# Self-monitoring and Technology: Challenges and Open Issues in Personal Informatics

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**Abstract.** Personal Informatics (PI), also known as Quantified Self (QS), is a school of thought which aims to use technology for acquiring and collecting data on different aspects of the daily lives of people. These data can be internal states (such as mood or glucose level in the blood) or indicators of performance (such as the kilometers run). Some research was conducted in order to discover the problems related to the usage of PI tools, although none investigated how common users use these tools for tracking their behavior. The goal of this paper is to provide some insights about challenges and open issues regarding the usage of PI tools from the point of view of a common user. To this aim, we provide a theoretical background of personal informatics and a brief review on the previous studies that have investigated the usage pattern of PI tools.

**Keywords:** Personal Informatics, Quantified Self, Behavior Change, Self-tracking, Gamification.

## 1 Introduction

Personal Informatics (PI), also known as Quantified Self (QS), is a school of thought which aims to use technology for acquiring and collecting data on different aspects of the daily lives of people. These data can be internal states (such as mood or glucose level in the blood) or indicators of performance (such as the kilometers run). The purpose of collecting these data is self-monitoring, performed in order to gain self-knowledge or some kind of change or improvement (behavioral, psychological, therapeutic, etc.). PI tools are systems that help users to collect their data, enabling self-monitoring activities, their aggregation through some forms of reasoning, and feeding them back through computerized visualizations. PI tools can be apps running on users' mobile devices (such as Moves for automatic tracking of steps or eDreams for manual collection of dreams) or they can be ad hoc smart devices (such as Jawbone UP).

Some research was conducted in order to discover the problems related to the usage of PI tools [1], [2], although none investigated how common users use these tools for tracking their behavior. To this date, research has been carried out through surveys or interviews with people who already have a strong interest in collecting

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personal information, such as users of blogs and forums dedicated to personal informatics and information visualization, or users with prior experience in using PI tools [1], [2], [3]. The goal of this paper is providing some insights about challenges and open issues regarding the usage of PI tools from the point of view of a common user. To this aim, we provide a theoretical background of personal informatics and a brief review on the previous studies that have investigated the usage pattern of PI tools.

## 2 Theoretical Background

Personal Informatics systems have been defined as "those that help people collect personally relevant information for the purpose of self-reflection and gaining self-knowledge" [1].

For collecting personal data, PI tools rely on *self-monitoring*, the activity of observing and recording one's own behavior (i.e., actions, thoughts and emotions). Self-monitoring is a well-known technique in cognitive and behavioral psychology, much older than the possibilities offered by current PI technologies. Originally conceived as a clinical assessment method for collecting data on behaviors that only the patient could observe and record (e.g. eating, smoking), self-monitoring has become a standalone intervention technique, because of its reactive effects. Reactivity refers to the phenomenon in which the process of recording behavior causes the behavior to change [4]: self-monitoring often changes behavior, and this change is typically in the desired direction.

In *cognitive psychology,* self-monitoring is often interpreted as the first stage in multistage models of self-regulation as it signals a disengagement from automaticity or a transition from mindlessness to mindfulness [5]. Bandura [6], for example, states that self-monitoring is a subfunction of the self regulative mechanism that motivates and regulates human behavior: people can discover the factors that influence their behaviors, thoughts and emotional states, gaining self-knowledge through personal experimentation. The Transtheoretical Model of Behavior Change states that people apply different *processes of change*, i.e., different self-change strategies, for moving and progressing through different stages of behavior change [7]. Self-monitoring could be used as means of intervention in some of these stages, as a technique for favoring the consciousness raising and developing realistic changes, e.g. for individuating potential triggers of undesirable behavior patterns and planning strategies tailored to the individual [8].

In *behavioral psychology,* self-monitoring is usually directed at specific target behaviors (such as the number of smoked cigarettes). Some behavior theorists suggest that self-monitoring is effective in changing the behavior since it evokes self-evaluative statements that could either reinforce the desired behavior or punish the undesired one [9]. Kanfer [10] proposed a three-stage model for explaining reactive effects of self-monitoring: in the first stage, the self-monitor observes and records the target behavior; in the second stage, the self-monitor compares the occurrence of the behavior to a standard performance; in the third stage, the self-monitor rewards or punishes herself for having matched or having failed to meet her self-standard.

Malott [11] suggested that self-monitoring improves performance because of guilt-control: seeing undesirable behavior produces guilt feelings that can be avoided by improving the performance. However, beside how exactly self-monitoring works, the reactive effects on the behavior are sometimes temporary and modest and thus may require other techniques for maintaining the behavior change. For this reason, self-monitoring is often part of a self-management procedure in which contingencies of reinforcement and punishment are included [9].

Personal Informatics technologies enhanced the self-monitoring process in different directions. First, they make the data tracking easier for users, allowing to record the data potentially everywhere at every time, even in automatic manner. Second, they allow collected data to be organized and then given back to users in an aggregated visualization. Fogg states that self-monitoring is one of the strategies for informing the design of persuasive technologies [12]. Eco-feedback technologies, that may be seen as an extension of research in persuasive technology [13], are based on the hypothesis that "most people lack awareness and understanding about how their everyday behavior, such as driving to work or showering, affect the environment; technology may bridge this "environmental literacy gap" by automatically sensing these activities and feeding related information back through computerized means" [13]. Most of PI tools rely principally on cognitive models, since giving behavior information back to the user for causing insightful reflections is their main objective. Thus, with their newfound understanding of themselves, people may tailor their behavior to match their goals [1].

This approach, however, has some problematic points since it relies on the assumption that individuals are rational actors that seek to optimize their activity based on what they know [14]. Nevertheless, it is known that even if a person knows well how a specific behavior, despite its short-term benefits, is harmful for her wellbeing in the long term, she may irrationally choose to persevere in that behavior, ignoring the future consequences [15]. During their everyday lives, individuals often do not act according to rational choices, rather according to irrational methods, such as heuristics and rules of thumb [16]. Irrational behavior persists even when the individuals have been properly informed [17].

However, regardless of the principles of behavior involved, the act of self-monitoring is often an effective procedure for changing one's behavior [9].

Self-monitoring itself shows some practical issues. Korotitisch & Nelson Gray [18] identify eight variables affecting accuracy of the data collected: awareness of accuracy checks (self-monitors are more accurate when they are aware of accuracy checks); topography of the target behavior (if the target behavior is well defined); training in self-tracking (if the individual is trained in the use of self-monitoring); compliance (compliance can be enhanced if, for example, verbal commitments or contracts are made); accuracy-contingent reinforcement (accuracy is improved if reinforcement is provided contingent on the accuracy of self-monitored data); nature of the recording device; concurrent response requirements (the accuracy decreases when self-monitors are required to engage concurrently in other responses); valence of the target behavior (the accuracy may be lower for negatively valenced behavior than positively valenced behavior). Moreover, they identify other eight variables affecting reactivity of self-monitoring: target behavior valence (positively valenced behavior increases in frequency); motivation for change (increased reactivity in persons desiring to change the behavior being monitored); topography of the target behavior (greater reactivity occurs for nonverbal behavior); schedule or recording (greater reactivity happens if each occurrence of target behavior is recorded); concurrent response requirements (reactivity decreases when multiple behaviors are monitored concurrently); timing of recording (reactivity is improved if the recording occurred before rather than after the behavior); goal-setting feedback and reinforcement (providing feedback and reinforcement contingent on behavior change improves reactivity); nature of the self-recording device (the obtrusiveness of self-recording device can influence reactivity). Other practical issues related to training, maintaining data quality and compliance are showed in [19]. For example authors highlight that systematic training improves performance, recommending multi-component training that provides self-observers with definitions of what they should observe, feedback on accuracy, models of correct performance, and so on [19].

## 3 Previous Studies on Personal Informatics

There are a number of research works in Personal Informatics. Some authors investigate the role of self-monitoring through technological means, such as Maitland & Chambers [23] who investigate the role of self-monitoring in health behavior change within the context of cardiac rehabilitation programs. Other authors design and develop systems that allow users to collect and visualize personal information for therapeutic and rehabilitation purposes or for promoting behavior change towards healthier and more sustainable habits. For example, we can cite UbiGreen [20], a mobile application that provides personal awareness about green transportation behavior through iconic feedback; Mobile Mood Diary [21], a mobile and online symptom tracking tool for adolescents with mental problems; and Lullaby [22] a system for tracking sleep that combines temperature, light, motion sensors, audio, photos and an off-the-shelf sleep sensor for helping people to understand their sleep behavior.

Currently, there are also many commercial applications and devices for self-tracking behavior data (see [24] for an overview). For example, among the most popular, Moves (movement), Nike+ (sport activities), MoodPanda (mood), MyfitnessPal (calories and food), Jawbone (sleep, physical activity, mood and food) track users' behavior and give information back to users, allowing visual exploration of the data gathered and showing patterns and trends. These applications are at the disposal of all individuals interested in self-monitoring, but the modalities of their usage by common users are not yet well investigated. In fact, researchers focus mainly on users with a previous experience with Personal Informatics tool. For example, Li et al. [1] carry out a survey with users with an intrinsic interest in Personal Informatics, i.e., participants to blogs and forums dedicated to personal informatics and information visualization. Based on their findings, they suggest a stage-based model for Personal Informatics usage. The *Preparation stage* occurs before users start collecting personal information: in this stage users have to choose the right tool for satisfying their needs, and they can have problem to find the most suited one among the available ones. In the *Collection stage*, users collect information about their thoughts, behaviors, interactions with people and the environment; some problems arise in collecting information (e.g. users fail to track their behaviors). The *Integration stage* is the moment when the information gathered is combined and transformed for the user to reflect on: users can encounter problems when data come from multiple inputs and are visualized in multiple outputs. The *Reflection stage* is when people reflect on their personal information: problems here occur because of difficulties in exploring and understanding information. Finally, in the *Action stage* people decide to change their behavior based on the understanding of their data. Li et al. [2] further investigate the usage of self-monitoring tools in another study, focusing on the Reflection stage. In this stage, people's information needs can change, from the *Discovery phase*, when users do not know theirs goal or the factors that influence their behavior, to *Maintenance phase*, when they already know their goals and the factors that influence their behavior.

Results of their work show that the current commercial tools do not have sufficient understanding of users' needs. They suggest to i) alert and assist the users when they don not meet their goal; ii) reduce the burden of data collection; iii) support different kinds of collection tools, integrating them in a system and presenting data together; iv) reduce the upfront cost of data collection v) support transition between Discovery and Maintenance phases.

As seen above, these two studies recruited i) participants from a blog dedicated to Personal Informatics (http://quantifiedself.com), a blog about general information visualization (http://flowingdata.com) and forums at two Personal Informatics web sites (http://slifelabs.com, http://moodjam.org), ii) participants currently using a Personal Informatics tool (they had to have used it for a month or more). Thus, these users are familiar with Personal Informatics. As the authors themselves note about the first research, there is the suspect that these participants encountered only a subset of problems that common users may experience: this limitation suggests to study users with little or no prior experience with Personal Informatics systems to find specific issues that they may encounter [1].

Following this suggestion, we decided to emphasize some open issues that common users could encounter with PI tools and the challenges that this kind of applications have to face in the next future. These remarks are conceived as a starting point for a further study in which we aim at investigating the pattern of usage of PI tools by common users.

## 4 Challenges and Open Issues from a Common User Perspective

We define "common users" as users that are not intrinsically interested in tracking their behavior and do not have prior experience with PI tools. Intrinsic interest for using PI applications could be related to: belonging to a community dedicated to self-tracking or believing that technology could lead to knowing thyself (as the members of the Quantified Self community), being affected by a chronic disease that requires a continuous self-monitoring (e.g., diabetes), or having a strong motivation for changing a specific behavior (e.g., going on a diet). On the other hand, common users can be seen as people with no familiarity with self-monitoring activities and tools, not belonging to a community of shared interests in self-experimentation, and not having strong motivation for changing their behavior. For such common users, an occasion for trying one of these applications could emerge from the suggestions of friends or significant others, the exposure to commercial ads, news or reviews, a casual glimpse to an application or device that attracts their attention.

The main differences that distinguish common users from intrinsically interested users (that we will call PI users from now on) are the lack of initially strong motivation for self-monitoring and the absence of prior experience with PI tools. Less motivation and less familiarity with self-monitoring activities and PI tools open new issues with respect to those already highlighted [1]. These issues are related to the process of tracking, managing and visualizing of self-monitored data.

First, regarding the *data tracking*, common users may not be so compliant in tracking their own activities. This issue is also present in clinical settings, where the therapist compels the patient to track her own behavior, and among PI users, as Li et al. [1] highlighted. Patients and PI users often fail to self-monitor themselves due to lack of motivation, time or forgetfulness. However, we may expect that common users would be even less compliant in tracking their own behavior. Since they are not compelled or intrinsically motivated for tracking each occurrence of the target behavior, we could imagine that self-report activity would be accomplished with less continuity, perseverance and accuracy.

Second, regarding the data *management,* common users may not be so interested in deeply investigating the data gathered by PI tools. One of the characteristics of PI users is their interest in self-experimentation, i.e., their willingness to discover patterns and correlation among data. At the same time, patients under psychological assessments, people affected by a chronic disease or individuals strongly motivated for changing an unhealthy behavior have a strong interest in searching for and knowing better the factors that may influence their condition. This interest could overcome the burden of choosing the right tool for tracking a specific behavior, exploring data with different tools and correlating information that could not be visualized together. Many PI users, in fact, as reported by Li et al. [1], use different strategies for managing their data, for example using paper graphs. For common users the situation is different. They most likely start from using a single tool or device without knowing what kind of information will be useful to them. The effort in exploring data for finding correlations between variables that may affect their behavior would probably be weak. The engagement in managing different sources of information would decrease rapidly if not supported and incentivized by the tool itself. However, forcing users to interact daily with the data gathered for enhancing their involvement, as suggested by Li et al. [2] for PI users, may not be the optimal solution for common users, since reports and alerts could be easily ignored by them, representing a source of noise.

Finally, regarding data *visualization*, common users are usually not very familiar with visualization of quantitative data that PI tools provide for them. In clinical settings, interpretation of the data gathered through self-monitoring is usually provided by the therapist/physician: she evaluates the patient's logs, discusses with her the data that represent potential triggers of undesirable behavior and plans strategies of intervention tailored to patient's behavioral patterns. PI users, instead, are used to interpret the data on their own, determine by themselves if their current actions are in line with their goals. However, also PI users can find some difficulties in retrieving, understanding and interpreting the data when they are not supported by the tool they are using [1]. This is especially true for common users. For them, a meaningful representation of their data, able to provide useful information, is essential for engaging them in the usage of the tool and for compensating the self-monitoring burden. Moreover, common users could be moved by unrealistic expectations and become easily disappointed by ambiguous representations, excessive complexity and unintuitive interaction modalities.

All these issues that we expect to encounter in common users should be investigated in an additional user study. However, we can highlight some challenges that PI tools will have to face in the next years for overcoming some of such problems.

*Personal Informatics has to find new ways for reducing the burden of self-monitoring.* One possibility is to completely automate the collection of data, improving sensor technologies and algorithms for inferring new information from the existing data. We could expect that in the upcoming years wearable technologies and ubiquitous computing could face this challenge providing new devices that could silently and invisibly track users' behavior. Problems of using this automatic tracking concerns confidence of data reliability and privacy issues. Furthermore, not all the data are suited to be automatically detected, such as mood and emotional states.

Another way for reducing these barriers is to make self-monitoring more fun and enjoyable. From this perspective, the world of games could suggest some strategies of improvement. *Gamification*, as the use of game elements in non game context [25], highlights how the addition of simple mechanisms derived from videogames can stimulate participation, improve motivation and make cumbersome activities more enjoyable. However, gamification, as it is currently conceived, shows many problems when it is applied to PI, since it is mostly based on design techniques that provide extrinsic rewards and stimulate competition among users, using points, badges and leaderboards. PI tools, instead, are mainly conceived as personal instruments, especially when the self-monitored data relates to sensible information (such as wellness, health, weight, dreams etc). Thus, the mechanical implementation of leaderboards and badges (that are often added without considering the context of their application) is not always appropriate in this context. Moreover, points and external rewards could reduce intrinsic motivation in users [26] and their effects could vanish in short time frame, after an initial hype.

*Personal Informatics tools should promote a long-term usage.* PI tools require a long-term compliance from their users in order to work well, since their benefits increase over time. For a long lasting engagement it is essential that users perceive the self-monitoring as meaningful *per se*, for the benefits that it provides, and not only as means for obtaining prizes, points and extrinsic rewards. Thus, it is necessary to go beyond the current gamification practices, considering more complex game elements and adapting them to the PI context, stimulating the self-monitoring and transforming it in a “playful” [27] and “gameful" [28] activity. Identification of kinds of game elements which are suitable for the PI context is the challenge that should be considered.

*Personal Informatics tools should provide meaningful data visualizations.* The data presentation should immediately engage users, giving sense to the self-monitoring activity. In addition, as we have seen above, the data gathered from different sources and related to different behavior should be integrated in an intuitive way that could reduce the cognitive load on the users. In the last years, many researches have focused on the role that storytelling can play in data visualization, since visualizing data has analogies with the ability to tell engaging stories [29]. However, very few applications tried to implement narrative elements within the flow of data visualization (e.g., [30], [31]). In PI tools, visualizing human behavior data means putting the individual at the center: thus, the character, the point of view from which a narration takes form, acquires a great importance. Considering this point, we can look once again at the video game world for taking inspiration, for finding novel modalities for displaying behavioral data. As a matter of fact, video games succeed where hypertexts failed, creating an engaging narrative form that requires active user interaction, deeply involving the players and, at the same time, leaving them the power to determine the story. Video games give the players the possibility to reflect and identify themselves in an alter ego, the avatar, that acts at their place in the game world. Reflecting in an image that user can recognize, at the same time, as herself and as something else (as usually happens when a player identifies with her avatar and simultaneously feels a sense of empathy that leads her to nurture the character) could be more effective than a simple presentation of behavioral data, because of the emotional link that could be established between the user and her avatar. How to adapt this peculiarity of video games in the PI field, taking into account the difference between a game and an application used for recording personal behavior, is another challenge that should be considered.

## 5 Conclusion and Future Works

Personal Informatics commercial tools seem nowadays more interested in collecting data and transforming them in beautiful representations and visualizations than improving people’s daily activities [32]. They open new problems and issues: how are they used by common people? How much are users accurate and compliant in using these applications? Could they be effective in changing user’s behavior? What kind of meanings are provided through the display of user’s behavior information?

As future work, we aim at answering these questions with a user study in order to discover how PI tools allow common people to self-track their behaviors, how they are perceived by individuals, which are the difficulties and the problems encountered during the self-monitoring process, whether the provided information is useful for the users, whether the information visualization is effective for the user purposes or it is necessary to move beyond and think about other design features that could leverage the act of self-monitoring.

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