Challenges, Feedback & Notifications: Empirical Explorations to Inform the Design of Interfaces to Motivate and Encourage Long-Term Personal Informatics Use

Abstract
In the IDIO research group, we are currently carrying out a number of empirical research studies to inform the design of future personal informatics (PI) systems. These studies include projects investigating the use of gamification elements to encourage engagement based on a user’s personality type, varying levels of feedback during day-to-day PI use, and categorizing and evaluating the suitability of dispatching PI notifications across a wide variety of worn devices and using different feedback modalities. We provide an overview of these projects and suggest ways that our early results might contribute to the discussion of next-generation PI systems at the UbiComp 2015 workshop.

Author Keywords
Personal informatics, motivation, affordances, feedback, notifications, empirical studies, interaction design

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.
Introduction
Li et al. have laid substantive groundwork for the design and study of personal informatics (PI), particularly systems that reflect facets of users’ behavior back to them in order to facilitate behavior change [5]. In the Interaction Design for Information Overload (IDIO) laboratory in the Indiana University School of Informatics & Computing at Indianapolis (IUPUI), we are currently undertaking several complementary research efforts to examine interface design principles for motivating people to adopt personal informatics technologies and adhere to their use over the long term. These research projects examine three facets of PI system design: the use of gamification elements, otherwise known as “motivational affordances”; the degree to which continuous or episodic feedback is (or is not) useful for motivating PI use; and the relative value of various kinds of visual, audio, and tactile notifications to prompt users to engage with PI systems.

Challenges: Examining Motivational Affordances of PI Systems
Gamified systems employ the use of motivational affordances in an effort to invoke positive, intrinsically motivating “gameful” experiences that can result in altered behaviors [2]. Hamari and colleagues divided these motivational affordances into ten categories: points, leaderboards, achievements/badges, levels, story/theme, clear goals, feedback, rewards, progress and challenge.

This prior research also suggested that engagement by gamification may depend on factors such as user motivations or qualities, including personality differences [2]. A study by Codish and Ravid examined the personality traits of extroverts, based on the Big Five Model, in conjunction with individual perceptions of different game mechanisms in a classroom-based gamification setting [1]. They found several significant differences between extroverts and introverts and their preferences for various mechanisms. These results suggest that there is an opportunity to examine individual personality traits and their relationships to the perceived usefulness of the aforementioned motivational affordances further.

Based on these findings, we developed a study to investigate whether individuals with different personality types are motivated by and respond to different motivational affordances used in gamified self-behavioral personal informatics applications. In our initial pilot study [3], we examined the following research questions:

R1. Which motivational affordances motivate users with each personality type to consistently track self-behaviors using gamified behavior-tracking applications?

R2. Is there a correlation between behaviors reported and motivational affordances?

R3. What types of behaviors do persons with each personality type prefer to report/track more often?

We recruited 35 graduate students and university employees (13 female, average age = 29.4 years) to take part in our study. We asked participants to (1) take the Big-Five personality test to assess their personality type; (2) set three daily habits (in categories such as mood, health & fitness, diet, sleep, anxiety/stress, mental health, social or other) that they would like to inculcate as goals in the application.
HabitRPG\(^1\) (Figures 1 and 2); (3) use the application for five days and complete a survey at the end of each day; and (4) complete an exit survey at the conclusion of their participation in the study.

We used one-way ANOVAs to examine correlations between (1) Big Five traits, types of behaviors tracked \((R3)\), and preferences for each affordance \((R1)\); and between (2) types of behaviors tracked and preferences for each affordance \((R2)\).

Users who tracked behaviors related to physical health (diet, health/fitness) also tracked mental health-related metrics (anxiety/stress), and users who tracked online presence also monitored mood- and sleep-related behaviors. Our results also showed that a PI system’s affordances and, thereby, visualization mechanisms should vary by category of tracked behaviors (see our UbiComp 2014 poster \([3]\) for details). Our participants reported that they preferred simple feedback visualizations about their goals to complicated graphs in order to motivate them to log their behaviors.

In our current research, we are running a follow-on study at a larger scale. In this online experiment, we are more rigorously examining respondents’ perceptions of the usability and usefulness of each of Hamari et al.’s motivational affordances \([2]\), when teased apart from one another. Instead of asking participants to comment on their experiences with an existing tool that incorporates a number of gamified elements together, we created short videos that show how a web-based self-tracking tool might implement each affordance independently. We will be examining people’s responses to these features—and looking for correlations between these responses and the respondent’s personality types—in a future publication.

**Feedback: Understanding the Amount of Feedback Required to Sustain PI Use**

A growing concern is how user-friendly the process and experience of collecting and understanding the data using a personal informatics system would be for a user. For example, the FitBit Flex device has five glowing dots that each light up when the user reaches a 20% goal completion interval. When the user attains the daily goal, the lights on the Flex flicker on and off in different sequences and the device vibrates. While some people may value receiving these kinds of notifications, others may view them as a nuisance. With the increased use of these devices, it is important to know what kind of feedback is beneficial and how much of that particular feedback is needed.

In order to answer this question, we designed a study that controls for both the social aspect of wearable system use and the amount and type of feedback that the device provides. Both independent variables have multiple levels. The first is whether or not the participant is in a squad of three participants or participating alone. The other variable, the amount and type of display feedback given, has three levels: full feedback (Phase A), partial feedback (Phase B), or no feedback (Phase C). In the full feedback phase, we allowed the participants to have unlimited access to both the website and all visual and tactile feedback that the FitBit device can display. In the partial feedback phase, we allowed participants to access the FitBit website once a day, but all visual displays on the wearable FitBit device were blocked (e.g., display

\(^1\) https://habitrpg.com/static/front
covered; vibrations shut off). The no feedback phase denied participants access to the website and blocked display of information on the FitBit device, itself; this condition will help us to understand whether simply wearing a device influences behavior. Every participant (in both the squad and solo conditions) experienced all three counterbalanced phases of the study. We employed counterbalancing to ensure that there are no learning or priming effects to confound our results.

A total of 24 participants were recruited from members of the IUPUI campus and their extended social networks. We have worked to recruit a blend of full-time and part-time students and full-time workers who are not currently attending a university.

After completing a survey to collect demographic data, record any previous experience with any wearable fitness devices, and establish a fitness baseline, each participant was issued a FitBit device to wear for a total of six weeks—two weeks in each of the counterbalanced conditions. At the conclusion of each two-week phase, a survey was administered, consisting of questions such as the participants’ current impression of the quality of feedback given by the FitBit device and website, and whether or not the device and/or the squad members motivated the participant to be active. At the end of the third condition, a final, in-person interview was conducted to record qualitative data about the participants’ personal experiences with the device and website over the entire course of the study. We also collected quantitative data about activity levels, as recorded by the FitBit device, itself.

Two by six MANOVAs will be conducted to analyze and interpret the data. In particular, we will look for any significant differences in the number of steps taken and in the subjective preference ratings across all conditions. All qualitative responses will be collaboratively coded by a team of investigators. We will look for common responses and themes that will be used to interpret the quantitative data and to better understand the range of experiences that participants had while using the overall device/website system.

Currently, we are still collecting data from participants. Our initial analysis, based on the data from our first 14 study participants, suggests a steady decline in the number of steps taken over the course of the study, regardless of what order that the participant experienced each of the three levels of feedback. However, the largest number of steps recorded over any two-week period was observed in the no feedback phase when it was experienced first. Although this trend does not (yet) show strong statistical significance, we hypothesize that the lack of feedback about how many steps is “enough” to meet an imagined goal (without receiving any feedback to more clearly define that goal or determine whether it is being met) might lead to an higher overall activity level in an effort to set a reasonable bar for later use of the system with more feedback.

This research project will continue into the summer of 2015, and we anticipate completing our analysis before the start of the fall term, 2016.

Notifications: Exploring the Role of Feedback across Complex PI Device Ecosystems
We are not only examining how much feedback PI systems need to provide in order to be effective, but we are also looking at leveraging the diversity of
display devices and modalities present in contemporary wearable computing "ecologies" (e.g., smartphones, smartwatches, wearable audiovisual display devices like the Google Glass prototype [7]; see also Figure 3). Expanding the scope of notifications across multiple devices begs several relevant research questions:

- How can these devices work together to minimize *information overload*, that is, continuous demands on the user’s attention, either related to an individual device or across the entire ecology?

- How can an interaction designer determine which device is the most appropriate site for a particular information display—or modality from which to expect a user's response, especially since the user may add or remove devices depending on the physical and social context (working out, attending a formal function, etc.)?

By examining both the information accessed through wearable display ecologies and developing technologies that allow these devices to work together in a more seamless fashion, we aim to advance the state-of-the-art for personal informatics system design for the emerging era of wearable computing.

In order to better understand the breadth of personal informatics data that will likely be handled by these kinds of systems, we are developing a taxonomy of the kinds of data that are currently collected by personal informatics systems (and other network-connected services) and displayed to users as notifications via on-body computing devices. Given the different modalities that wearable display ecologies can use to reflect these data back to a user and the characteristics of these modalities (e.g., whether the information is shared privately, semi-privately, or publicly), we are in the midst of conducting a card-sorting activity (partially inspired and informed by a survey of information sharing preferences [6]) to help categorize these personal informatics data based on the ways that people currently consume them—and would like to do so in the future. Our card-sorting activity is designed to help people to talk about their expectations related to accessing different kinds of data without tying the discussion directly to a technology that they may or may not have actually used to date. We anticipate that this approach will enable us to develop personas and models of information use that can help guide future interaction design for these kinds of systems, similar to the approach that we took in previous research [8].

Based on the outcomes of this study (currently in progress; we hope to share some of our initial findings during the UbiComp workshop), we aim to develop a suite of interface proposals that enable users to more clearly specify the rules by which notifications are disseminated across their wearable display ecologies. We also anticipate being able to provide the designers of PI systems with a series of design guidelines to help them more effectively use mobile and wearable device notifications to draw users in to use of PI systems; for example, to remind them that it is time to log a recurring bit of data, to acknowledge met milestones, or to cue the review of progress or self-tracking goals.

**New Frontiers of Quantified Self Workshop Participation Goals**

The members of our research group share an interest in understanding the everyday use of PI technologies and in utilizing a combination of empirical and design research to advance the state of the art in this domain.
If accepted to participate in this year’s QS workshop, we look forward to sharing some of the early results of our diverse studies about ways that the design of PI systems can be informed by research on motivation and perception. We are also particularly excited about many of the proposed topics of discussion/presentation for this year’s workshop—design techniques, user modeling, visualization, and long-term use—many of which significantly overlap with the research interests of the members of our group.

**About the Authors**

Stephen Voida is an assistant professor in human-centered computing at the Indiana University School of Informatics and Computing on the IUPUI campus in downtown Indianapolis. He directs the Interaction Design for Information Overload (IDIO) laboratory, where he and his students study personal information management, pervasive healthcare, and ubiquitous computing.

Yuan Jia is a Ph.D. candidate in human–computer interaction in the IU School of Informatics and Computing; Yamini Karanam is a pre-qualifier Ph.D. student in the same program. Both share interests in the psychology of human–computer interaction and about how interface design can motivate long-term technology use.

Alex Chambers, Joe Dara, Abdulaziz Alderhami, Kunal Bodke, and Dushyant Shrikhande are M.S. students studying human–computer interaction at Indiana University, Indianapolis (IUPUI).

Jessica Despard is a recent graduate from the Purdue University School of Science at IUPUI with a B.S. in psychology. She will join the School of Informatics and Computing as a Ph.D. student in HCI this fall.

**Acknowledgements**

We gratefully acknowledge Google’s support of this research through a 2014–2015 Google Faculty Research Award.

**References**


