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Envisioning the Future of Personalization Through Personal Informatics:
A User Study

Federica Cena, Computer Science Department, University of Torino, Italy
Amon Rapp, Computer Science Department, University of Torino, Italy
Silvia Likavec, Computer Science Department, University of Torino, Italy
Alessandro Marcengo, TIM, Torino, Italy

ABSTRACT

In recent years, User Modeling (UM) scenery is changing. With the recent advancements in wearable and mobile technologies, the amount and type of data that can be gathered about users and employed to build User Models is rapidly expanding. UM can now be enriched with data regarding different aspects of people's daily lives and is likely to deliver novel personalized services. All these changes bring forth new research questions about the kinds of services which could be improved, which of them would be the most useful, the ways of conveying effectively new forms of recommendations, and how users would perceive them. In this paper the authors tried to find answers to some of these questions by exploiting a novel personalized system to conduct a qualitative user study, with the aim to understand users' needs and expectations w.r.t. personalization enabled by the presence of wearable and mobile technologies.

KEYWORDS

Personal Informatics, Personalization, Quantified Self, Recommendations, Self-Tracking, User Model

INTRODUCTION

With the recent development of wearable and mobile technologies, the amount and type of data that can be gathered about users is rapidly increasing (Rapp et al., 2015). There are many aspects which contribute to this trend. First of all, the paradigm of Internet of Things (IoT) (Gubbi et al., 2013) digitally connects everyday objects in the real world making data pervasive. IoT brings to life Weiser's vision of ubiquitous computing (Weiser, 1998) which tries to bring intelligence to our everyday environment and make it sensitive to our presence. It builds upon advances in sensors and networks, pervasive computing, and artificial intelligence. Then, Personal Informatics (PI) (Li, Dey, Forlizzi, 2010) is a set of tools which use increasingly popular wearable technologies for acquiring personal information on relevant aspects of people's daily lives. They allow users to self-track a variety of data about themselves: from user's physical states (e.g. blood glucose level), psychological states (e.g. mood or stress), behaviour (e.g. movements) and habits (e.g. food intake, sleep) and contextual information (e.g. people met). With self-tracking we intend systematic recording and collection of personal data, usually by using various technologies, with the aim to improve some aspects of daily life. Personal

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Informatics systems best show an expanding trend in acquiring personal data for providing support to users, from increasing their self-awareness to improving their self-knowledge and motivating self-reflection (Rapp & Cena, 2014; Rapp & Tirassa, 2017). Although PI systems may provide users with complex images of themselves, offering opportunities for personal growth and change, as well as health management, self-tracking also introduces the problem of information overload and the need to filter the collected data (Rapp et al., 2016). The influence of the PI systems can be overly invasive and dominant in a person's life. Also, some suggestions could arrive in inappropriate moments, posing some privacy concerns.

Quantified Self (QS) or life logging is a movement which tries to integrate developing technology into the process of personal data acquisition and analysis and relies heavily on IoT and PI tools (Marcengo & Rapp, 2013). With such technological advances, the amount and the type of data that can be collected about users is exponentially increasing, creating a constant stream of information that may reveal many aspects of their daily lives. This is when User Modeling (UM) process come to play since it creates digital representations of users, used to calibrate and adapt the interaction with a system, or to provide personalized recommendations (Brusilovsky, Kobsa, & Nejdl, 2007). Until recently, UM field has focused mainly on web data (Kobsa, Koenemann, & Wolfang, 2001), thus creating User Models using data from web usage behaviour and providing primarily personalized web applications and systems. As many real-word data (hours of sleep, blood pressure levels, locations visited, etc.) are becoming easily available due to self-tracking methodologies and PI tools, interesting opportunities for user modeling arise. UM's could be enriched with data concerning users' real-world characteristics and activities and could incorporate such information to create an "enhanced" model of the user, i.e. a holistic representation of her body, activities, and habits. The "enhanced" user model could enable highly personalized services, since the personalization process would be based on real human beings rather than on Web behaviour. This could further support new forms of personalized and highly dynamic services directly integrated in the users' real lives, by adapting themselves almost in real-time depending on the ongoing users' internal states and external contexts. So, the inevitable symbiosis between User Modeling and PI systems is being born. On one hand, UM can be filled with data coming from PI systems, providing more effective adaptive services in UM-based applications (Cena, Likavec, & Rapp, 2015). On the other hand, PI systems, as a result of UM usage, can provide personalized visualisations and recommendations that improve their efficacy in promoting behavioural change.

In this scenario new research questions arise: What kind of personalization enabled by PI systems would be the most useful in the users' eyes? What are the opportunities for user modeling coming from PI systems? What worries would the users have regarding personalization? Hence, there is a need of further research in the field of personalization. To answer these questions, we used a PI system, developed previously by our research team, to ground a user study. The system can be used to collect and aggregate data from different self-tracking tools and provide useful visualisations and correlations to users. The focus of this paper is not on the system itself and on the design choices made when building it, rather on the user study enabled by the system. The system was used to trigger reflections on the future of personalization and on how PI data could enable new forms of recommendation. Our final aim was to gather insights from users on how to build an "enhanced" UM for designing novel personalized services. As opposed to other works in this field, our study was not conducted with the aim of designing a particular system, rather to gather knowledge which could be used by a wide spectrum of researchers when designing personalized services and which would take into account users' perspective on future of personalization.

RELATED WORK

Both the commercial and research contexts are witnessing rapid increase in the number of available mash-up systems and other services which can enable and support the Quantified Self process. These services are used to collect and aggregate user data and present them back to the user. Many of these services, such as Google Fit[1] (Fitness Data), Apple Health[2] (Fitness/Health Data), Tictrac[3] (Health Data), Headsup health[4] (Fitness/Health Data), Beeminder[5] (Goals/Productivity Data) focus on data describing one's physical state and usually regard only a single domain (health, fitness, etc.), with limited aggregation facilities. This means that they simply import the data from different sensors/applications into a single user account.

A step forward is to offer meaningful aggregations and correlations to users. This is done by some academic projects, as the following ones. Salud! (Medynskiy & Mynatt, 2010) aggregates data from different sources but lets users interpret freely the gathered data. Finally, Bentley et al. (2013) designed a health mashup system which emphasizes some relations between diverse behavioural data using natural language.

However, none of these systems exploits the big amount of personal data to provide personalized features or enable personalized services (such as recommendations or adaptive information provision/adaptive interface reconfiguration). One exception is the work of Schmidt, Benchea, Eichin, and Meurisch (2015) who proposed to support user goal achievement through the combination of goal data with performance data, i.e. they provide personalized training plans based on the gathered performance information. Another work in this direction is the work of Lee, Kim, Forlizzi, and Kiesler (2015) who prompted the users to reflect on their own goals encouraging them to personalize their training programs by themselves. We can also mention Google Now, an intelligent personal assistant developed by Google. Along with answering user-initiated queries, Google Now pro-actively delivers the information that it predicts and that the users might want and need, based on their search habits and data obtained from their smartphones (location, interests, calendar entries etc.). Thus, it provides suggestion that are context-aware and user-dependent. Similarly, there are some activity/food trackers (e.g. MyFitnessPal[6], SuperTracker[7], LoseIt[8]) which make recommendations about nutrition and goals, but they provide only simple static personalization based on user-compiled profile, and not dynamic recommendations created on the fly based on context and user features detected in real time. W.r.t. emotional content, we can cite the work of Nielek & Wierzbicki (2010) which presents a framework for emotionally aware mobile application. The data containing the information about the emotions (SMS's, background noises, etc.) are collected and used to determine the user's mood, based on which the application can behave differently, but no recommendations are provided to the user.

Another closely related field is lifelong user modeling. In lifelong learner modeling the data about the users' learning behaviour is used for the creation and management of lifelong learner models which capture various aspects about the user's learning activity over long periods of time. Kay (2008) provides such a framework where data for learner modeling is obtained from wearable sensors, interactive learning activities, Web trace analysis and explicit information provided by the user. These data are scattered across many devices and storage media and used to reason about the values to create a complete User Model. Elliott et al. (2009) provide a general architecture which can gather, store and process data from various data sources. Their aim is to capture the heterogeneous data regarding various aspects of a person's life and extract the relations between different features which would improve recommendation of relevant information. ARBUT (Hohwald, Frias-Martinez & Oliver, 2010) is a system which can process large amounts of heterogeneous sensor data and produce numerous complex User Model. Some of its reusable components can be shared in various application domains. Finally, PersonisAD (Assad et al., 2007), is a framework which models people, sensors, devices and places and provides this information to other applications. The users can control the information being modelled and how it is being used.

Although many user studies have been conducted to investigate how PI systems impact on users' everyday lives, none of them has specifically investigated how personal data collected by PI systems could improve personalization. As examples of user studies of this type, we can cite Li et al. (2010), who studied how experienced users use PI systems, Choe et al. (2014), who investigated Quantified Selfers' practices, focusing on people motivated in tracking personal data in order to see what effects on their behaviour; Fritz et al (2014), who studied in the field the long term usage of wearable devices for physical wellness, focusing on the behaviour change; Rooksby et al.(2014) who investigated the tracking process, identifying some different "personal tracking styles"; Rapp & Cena (2016) who focused on how people without previous experience in self-tracking use PI systems. Finally, we mention some few works partially devoted to study personal data for personalization. In Barua, Kay & Paris (2013b), authors investigate people's perception of control over their data (scrutability). In Barua, Kay & Paris (2013a), automatic data capture over long periods of time and control over data storage are explored from the users' perspective. Moreover, Warshaw et al. (2015) studied how a system that lets users see their personality is perceived by them. Participants found their personal traits profiles creepily accurate and did not like sharing them in many situations. However, they were enthusiastic about the possibility of being provided with personality-based recommendations. Such studies, nevertheless, were not connected to PI field.

USER STUDY

In this section, we report the results of our user study in which our main focus was on obtaining insights on how PI data could be exploited in the future to provide new types of personalized services and recommendations. To this aim we invited the participants to collect personal data through self-tracking tools and visualize them in a system developed previously by our research team, in order to anchor their insights in a real use case. As mentioned in the Introduction, the focus of this paper is not on the design of the system itself, rather the system was used to trigger reflections on the future of personalization and on how PI data could enable new forms of recommendation.

System

The system we used in our study was developed previously by our research team. Here we report briefly its main functionalities. The system is able to:

- Gather and integrate heterogeneous types of personal data from various wearable devices and PI mobile apps; it aggregates different data channels, such as sleep and steps from Jawbone Up bracelet or Withings Activité smart watch, skin arousal, heart beat and body temperature from Empatica E3 bracelet (https://www.empatica.com/), as well as locations, transport means, calories and food intakes from mobile apps like Moves and MyFitnessPal;
- Find similarities and correlations among data;
- Visualize the gathered data.

In particular, the system provides two different kinds of visualization. In the first one the user is provided with a snapshot of a specific tracked parameter using colour codes. By positioning herself in front of the screen, the user can see a data-driven image of herself, consisting of the data of a specific channel (e.g. her heart rate today). In the second visualisation type, the system provides an overview of all the different data collected, displayed simultaneously on parallel timelines. The user can also visualize the location in which she was in a specific moment, and the photos she made in a specific place. Such information is aimed to contextualize the data she is looking at.

However, a complete illustration of the system's features is beyond the scope of this paper. More details about the system can be found in Rapp et al. (2017). In this work, it has been used only to generate reflections on the future of personalization. The aim of this work is to reflect on how personal informatics systems could enable new personalized services, and not to describe or assess the system's functionalities. This research follows a previous study where we evaluated the system with reference to usability and compliance to a series of user requirements: in that occasion, we incidentally gathered some initial insights also on personalization (Rapp et al., 2017). This motivated this second study which deals with completely different research questions and provides new findings: here, we are not interested in evaluating our system, but in using it as a trigger to thoroughly investigate how personalized services could evolve in the future due to the availability of PI instruments.

Method

We conducted a qualitative study using a thinking aloud protocol, semi-structured interviews and focus groups to investigate how users might perceive and envision the future of personalization triggered by the availability of different personal data. Thinking aloud is a user study protocol where participants have to verbalize everything related to a given system coming to their mind during its usage. Although this method can provide insightful qualitative results it may risk to distract the user, jeopardizing the gathering of data related to the efficiency and efficacy of the system under evaluation. We chose this methodology since we were not interested in assessing our PI system's efficacy and efficiency: instead, we wanted to use such system to generate insights about the future of personalization anchored in a real case of use. Therefore, a technique that leaves participants free to express their thoughts, needs and desires while completing a task was considered the most appropriate. Semi-structured interviews were used to gather more focused data. Finally, focus groups were used to generate further insights from group discussion.

Sample

Our study involved 18 participants (age M = 29, 5, SD = 8, 6, females = 10). The sample size was set according to the standards in qualitative research (Marshall, 1996; Marshall, Cardon, Poddar, & Fontenot, 2013). Nine participants (P1-P9) did not have any previous experience with PI, since we wanted to investigate also how individuals that are not used to collect data about themselves perceive the new opportunities offered by PI devices with respect to personalization. The remaining participants (P10-P18) have been using self-tracking instruments for almost six months.

Procedure

Each participant had to use a wearable device and a set of PI apps for four weeks. We gave the participants the possibility to choose among three different PI tool sets. We wanted to represent different cases by providing users with different self-tracking instruments, accordingly to their interest. This increases the heterogeneity of the sample, allowing the generalization of our results (Gobo, 2008). However, at the same time we needed to partially homogenize the sample for the study purposes: leaving the users completely free to select the PI instruments would have excessively multiplied the heterogeneity of the cases under study. We finally set three groups of tools, allowing us to have groups of six participants each.

During the study, we met the participants two times. During the first meeting, we set the wearable devices and the applications on their smartphones, and provided instructions for collecting data. After four weeks, they came to our lab, transferred the gathered data into our system, and were provided with the visualizations. During this time, they could freely comment on our system in a thinking aloud session. Then, after the trial, we interviewed participants singularly for 30 minutes, asking them to report their first impressions about the possibilities that all these data could open in the future. Since the interviews were semi-structured, questions were the same for all the participants, but they were left free to divert from the track and explore the themes that we had not foreseen in advance. We asked the participants the following questions: What kind of data you consider most useful to enable new personalized services? What kind of opportunities and threats do you see in the evolution of personalization triggered by self-tracking instruments? What kind of personalized services you consider the most suitable to you everyday needs?

Finally, we divided participants into three groups (P1-P6, P7-P12 and P13-P18) inviting them to collectively discuss opportunities for future personalized services, enabled by the data collected by wearable and mobile technologies. Participants were allocated to each group accordingly to their experience in using self-tracking tools: one group of experienced users, one group of inexperienced users, and one group where half of the participants had previous experience with PI tools, and half of the participants had no previous experience with PI tools.

Group discussions lasted for about 90 minutes. The researcher only managed the turn-taking without intervening in the discussion. As the participants had the opportunity to gather their own data and put them into use in our system, the discussions were grounded on a real use case. Interviews and group discussions were audio recorded through a portable audio recorder.

Data Collection

P1-P3 and P10-12 used an Empatica E3 bracelet for tracking arousal, body temperature, and heart rate, Moves app for keeping track of locations and SleepBot for sleep tracking; P4-P6 and P13-P15 were given Withings Activité smart watch for tracking sleep and steps, Moves for tracking locations and Expereal for mood tracking; P7-P9 and P15-P18 were given Misfit Shine bracelet to track sleep and fitness activity, Moves for tracking locations and an app developed ad hoc to keep track of the phone calls, emails and SMS's sent. We selected the wearable devices and the mobile apps after a desk analysis. We chose a specific app or device because we considered it the best tool for tracking a specific parameter. For example, Expereal was judged the best app for tracking mood, since it provides an intuitive interface and, at the same time, a reliable way to specify the mood by using a scale from 1 to 10. Other apps were considered not usable, requiring, for example, to collect too many parameters for assessing the mood, thus requiring burdensome activity on the user's part. Participants had to keep the apps active and wear the devices for the whole period of the study. Specifically, this meant to charge the device every day and wear it during day and night. Apps were supposed to be used at least once a day, reporting and visualizing the collected data. Participants reported high compliance in following the study's instructions. Only 3 participants, during the interviews, reported to have forgotten to wear the device for one entire day or more.

Data Analysis

We analysed the data coming from the thinking aloud session, the interviews and the group discussions together using a thematic analysis. Data analysis followed open and axial coding techniques (Strauss and Corbin 1990). Results were coded independently by the first and the second author: they were broken down by taking apart sentences and by labelling them with a code. Then, we compared the outcomes discussing and managing all the inconsistencies (MacQueen, McLellan-Lemal, Bartholow, & Milstein, 2008). Users were not given compensation for their participation (see Table 1).

RESULTS

Having all their data available in a single centralized location, participants perceived the system as being capable of knowing different aspects of their daily lives and, on the basis of this knowledge, wished for a series of services tailored to their idiosyncratic habits, preferences, activities. Results

Table 1. The user study process

1 Step	2 Step	3 Step	4 Step
- Wearables and apps are provided to participants	- Participants are provided with visualization of their data with our systems	- Participants are interviewed individually	- Comments and interviews are analysed and coded by authors
- Participants use devices and apps for 4 weeks	- Participants can comment freely through a thinking aloud session	- Participants are divided in 3 groups and discuss about personalization	

show that participants wished for recommendations that could consider different aspects of their life, from “internal data”, like cognitive states and emotions, to contextual factors. Moreover, participants highlighted the potential risks that the pervasiveness of data collection could entail for them. We now report our findings by dividing them into the major themes emerged during the analysis. While Table 2 maps the result to the initial research questions.

Personalized Goals Setting

Participants already used to self-tracking focused their considerations and expectations mainly on wellbeing domain. They emphasized that the system should help people set personalized goals related to their physical activity and lifestyle, with the aim of improving their overall health. P11, for example, emphasized during the interview: “I’d like to have personalized future objectives… I don’t know how it could be done, but I expect that it could foresee what would be useful for me in the future on the basis of my actual condition, suggesting also how to reach my goals”. The majority of these participants (5 out of 9) highlighted also that it would be desirable if personalized systems would work with them to define goals and plans, as if they were some sort of companions, rather than mere top-down prompters. These participants agreed on this point during the group discussion, confirming that the possibility of achieving specific objectives with the help of goal-based recommendations could represent an important step forward in personalized services.

Holistic Data Collection

Several participants (8 out of 18) also emphasized that it would be promising to widen the type of information collected by the system for creating a complete digital “double”, a holistic representation of the user, on the basis of which to build personalized services. The idea of expanding the kind of tracked data and moving beyond wellbeing, came mainly from those who did not have any previous experience with PI tools (6 out of 9) during the group discussion. These participants were not focused (as the remaining ones) on behaviour change, and explored different contexts in which personalization could improve their daily activities. They were struck by the opportunity to track “internal parameters” such as physiological states and emotional levels, especially when this was done automatically. Physiological parameters were considered useful for medical purposes, but some participants, like P3, perceived them as an aid to improve daily nutrition, for example by suggesting how many coffees she should drink depending on her arousal level. Others reflected on how continuous self-tracking of emotional states would enable recommendations based also on their unconscious preferences and wishes, supporting better their decision-making process and their choices during their everyday activities. P2, for example, suggested that by using emotional data the system could make suggestions without relying on her rational thinking, but exploiting her visceral tastes, which she considered more sincere. This could happen, for example, before buying something in a store, as suggested by P3, or when choosing a book to read, or a friend to call, as suggested by P6 and P7. All these participants perceived this kind of emotion-based recommendations closer to what they really want and feel, thus

Table 2. Answers to research questions

Research Questions	Answers from the Study
What kind of personalization in PI systems would be the most useful in the users’ eyes?	- Personalized goal setting - Contextualized recommendations - Data exchange and sharing for personalization “on demand”
What are the opportunities for user modeling coming from PI systems?	- Holistic data collection
What worries would the users have regarding personalization?	- Wide dissemination of personal information - Control exerted by the system over the information made available

they were more inclined to follow them. On the other side, other users imagined how having cognitive data, such as level of attention, interest, mental workload, could provide recommendations on the work tasks to be prioritized, or what and how they should study, improving working and learning activities.

Contextualized Recommendations

If physiological, emotional and cognitive data may serve for different kinds of personalized services, participants (13 out of 18) expected that a future personalized system could combine them all to take into account all the conditions that may affect a particular activity. "When suggesting to me to lengthen my run, the system should be aware of my current mood, my health condition, for example my actual heartbeat, and formulate a suggestion on the basis of this information… for example telling me that I should run for twenty minutes more to reach my goal, but with a lower pace, because my heart rate is too high, and following another route, because this street is making me nervous.", said P14 during the group discussion. "And maybe also that I should lower my music because the traffic is growing and my level of attention is lowering.", added P17 in the same group discussion. This points to the need of considering the wider context in which the recommendation is provided.

Most of the participants (14 out of 18) believed that due to the availability of all these personal data and their integration in a unique system, personalization could become pervasive and integrated in their everyday activities. Some of them pointed out the possibility of suggesting alternatives to their current behavior based on the system's knowledge of their habits, the contextual conditions and the considerations of what they will do in the immediate future. P9, for example, during the interview, said: "It should be possible to recommend to me not to take the car today, as I am used to, but to use the bicycle, since this night I need to go to bed early given my travelling tomorrow, and it would be better to be a bit more tired.". Others, like P15, when interviewed stressed the need of having these suggestions just before making a decision: "If the system knows that I go out everyday at 6pm for a walk and at the same time recommends to me to walk more, it should suggest it along with another route to follow for my daily walk just in time, namely when I'm already out and about to do my daily activity". All these recommendations were expected to be delivered for the target activity at the right time and at the right place by almost all the participants (16 out of 18). "The great potential that I see here is that this system can always know what I'm doing. So it should suggest to me what to do when it's really needed", said P3 during the group discussion.

Data Sharing and Exchange

Participants (7 out of 18) highlighted that it would be useful to make all the data coming from PI tools exchangeable with other applications, with the sharing of the data under their complete control. "It should be possible to use an existing service or application and maybe pour all the knowledge related to me in there to get something that is tailored only to me. I don't know… like providing all the data related to my mobility behavior when buying a car and having recommended the right car for me. But only when I want it and for that particular moment or need.", noted P14 during the interview. This attitude shows that users wished for sharing their data among different platforms and services. However, during the group discussion it emerged that they wanted to be the owners of their own knowledge about themselves, a knowledge to inject in existing systems for having personalized outcomes for specific and momentary goals, in a sort of personalization "on demand". In fact, the majority of participants (16 out of 18) stressed how the control of their data should remain in their hands, confirming a scepticism, or more precisely a worry, in the wide dissemination of personal information. For this reason, they wanted to store the data on their local device rather than on a remote server. Exceptions were represented by two participants with previous experience in self-tracking, who did not have any privacy concerns.

Control

Another shared concern (11 out of 18) was related to the control exerted by the system over the information made available, as well as the reduction of choice. P16, for example, during the group discussion emphasized that "Such recommendations are useful without any doubts. But the system may also recommend what is useful for it… There could be many commercial, or political, reasons for which it could recommend me something". While P18 added that "It is as if all these recommendations design a circle around me that defines what is right for me… what is outside the circle is completely subtracted from my sight. This could be a problem… not only because of a sort of control the system has over us, but also because of the recommendations themselves… I mean, sometimes maybe I like things that I do not expect at all, or things that are not addressed to my wellbeing or to satisfy me in the habitual way… how could the system deal with such desires?".

DISCUSSION AND DESIGN IMPLICATIONS

Our study shows that people expect advanced forms of personalization from systems that have certain information about them. This seems to be a requirement for all the tools that gather personal data, and consequently for all PI systems. Most of the users without previous experience with PI tools (8 out of 9) would have continued to use the self-tracking tools if such instruments would be able to offer them some useful recommendations. This suggests that content personalization could represent a key value for users who are not "behavior-change oriented", and actually do not find sufficient motivation to be engaged in self-tracking (Perera, Zaslavsky, Christen, & Georgakopoulos, 2014). However, experienced self-trackers proved to be focused more on goals, confirming the preliminary findings from our previous study, where experienced participants highlighted the need of having personalized plans to achieve behaviour change goals, especially in the long term (Rapp et al., 2017).

Personalized technologies based on PI data have also been imagined as capable of satisfying users' inner desires: the possibility of receiving recommendations based on their emotions and on their unconscious, non-rational intentions were welcomed with enthusiasm, as a way for being more satisfied. This somehow contrasts the findings of Warshaw et al. (2015) who emphasized how being "known" in their inner traits by an artificial entity is perceived as "creepy" by users. This is likely due to the fact that our study focused on personalization matters while the Warshaw et al.'s study focused on users' profiles. Being "scanned" by a computer system may be perceived more favourably if the focus is on the personalized services it may enable, as also the Warshaw et al.'s study noted, by highlighting that their users were overwhelmingly positive about getting activity or event recommendations.

However, benefits of personalization were not considered risk-free even by our participants. The participants especially emphasized the fear of a hidden persuasion. Even a form of soft-paternalism (Thaler & Sustein, 2008), in which recommendations could be used to subtly transmit ways to behave, not welcomed otherwise, raised many concerns. This risk has been also noted in behaviour change technologies, which may provide goals not chosen by the individual, rather reproducing values taken for granted in a given society (Purpura et al., 2011). For this reason, personalized technologies have been perceived more favourably if acting as companions, committed to work with the users, in order to find relevant goals and plans for them. Moreover, participants also highlighted that recommendations could include only a small subset of the multiple possibilities for acting and knowing that the users may have by accessing all their personal data, hiding somehow all the rest. On the basis of these results we outlined a series of suggestions for designing novel PI systems, able to provide personalized services that can meet users' expectations:

- Create a complete UM on the basis of the PI data collected. Almost all inexperienced participants and a minor part of experienced ones wished for receiving recommendations based not only on specific, singular parameters, but also on a holistic representation of themselves. Different research in UM, tried to use emotional (Tkalčič, Burnik, Odić, Košir, Tasič, 2012), environmental (Adomavicius & Jannach, 2014), and physiological (Bennett & Quigley, 2011) data to provide tailored recommendations. However, no attempts were made to combine such data in order to build a complete, dynamic, and situated (in the current context) mirror of the user through which giving just-in-time recommendations is possible. UM researchers could explore techniques employed in context-aware systems in pervasive environment (Perera, Zaslavsky, Christen, & Georgakopoulos, 2014), to deal with data heterogeneity;

- Support reasoning on the collected data, to suggest alternatives based on the user's actual context. The majority of participants expressed the need of having recommendations on the basis of their current situation, either the environmental context or their "internal states". This would enable, in the participants' eyes, the possibility of being provided with alternatives to their usual behavioural pattern. New personalized systems should formalize the knowledge they collect to enable reasoning over the data and suggest different alternatives that may fit diverse situations. Ontologies, for instance, might map the concepts in a specific domain enabling ontological reasoning which could expand the range of the recommendations provided (Cena, Likavec, Rapp, & Marcengo, 2016). We could suggest a behaviour that is similar or different but somehow related to what the user is used to doing in order to maximize the benefit of the suggestions given. Mobile sensing capabilities could further help in recognizing the user's current context and adapt the recommendations accordingly. For example, we may know that the user loves running, but according to her historical data this activity is correlated with bad sleep. Since today she needs to sleep well, as she has planned a long trip for the next day, the system might suggest a similar activity, such as swimming, to satisfy her need of doing sport. This suggestion could be provided in proximity of the swimming pool by recognizing the user's current position;
- Use the UM to help set objectives and ways to achieve them. All experienced participants focused on the possibility of having personalized goals and plans, tending to use self-tracking devices for achieving specific goals that they have in mind. To support this kind of users the system could set long-term goals based on the user's past behaviour and on the prediction of future situations. It could provide recommendations triggered by the user's current condition, suggesting which kinds of actions and changes the user should put in place to meet the set goals. Such plans should be built together with the users, as the majority of the experienced self-trackers noted, in a continuous exchange of perspectives between the user and the machine, as a form of cooperative action orchestration where sometimes it is the user to drive the cooperation, other times it is the machine (Ohlin & Olsson, 2015);
- Make the stored data "exchangeable" among different services and applications but only for specific purposes. Participants expressed the need of exchanging data among different applications. Users should be able to use all their personal data (or a subset of them related to a specific parameter tracked) in other systems. This "data interoperability" (Carmagnola, Cena, & Gena, 2011) would supply digital applications and services with additional data about the users, gathered in time due to the capabilities of mobile and wearable technologies, as well as stored in the UM, enabling supplementary personalized features. This sort of "portable personalization" could allow users to have adaptive interaction modalities and tailored recommendations practically everywhere at any time, apart from the specific system or service they are using. However, as the majority of our participants emphasized, users should always decide which kind of data they want to provide, for what purposes and for how long, in a sort of a goal-driven and controlled personalization;
- Allow for novelty, serendipity and a possibility to exit from the "magic circle". Serendipity is a well-known issue in content-based recommender systems, which tend to produce recommendations with a limited degree of novelty due to over-specialization (Lops, de Gemmis, & Semeraro, 2010). Personalization based on PI data should allow users to look outside the circle circumscribed by the recommendations provided. Our participants, in fact, expressed a serious concern related to

the control that recommender system could exert on the information provided, actually limiting the information available. This means, on the one side, that they should be provided also with suggestions not directly tied to their UM; on the other side, that they should have the permission to access the whole load of knowledge that their data entail. This could be achieved by both making their UM scrutable (Kay & Kummerfeld, 2013), and by giving them the means to access the information and the opportunities excluded by the recommender.

CONCLUSION

In this paper, we employed a PI system to conduct a user study with the aim to understand users' needs and expectations w.r.t. personalization and recommendation, particularly enabled by the presence of mobile and wearable technologies. We outlined how users that have previous experience in self-tracking, as well as individuals that are not used to track, envision the future of personalization. While expert trackers prefer to have personalized plans to achieve their goals, inexperienced ones wish for a digital double, capable of accounting for all the different aspects that characterize their "self", from cognitive to emotional states. Moreover, participants highlighted the need for providing recommendations on the basis of the entire context that characterizes an individual in a given situation. All these data, in the participants' eyes, should be made exchangeable among different systems allowing for "pervasive" personalized services. However, participants also highlighted privacy and control concerns, which could jeopardize the acceptance of such services in the future. On the basis of such results we pointed to five design recommendations which aim to provide suggestions on how to satisfy the users' needs. In our opinion both practitioners and researchers could use these suggestions as a guide for designing novel personalized services which would embed the most wished features, as well as avoid the most pressing concerns, pointed by different categories of users.

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ENDNOTES

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Federica Cena is Assistant Professor at the Department of Computer Science of the University of Torino. She is currently the head of Smart City Lab at the Center for Innovation for the Territory. She is working on user modeling and personalization, with a special focus on the implications of IoT for user modeling.

Amon Rapp holds a degree in Communication Sciences from the University of Torino, Italy. Since 2006 he's been working in the Research and Trends department in Telecom Italia as a Human-Computer Interaction Researcher. At present, he's a short-term researcher at Computer Science Department at University of Torino. His main research areas are about the use of game design elements in interactive systems, user research methodologies and Personal Informatics tools.

Silvia Likavec is a post-doctoral researcher at Computer Science Department, University of Torino, Italy. She obtained her PhD in Computer Science from University of Torino, Italy and École Normale Supérieure de Lyon, France in 2005 and her Master in Applied Mathematics from University of Novi Sad, Serbia in 2005. Her research activity is focused on the following: (i) modelling the user in social systems, in particular the design of the ontology-based user model and the propagation of user interests using this model; (ii) semantic similarity among ontological concepts; (iii) theoretical computer science, in particular type assignment systems, resource control calculi and semantics of programming languages. She is the author of more than 40 articles in prestigious international journals, monographs and peer-reviewed conferences and workshops and two text books for university level courses.

Alessandro Marcengo is a Psychologist and Researcher with extensive expertise both in clinical domain and in Human Computer Interaction Research. As a researcher, he is author of numerous international publications in the field of HCI and participated in different European projects with various roles. His current research interest focuses on Quantified Self arising issues, on the impact of new technologies in terms of awareness and personal well-being and in the construction of meaning through Data Visualization systems. He is also chair and organizer of different tracks and workshops within different international conferences related with all the above Topics.