in connected workplaces. Through an emblematical example of IS implementation in connected workplaces – physiolytics, which are wearable data-driven systems commonly used as part of workplace health programmes – we seek to investigate the potential of nudges to support data-driven IS initiatives. In order to do so, we set out to answer the following research question: *Which forms of nudging would be perceived as acceptable by employees in a connected workplace?*

To help uncover acceptable nudge strategies for connected workplaces, we decided to employ the Q-methodology research approach (Stephenson, 1986). This method offers a robust procedure to systematically explore subjectivity by measuring individuals' mindsets and opinions (Brown, 1993). It differs from a typical survey-based research design, because the wide range of individual perspectives is captured by using self-referencing statements and asking respondents to sort statements according to specific sorting instructions (Brown, 1993; Mettler *et al.*, 2017; Stephenson, 1986). Moreover, the Q-methodology provides the opportunity to operationalize employees' subjective opinions about their work environment fit, which has been a consistent shortcoming of previous research on person-organisation fit (Wingreen & Blanton, 2018).

The remainder of the paper is structured as follows. In Section 2, we provide an overview of the conceptual foundations of this study. In Section 3, we explain our research method, data collection, and data analysis. In Section 4, we present and interpret the empirical results. In Section 5, we conclude with a discussion of the study's limitation and implications for research and practice.

2. Background

2.1 Physiolytics and connected workplaces

The emergence of connected devices, systems and applications that process huge amounts of information is widespread among organisations in industrialised countries. It is hard to find a workspace in which data-driven IS do not support employees in their daily activities, since even unskilled work duties often necessitate the use of a connected ecosystem (Al-Dabbagh *et al.*, 2015). From simple mobile apps to digital calendaring systems, data analytics dashboards, sensors and many others, organisations perceive these systems and their abilities to integrate (often real-time) information as opportunities to enhance collaboration, increase productivity, improve and harness employees' knowledge, or ensure workforce safety (Dawson-Haggerty, 2019). In this sense, organisations often consider them to be the infrastructural foundation of an innovative and interactive workplace (Tan *et al.*, 2015). Nonetheless, these technologies also bring new challenges to the workplace, because they constantly reshape how employees and organisations interact and communicate within the workspace and profoundly transform both work practices and work governance (Lyytinen *et al.*, 2004). In particular, the user-technology relationship becomes more complex: system use often necessitates accuracy, consistency and effectiveness (i.e. it must relate to organisational goals) or needs to meet certain standards and norms (Burton-Jones & Grange, 2012). We see the development of new matters and issues associated with tensions regarding system use, employees' adaptations in new workflows or layers of embeddedness in the network (Majchrzak *et al.*, 2016; Yu *et al.*, 2019).

Physiolytics constitute a typical instance of new data-driven systems that are appearing in connected workplaces (Mettler & Wulf, 2019). These wearable computing systems (mainly integrated into smartphones, bracelets or watches) use machine learning algorithms to process physiological and behavioural data (e.g. movement, pulse or heart rate) and then generate analytical feedback (Wilson, 2013). Following the development of *quantified-self* practices, which promote health empowerment via monitoring personal data (Lavallière *et al.*, 2016; Lupton, 2014; Moore & Robinson, 2016), they are now being provided by organisations to help employees manage their stress levels or to encourage them to be physically more active (Gorm & Shklovski, 2016; Yassaee & Mettler, 2017). Reports estimate that 27.5 million physiolytics units will be sold by 2020, compared to only 166,000 in 2013 (Chung *et al.*, 2017; Olson, 2015). The current sanitary crisis might have accelerated and exceeded these projections since more work has moved online (Kudyba, 2020; Waizenegger *et al.*, 2020) and monitoring employees has become a priority for many organisations (Cox, 2020).

Physiolytics, which are fairly intuitive and easy to use, stand out for their capacity to gather a large amount of data, their high accuracy, and their relative affordability (Demiris, 2016; Lavallière *et al.*, 2016; Lupton, 2014; Patel *et al.*, 2015; Wilson, 2013). Besides being a convenient tool to enhance employees' health and well-being, physiolytics are particularly favoured by organisations due to their capacity to collect data about the work environment, which can be then examined and acted on (Khakurel *et al.*, 2016; Moore & Piwek, 2017; Swan, 2013). Put differently, organisations can reason in terms of numbers and measurements to fix precise goals, to better understand the work context, or to calculate performance and efficiency (Moore & Piwek, 2017; Moore & Robinson, 2016). Not to mention that these technologies provide real-time and tangible metrics to process subjective phenomena (e.g. the feeling of being stressed), allowing organisations to tailor interventions to an individual's needs (Lippke *et al.*, 2015).

Hence, for organizations, the first challenge regarding physiolytics is that employees engage in the use. Because these instruments may potentially gather sensitive and highly personal health data, regulations and personal data protection laws hinder organisations from establishing mandated use (Dinev *et al.*, 2013; Li *et al.*, 2016; Malhotra *et al.*, 2004; Yassaee & Mettler, 2017). Organisations must incite employees to participate in such health initiatives while responding to eventual workforce issues, such as the disclosure of health conditions, the repurposing of huge volumes of data for performance management and corporate restructuring, or resulting changes in work cultures and practices (Mettler & Wulf, 2019; Schall Jr *et al.*, 2018). While evidence suggests that organisations may achieve good results in this area, with decent numbers of employees choosing to get involved in such workplace health initiatives (e.g. Hamblen, 2015; Mathur *et al.*, 2015; Moore & Piwek, 2017; Schall Jr *et al.*, 2018), surveys also indicate that organisations often fail to sustain employee participation, since roughly half of the participating employees do stop using physiolytics regularly after the first months of use (Akter *et al.*, 2013; Canhoto & Arp, 2017; Grossmeier, 2017). For organisations, this is therefore another considerable challenge, given that these systems are only valuable and effective when participants engage in a sustained use: data can be consequently collected over time (1) to ensure that relevant information and feedback are displayed, (2) to eventually enhance employees' awareness of possible health and safety risks (e.g. elevated stress levels or sedentary behaviours), and (3) to prompt them to adopt better health attitudes and behaviours.

2.2 Person-organisation fit theory

The theoretical foundation of this study is the person-organisation fit theory, which stems from interactive psychology and suggests that employees attitudes and behaviours are conjointly defined by their personal characteristics and their work environments (Kristof-Brown *et al.*, 2005; Pee, 2012). This theory also posits that the person-organisation fit is a greater predictor of individual outcomes in organisational settings (e.g. productivity or system use) than either of the components (employee and the work environment) taken separately (van Vianen, 2018). Personal characteristics typically correspond to individual attitudes and traits, such as preferences, personality attributes, values, literacy, or beliefs (Cools *et al.*, 2009; Kristof-Brown *et al.*, 2005). On the other end, work environments encompass organisational culture, workload, norms and rules (Cools *et al.*, 2009; Kristof-Brown *et al.*, 2005).

When a fit occurs – whether it is a *supplementary fit* (i.e. a fit that is founded on similarities between employees' views and organisations' ones) or a *complementary fit* (i.e. a fit that is based on an organisational gap that is filled by an individual with particular characteristics) – both entities are expected to profit (Cools *et al.*, 2009; Das Swain *et al.*, 2019; Wingreen & Blanton, 2018). Such positive outcomes can be associated to higher levels of job commitment, better staff morale or more efficient use of IS. For employees, this may translate into lower stress levels or better job satisfaction (Cools *et al.*, 2009; Pee, 2012). Conversely, in case of a misfit between individual characteristics and the work environment, dysfunctional attitudes may prevail. Employees may develop a sentiment of strain and distrust regarding their employer while organisations may encounter more issues in realizing their organisational objectives (Ayyagari *et al.*, 2011).

For organisations, it is therefore fundamental to nurture favourable practices, values and norms in order to strengthen the person-organisations fit (Pee, 2012). This mainly goes through positive and well-suited management strategies (Andersson *et al.*, 2017), such as nudging. In fact, as indicated by Rauthmann (2021), nudging may serve as an environment-person calibration, where mechanisms in the work environment help to affect employees' comportments. The circumstances, practices, personalities present in the workplace offer possibilities for particular individual tendencies to be revealed and supported (Ickes *et al.*, 1997). Environments thus provide a framework in which an attitude or a behaviour can be reinforced and encouraged, meaning that this attitude and behaviour can also be considered as a top-down outcome of environmental influences (Rauthmann, 2021).

In this regard, investigating nudging through the person-organisation fit theory offers an alternative framework to classical IS adoption and use models, such as *the Technology Acceptance Model* (Davis, 1989) or the *Expectation-Confirmation Model* (Bhattacherjee, 2001). These theories propose to study attitudes and behaviours regarding IS use through rather static, technocentric, deterministic and disconnected variables, such *as perceived usefulness* or *perceived ease of use* (Wingreen & Blanton, 2007). While these models offer perfectly valid measures, it is essential to complement their contributions with more interpretative paradigms that connect the individual to the environment. In this respect, the person-organisation fit theory provides a conceptual structure that considers the interaction between employees and their work environment. As denoted by Wingreen & Blanton (2018), this theory emphasizes the subjective evaluation of a situation (i.e. how an individual perceives a situation), which is determinant because it may explain why two individuals in similar organisational settings, with similar socio-demographic attributes and similar trainings have two different reactions regarding a situation in the workplace. Such alternative angle of analysis has been especially fruitful for studying phenomena, such as technostress (e.g. Ayyagari *et al.*, 2011; Stich *et al.*, 2019) or job satisfaction (e.g. Arbour *et al.*, 2014), which typically are difficult to objectify and often require subjective measurements in addition to quantitative measurements to be comprehensively captured (Goetz & Boehm, 2020; Riedl, 2012).

2.3 Nudging

An approach that equally deals with strategic modifications of the environment and personal behaviours is called *nudging*. The main goal is to alter people's behaviours and attitudes in predictable ways, without forbidding any options or significantly changing people's economic incentives (Hausman & Welch, 2010; Sunstein, 2014; Sunstein, 2016). The core idea is to address a wider spectrum regarding an action by considering all the environmental components and stakeholders, rather than solely targeting the individuals' rationales (Bucher *et al.*, 2016). This refers to how choices are presented so that individuals' cognitive biases (i.e. people's subjective realities) lead them to act in their best-defined self-interest and/or in society's interests (Sunstein, 2014; Sunstein, 2016; Woodend *et al.*, 2015). An example of a popular nudge is having people automatically register as organ donors, with the possibility of opting out. This leads to a substantially higher donation rate than a system in which donors must actively opt in. Altering how a choice is presented means changing decisions that otherwise were made unconsciously (Sunstein & Thaler, 2008). For that matter, nudging does not always involve reflective thinking. Based on Kahneman & Egan (2011) *dual process theory*, Hansen & Jespersen (2013) differentiated between *System 1* nudges, which are nudges that influence behaviours via maintained automatic thinking (i.e. they don't seek to create awareness among the decision-makers) and *System 2* nudges, which operate more on cognition, to drive decision-makers' attention about potential choices. *System 1* nudges typically work as a default option, such as a predefined choice, automatic enrolment in diverse programmes, and grocery store displays. *System 2* nudges are more transparent in that their presence is noticeable in order to attract attention and ultimately lead to reflective thinking about an action. They are mainly channels that provide information, signals and notices to trigger a desired behaviour (Hansen & Jespersen, 2013; Jung & Mellers, 2016; Sunstein, 2016). Indications of calories on sweets or warnings on cigarette packs are examples of *System 2* nudges. In our case, this is particularly interesting when we consider that extended IS use is defined by the capacity to attain a form of automation and habitual behaviour. While habits can be hard to change, they are also strongly influenced by cues in an environment, which are often processed outside conscious awareness. Thus, modifying an environment in which IS use occurs may be an effective approach to consciously or unconsciously help to attain a more effective use of physiolytics.

There have been attempts to make taxonomies of nudges (e.g. Dolan *et al.*, 2012; Hollands *et al.*, 2013; Johnson *et al.*, 2012; Sunstein, 2014) as well as systematic classifications (e.g.Broers *et al.*, 2017; Szaszi *et al.*, 2017). However, most current taxonomies and categorisations describe a decision situation but provide little guidance concerning concrete interventions that can be empirically tested, since they characterise more than they make recommendations. Following Münscher *et al.* (2016), we divide nudges into three ideal-types: *decision information nudges*, i.e. choice architecture techniques that focus on the production and management of decision-relevant information without altering the options, *decision structure nudges*, i.e. structuring options and their format, by modifying the available options in the decision situation, and *decision assistance nudges*, i.e. providing decision-makers with further assistance (e.g. reminders, commitment mechanisms) to help them to complete their intentions (Münscher *et al.*, 2016; Szaszi *et al.*, 2017). In fact, it is hard to provide organisations with a straightforward toolkit of nudging interventions because, as noted, choice architecture calls for context-based research (Lunn, 2012; Münscher *et al.*, 2016). Hence, beyond a predefined list of nudges (often created in a different discipline with partially different goals), designing a nudge or choosing the right one is a matter of collecting data on the decision-makers and understanding the setting(s) in which they operate (Hummel *et al.*, 2017).

Nudging is receiving increasing interest in the IS field, mainly owing to the fact that many nudges relate to behaviours regarding the use of an IS. In particular, the notion of *digital nudging* is emerging. Defined as "the use of user-interface design elements to guide people's behaviour in digital choice environments" (Weinmann et al., 2016) or "subtle form of using design, information and interaction elements to guide user behaviour in digital environments, without restricting the individual's freedom of choice" (Meske & Potthoff, 2017), digital nudging relates to the fact that decisions are increasingly made on screens (e.g. on mobile or desktop devices). These digital nudges vary from options shown in a particular order when purchasing something on a website or getting a notification on a mobile phone. Thus, it differs from a persuasive technology approach (which also seeks to influence individuals' behaviours) in the sense that nudges keep all the possible options open, while the only restriction for persuasive technology is to avoid the use of correction or deception (Karlsen & Andersen, 2019; Meske & Potthoff, 2017). Accordingly, as Karlsen & Andersen (2019) indicated, persuasive technology primarily refers to motivations, while nudging connects to motivations and capabilities.

In practice, digital nudges are likely found in diverse domains, such as e-commerce, e-government and e-health (Hummel *et al.*, 2017; Weinmann *et al.*, 2016). Because digital nudging is still nascent in IS, most of the research into digital nudges has considered these interventions' efficacy in particular contexts, such as privacy purposes (Balebako *et al.*, 2011), multi-channel choices of digital services (Hummel *et al.*, 2017), crowdfunding (Simons *et al.*, 2017), password management (Kankane *et al.*, 2018), the mitigation of online security risks (Yevseyeva *et al.*, 2014), or increasing engagement with banking applications (Wijland *et al.*, 2016). In parallel, scholars have also begun to investigate ethical components in designing and implementing nudging in digital environments (Coventry *et al.*, 2014; Lembcke *et al.*, 2019;

Renaud & Zimmermann, 2018) and potential negative outcomes regarding the introduction of digital nudges (Kissmer *et al.*, 2018; Li *et al.*, 2018).

While most of the IS literature concerns the digital world, the concept of nudging can also contribute to further research areas, such as IS use or governance (Larosiliere *et al.*, 2015; Meske & Potthoff, 2017). Our research is rooted in this perspective, considering that individuals can be nudged in a physical environment in which an IS is implemented and used. IS research has also shifted from purely technocentric considerations regarding IS designs and interventions (i.e. an IS system is sufficient to trigger the adoption and use of systems and devices) to approaches that focus on the importance of human, social and environmental components (Alter, 2003; Bøe *et al.,* 2015; Heeks, 2006). Thus, in organisational settings, in which firms must establish how to ensure effective IS use after implementation, a relevant approach is to draw on positive reinforcements to distinguish such efforts and increase employees' perception of congruence.

However, this approach also raises questions on whether nudges are acceptable for employees and in what form they may be used as part of an organisational management strategy. Seeking to subtly modify behaviours, especially across a context such as the workplace, requires caution. Such manipulations by an organisation may create misfits on the relationship between employees and organisations: it may as a consequence cause resistance among employees and create counter-effects to an organisation's expectations (Benartzi *et al.*, 2017; Li *et al.*, 2018. In the same vein, there is always the risk that, if done inappropriately, nudges may not be noticeable or may not stimulate subconscious favourable employee attitudes. In any cases, lessons that can be drawn from nudge literature are that nudges are supposed to be transparent, in the sense that every actor in a nudged environment should be able to identify the nudge and the channel through which it operates. This specifically excludes "subliminal messages", which subvert individuals' control over their own actions (Bovens, 2009; Hausman & Welch, 2010). Still, requirements that delimit a red line have not yet been defined, since researchers mostly state that transparency is a question of degree (Bovens, 2009; Grüne-Yanoff & Hertwig, 2016; Hausman & Welch, 2010). In other words, nudges must be sensible, with close reference to how persons actually think and behave (Sunstein, 2014), and they must be useful in achieving specific policy goals that citizens have somehow have agreed upon without affecting individuals' autonomy and integrity (Lembcke *et al.*, 2019; Schubert, 2017).

3. Research approach

To extract subjective opinions from employees regarding nudging in a connected workplace, we decided to draw on a mixed-method approach called Q-methodology (Stephenson, 1986), which offers a rigorous structure to systematically explore subjectivity by measuring individuals' mindsets and perspectives (Brown, 1993). Although individual viewpoints may change over time according to environments and personal circumstances, Q-methodology focuses only on salient viewpoints, which are likely to be more enduring (Lobo *et al.*, 2012). This approach is often employed to frame problems characterised by uncertainty and by value conflicts (Nijnik *et al.*, 2014). As a combination of both quantitative and qualitative approaches, Q-methodology combines mathematical rigour (it provides numerical measures) and an interpretive component (the numerical results are then interpreted) (Brown, 1993).

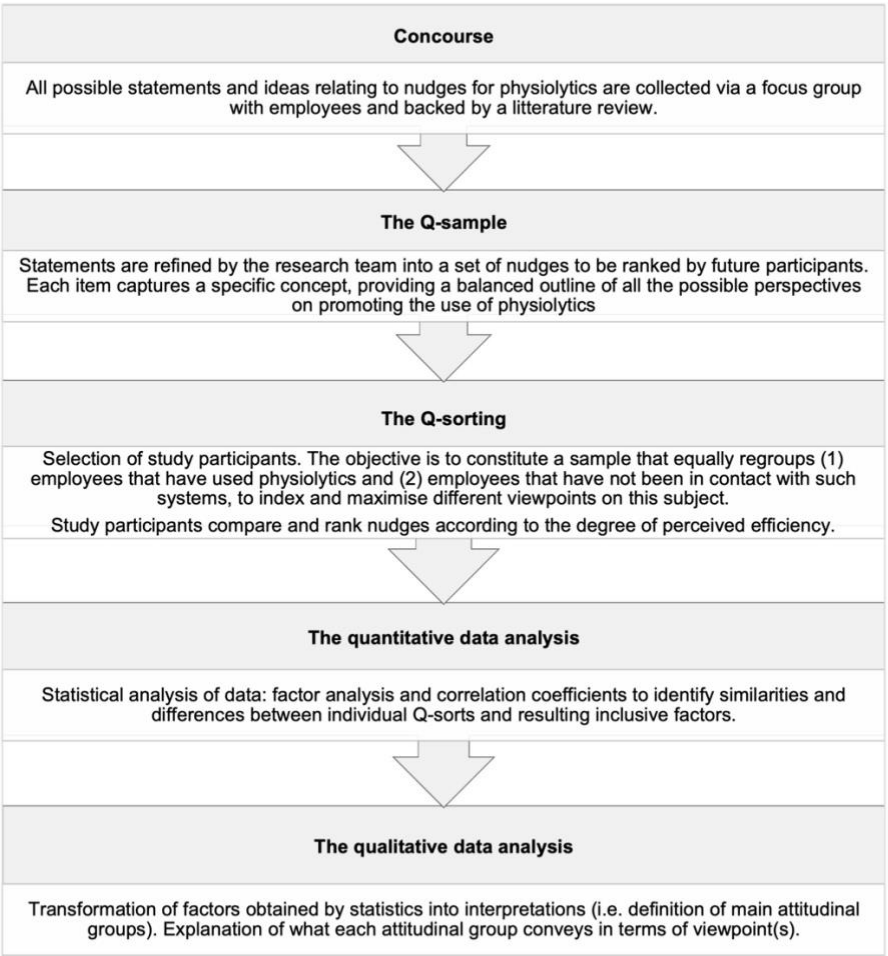

Figure 1. The steps in our Q-methodology study

The general procedure of Q-methodology is illustrated in Figure 1. Starting point is the gathering of opinions on a subject. Across these viewpoints, prevailing variations are identified and then connected in a logical and organised way. The relationships are obtained following an individual rank-ordering of viewpoints that are statistically compiled through an inversion of conventional factor analysis (Kelly *et al.*, 2016; Watts & Stenner, 2012). Finally, the assessment of the correlation is done by an interpretative process (rather than a mathematical procedure) to map the results, labelled as *factors*. These resulting factors represent participants' subjectivity on a topic and tell specific stories about their beliefs, values and perceptions (Brown, 1993; Kelly *et al.*, 2016; Watts & Stenner, 2012). Thus, this methodology enables researchers to identify patterns in respondents' perspectives on these problems, reducing some of the complexity surrounding them (Cuppen, 2010; Nijnik *et al.*, 2014). Further, a Q-methodology approach offers relative freedom to express opinions and attitudes, since the rank-ordering of viewpoints is done as an individual task and with minimal researcher presence. Consequently, no opinion is imposed, and no group dynamics appear, as could be the case during group sessions. The participants may proceed to the classification based on their experience and without embarrassment, while taking the time they deem necessary (Hughes, 2012). Only after conducting the analysis do shared viewpoints emerge, permitting one to hear each individual voice and, at the same time, outlining a collective view (Plummer, 2012).

In IS research, Q-methodology has been employed to explore relationships to health-care informatics (Valenta & Wigger, 1997), evaluate health data platforms' impacts (Connolly *et al.*, 2018), and investigate decision support system user satisfaction (Kendall *et al.*, 1987), but also to establish the adoption and use of new technologies in different domains or settings (Baker *et al.*, 2014; Bouwman *et al.*, 2012; Klaus *et al.*, 2010; Mettler *et al.*, 2017; Mettler & Wulf, 2019; Rahim *et al.*, 2011). For studying use behaviours, the added value of this approach relies on the focus of the construction behind the use and not directly the constructors, i.e. the people and their characteristics (Stainton Rogers, 1995). The objective is not to obtain "truth", but to collect and investigate people's various accounts. Thus, it helps to unveil different thought patterns rather than demographic characteristics (e.g. gender, age, education level), which frequently remain undetected with typical survey-based studies (Mettler & Wulf, 2019; Zabala & Pascual, 2016). Let us now explain the detailed procedure we followed.

3.1 Concourse

The first step in Q-methodology is called *concourse* (from the Latin *concursus*, i.e. 'a running together'), which consists of capturing a comprehensive set of social discussions and relevant discourses about a topic (Brown, 1993; Kelly *et al.*, 2016; Nijnik *et al.*, 2014; Stainton Rogers, 1995). It is not necessary to capture every single aspects of a domain, but to offer a representative sample of relevant discourses (Wingreen & Blanton, 2018). For this purpose, the research team called a focus group session with six employees from a medium-sized public administration in Switzerland who have worn a physiolytics device as part of a previous workplace health initiative[1] to discuss how to ensure uses of physiolytics in workplaces. The only imposed constraint was to avoid the elaboration of nudges that necessitate financial retributions or consequent financial/technical investment from organisations. In most cases, organisations opt for physiolytics as part of workplace health initiatives because they see these as low-priced, off-the-shelf end-products (Marquard & Zayas-Cabán, 2011). We assumed that proposing nudges that call for significant further investment from organisations would not match the realities in practice (both for physiolytics implementations than other IS initiatives). Two researchers were involved in the meeting (one took notes while the other was moderating the session). We recorded the event with the participants' consent and then transcribed the notes non-verbatim. At the end of the session, the general consensus was to thoughtfully research scholarly sources about nudging interventions so as to complete and structure ideas that emerged from the focus group session. While the concourse was not theory-driven – as established in survey studies – the focus group discussions were backed up by evidence from printed sources such as journal publications, news articles, essays or other sources (Mettler & Wulf, 2019; Valenta & Wigger, 1997). By considering opinions and evidence from other sources, we were able to formulate an initial set of 40 strategies that could reproduce different opinions and discourses about the topic.

3.2 The Q-sample

The second step mainly corresponds to a refinement of the nudges developed in phase 1. As a subset of the concourse, the *Q-sample* seeks to merge duplicates and to consolidate statements of opposite meanings. There is no sole or exact way to produce a Q-sample (Kelly *et al.*, 2016). According to Q-methodology theorists, the development of the Q-sample must be adapted to the demands of the research question and the requirements of the analysis (Akhtar-Danesh *et al.*, 2011; Brown, 1993). Thus, it may either follow a structured procedure or an unstructured approach. Given that an unstructured method arguably allows more freedom and flexibility to arrange a series of items into a comprehensible set (Kelly *et al.*, 2016; Stainton Rogers, 1995), we decided to not reorganise nudges according to a defined theory. Thus, our Q-sample provides in miniature an entirety of opinions that are present among participating employees

[1] The selection process and the concourse were done independently of these employees' use patterns in this programme, since the research team did not have such information.

(Valenta & Wigger, 1997). To obtain a manageable yet comprehensive set of nudges, we merged together similar statements, reducing our initial set of 40 nudges to 27.

3.3 The Q-sorting

In the third step, the *Q-sorting*, participants sort the statements according their own subjective understanding and opinion. This is the core of Q-methodology (Donner, 2004; Mettler & Wulf, 2019). We selected the participants, generally referred to as the *P-set* (Brown, 1993; McKeown & Thomas, 2013), in order to gather different actors in the area and thus collect a representative and comprehensive panel of perspectives. The P-set does not necessarily need to be completely archetypical of a population, it rather needs to assemble people who may possess defined viewpoints on the studied objects. We accordingly invited 30 participants to take part in the Q-sorting: half were employees of a medium-sized public administration in Switzerland who wore a physiolytics device as part of a workplace health initiative, while the other half were employees from another comparable public administration in Switzerland who did not have contact with such technology. As hinted above, the sample size had a low determining role, since small samples are appropriate as long as all potential perspectives are covered (Kelly *et al.*, 2016; Watts & Stenner, 2012). In fact, Q-methodology seeks to be able to describe typical representations of different viewpoints rather than to find the proportion of individuals with specific viewpoints (Akhtar-Danesh *et al.*, 2011).

The sorting was done online and with the support of Q-sortware, a tool that allows researchers to create, collect and administer all necessary data for Q-methodology studies online. We adopted a design inspired by O'Leary et al. (2013) that had three steps: first, through Q-sortware, participants were randomly presented with one nudge at a time and were asked to drag and drop each element into one of three boxes: relevant, neutral or irrelevant. After completing this first step, we asked the participants to rank-order the pre-ordered nudges along a grid, which was predetermined along a quasi-normal distribution. Such a pyramid-shaped grid, as the one we used shown in Figure 2, is typically applied for topics that are not well known to the general public, so that participants have more room to express ambiguity, indecisiveness or errors in the middle of the distribution (Mettler & Wulf, 2019; Van Exel & De Graaf, 2005). Every employee had the possibility to order items in cases (with values ranging from +3 for items considered as the most relevant, through 0 for indifferent, to -3 for items perceived as least relevant). We purposely chose *relevant* so as to make participants reflect about both the effectiveness and the appropriateness of proposed nudges in organisational settings. Notably, there is no ideal range, since this greatly depends on the number of different viewpoints collected. Researchers are primarily bounded to produce a structure that facilitates the rank-ordering for participants and to make distinct responses emerge (McKeown & Thomas, 2013). As a final step in the procedure, participants had the possibility to review the whole process and had the possibility to change the nudges' order. We had to remove two respondents owing to speeding in their rank-ordering (they completed this step in less than 3 minutes, while the retained participants spent on average 11 minutes on the sorting).

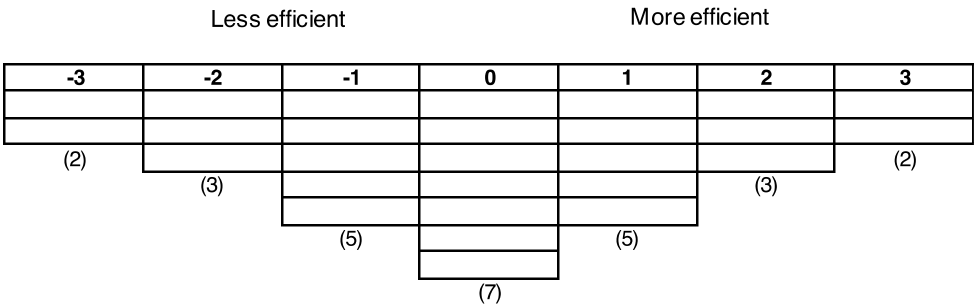

Figure 2. The employed Q-grid

3.4 The quantitative data analysis

Once we had collected the data, the next step was to analyse the *by-person* correlation and the factors the respondents loaded onto. Factor analysis seeks to detect correlation coefficients in a study, which are represented in the Q-sort in order to identify a small number of shared beliefs on a subject (Brown, 1993; McKeown & Thomas, 2013). One of Q-methodology's main assumptions is that respondents who load onto the same factor have fairly similar responses, and by extension that they represent a same attitudinal group. Watts & Stenner (2012) recommended using PCA with Varimax rotation to calculate these factors and to pursue a rotated solution, which maximises the amount of variance explained by the extracted factors. The factors are determined with eigenvalue $\geq$1.00, which means that they were unlikely to have been grouped by chance. Otherwise, Donner (2004) stated that a factor can be outlined when participants load on a single factor with approximately 0.45 or greater. In fact, as Iofrida *et al.* (2018) noted, there is not necessarily only one aim or mathematically correct final solution regarding how many factors are determined in this step, since clarity and distinctness should also be considered. Significance at the $P < 0.01$ level is attained when a factor loads > 2.58 times the standard error for the loading, which is calculated as $1/\sqrt{N}$, where N is the number of statements (McKeown & Thomas, 2013).

To realise these statistical analyses, we used STATA software version 13.1. As shown in Table 1, we extracted five factors (that regroup participants' loadings on a factor with 0.45 and greater), which collectively explained 44.09% of the total variance.

ID	P-set group	A	B	C	D	E
9	Familiar with physiolytics	**0.81***	-0.05	0.02	-0.02	0.08
5	Familiar with physiolytics	**0.80***	0.01	0.08	0.17	-0.12
16	No contact with physiolytics	**0.76***	0.19	0.08	0.04	-0.15
23	No contact with physiolytics	**0.75***	0.21	-0.32	-0.02	-0.17
6	Familiar with physiolytics	**0.71***	-0.27	-0.06	0.18	-0.14
26	No contact with physiolytics	**0.67***	0.06	0.14	-0.19	-0.29
27	No contact with physiolytics	**0.62***	-0.15	0.26	0.18	0.02
15	No contact with physiolytics	**0.61***	-0.02	-0.13	0.09	0.27
1	Familiar with physiolytics	**0.58***	0.37	0.20	0.33	-0.01
18	No contact with physiolytics	**0.58***	0.27	0.14	-0.16	0.06
28	No contact with physiolytics	**0.55***	0.49*	0.47*	0.07	-0.03
7	Familiar with physiolytics	**0.49***	0.10	0.14	0.32	0.31
4	Familiar with physiolytics	**0.48***	0.27	-0.45	0.05	-0.27
19	No contact with physiolytics	0.27	**0.77***	-0.05	0.03	-0.20
8	Familiar with physiolytics	0.01	**0.74***	-0.03	0.24	0.19
20	No contact with physiolytics	-0.37	**0.71***	0.10	0.22	0.08
22	No contact with physiolytics	0.13	**0.56***	-0.02	-0.14	0.34
10	Familiar with physiolytics	-0.12	0.05	**0.79***	0.02	0.27
24	No contact with physiolytics	0.08	0.40	**0.65***	0.13	-0.19
12	Familiar with physiolytics	-0.12	0.03	**0.61***	0.40	0.14
3	Familiar with physiolytics	0.35	-0.27	**0.57***	-0.08	-0.10
14	Familiar with physiolytics	-0.15	0.00	-0.13	**0.84***	-0.28
17	No contact with physiolytics	0.54	0.14	-0.03	**0.67***	-0.19
26	No contact with physiolytics	0.29	0.21	-0.04	**0.62***	0.36
13	Familiar with physiolytics	0.27	0.34	0.48*	**0.55***	0.02
2	Familiar with physiolytics	0.04	0.03	-0.12	-0.17	**0.74***
11	Familiar with physiolytics	-0.10	0.21	0.02	-0.01	**0.59***
25	No contact with physiolytics	0.28	0.17	-0.36	-0.15	**0.58***
Eigenvalues		5.59	1.95	1.74	1.84	1.23
Percentage of variance explained (%)		19.96%	6.96%	6.21%	6.57%	4.39%

* = factor loadings that are significant, i.e. SE = $1/\sqrt{N}$, with SE = the standard error and N = the number of Q-sort statements (Brown, 1993). Here, the standard error = 0.180 (SE = $1/\sqrt{28}$) = 1/5.29 = 0.18). Correlations are considered to be statistically significant at the 0.01 level when they > 2.58 standard errors (irrespective of sign), i.e. 2.58 (0.18) = 0.46.

Table 1. The matrix of the factor loadings

3.5 The qualitative data analysis

The fifth and last step of the Q-methodology application is the interpretation of the factors uncovered by the quantitative analysis. The researcher must assign significance, in an a posteriori approach, to structures that emerge from statistical procedures (Brown, 1993; Mettler & Wulf, 2019). The sensemaking practice commonly consists in finding distinguishing statements that help to uncover each factor's uniqueness. These distinguishing statements (in our case, nudges) are items with extreme scores on either end of the sorting continuum that represent the largest variance in response across all identified factors (Akhtar-Danesh *et al.*, 2011; Valenta & Wigger, 1997). Accordingly, items with the smallest variance constitute consensus items. Such nudges are similarly perceived across all the attitudinal groups. Thus, when interpreting outcomes, researchers must pay particular attention to distinguishing and consensus nudges. These allow one to situate items compared to their status within the other factors (Brown, 1993; McKeown & Thomas, 2013; Valenta & Wigger, 1997) and help to appraise dominant nudges for each factor. Thus, researchers can identify distinct patterns in respondents' perspectives. We did the qualitative data analysis with the active participation of an experienced researcher in Q-methodology in order to control the different interpretations' validity, increasing the evaluation's robustness.

4. Results

Table 1 displays the factor loadings of the rotated factor matrix for each participant. The numbers represent the factor loadings, which are correlation coefficients that indicate the extent to which each of the 28 individual Q-sorts was (dis)similar to each of the five composite factor arrays. In other words, these allow us to underline five distinct types of expectations and attitudes regarding acceptable nudges for physiolytics applications to be used at the workplace. Still, the fact that more people loaded on Factor A does not necessarily mean that there is a proportional distribution among a larger population and that most people think along the lines of Factor A. Q-methodology seeks to structurally map all opinions. The idea is to create a typology of opinions, not to test the typology's proportional distribution in a wider group (Brown, 1993; Valenta & Wigger, 1997).

To illustrate our findings, we present the nudges that the members of each attitudinal group have perceived as the most and the least relevant. In accordance with the results obtained through the Q-sort rank-ordering, items considered as most relevant were assigned +3, and those perceived as least relevant as -3 (0 = neutral). For clarity, we labelled distinguishing items with the superscript [a] and consensus items with the superscript [b].

4.1 Factor A: Nudging through positive reinforcement and fun

Factor A or attitudinal group A is characterised by a focus on nudges that frame information in positive, simple and empowering ways. The most prevalent nudges emphasise entertainment and increased access to information. Quantifying employees' environment in synchronisation with the systems (e.g. "if you use the office's entrance stairs, you will take X steps…") and symbolic health goals confirm the inclination to provide material for employee self-reinforcement.

We label this factor *positive reinforcement*, because this attitudinal group systematically refuses nudges that employ any form of automaticity, constraint or limitation. In fact, mechanisms that nudge these users to avoid a negative result are systematically voted down compared to the other nudges. Levers such as social norms, time limits to create pressure, or displaying warnings are therefore undesirable to this attitudinal group.

Nudges	A	B	C	D	E
Provide punctual information and feedback (e.g. visualisations) on the general progress of the digital workplace health initiative.[a]	3	3	3	3	-2
Establish a fun ritual regarding the use of the sensor.[a]	3	0	-3	3	0
Display warnings (large fonts, bold letters and bright colours) relating to health issues (e.g. lack of physical activity, stress) in a frequented area in the office.	-3	0	-2	-1	1
Generate discomfort or fear by showing clips about negative impacts of burnout or a lack of physical activity.	-3	1	-1	0	-1

[a] = distinguishing items.

Table 2. The most and the least relevant nudges according to Factor A

4.2 Factor B: Nudging through controlling an organisational environment

Automaticity and the establishment of personal reminder cycles are the main determinants of Factor B. Although the need for information (feedback, informational leaflets) is also present, this attitudinal group differs from Factor A owing to the presence of mechanisms that specifically help to mitigate inertia. It builds on a more rational approach, in which individuals value decision assistance mechanisms to support the use of the systems. The overall setting is controlled, and employees are pre-set in an environment that nudges them to use the systems and eventually improves their well-being.

Another characteristic of this attitudinal group is the prevalence of the individual level of action. The highlighted nudges target each user directly. Nudges involving co-workers or nudges that modified the workplace environment are systematically rejected. Also, comparisons, social interactions and situational cues (i.e. the reliance on specific objects to trigger an automatic action or to make an action easier to remember) are disapproved of.

Nudges	A	B	C	D	E
Provide punctual information and feedback (e.g. visualisations) of the general progress of the digital workplace health initiative.[a]	3	3	3	3	-2
Automatically enrol employees in the digital workplace health initiative (but they can freely opt out).[a]	-2	3	-1	1	1
Place motivational pictures (e.g. a person running) on employees' desks or above the charger of their personal device.	0	-3	0	-2	1
Insist on the gaps (e.g. in term of health, experience, etc.) that eventual non-participation may create between the participants and the non-participants in the organisation.	-2	-3	-1	2	-1

[a] *= distinguishing item.*

Table 3. The most and the least relevant nudges according to Factor B

4.3 Factor C: Nudging as personal commitment and self-responsibility

The central element in Factor C is the importance of personal commitment. Along the same lines as attitudinal group B, members of Factor C exclusively retain nudges that focus on the individual user. However, the dominant key is the notion of commitment. Nudges that ask for a personal commitment at the beginning of the workplace health initiative or nudges that rely on personal interviews regarding the participation in the workplace health initiative, are most relevant to the members of this attitudinal group. For employees in this category, the use of physiolytics should be part of a process that is premeditated and thought through. The targets of such workplace health initiatives should be tailored to each individual, since employees set their own health objectives. Further, this process should result from a personal initiative in order to be acknowledged. All external stimuli such as warnings, motivating messages or changes in the environment are strongly disapproved of. Customisation and fun elements are less relevant to this group, since the main cue is primarily self-motivated and planned engagement. The fact that the nudge "*Setting a time limit in which employees can sign up to participate"* is only present in this attitudinal group reinforces the notion of planning the de facto use of physiolytics.

Nudges	A	B	C	D	E
Provide punctual information and feedback (e.g. visualisations) of the general progress of the digital workplace health initiative.[a]	3	3	3	3	-2
The employees who wish to participate in the digital workplace health initiative commit in writing (e.g. sign a document).	0	1	3	-1	0
Establish a fun ritual regarding the use of the sensor.[a]	3	0	-3	3	0
Allow participants to customise their device - without altering its functioning (e.g. with stickers).[a]	1	1	-3	-1	3

[a] = distinguishing item.

Table 4. The most and the least relevant nudges according to Factor C

4.4 Factor D: Nudging as group effort and collective responsibility

Attitudinal group D is relatively similar to group A: nudges that provide fun and that increase access to information prevail. Yet, in Factor D, there is an additional notion of creating a favourable environment for the sustained use of physiolytics. Attitudinal group D is the only group to support the establishment of a *situational cue* (+2) that connects the use of sensors to a frequent employee task (e.g. "*I first put on my physiolytics device before opening my mailbox*"). Likewise, members of this group are the only ones to rate the nudge "*Insist on the gaps (e.g. in terms of health, experience, etc.) that eventual non-participation may create between the participants and the non-participants in the organisation"* positively (+2). These individuals expect such workplace health initiatives to positively integrate the workspace in order to make use of its specificities so as to increase entertainment and information. They are also the employees who wish a strong collective dynamic in the workplace in order to successfully support engagement with physiolytics. Individual commitments, comparisons to other organisations, and motivating messages are appreciated less, since sustained use is linked to the capability to drive all participating employees in a positive and collective experience to improve their well-being.

Nudges	A	B	C	D	E
Provide punctual information and feedback (e.g. visualisations) on the general progress of the digital workplace health initiative.[a]	3	3	3	3	-2
Establish a fun ritual regarding the use of the sensor.[a]	3	0	-3	3	0
The participants make a small public commitment before embracing the digital workplace health initiative (e.g. oral commitment during a group session).[a]	-1	-1	2	-3	2
Inform participants that employees from other organisations strongly participate in such workplace health initiatives.	-1	-2	-1	-3	-1

[a] = distinguishing item.

Table 5. The most and the least relevant nudges according to Factor D

4.5 Factor E: Nudging through adapting an individual environment

Factor E distinguishes itself by negatively rating the nudge "*Provide punctual information and feedback (e.g. visualisations) on the general progress of the digital workplace health initiative*" compared to other nudges. While this nudge is perceived as very relevant by all other the attitudinal groups (+3), it is relatively unpopular among members of this category (-2). Situational cues, reminders and other tools that provide information or support the creation of a routine regarding the system are also not considered to be very relevant. The reordered high values for customisation, commitment and display of motivation messages in the workplace suggest that this group's members primarily focus on reinforcing self-goals. System use is a matter of individual choice, and we can therefore assume that members of this group do not appreciate their management priming IS use. Factor E users who want to change their health behaviours will use a system anyway. Accordingly, *one's own will* is fundamental to this group.

Nudges	A	B	C	D	E
Allow participants to customise their devices - without altering their functioning (e.g. with stickers).[a]	1	1	-3	-1	3
The participants have to set symbolic health goals in relation to the sensor (e.g. 6,000 steps per workday).	2	2	1	0	3
Deliberately place certain objects in the office environment (e.g. running shoes and runner's magazines) to prime a healthy lifestyle among participants.[a]	0	-1	0	-2	-3
Ask participants to think about, design and/or introduce their own reminder system in order to use the sensor.[a]	1	0	-1	1	-3

[a] = distinguishing item.

Table 6. The most and the least relevant nudges according to Factor E

4.6 Consensus and distinguishing statements

Figure 3 illustrates by means of a heatmap how each nudge is perceived by each altitudinal group. Some nudges are not distinguishable among attitudinal groups, which means that there is some concordance. As seen in the methodology section, these statements are called *consensus items* and have the lowest variance across all identified factors. They represent shared beliefs and common conceptions on how to support the use of physiolytics in the workplace. In our case, the items that generate the most consensus are "*Health buddy: a peer (an employee) is in charge of providing information to the group*" with a variance of 0.2 and "*Ask participants at the start of the digital workplace health initiative how well they think they will perform*" with a variance in the ratings of 0.3. However, as deducible from Figure 3, these nudges are perceived as fairly neutral concerning relevancy (an average of 0.2 and 0.6, respectively), which provides very little evidence on whether or not they are worth implementing in organisational settings. Due to the forced distribution, zero scores may indicate indifference or unimportance rather than careful consideration (leading to placement in the middle), which may be the case in questionnaires and surveys (McKeown & Thomas, 2013).

On other hand, disagreement across attitudinal groups is measurable by *distinguishing items* that have a large variance between the factors. These nudges strongly shape our attitudinal groups, as they translate major divergences of opinion about nudges' perceived relevancy. Hence, we can notably see that relying on automaticity, public commitment, fun and information or feedback to support the use of physiolytics may be a double-edged sword. By implementing such nudges, some employees may consider them as extremely worthwhile and suitable approaches, while others may discard them. The case of punctual information and feedback is particularly interesting, because it would be a clear consensus strategy concerning perceived relevancy if Factor E was not present. Nonetheless, even with the negative appraisal from this attitudinal group, this nudge (information/feedback) averages the best score concerning perceived relevancy (average: +2).

Q-SORT STATEMENTS	**Group 1**	**Group 2**	**Group 3**	**Group 4**	**Group 5**
"Health buddy". One of the peers (employee in the organization) is in charge to provide information to the group (after being instructed).	0	0	0	0	1
Ask participants at the start of the digital workplace health program how well they think they will perform (e.g. in terms of steps number increase).	0	1	1	1	0
Divide participants into duos or small groups - as part of the digital workplace health program - to create a positive drive.	0	0	1	1	2
Designate a volunteer among the participants to be in charge of reminding the others to use the sensors.	-1	-2	0	0	-1
Inform participants that employees from other organizations participate at a high frequency in such workplace health programs.	-1	-2	-1	-3	-1
Establish a reminder cycle as regards the use of the sensor (e.g. via email, SMS).	0	2	0	0	0
The participants have to set "symbolic health goals" with relation to the sensor (e.g. 6,000 steps per work day).	2	2	1	0	3
Question employees about their future conduct, such as "do you plan to reduce your work stress?" (e.g. via a questionnaire, personal interviews).	-1	0	2	0	1
Place great expectation on people and quantify objectives (regarding the participation in the digital workplace health program). E.g. "I know you can achieve this objective at the end of this month").	-1	-1	-2	1	0
Provide each employee a detailed informational leaflet about the digital workplace health program.	2	2	1	-1	0
At the first meeting with the employees, introduce the presenter that will deliver instructions/be in charge of the digital workplace health program as a health specialist (e.g. practitioner).	1	1	0	-1	-2
Deliberately place certain objects in the office's environment (e.g. walking shoes and runner's magazines) to prime a "healthy lifestyle" in participants.	0	-1	0	-2	-3
Define a time limit in which employees can sign up to participate in the digital workplace health program.	-2	0	2	0	0
Generate discomfort/fear by showing clips about negative impacts of burn-outs/lack of physical activity.	-3	1	-1	0	-1
The employees that wish to participate in the digital workplace health program commit in writing (e.g. sign a paper).	0	1	3	-1	0
Ask participants to define a "situational cue", i.e. connect the use of the sensor with a task they frequently do (e.g. I first put my sensor before opening my mailbox).	1	-1	0	2	-2
Display warnings (large fonts, bold letters, and bright colors) related to health issues (e.g. lack of physical activity, stress) in a frequented area of the office.	-3	0	-2	-1	1
Place motivational pictures (e.g. a person running) on employees' desks or above the charger of their personal device.	0	-3	0	-2	1
Ask participants to think/design/introduce their own reminder system in order to use the sensor.	1	0	-1	1	-3
Quantify the employees' environment in synchronization with the device (e.g. if you go by feet to the Migros for lunch, you'll walk X steps, burn X calories..).	2	-2	1	2	-1
Display - in a frequented area of the office - inspiring, positive and motivating messages (large fonts, bold letters, and bright colors) about the importance of improving one's health behavior.	1	-1	-2	-2	2
Insist on the gaps (e.g. in terms of health, experience etc.) that an eventual non-participation may create between the participants and the non-participants inside the organization.	-2	-3	-1	2	-1
Automatically enroll employees in the digital workplace health program (but they can freely opt out).	-2	3	-1	1	1
The participants make a small public commitment before embracing the digital workplace health program (e.g. oral commitment during a group session).	-1	-1	2	-3	2
Provide punctual information and feedback (e.g. visualizations) on the general progress of the digital workplace wellness initiative.	3	3	3	3	-2
Allow participants to customize their device - without altering its functioning (e.g. with stickers).	1	1	-3	-1	3
Establish a fun ritual regarding the use of the sensor.	3	0	-3	3	0

Figure 3. Nudges and the degree of consensus and disagreement with them

5. Discussion

Person-organization fit perceptions are good indicators of the course of interactions between employees and organizations. In connected workplaces, data-driven systems integrate the relationship between employees and organizations, with a propensity to complexify this relationship (due to the mass collection of individual data) and the environment in which it takes place (Bakewell *et al.*, 2018). Accordingly, individual fit perceptions may change, potentially generating dysfunctional attitudes which may be damaging both for employees (e.g. technostress) and organizations (e.g. lower productivity) (Ayyagari *et al.*, 2011; Pee, 2012)). In this regard, nudges might be a powerful means to act on employees' attitudes in connected workplaces. Changing routines, norms and environments around an implemented system might subsequently change the perception of such system in work settings. By targeting subjective views, nudges constitute an instance of mechanisms that may stimulate person-organisation fit. However, as opposed to the consequences of person-organisation fit and misfit (Venkatesh *et al.*, 2017), they have not received much attention yet.

Our Q-methodology procedure yielded five typical nudging strategies that may forge favourable practices around data-driven initiatives, such as physiolytics. These may subsequently be enhanced through positive reinforcement and fun elements (Factor A), controlling the organisational environment (Factor B), expanding personal commitment and self-responsibility (Factor C), increasing group efforts and collective responsibility (Factor D), or by allowing users to adapt their individual environment as much as possible (Factor E). When we consider particular nudges, the only pattern that arguably emerged among employees was increased *access to information*, which may be more oriented toward metrics (i.e. an increased feedback loop that show data under various forms) or toward the communication of processes.

5.1 Practical implications

5.1.1 Mechanisms of nudging and person-organization fit

Our results show a large heterogeneity of opinions on nudging strategies and their impact on person-organization fit. In our example, for some employees, fun and entertainment (Factors A and D) are the main drivers for using physiolytics, while for others physiolytics is more of a tool to proactively improve their performance (Factor B), or to comply with an initiative important to their employer (Factor C). Such dimensions outline that various orientations exist for the purposes of making data-driven initiatives simpler or more desirable. It may be through praising an effort that is identified as positive, or operating on a sentiment of commitment,

which can be typically employed in an environment with strong workplace culture or during the implementation of IS with environmental objectives. Our results therefore illustrate the complexity respectively possible ineffectiveness of applying one-size-fits-all approaches when implementing nudging strategies (Weimer, 2020; Wingreen & Blanton, 2018). Fit perceptions are by essence dynamic and unsettled (Cools *et al.*, 2009). A single procedure might hardly affect all the spectrum of different sensibilities. In particular, data-driven systems are often blurring the line between what people consider as private or organizational sphere (Ajana, 2017) and the tipping point which marks the failover in perceived systematic surveillance is often difficult to evaluate. In the same way, most of the nudges are divisive and may accentuate existent misfit perceptions (e.g., feeling that organizations are covertly trying to establish systematic surveillance). For instance, fun rituals, which are at the top of the list for Factor A are, at the same time, at the bottom of the list of Factor C. Such polarising distributions certainly point to the importance of participatory initiatives when considering nudges in connected workplaces. Simple appraisals such as discussions, questionnaires or surveys may help to rapidly unveil (1) which precise nudging strategies to implement, (2) in which proportions, and (3) for which employees. By doing so, organisations may be in a position to apply different mechanisms depending on their employees' mindsets. This could increase the odds of a successful implementation and the success of data-driven IS, which is essential for an organisation as it invests its financial resources, time and efforts (Dunkl & Jiménez, 2017).
Organizations may be tempted to adopt the most consensual approach, by selecting a nudge that is accepted by all the groups (but not particularly evaluated as relevant). In our case, one item was more or less positively rated by all the groups was "*The participants have to set symbolic health goals in relation to the sensor (e.g. 6,000 steps per workday)"*, with a variance of 1.3 and a mean of 1.6. The risk of choosing such a nudge is that it may not appropriately fulfil the goal of its implementation, which in this case is to support the use of physiolytics. In fact, as noted, the forced distribution in the Q-sort offers a well-defined rating among the presented nudges, so that nudges that are not at the most relevant end of the continuum more likely indicate lower perceived importance (Valenta & Wigger, 1997).

5.1.2 Rational or emotional nudging and person-organization fit

Clear dichotomies also emerge among employees regarding the roles of emotion and cognition as drivers of physiolytics use. Some advocate a nudging approach that targets thinking (i.e. increase the possibility to think about the negative effects of a lack of physical activities - characteristically *system 2* nudges), while for others feeling is the main driver of sustained use (i.e. increase the pleasure to use the system). Although they are both feasible in workplace settings, organisations have to reflect on whether it is more suitable to impact data-driven IS implementation by acting on purely automatic and institutive behaviours, or by dispensing information to enhance rationality in the reflective decision-making process (Baldwin, 2014). The nudge "*Provide punctual information and feedback on the general progress of the digital workplace health initiative"*, which is positively ranked by several groups, expresses this research of empowerment. In our case, we found that employees often seek additional progress support from their employer, even though physiolytics-driven initiatives often rely on self-help and automated functioning. This is in line with research that considered (non-mandated) Internet-based interventions for health promotion in the workplace. These studies have shown that additional support helps to minimise drop-out rates compared to implementations that strictly rely on an automated Internet-based intervention (Donker *et al.*, 2009; Dunkl & Jiménez, 2017; Proudfoot *et al.*, 2011; Spek *et al.*, 2007).

According to Münscher *et al.* (2016), nudges that make information visible have two dimensions: providing external information and providing feedback. First, nudges may deliver pertinent information about a general situation (e.g. they may inform about the benefits of using a stress management tools, how to use the physiolytics device to achieve a certain goal, or examples of burnout the devices helped to detect). This complementary information seeks to empower a user, which often remains invisible if it is not implemented through a nudge (Münscher *et al.*, 2016; Santiago Walser *et al.*, 2019). Also, nudges that render information visible may be more oriented to information resulting from one's behaviour or performance. In our case, these nudges may include feedback on the general progress, such as sensor use times, self-shared data by participants, or reports from participants. Altogether, nudges that provide information and feedback hold the promise to give employees access to more data about their work environment and about themselves. Typically, these can be implemented in the form of informative papers, e-mails, forums, instant messaging communication, mobile features, phone calls, or webcam or face-to-face meetings or reunions (Dunkl & Jiménez, 2017; Proudfoot *et al.*, 2011; Ritterband *et al.*, 2009).

5.1.3 Individual or group approach to nudging and person-organization fit

Concerning the focus and the target of the intervention, we found that both group interventions (e.g. socialisation supported by Factor D) or strongly individually oriented nudges (e.g. self-responsibility supported by Factor C) are represented. For instance, concerning Factor D, organisations may reasonably consider the introduction of nudges that build on social support and seek to create a sense of community around shared goals (Chen & Pu, 2014; Santoro *et al.*, 2015). This could be provided via offline relationships (discussions, exchanges, events) or online ones (enabled by social media and networking sites), so that users of physiolytics (or similar IS initiatives) create group dynamics experiences that enhance motivations to stick to their objective.

Ultimately, it is noteworthy to acknowledge that Factor E depicts a certain degree of cynicism that some employees may show regarding physiolytics in the workspace. As described by Mettler and Wulf (2019), cynical users are employees that are in a cognitive dissonance with their employer, meaning that they have a form of person-organisation misfit regarding such data-driven systems. They use physiolytics, in our configuration, at their own will and without recognising nudges and organisational management. This is a form of passive resistance (Selander & Henfridsson, 2012) that organisations have to be aware of as a component of connected workplaces.

5.2 Research implications

5.2.1 Nudging as a management strategy for person-organization fit in connected workplaces

If we prescind from the illustrated practical design considerations, our work advocates for the importance for organisations and individuals to find a common ground in connected workplaces, where employees' perspectives are respected (Bakewell *et al.*, 2018; Zhao *et al.*, 2019). To date, organisations had few proactive management strategies to enhance the fit around their implementations. Typical responses were, on the contrary, rather reactive attempts to handle misfits, such as resistance to continuously use data-driven systems. Coping strategies or new practices were implemented in retrospect to address eventual concerns and improve company culture (Bakewell *et al.*, 2018; McAfee *et al.*, 2012; Wingreen & Blanton, 2007). In this context, our nudging strategies represent elements of a structured management approach that concretely impacts on subjective perceived fits in connected workplaces. It constitutes what Stephan *et al.* (2016) name *surface-level strategies*, which are mechanisms that aim to produce external adjustments in order to orient behaviours in a rapid and wide-reaching way. The idea is to promote organisational practices through opportunity processes and external stimuli, which may ensure the best environment possible in which favourable attitudes and behaviours may flourish (Stephan *et al.*, 2016; Wu & Paluck, 2018). It is in fact difficult to change how employees intrinsically consider data-driven systems (as organizations can hardly alter strong inner beliefs and rooted values), leaving organisations to primarily act on the environment in which employees evolve. Perceived fits are in that regard constructed on multiples sources of information (Überschaer *et al.,* 2016), with work routines, norms and organisational practices forming fragments that can add up and weigh towards better employees' engagement and use of a data-driven system. Our example on physiolytics, in sum, concretely illustrate the importance for organisations to proactively manage the use of these complex systems, in order to augment adherence to a sustained use, rather than risk implementation failures.

5.2.2 Nudging as a means to value individuals in connected workplaces

The importance of person-organization fit and nudges (i.e. mechanisms to encourage person-organization fit) in connected workplaces emphasises the significance of individual subjectivity. In connected workplaces, IT departments with strong technical skills are not sufficient anymore to ensure a fruitful data-driven implementation. Employees play a fundamental role as they carry part of the organisation's change effort towards connected workplaces, because they enact this change on a day-to-day basis (Dawson-Haggerty, 2019; McAfee *et al.*, 2012; Überschaer *et al.*, 2016). It thus is crucial to focus on individuals and their environment if one is to understand how employees consider and use such IS in the workplace (Tabrizi *et al.*, 2019). This can be done, as in our case, through the angle of behavioural strategies. This approach specifically helps to better appreciate user decisions, how they are rooted in a context, and how they are centred on potential gains or losses for individuals (Liu *et al.*, 2017).

Still, developing nudges that engender some design decisions that may benefit a system owner more than a user may create tension in the relationships between employees and employers. Even if nudges are meant to be unintrusive, easily scalable and non-coercive regarding employees' work habits, highlighting employees' beliefs regarding nudges for physiolytics is critical to offer a bottom-up vision and a participatory mean on the feasibility of nudging in connected workplaces.

This is an important first step when developing strategies with systems that target use behaviours, because it is crucial to first adopt a perspective at the user level to then accordingly develop strategies at the organisational level (Yu *et al.*, 2019). In this respect, our delineated attitudinal groups give more substance to the conceptualisation of IS users in connected workplaces: more than a constant, distinct, independent and stable notion, a user is defined by diverse opinions, attitudes and actions that generate impacts on IS use (Cuppen *et al.*, 2010; Forrester *et al.*, 2015; Mettler & Wulf, 2019). This is in line with the interpretative approach that can be grasped through the person-organisation fit theory. Providing insights on the interaction between an individual and its environment offer new explanations on *why* and *how* an individual use a system. It therefore serves to complement the traditional IS models on adoption and IS use, based on an objective operationalisation of measurements through separate variables (De Guinea & Markus, 2009).

In the same vein, our work promotes a transparent dialogue between *nudgers* and *nudgees*, which had been lacking in current IS research (Meske & Amojo, 2019). In fact, empirical studies in the IS domain have mainly focused on the capacity of nudges to achieve specific targets goals, but lightly considered users' preferences before acting on their choices. Yet, this is a fundamental aspect in nudging because nudges must maintain freedom of choice for users, and must remain transparent and legitimate in the ways they provide benefits to users (Lembcke *et al.*, 2019). By involving users in our study, we are able to empirically validate our nudging propositions and to minimise the risks of manipulation. Further, supporting this autonomy for users is what defines nudges in relation to other persuasive elements in IS (Lembcke *et al.*, 2019; Santiago Walser *et al.*, 2019). In this sense, nudging is not only an investigation of elements that persuade individuals, but also research into a suitable environment for these individuals, to enhance their decision-making processes (Meske & Amojo, 2019).

5.2.3 Nudging as a real-world management strategy in connected workplaces

Likewise, we have sought to show how nudges can be used to modify IS use behaviours without necessarily going through an online environment. The decision to use an IS does solely relate to interactions with a system, but also greatly depends on how it is integrated in the environment and how it is impacted by social and human components (Alter, 2003; Bøe *et al.*, 2015). In our case, increasing the use of physiolytics accordingly means creating a positive atmosphere for health behavioural change in the workplace, with for instance enjoyable rituals or an activity sharing structure in which participants can create engaging experiences. Nudges can therefore be understood as both online and offline management strategies to modify organizational routines or work environments (e.g. fit perceptions), particularly in connected workplaces.

5. Limitations and outlook

Our study has limitations. From a methodological perspective, although a large sample size is not a prerequisite for a Q-methodology procedure's success, the small number of participating employees does not allow for further statistical tests to assess the relationships between attitudinal groups (e.g. age, profession, prior use of physiolytics), nor to detail the structure and causality that led to the formation of such groups (Akhtar-Danesh *et al.*, 2011; Brown, 1993; McKeown & Thomas, 2013; Mettler *et al.*, 2017). As noted, representativeness and causality are not the goals of a Q-methodology study. To get an overview over the dominant groups in an organisation, classic survey techniques can be used. Since Q-methodology has an interpretative component, there is also a risk of bias at this stage of the process. Researchers must make sense of numbers and aggregated data if they are to derive sensible hypotheses and propositions (Cross, 2004).

Concerning nudges and their designs, we did not consider the level of effort or the degree of difficulty that an implementation would require. Some interventions may need greater involvement on the part of an organisation, which may not be aligned with its goals and development plans. This could also impact on the frequency of nudges used (Hummel *et al.*, 2017). In this sense, our presentation of nudges is solely descriptive and did not consider existing cultures in organisations. We chose this because we did not want to limit thinking at this very first stage, preferring to provide employees with a broad set of nudges. Implementation requires further consideration of the organisational environment and may be more restrictive. Therefore, we see our results concerning nudges less as a contribution to a cross-field and 'omnipotent' explicative model, since it is paradoxical to bring too much rationality (in terms of expected results) into a methodology that is founded on subjectivity and a theory that on bounded rationality (Lodge & Wegrich, 2016), but more as a descriptive account for design guidelines in connected workplaces.

This work therefore opens several possibilities for further research. First, it illustrates how person-organization fit can be used as a valid framework in IS research, as fit perceptions can be indicative of the likelihood of success of nudging strategies. Such approach allows to deepen investigations on adoption and use by considering interactions between organizations, individuals, technology and culture, rather than through one-dimensional and progressive step by step processes. Likewise, this work calls for additional comprehension of the role of individual and environmental factors (e.g. organizational policies, technology literacy, technical trainings) in the implementation of data-driven initiatives, because they may be the largest contributors of success or failure (Heo & Cheon, 2009).

Next, there are significant perspectives on testing nudges' capacities to positively impact on IS behaviours in connected workplaces as well as their abilities to be incorporated in IS management strategies. By adding empirical evidence on nudges that are accepted by employees, we have laid the necessary foundations (and boundaries) to facilitate further considerations on nudges' relevancy and/or their implementation on a wider scale. In particular, nudges that make information visible constitute an interesting avenue to explore, since they have a relative prevalence of positive opinions among our attitudinal groups. Such nudges, which seek to improve decision environments regarding IS (Kroll & Stieglitz, 2019), may structure information loads faced by employees in connected workplaces.

Nudging and its related concepts, such as transparency, integrity and autonomy are primarily a matter of appreciation, understanding and interpretation and must be considered on a case-to-case basis. Additional work could help to unveil the particularities of nudging in different contexts and can further build the empirical basis to strengthen this notion in IS research (Avgerou, 2019). For this purpose, the Q-methodology approach is an effective instrument for exploring diverse opinions and a way to identify possible poles of resistance. In our instance, it has helped to enhance organisational interventions' credibility (Iofrida *et al.*, 2018) and to support management strategies' applicability (Klaus *et al.,* 2010). We encourage IS researchers to employ Q-methodology in order to gain a novel perspective in the appraisal of challenging questions (e.g. nudging) in complex contexts (e.g. connected workplaces), as well as to consider other person-organisations fits (e.g. technostress).

As illustrated by our study context, the phenomenon of the connected workplace is marked by several rising issues. The present rush of organisations to implement sensors, predictive analytics and other connected systems have created new challenges in the management of IS (Beane, 2020). There are therefore opportunities to explore how metrics and real-time feedback impact on relationships between individuals, technologies and work environments (Moore & Piwek, 2017) or to consider eventual ethical problems linked to connected workplaces where organisations may harness private information (e.g. employees' health data). In any case, connected workplaces ask for more granularity in the appraisal of IS use, which can be done through interpretative paradigms as well as trough interdisciplinary approaches and methods, such as behavioural economics, social sciences or psychology.

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