Article

Self-Quantification Systems to Support Physical Activity: from Theory to Implementation Principles

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Abstract: Since the emergence of the quantified self movement, users aim at health behavior change, but only those who are sufficiently motivated and competent with the tools will succeed. Our literature review shows that theoretical models for quantified self exist but they are too abstract to guide the design of effective user support systems. Here, we propose principles linking theory and implementation to arrive at a hierarchical model for an adaptable and personalized self-quantification system for physical activity support. We show that such a modeling approach should include a multi-factors user model (activity, context, personality, motivation), a hierarchy of multiple time scales (week, day, hour), and a multi-criteria decision analysis (user activity preference, user measured activity, external parameters). Although the implementation still raises many challenges, principles linking theory and implementation should facilitate the design of effective self-quantification system aimed at physical activity increase, and more widely for behavior change.

Keywords: quantified self; health; physical activity; behavior change; model; support system; persuasive design; user centered design

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1. INTRODUCTION

The quantified self movement has raised in 2007 and has been growing since then to a point where more than one third of American adults currently use a self-quantification tool to track their health and fitness [1]. In terms of volume, 255 million wearable devices were sold worldwide in 2019 and this market is expected to keep growing by more than 20% annually for the upcoming years [2].

On the scientific side, a major descriptive effort has been carried out since 2010 to define this quantified self movement, showing that the most popular objective is behavior change. Researchers agree that self-reflection and contextual factors are indispensable to achieve behavior change [3–6]. Self-reflection means that a user needs to understand his or her habits and their variations within his/her environment through collected data. The user's environment is referred to as contextual factors or parameters: e.g. weather or schedule are parameters that influence the user's context. Consequently, a self-quantification system must be customizable and adaptable to the user's life to really help people change their behavior [3–7].

However, current self-quantification systems are too generic: in the case of physical activity monitoring, for example, they collect data such as the number of steps or the user's heart rate but no contextual information, and they provide only a few not very personalized tips to users such as "try to walk more". Thus, significant commitment is required from the user in data collection, management, and analysis in order to achieve a good understanding of his/her habits. Today, the steps that quantified selfers go through in a self-quantification experience have been characterized (e.g., collecting data, displaying it in a meaningful way), and guidelines for more effective self-quantification systems for behavior change have been identified (e.g. need for context, holistic approach). Nevertheless, established descriptive models or guidelines for future designs are not sufficiently precise to guide the implementation of effective, user-adaptive self-quantification systems. It is therefore essential to derive implementation principles from the established theoretical framework and associated guidelines.

In this respect, we have designed a minimal user model whose four components bring together the guidelines from previous research while respecting the existing theoretical models: usual quantified self user data goes into *activity data* (heart rate, number of steps, etc.), external data to evaluate the user's context is referred to as *contextual factors* (weather, schedule, etc.), the user's *personality* traits provide basic levers to personalize the user experience, and the user's *motivation* reports on his/her level of exercise adherence. We then propose, in this paper, a model of a **self-quantification system for physical activity support** as a solution to bridge the existing gap between a well-defined quantified self conceptual framework and limited implementation principles. Our model is structured around a *multi-factors user model* (activity data, contextual factors, personality, and motivation), a hierarchy of *multiple time scales* (week and day to account for human activity patterns, hour for user monitoring and feedback), as well as a *multi-criteria decision analysis* approach (user activity preferences, number of steps toward the goal, weather) for physical activity recommendations. For this reason, a system built on our model should, by design, be capable of assisting a quantified selfer to understand and change his or her physical activity.

The paper is organized as follows: we begin by providing background on the quantified self movement and the main descriptive axes that have emerged from research during the past decade. Next, we explain what previous studies have done in the light of these axes, models and guidelines. We then detail our model for an adaptive and personalized self-quantification system for physical activity support. Lastly, we will discuss the challenges of designing and developing such a self-quantification system based on our model.

2. CHARACTERIZATION OF THE QUANTIFIED SELF MOVEMENT

The quantified self movement was allowed by the technological advances in electronics and computer science of the early 2000s, but the action of collecting information about oneself has a long history.

2.1. Self-Tracking Background

Terms like "quantified self", "self-tracking", "personal analytics", or "personal informatics" refer to systems and practices that help people collect and reflect on their personal information [4,8,9]. In any cases, we are talking about a class of human-computer interaction covering the activities that *help people collect personally relevant information* for the purpose of self-reflection, gaining self-knowledge, and better understanding their own behavior [4,5]. Broadly speaking, the current "quantified self" definition refers to the community as well as the practices of self-tracking [6]. According to Lupton, it encompasses the incorporation of technology into data acquisition of daily life in terms of inputs, states, and performance to achieve self-knowledge and self-reflection [10].

Self-tracking is over two centuries old. For example, in the 18th century, Benjamin Franklin used to track the days in which he accomplished one of his 13 virtues (like Sincerity, Moderation, or Humility) for 60 years [11]. In the 1900s is Buckminster Fuller (an architect, designer, inventor and futurist) kept a scrapbook in which he registered every 15 minutes of his life [12]. More recently, Nicholas Felton, a computer graphic designer, has published famous annual reports (http://feltron.com) between 2005 and 2014 focusing on "*translating quotidian data into meaningful objects and experiences*" [13], and, finally, Chris Dancy (https://www.chrisdancy.com/) is now known as the most connected human on the planet to track every single bit of his life for several years.

2.2. Modern Quantified Self and Personal Informatics

Behaviors recording, in the form we know today, was initiated by technophiles in Silicon Valley in the 1970s. The process of quantifying one's life was traditionally used in behavioral psychology for clinical and research environment [6,14]. Quantifying one's life could help diagnosis, selection of treatments, and help to monitor changes after a treatment [15]. In the late 1990s, with the democratization of computers, microelectronics, and the development of the internet, sensors have become cheaper, smaller, and information could be accessed anywhere, hereby expanding the use of wearable quantification technologies [6]. Consequently, sensors became available to the general public which led to the rise of the quantified self movement [10]. Today, there is an active international community sharing practices through Meetups (in more than 40 countries), blogging, and annual conferences [6].

Health tracking has rapidly developed as an emerging paradigm for health care self-management [16]. Health tracking is facilitated by wearable sensors which enable general public to easily capture health data daily [17,18]. Nowadays, health tracking technologies have overall proven to be effective on increasing awareness and behavior change [6,10].

2.3. Goals of quantified selfers

Before going any further, we need to understand what are the quantified selfers' goals. Quantified selfers' goals may relate to self-management of chronic diseases [19], to general personal informatics [4], or to tracking health as a preventive tool [20].

The goals can be divided into three categories (see table 1) [6]. **Improving health** includes both treatment follow-up and prevention. Quantified self techniques can be used to monitor the impact of a treatment (e.g. cardiac arrhythmia medications in a case of tachycardia), to manage a particular condition (e.g. glycemic control through diet), or to answer specific questions (e.g. what factors make one feel energetic in the morning). **Improving various aspects of life** includes, for example, determining when one is most productive or managing a budget to maximize savings. **Finding new**

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Table 1. Quantified Selfers Goals Categorization, adapted from Choe et al. This table summarizes quantified selfers' goals into three groups with relevant examples.

Improving.Health	Improving.other.aspects.of.life	Finding.new.life.experience
- to cure or manage a condition - to find triggers - to answer a specific question	- to maximize work performance - to be mindful - to trigger events	- to satisfy curiosity and have fun - to explore new things and discover new tools - to learn something
- to identify relationship - to execute a treatment plan - to make better health decisions		interesting - suggestion from another person
- to find balance to improve health		

life experiences includes anything that doesn't have a specific goal, such as discovering new tools, learning interesting things, or having fun. Finally, people sometimes have no particular objective when starting self-tracking and want to figure out what goals would be appropriate to pursue. These people indeed use self-quantification tools in order to determine what actions they should take to fix a problem, or simply to establish a baseline of their activities to determine whether they have a problem [4].

In this paper, we focus on health aspects as this is the most represented category among the objectives of quantified selfers, and more specifically on physical activity which is the predominant monitored element in the health category: activity (40%), food (31%), weight (29%), sleep (25%), and mood (13%) [6]. Activity tracking is usually associated with a concern for health risk prevention, which, for quantified selfers, translates into a final objective of health behavior change [17,18]. Quantified selfers' goals have been identified and described precisely by previous research, but what barriers do they face in implementing a system to achieve their objective?

2.4. Barriers and limits

Previous research has also investigated the limitations in self-quantification experiences that prevent quantified selfers from successful outcomes. They have identified guidelines for system design to overcome these barriers as well.

To start with, human factors are the basic reason for the need for technology in quantified self. Pure self-reflection is indeed often flawed: people have limited memory, cannot directly watch some behaviors like heart rate, and may not have the time to constantly observe some behaviors like manually counting steps throughout the day for instance. Reflecting by using memory alone makes it difficult to see patterns and trends, especially over long period of time. People may also not have the expertise or knowledge to make the correct conclusions about their observations [4]. On this basis, Choe and Li studies highlighted common limitation factors on the human side which are "**lack of time**", "**insufficient motivation**", and "**difficulty in data integration and interpretation**" [4,6].

From the same studies, some limits have been identified regarding the tools used: they talk about "**unsuitable visualization and analytics tools**" and "**fragmented data scattered across multiple platforms**". Vizer and colleagues similarly underline these inherent barriers to tools, and an article from Epstein even reports that some people find the commercial self-quantification tools useless[3,21]. Finally, from a general perspective, Almalki and colleagues have highlighted that achieving useful health outcome is pretty difficult in terms of managing data and reflecting on it because it involves systematic understanding of tools and complex undertaking of user activities [17].

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More generally, they identified a lack of systematic approach for conceptualizing and mapping essential activities undertaken by quantified selfers. Li, on the other hand, explained in 2010 that there was no comprehensive list of problems that users could experience with personal informatics and, hereby, self-quantification systems [4]. Choe and colleagues alleviated this shortcoming in 2014 by emphasizing the common pitfalls among quantified selfers' practices which are "**tracking too many things**", "**not tracking triggers and context**", and "**lack of scientific rigor**" [6]. They also mentioned that some open questions were inherent barriers to a self-quantification experience: *how to easily explore data? How to bring scientific rigor to the quantified self movement?*

2.5. Conceptual Models

In order to better characterize the quantified self experience users go through, some researchers have attempted to derive conceptual models. In 2019, Vizer et al. have identified four main models related to the tracking process but we will ignore two of them as they focus on users who are already patients, hereby involving a specific clinical context which is out of scope for our study [3,22,23].

Stage-Based Model

The first model, and the more widespread one, is Li's Stage-Based Model of personal informatics which dates back to 2010 and classifies quantified selfers' practices into five main stages 1 [4]:

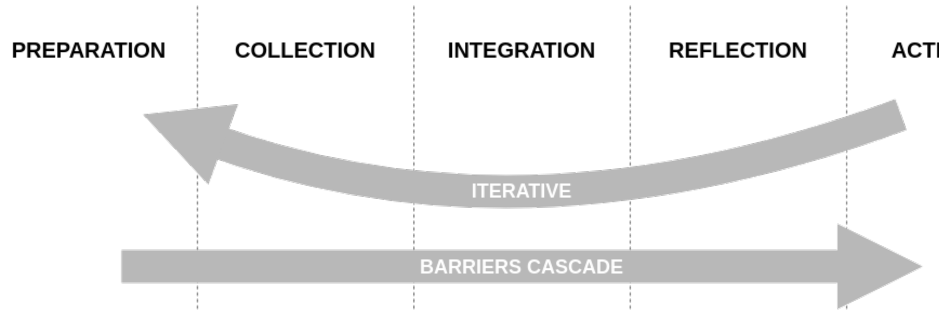

Figure 1. Adapted from Li et al.'s Stage-Based Model of Personal Informatics Systems: this shows the progression of a person toward behavior change through the different stages of a self-quantification experience with its iterative nature and its barriers.

The **preparation stage** is the very first step in a quantified self approach and occurs before information collection: people think about what information they will record and what tools they are going to use. The **collection stage**, as its name implies, occurs when people collect information about themselves, their frequencies, observations, etc. This refers to the self-tracking activity from Almalki's definitions [17]. The third step is the **integration stage** where the information collected are prepared, combined, and transformed for the user to reflect on. It duration can vary a lot depending on the tools used or the information tracked and requires effort for data preparation. With the prepared data, the **reflection stage** starts when users reflect on their personal information. It involves looking at collected information or interacting with information visualization. Reflection can be short-term (makes users aware of their current status) or long-term (allows users to compare information between different times and reveals trends and patterns). Finally, the last **action stage** occurs when people choose what they are going to do with their newfound understanding of themselves.
The model describes the iterative nature of these stages and the barriers that prevent transitioning between them. However, although this model is very clear regarding the different phases a user experiences and has serve as a basis for a great deal of research, it does not represent the fluidity of work in a self-quantification experience and can break down when encountering the realities of everyday life [24,25].

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Lived Informatics Model

Then, in 2015, Epstein and colleagues have proposed a Lived Informatics Model of personal informatics 2. It remains about general tracking in everyday life and aims to be an enhancement of Li's model by dividing *preparation stage* into *deciding* and *selecting* as well as introducing a *tracking* and *acting* cycle for iterative progression through *collection*, *integration*, and *reflection*. Its most interesting characteristic is that it anticipates human lapse as it is not oriented toward behavior change only.

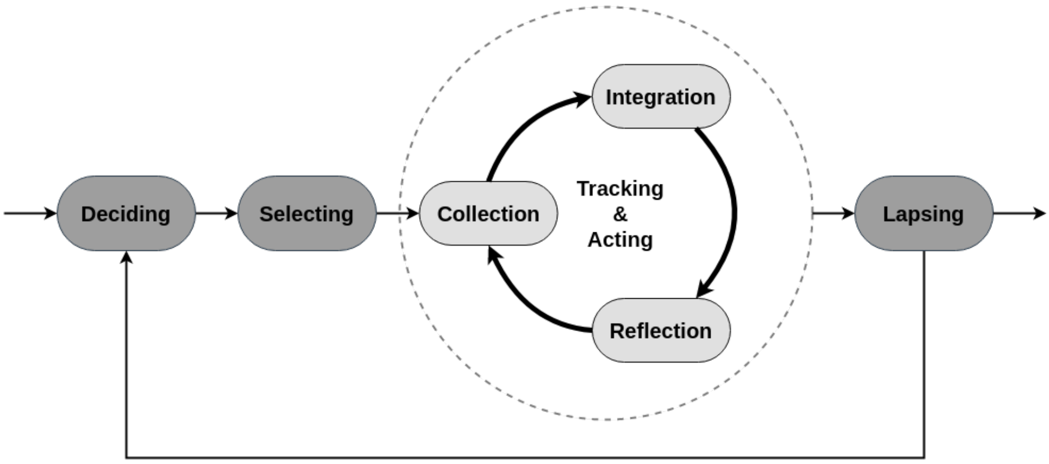

Figure 2. Adapted from Epstein et al.'s Lived Informatics Model of Personal Informatics: this model is based on Li et al.'s model and highlights the essential fluidity and iteration of a self-quantification process. It is not specifically oriented towards behavior change though.

Conceptual Model of Shared Health Informatics

From their analysis of past literature and existing models, Vizer and colleagues have noticed a strong need for a model that more closely aligns to the unique needs of health context [3,26,27]. In the light of these observations, they propose a new model which bridges the gap between current personal informatics models and tracking for chronic illness self-management. This new Conceptual Model of Shared Health Informatics (CoMSHI) is based on Li's model, but adds *communication* to incorporate interactions between actors and redefines *preparation* to *information* 3.

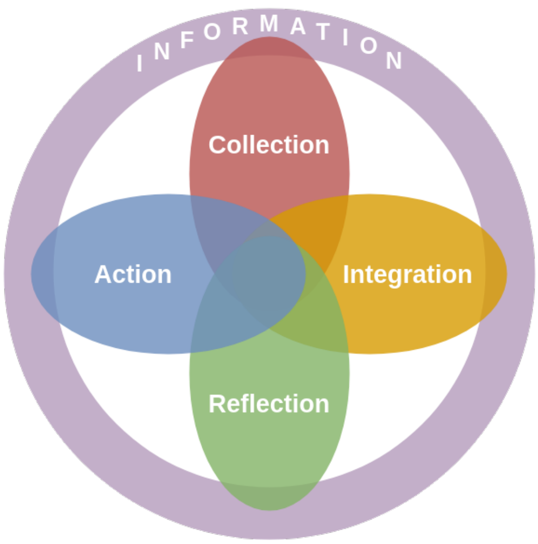

Figure 3. Adapted from Vizer et al.'s Conceptual Model of Shared Health Informatics (CoMSHI): also based on the Stage-Based model, the CoMSHI enhances the fluidity of the process by facilitating transitions between stages. It reflects the need for context raised by previous research as well.

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In terms of representation, the initial discrete stages become unconstrained transitions which better represent the smoothness necessary to self-quantification experience. It thus allows different types of work to happen simultaneously as describe by Epstein and Figueiredo, and this is why this model remains interesting for our approach although it concerns treatment self-management of patients with chronic illness [24,28].

The models described in this part are mature and accurate enough to account for the different stages and needs occurring during a self-quantification experience: the Stage-Based model is well established in quantified self research and accurately reflects the different stages of the process but it is too linear and leaves little room for flexibility. The Lived Informatics model account for the inherent fluidity of the self-quantification process and focuses on the continuity of experience. It is not oriented toward behavior change only however. Finally, the Conceptual Model of Shared Health Informatics is based on the need for context around a flexible process but focuses on chronic illness management.

2.6. Existing Barriers and Guidelines for Design

By attempting to characterize the quantified self movement and self-tracking process with models, researchers have identified numerous barriers from which they derived guidelines for a better design of personal informatics systems. We will address the most relevant ones for our approach in this part.

Barriers

To start with the base of the aforementioned models, Li et al. highlighted specific barriers for each stage of a self-quantification experience and how they can chain themselves together in a cascade of barriers [4]. This aspect has been further developed by Vizer and colleagues who identified precise relations between stages [3]. In a few words, this is about not using the right tool, not collecting the right data, sparse data sets, scattered and/or ineffective visualizations, and difficult organization. In addition, they indicate that effective tracking improves health outcomes but they also draw our attention to the fact that health informatics tools often fall short of supporting the true range of work involved as they limit how we think about and design to support tracking. Those barriers for design are summarized in table 2.

Guidelines

In the light of these different barriers and flaws in tracking tools design, researchers suggest strong guidelines for design of self-quantification systems.

The first and more general one is to adopt a **holistic approach** as focusing on one stage ignores the whole experience [4]. Then, it is required to develop a deep understanding of the users of the technology and their goals for tracking in order to determine the extent of the tracking practice the tool must support. In this way, for instance, the CoMSHI model is agnostic to specific tools or data elements [3]. Finally, Li highlights the need to explore support for associating multiple facets of people's lives in order to enrich the value of the systems [4].

Secondly, Vizer and Li also state that the system must be **iterative** and **flexible** by defining the functionality necessary to facilitate transitions between types of work: as users go through the stages, they might change their mind on tools used, what to collect or collection methods [3,4]. We must consider how to empower people to track the data they need, and transition between tools that support various tracking tasks. Indeed, a single tool does not need to support all aspects of tracking work [3].

Another critical guideline which emerges from identified barriers is **data management**. Previous research also indicates that we must select which stage should be facilitated with technology to benefit the user the most. This means applying an appropriate balance of automated technology and user control within each stage to facilitate user experience [4]. As a matter of fact, Choe et al. talk about maximizing the benefits of manual tracking which cannot be done within a fully automated system [6].

Last but not least, a personal informatics system aiming at supporting health behavior must **support**

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Table 2. System Design Barriers and Guidelines. This table summarizes the identified barriers and resulting guidelines to design an effective self-quantification system.

Barriers	Guidelines
- not using the right tool	- adopting a holistic approach
- not collecting the right data	- designing an iterative and flexible system
- sparse data sets	- facilitating data management
- ineffective visualizations	- supporting user behavior change
- difficult organization	

user's behavior change by design. To achieve this goal, Consolvo and colleagues have used various psychological theories to describe design strategies to support behavior change which we discuss in the following section (section 3) [29]. On the other hand, Choe indicates the need to promote self-reflection as research has shown that reflection plays an important role in changing behaviors [6,30]. As an example, reflection can be facilitated by early feedback to help the user identify what to track, and Froehlich et al. described different ways of designing feedback technologies [6,31].
Aforementioned guidelines for design are reported side by side with the previous barriers in table 2.

3. CRITICISM OF GUIDELINES FROM THE LITERATURE

As reported in the preceding section, previous research has identified some guidelines that are intended to provide guidance in the design of more effective self-quantification systems in terms of user experience and potential outcomes in understanding, discovery, or behavior change. However, an implementation of such a system following these guidelines remains, in our opinion, complicated because it is very indirect: the theoretical framework being too abstract, there is a need to formalize its principles by adopting a point of view closer to the implementation.

Among the previous guidelines, only data management can be considered sufficiently low level and actionable as data storage and format or the automation of certain tasks can only be taken into account when developing a self-quantification system. On the other hand, guidelines such as "holistic approach" or "iterative and flexible system" need to be further specified in order to become actionable. Concerning the "holistic approach" to be adopted, some questions emerge that need to be answered: how to focus on the overall experience rather than discrete stages ? How to reach a good understanding of the user and his/her objectives? How to combine different aspects of the user's life? For instance, CoMSHI model is agnostic to specific tools or data elements: it adequately describes the context of tracking for chronic illness self-management, but does not provides any clue on how to build a self-quantification system on. Similarly, for system iteration and flexibility, how can we ensure smooth transitions between the different phases of a self-quantification experiment? How to design a system adaptable to the user?

Finally, regarding health tracking and behavior change specifically, the requirement to support user behavior change by design remains a vague guideline that must be more clearly defined. Consolvo and colleagues' [29] investigations goes in that direction by identifying eight design strategies derived from the analysis of psychological theories (Goal-Setting Theory [32], Transtheoretical Model of Behavior Change [33], Presentation of Self in Everyday Life [34], Cognitive Dissonance Theory [35]) as well as from anterior persuasive technology projects such as Fish'n'Steps [36] or Breakaway [37] that they complemented with their own analysis:

1. **Abstract & Reflective** - use data abstraction, on Li's integration stage for example, to encourage the user to reflect on his/her behaviors.
2. **Unobtrusive** - collect and present data unobtrusively by limiting interruptions and making data available anytime.
3. **Public** - present personal data to the user in a way that s.he is comfortable with if other people see it.

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4. **Aesthetic** - devices and displays must sustain interest, be comfortable and attractive to support the user's personal style.
5. **Positive** - use positive reinforcement to encourage change, reward the user for performing the desired behavior and attaining a goal.
6. **Controllable** - permit the user to manipulate data so that it reflects the behavior he/she deems suitable.
7. **Trending / Historical** - provide information about the user's past behavior relating to his/her goals.
8. **Comprehensive** - account for the range of behaviors contributing to the user's desired lifestyle.

Although these interesting results provide a more precise look at the support *by design* of user behavior change, we believe that they are not all at the same level with regard to the implementation of a self-quantification system.

All things considered, there is still a need to work on integrating these guidelines in order to build an adequate self-quantification system. Naturally, these guidelines cannot be taken into account in the same way depending on the self-quantification system aimed at: while the unobtrusive strategy of a system can probably remain similar from one implementation to another, its iterative nature must certainly be adapted according to the behavior change aimed at.

As the difficulty is to have a good theoretical framework as well as implementation principles, we therefore propose in the following section an applicative and hierarchical model for a self-quantification system for physical activity support illustrated by a use case example.

4. MODEL FOR A SELF-QUANTIFICATION SYSTEM FOR PHYSICAL ACTIVITY SUPPORT

Even if quantified-self research over the past decade describe precisely enough the environment of a user involved in a self-quantification experience, the presented models remain at a rather high level of abstraction which is good for describing the framework of a system but impractical for designing such a system addressing a specific aspect of self-quantification. Based on this analysis, we identified a need to move from abstract theoretical models to applicative models in order to be closer to actual as well as personalized self-quantification systems and we propose to do so for the case of physical activity tracking which is the main concern of quantified selfers. The need for a personalized approach shown by previous research comes from the fact that most of the commercial systems used by quantified selfers today, like Fitbit or Garmin, only offer limited adapted experience and personalized advice [3–7]. As an example, the Fitbit app allows users to set personal goals like daily steps or an activity reminder such as a vibration of the tracker every hour if 250 steps have not been taken, but neither takes into consideration the user's physical health status to assist in goal settings nor the user's context so as not to disturb him/her with activity alerts when he or she is usually inactive while at work. A better approach would be to accompany the user in the evaluation of his or her physical health status as well as in the management of his/her progress and motivation.

4.1. Use Case Example

Let's imagine an IT professional, Phil, 40 years old, who spends most of his working day sitting in front of a computer. He is quite aware that inactivity is bad for health so he forces himself to do one workout a week, on the weekends, like short run or walk on sunny days, but he would still like to be in better shape in order to improve his health status.
Every day, Phil drives to work in less than fifteen minutes but loses five minutes in traffic. He then parks at the bottom of the building where he works and goes up two flights of stairs instead of using the elevator because he knows that this is better for health. Once at his office, he cannot move a lot during the working day because his job mainly consists of computer work and meetings. Actually, the only significant activity he gets during the day is for lunch break as he goes downstairs and walk to a food truck.

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Phil is willing to improve his physical condition a little but lacks the motivation, the time, and most importantly the knowledge to understand how to do it. To help him with motivation, his wife gives him a new activity tracker for his birthday, but even if it is fun seeing his daily number of steps and his heart rate at first, he feels quickly perplexed by the meaninglessness of the data he is presented with after a few weeks of testing: indeed, his tracker wants him to walk 250 steps hourly and to reach 10,000 steps daily whilst he is currently not even reaching half of it. In addition, he can see data on his activity, his heart rate, and his sleep, but there is no obvious connection between them.

With the feeling of forcing himself towards activity goals that are radically different from his current lifestyle and not adapted to his job and availability, Phil decides to try an experimental self-quantification system for physical activity support a friend told him about. Apparently, this open source and self-hosted software is compatible with different activity trackers and, as an IT man, he is aware of the potential risks associated with personal information and health data analytics. Thus, having such a local solution suits him very well. He downloads the said software, installs it on his computer following the instructions, and adds the associated app on his smartphone.

For the first day, Phil is asked to answer a personality questionnaire which identifies him as rather opened to novelties but more introvert than extrovert, conscientious and agreeable. He also answers several questions regarding his lifestyle and physical activity preferences. Phil sees no action afterwards but he knows from the documentation the system is learning his habits and activity patterns by retrieving and analyzing the data from his tracker.

Then, after this first typical working week, the self-quantification system informs Phil that he is not very active on weekdays: this can be summed up as a couple of minutes' walk and two flights of stairs in the mornings, a total of ten minutes' walk during lunch breaks, another couple minutes' of activity in the evenings after work, and some scattered steps in between. He also learns that he was not particularly fit (this is OK, he already knew that) with a resting heart rate around 80 bpm and that his physical activity is very similar from one day to another during the working days regardless of the weather (this is new insight to him however). On average, Phil reaches 4,000 steps per day with a peak of 6,000-7,000 steps on Saturday and mostly light activity on Sunday which corresponds to a sedentary lifestyle. As he goes through the information he is provided with on this lifestyle, Phil is alarmed: he did not know quite as much about the risks associated with inactivity.

Ready to improve, our user is explained by the system that his activity characterization is based on the past week learning phase (so it might be a little inaccurate but will be continually refined over the coming weeks) and that the self-quantification system is now able to support him with personalized recommendations to help increase his physical activity levels. Phil learns that his general objective will be twofold: spreading physical activity over the week to achieve a more homogeneous profile as well as increasing daily activity to reach higher levels.

To this extent, on the first Monday of the support phase, the self-quantification system estimates an optimal challenge point: last Monday, during learning phase, Phil reached 3,500 steps, had slept moderately well, and the weather was pleasant. This Monday is not particularly sunny but the system has assessed that Phil's activity does not depend on the weather, that he had a good night sleep, and that he is also rather conscientious. Thus, the self-quantification system might set an optimal challenge point to 4,200 steps with a half-day goal of 2,000 to start with. Phil is pretty confident with a goal within his grasp. So, after having lunch with his colleagues, he goes out for a walk rather than going straight back to his office, which allows him to go beyond his sub-goal before returning to work. The app congratulates him by displaying his progress, and informs him that he should reach the 4,200 steps smoothly by tonight. While parking at home, the IT expert realizes that he is still 500 steps short, so he decides to take a short walk before returning home.

After three weeks, Phil is still achieving his daily objectives, compensating for sub-goals failure due to unforeseen circumstances when necessary, and actually had the idea of scheduling his meetings in rooms on the upper floors to walk more at work. His support system even informed him that his

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resting heart rate had decreased slightly, which was the beginning of an improvement in his physical condition.

However, today is Saturday and this is a rainy weekend: usually it is on sunny Saturdays that Phil is most active because he goes out running. Even if the day's objective has been revised downwards to take into account the context (rainy, slept quite well but moderately motivated), Phil has already missed his half-day goal. The system determines that he is likely to end the day very far from the initial objective, so the support loop is activated to offer him personalized activities classified by "adaptation to the current context": play hide-and-seek with his children, follow a short indoor sports session, go out for a walk, go for a run outside. Phil chooses the first suggestion because he did not think that this could be considered as physical activity. In the end, even though he reached a lower level of activity than usual, Phil learned that an hour of hide-and-seek is equivalent to 2,000 steps, which he never would have imagined. He plans to play another game to get even with his children tomorrow, which will not only allow him to spend time with them, but will also keep him active over the weekend. Finally, Phil also plans to go for a run on a weeknight when the weather is better in order to keep his weekly workout going.

After a few months, Phil now regularly achieves 6,000 steps on working days as he decided to cycle to work when it does not rain: it takes a little bit longer than driving but he knows that he arrives relaxed and wide awake having taken around 2,500 steps. He has made good overall progress and has learnt how to manage his activity: as an example, he is aware that he is going to lack some activity if it rains and drives to work instead, so he tries to compensate with indoor activities or more frequent short breaks whenever possible. Phil was also able to assess the effects of increased activity levels on his health as he now sleeps better, has lost a little weight and feels more in shape. He is even willing to set a personal target of at least 7,000 steps per day in order to attain an active lifestyle.

This scenario illustrates the use we intend to make of the data from the literature to address the problem of genericity of current tools. We therefore propose a hierarchical model relying on an **evolutive user profile** as a design basis for a self-quantification system for physical activity support. This applicative model relies on the conceptual ones previously described in section 2.5 and follows previous research guidelines explained in section 2.6: it aims to be **flexible**, **adaptive**, and aware of the **user's context** to support him/her on a **personalized basis** towards his or her goal of **health behavior change**.

4.2. Learning Phase

The goal of this initial phase, named learning phase, is to understand the user's health behavior pattern in his or her context, which means that we want to discover the user's physical activity patterns, health status, and habits in order to develop a deep understanding of the user. Physical activity patterns are relatively similar from week to week [38–41]. We thus need to monitor the user for at least an entire week by recording daily steps, heart rate, sleep, weather, etc. to be able to estimate with sufficient precision how he/she behaves in terms of physical activity in his or her particular context: for instance, we are interested to know if a user's activity is evenly distributed throughout the day, or if it is more concentrated in the morning and evening in the case of a desk job, as well as how much it depends on the weather or sleep quality [42].
Consequently, user profiling for physical activity is based on a recurring weekly time scale while user behavior change will rely on adapted objectives based on daily and hourly time scales (see section 4.3). In addition, because this is the type of self-quantification experience we focus on, research related to trait theory in psychology has shown that relying on the user's personality traits is also interesting to better support behavior change through exercise adherence [43–46].

This learning phase corresponds to the first three stages of Li's model (Preparation, Collection, and Integration), includes Vizer and colleagues' contextualization and fluidity aspects, and should establish four parameters: **1.** the user **personality traits** from the questionnaire of the five-factors

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model (Openness, Conscientiousness, Extraversion, Agreeableness, Neuroticism), **2.** a **preference model** of the user in terms of physical activity (when is the user most motivated for physical activity [47,48], what kind of activities does he/she usually do, what is the intensity of the activity), **3.** the **influence of the user's context** on his/her activity (does the user have a desk job, does the weather affect her activity level because of her mean of transport, how motivation affects her level of daily activity), and **4.** the user's general **health status** (how fit is he or she).

Following a Multi-Criteria Decision Analysis (MCDA) [7,49] approach employing three different time scales (weekly scale as user activity profile, daily scale as a definition of day-to-day objectives, and hourly scale as user monitoring in objectives achievement), an effective self-quantification system for physical activity support should be able to supply the user with significant advice and personalized recommendations as well as proposing context-specific activities in order to improve self-reflection, understanding of health behavior, motivation and exercise adherence hereby leading to behavior change.

4.3. Support Phase

After an initial learning phase, we enter a support phase which is where a self-quantification system will actually support the user towards the desired change in health behavior. Adding Li's Reflection and Action phases, the main constraint here is adaptation, so we rely on Epstein and Vizer models to account for the required flexibility of the experience and potential user failure to meet an objective [28; 2019]: indeed, we want the user to achieve higher activity level but, as noted by Frost and Smith, "*Anyone who has tried to go on a diet or exercise plan can relate to this: It is always hard to adhere to rigorous behavior modifications*" [50]; so an adaptive system must respect the user regarding his or her current state of mind, availability, and motivation.

To this extent, it must propose personalized objectives on a *daily time scale* according to an **optimal challenge point** that is based on the newly acquired knowledge of the user: the difficulty of the goal must indeed be in line with the user's physical condition, motivation, preferences, context, etc. [51–55]. For instance, if one usually achieves around 5,000 steps on Tuesdays without significant intensity, prefers to walk alone, is more motivated than usual, and the weather is sunny, an adequate optimal challenge point might be to set a daily activity goal of 6,000 steps with a moderate intensity walking recommendation during lunch break if necessary.

As an overview of our approach, we rely on three different time scales to support a user regarding physical activity: a *weekly time scale* as a basis for a user profile (corresponding to the learning phase which has been described in section 4.2), a *daily time scale* that is used to set optimal objectives based on the previously determined user profile, and an *intraday time scale* (e.g. hourly) which is necessary to monitor the user's progress toward the objective of the day and to help him/her if necessary. This aims to maintain a sufficient motivation to achieve unusual level of physical activity while avoiding disengagement.

4.3.1. Daily time scale

As illustrated in the flowchart figure 4, every day starts by setting an **optimal activity goal** for the user. This objective is determined according to the **user profile**: activity levels achieved from previous weeks, context (weather and schedule), personality, and motivation. With this optimal challenge set, this adaptive model goes down one level through intraday loops (see figure 5) as long as the day's objective has not been met or the day has not ended in order to continuously monitor the user's progress as well as context, and to react accordingly.

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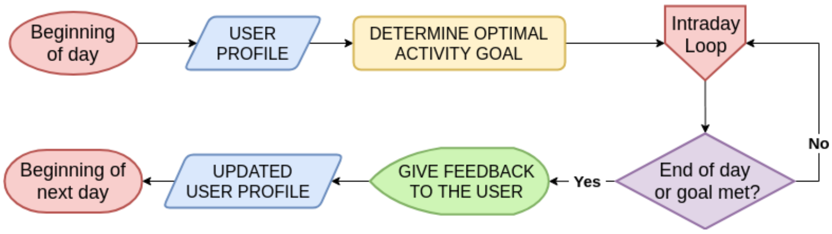

Figure 4. Adaptive System for Physical Activity: Support Phase - Daily Time Scale. After the initial learning phase, we know the user's activity patterns as well as physical health, personality, and context that compose the user profile. Hence, we are able to determine an optimal challenge point for the current user's day based on his/her profile before monitoring his/her progress in separate intraday loops.

At the end of the day, or when the goal is met, it is important to give feedback to the user regarding his/her progress as this can be employed as a behavior change technique by leveraging the user's motivation [56]. Feedback should also be used to reinforce the user's understanding of his or her physical activity habits and their impact on the overall activity level, sleep quality, mood, etc. The last step of this daily loop is to update the user's profile at the end of the day given his or her performance to help adjusting the optimal challenge point for the following day.

4.3.2. Intraday time scale

From the daily loop of the support phase, once the optimal challenge point for the day has been set, we enter the intraday loops of the model which allows the self-quantification system to monitor the user and his/her context. At the start of each intraday loop (e.g. hourly), the support system determines an ideal sub-goal which would allow the user to reach the optimal challenge point set before by the end of the day and achieve a higher-than-usual activity level: this is indeed easier to walk 200 steps five times in a day than walking 1,000 steps at once in the evening. This operation thus allows the self-quantification system to continuously monitor the objectives achievement rate and to adjust subsequent sub-goals according to the general objective of the day. This process is repeated until the goal is reached or there is no time left for it (flowchart figure 5). In these intraday loops, there are three possible ways for the user: either self-management, system support, or failure.

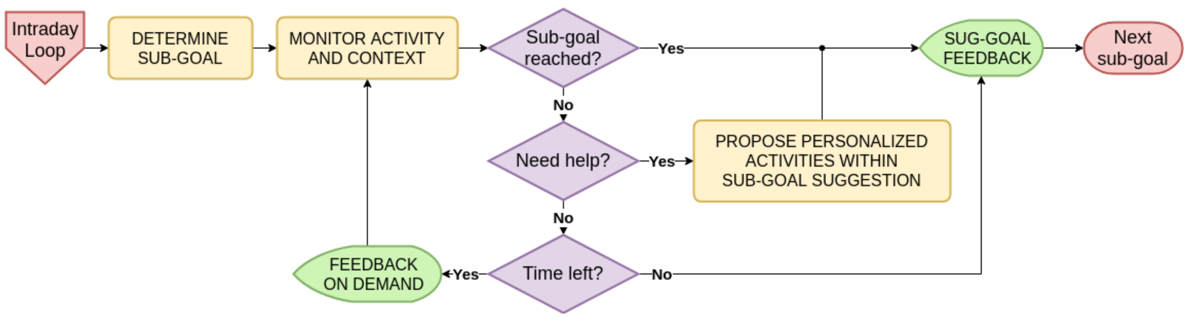

Figure 5. Adaptive System for Physical Activity: Support Phase - Intraday Sub-Goal Time Scale. An ideal sub-goal (3,000 steps halfway through the day for instance) is determined according to the objective of the day (e.g. 6,000 steps), and a control loop is run hourly to monitor the user's physical activity level as well as evaluating if she/he is making good progress toward the sub-goal. If self-management (left loop) is not sufficient, the system can intervene to propose the user a personalized physical activity adapted to the current context (right inner loop), or move to the next sub-goal in case of failure (right outer loop).

In the first case, **self-management (left loop)**, user's motivation is sufficient to reach higher levels of activity on his/her own with no help nor recommendations, only by having objectives set [47,48,57]. Albeit this is the best case scenario for a health behavior change, a support system still has to ensure

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that user's motivation will not vanish in the long run.
If the user is not able to achieve a sub-goal, the self-quantification system can **support (right inner loop)** him or her with a set of personalized physical activity suggestions (see section 4.3.3 for details) which best suit the user's preferences, current context, and current sub-goal: for instance, if a user working at a office usually prefers walking outside as physical activity, a personalized and adapted physical activity in *rainy* weather could be instead to take 300 steps by going down two floors and up the stairs on the opposite side.
Finally, the worst case scenario that must be taken into account is user **failure (right outer loop)**, as highlighted by Epstein et al. [28]: although this is a quintessentially humane outcome, an adaptable self-quantification system must manage this unpredictable possibility by design as a user may experience temporary demotivation or unexpected unavailability. In such a case, the model simply moves on to the next sub-goal which will be adapted according to the circumstances.

In any event, feedback is necessary to help the user understand the impact of his/her actions on his or her physical activity for the day.

4.3.3. Personalized and adapted physical activity choice

With the functioning and sequencing of the different time scales of the model now explained, the description of the support loop presented above needs to be further developed. While the first part of our multi-criteria decision analysis approach concerned the setting of personalized and adapted objectives for the user, the second part of this process deals with the selection of personalized and adapted physical activity in the support loop: the main question here is *"how should a self-quantification system for health behavior support applied to physical activity select appropriate activities for a user?"*
On the basis of the user profile previously described, we can derive a user preference model for physical activities, complemented by questionnaire if necessary, which aims to identify the user's preferred activities: if the self-quantification system detects cycling every day, occasional running, but relatively little walking, there is a good chance that our user would prefer a run rather than a longer walk. This can be verified and complemented by requiring some user inputs to ensure the preference model is accurate.
From the list of physical activities preferred by the user, we filter out unsuitable activities regarding the current contextual elements like weather, availability, or health parameters in order to obtain a list of context-sensitive activities. Lastly, the initial user preference model is updated with the user's choice to refine future suggestions as illustrated in figure 6.

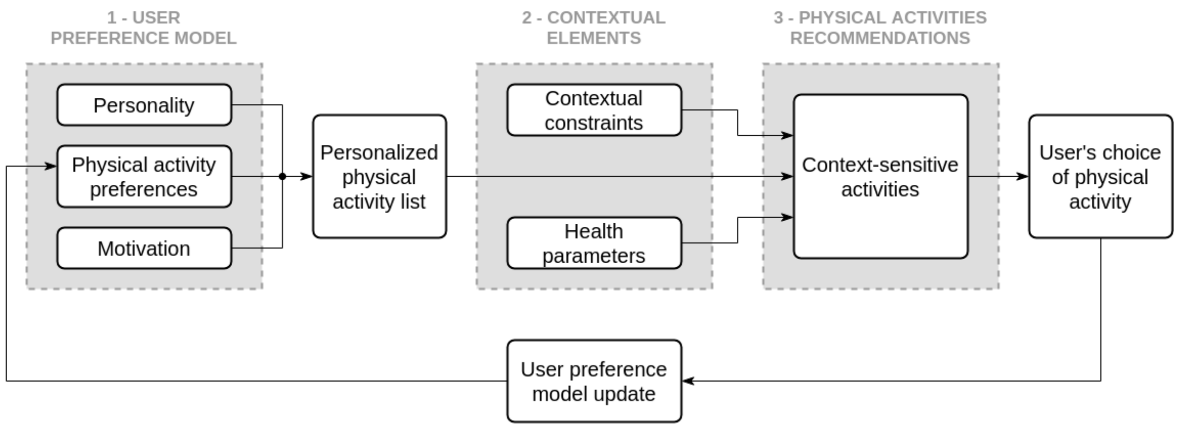

Figure 6. Personalized and Adapted Activities Suggestions Process: this figure details how a self-quantification system for physical activity support should rely on a user preference model of activities (1) before filtering it with monitored contextual elements (2) in order to produce its recommendations (3). A personalized list of context-sensitive activities is proposed to the user from which he/she can choose.

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As an example, if the weather is damp for a user who enjoys cycling and running more than walking, feels drowsy because of a bad night sleep, and needs helps to reach the missing 500 steps to his/her half-day sub-goal; he/she may be presented with a choice of activity ranging from most to least adapted to the context between stretching (calm and indoor but might not reach the sub-goal so this will require to be compensated for later), or a moderately active indoor activity (easier to meet the half-day target but physically more demanding), etc. All things considered, our user could simply choose to go for a short walk outside despite the weather because he/she wants to get some fresh air. This choice is then logged to update our user's preference model for the future personalized and adapted physical activities suggestions.

The support phase shall accompany the user during the entire self-quantification experience until higher daily activity levels become habitual for him/her. Ideally, when new activity patterns are established, the user should be able to maintain these habits without the help of a self-quantification system.

4.4. Towards an Application of the Model: Design and Development Challenges

The various design and development challenges all stem from a highly constrained framework. The issues raised in this section are evidence that our model transitions from abstract frameworks to an applied system.

First of all, our model implies an important challenge regarding its cornerstone, the multi-factors user profile: how to mix different parameters such as personality traits, contextual variables, activity tracker data, and motivational questionnaires answers in a significant way? This challenge requires integrating several tools including a reliable personality test: we propose to use the Big Five Inventory as it tends to be the most trusted and tested model regarding treatment acceptance as well as easily usable from an IT point of view [58,59]. Then, relevant contextual parameters are required (some APIs can regularly be used to collected weather data or user availability from a connected agenda for instance), and physiological data can be retrieved from an activity tracker worn by the user. The last tool that needs to be integrated is a motivation and exercise adherence assessment tool: the literature is quite extensive in psychological research and interesting possibilities may be the prediction of motivation and behavior change or an "approach and avoidance" mathematical modeling that involves user input in the form of a questionnaire [48,60,61].

As we have seen, good feedback is mandatory for a self-quantification system aiming at supporting health behavior change [31,56]. This essential part of a self-quantification experience should ease the user reflection regarding his/her health status and habits, hereby alleviating the task of retrieving, formatting, and analyzing data by associating contextual elements with his or her physical activity data. In this case the main challenge is how to present efficient and meaningful feedback to the user? Is it feasible to use automatic statistical analysis and correlations? How to combine context elements with statistical analysis? How to personalize user feedback depending on the user profile? Some trails of reflection have already been explored by previous projects such as the role of feedback in the process of change, effects of immediate feedback, or using personality traits to support personalization and feedback in a sleep health behavior change support system [30,43,62]. Such research showed for example that feedback helps to reach more directly decisional consideration and to increase motivation.

After these aspects have been addressed, a significant work has to be carried out on defining the user's optimal challenge point in order to adapt the difficulty of the daily objectives: how to weight the established user profile with contextual elements to best match the user's capacities, motivation, and availability? On this point, results from medical and psychological research can be exploited, but it would also be interesting to explore the potential links between goal-setting theory [32], optimal challenge point [51–55], personality, and physical activity [45]. Obviously, this is left for future research as all the other challenges. This is because our goal is to provide a model/framework that explicitly

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identifies the challenges, which is a necessary first step before running novel research to address the challenges.

One last implication for design and development is the adaptability of time dimensions: here, user analysis, goal settings, recommendations, and monitoring are based on different time scales which is fundamental for a tool adapted to humans. As a consequence, the time constant of each scale can be modified to better suit a user: depending on his/her job for example, a user may have very different availability so the sub-goal time scale can possibly shift from half-day to every two hours. Here, the challenge is to determine on which basis the time scales can be adjusted to the user.

Finally, because we are dealing with sensitive health data, this comprehensive approach inevitably raises security and privacy issues: although our model cannot be inherently thought to be privacy-proof (a system can be built on using commercial tools and several servers around the world), we strongly recommend the usage of open source, local, and self-hosted tools. If the need to move to cloud computing is preponderant, it becomes critical to secure hosted health data, so relying on trusted third parties subject to European legislation would be a guarantee of a better user acceptance factor [63–67].

5. CONTRIBUTIONS AND LIMITATIONS OF THE MODEL

In the last section, we presented an original and minimal model as a basis for the design of personalized and adaptable self-quantification systems to support physical activity for more active lifestyles. In this final part, we are going to summarize our model's framework and discuss its contributions and limitations.

5.1. Summary of our Model's Framework

This article proposes a model for the design of self-quantification systems for physical activity support as an applicative response to the abstract models specifying the quantified self framework and to quantified selfers' main interest in health tracking. Our objective is to rely on the identified characteristics of the quantified self movement. We thus based our framework on quantified selfers' goals and barriers, on previous theoretical models, and on highlighted guidelines from past research for self-quantification systems design [3,4,6,28]. This approach is supposed to facilitate future designs by creating an applicative model acting like a bridge between a well-defined quantified self framework and limited current solutions.

5.2. Contribution

The current inherent barriers to self-quantification experiences are related to the lack of implementation principles of the theoretical framework established by previous research. We have therefore presented a minimal applicative model of a self-quantification system that emphasizes such implementation principles for the support of physical activity: several original elements have been integrated within the same model, which is thus structured around a **1. multi-factors user model**, a hierarchy of **2. multiple time scales**, as well as a **3. multi-criteria decision analysis**.

To the best of our knowledge, such a multi-factors user model mixing psychological aspects like personality traits or motivation together with quantitative data like physical health, activity patterns analysis, or contextual parameters has never been proposed in previous research. The need for iteration and flexibility is inherently implemented thanks to the different time scales and loops used to account for the need of adaptability: activity pattern is on a weekly scale, the user gets daily objectives, and the progress are monitored hourly. Finally, a multi-criteria decision analysis based on a user activity preference model, measured variables, and external parameters allows a self-quantification system to produce suggestions of personalized and adapted physical activities.

Based on the guidelines already set out, we adopted a holistic approach by considering the user experience and the system as a whole: indeed, our model first focuses on user understanding by modeling and analyzing his/her activity patterns, habits, and physical data, then on tailoring a personalized and adapted support by determining optimal challenge points, sub-goals, and support loop. In that sense, removing any part of the model would inevitably deviate from the holistic approach advised by previous research and would no longer allow to build a self-quantification system for physical activity support in a personalized and adaptive way for the user.

This contribution can be seen as the groundwork necessary for the design and development of future prototypes and experiments.

5.3. Limitations and Future Works

We are aware that our research implies at least four main drawbacks that will require future work.

The first one is linked to the usage of the system and is the human factor: we cannot indeed force a user to perform an activity if he or she does not want to, nor we can oblige a user to supply a self-quantification system with inputs when this is required. Thus, we might not obtain all of the necessary data from the user every time we will need to, and this is a point that must be taken into account when designing and developing a system. User freedom however limits the effectiveness of any device, hence that is not specific to our model but to all self-quantification approaches.

The other ones are more linked to the implementation of the system and primarily concern the use of the Big Five personality traits: this might be a controversial topic as there is currently no general consensus in psychology research [68]. However, ongoing research on patient treatment acceptance or exercise adherence looks promising and can be adapted to our applicative model [43,45,59,69]. If future experiments show a relevant impact of personality traits on physical activity, motivation, exercise adherence, or data visualization, this would allow to better tailor self-quantification systems to every single user, hereby improving their ability to understand their behaviors and change them [70].

The third drawback relates to motivation and behavior change and this is similar to the use or personality traits: in the field of psychology, several theories of behavior change are in competition without clear consensus. As an example we can cite the Transtheoretical Model of Behavior Change from Prochaska that describes people's different levels of motivation and ability to change behavior (used to classify people's readiness to change behavior), Bandura's Self-Efficacy Theory that relies on competence alone for ensuring adherence, or Ryan's Self-Determination Theory that takes into account volition and autonomy [47,71,72]. Future work will have to assess the most suitable theory to build a self-quantification system on as well as to explore how motivational aspects can be incorporated in the design and development of such a system.

The last one is the use of commercial activity trackers, and this is the only point that does not respect our will of free and open source tools: in the current market and research configurations, activity trackers usually synchronizes user data on the brand's servers via their smartphone app. In the case of Fitbit for instance, collected data is sent to servers in America without the user being informed of the operations that are carried out on it. The ideal solution would be to use an open source activity tracker like OpenHAK or okinesio (https://www.openhak.com; http://okinesio.org) but these are very experimental, if not abandoned, solutions which are not mature enough for our purpose.

6. CONCLUSION

Literature from past research on the quantified self has shown that this movement is well characterized today with conceptual models and identified mechanisms, but that quantified selfers encounter many barriers in their experiences: most of them use commercial tools such as Fitbit or Garmin trackers to monitor their health, and more specifically their physical activity, which has become a major health problem over the last century. The main problem with these trackers is that they remain too generic in their approach to the user: despite the impressive amount of data they generate and make available to their users, there is not enough personalization or adaptation to the user's lifestyle. Consequently, only sufficiently motivated quantified selfers achieved positive outcomes from self-tracking, the rest of them facing the inherent barriers of the tools they use which prevent them from achieving good understanding of their health habits or changing behaviors.

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As research has shown, personalization, application of motivational theories, or good understanding of one's habits can significantly increase positive outcomes from self-quantification experiences such as behavior change to improve one's health status. We thus proposed a model for physical activity support which can be used for the design and development of a personalized and adaptable self-quantification system. This model bridges the gap between an established theoretical description and the highlighted need for people willing to change a health behavior to benefit from a truly comprehensive system.

Designed from several levels of adaptation (multi-factors user model, multiple time scales, multi-criteria decision analysis), we believe this model for a self-quantification system for physical activity support will be valuable for future designs and developments because it synthesizes observation, advice, and guidelines from previous research in an applicative way.

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