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# LOL: Levels of Learning Through Personal Informatics

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## Author Keywords

Activity tracking; self-knowledge; learning; personal informatics.

## ACM Classification Keywords

H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous;

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*Ubicomp/ISWC'16 Adjunct*, September 12-16, 2016, Heidelberg, Germany  
ACM 978-1-4503-4462-3/16/09.  
<http://dx.doi.org/10.1145/2968219.2968313>.

## Abstract

Users of self-tracking (such as tracking steps) tend to abandon the technology after a few months of using it. Previous user research suggests that users have “learned enough” and feel they no longer benefit from the technology. However, what exactly does “learned enough” entail? What, when, and how do users actually learn? This paper reports our initial efforts to investigate these questions. We (a) present a small-scale mixed-method pilot study in which we explored learning with step trackers; (b) suggest four levels of learning that Personal Informatics tools can foster: data level, routine level, correlational level, and problem-screening level; and (c) discuss how future research can use and extend this initial framework to study what and how people learn with self-tracking technology.

## Introduction

Wearable self-monitoring technology such as fitness trackers have reached a wide customer base. However, a recent study suggests that a third of the people who purchased a self-monitoring device have abandoned it after 6 months of use [6]. Researchers in Personal Informatics have started to investigate the causes underlying the abandonment of these technologies [3,4]. Their findings indicate that technology abandonment can be regarded as a sign of success. That is, it indicates that users have “learned enough” about their bodies or behaviors. In Epstein et al.’s [4]

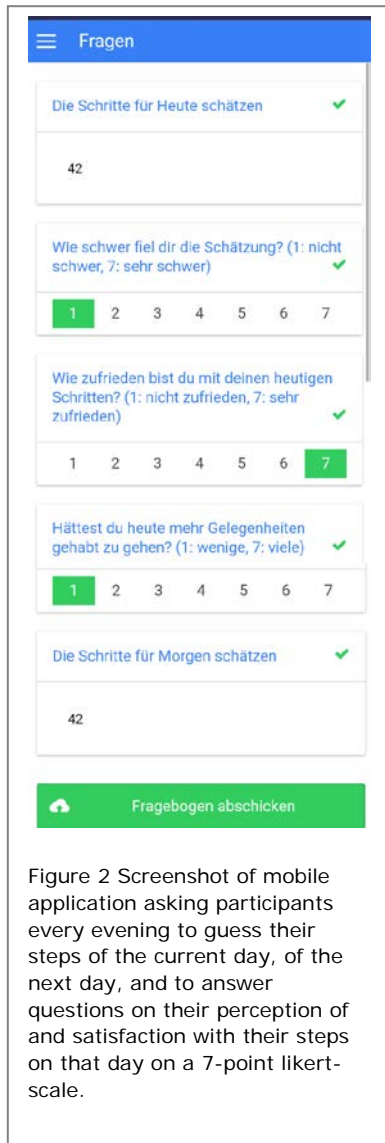


Figure 2 Screenshot of mobile application asking participants every evening to guess their steps of the current day, of the next day, and to answer questions on their perception of and satisfaction with their steps on that day on a 7-point likert-scale.

interviews, for example, a participant stated to be “able to figure my distance and calories burned without [MapMyRun]”. These observations resemble research on sensory augmentation devices, such as the electronic belt feelSpace. feelSpace trains the user’s sense of direction by always vibrating where North is. Studies have shown that the improved ability to navigate does not diminish immediately after wearing the belt [7,8]. These observations trigger the question whether technology can train our senses so that we develop awareness and skills that last even when we abandon the technology. If so, do these improved skills last forever once acquired or do they diminish like newly learned behaviors often disappear after the abandonment of behavior change interventions [5]?

To tackle these questions, we first need to operationalize the awareness or skills acquired through the technology, in the following called *learning*. What exactly do we learn and how can we measure it? We explored a possible study design in a small-scale mixed-method pilot study investigating whether users get better at estimating their daily step counts.

### Pilot Study

#### Participants and Set-up

We recruited three participants (one female, all aged between 21 and 23, in the following P1,P2, and P3) who had never used an activity tracker before. Each participant received the commercial activity tracker Fitbit One (Figure 1) and was compensated €15. To prevent participants from retrieving their step count, the display of the Fitbit One was masked with tape throughout the study.



Figure 1 The commercial activity tracker used for the pilot study, Fitbit One, compared to a 2 Euro coin.

#### Method

We combined both (1) quantitative and (2) qualitative measures to assess participants’ learnings with the activity tracker:

(1) We quantitatively assessed how participants’ ability to estimate their daily step count improved during fifteen days of wearing the tracking device. A smartphone application, installed on participants’ phones solely for the study purpose, asked users to estimate their daily step count every day at 9pm. Figure 2 displays a screenshots of the application. Additionally, the application asked users to estimate how many steps they would walk the next day and to answer several additional questions on a 7-point likert-scale (How hard was it for you to estimate your step count? [1 not hard; 7 very hard], How satisfied are you with your steps today? [1 not satisfied at all; 7 completely satisfied], Did you have many opportunities to walk more today? [1 none; 7 plenty]) The baseline step estimation accuracy was determined in the first five days on which participants did not receive any feedback. On all following days participants received

	Days 1-5	Days 6-10	Days 11-15
P1	1332	1903	2779.3
P2	5748.2	4126	1882.5
P3	1746.8	1405.8	1288.5
Ø	2942.3	2478.3	1983.4

Table 1 Estimation error (absolute value of estimated steps subtracted from actual steps) averaged over days 1-5, 6-10, and 11-15. P2's and P3's estimation error declined over the course of the study, while P1's did not.

their actual step counts by the application after estimation.

(2) Before and after the study, we conducted semi-structured interviews<sup>1</sup>. The interview before the study included questions such as *"How satisfied are you with your daily physical activity? How does a typical day look like? Is your day very predictable? How many steps do you think you perform on average on one day?"* Interviews after the study included questions such as *"How was your tracking experience? Did you become more aware of your activity? Would you continue wearing an activity tracker?"*

### Results

Participants' *step count estimations correlated loosely with their actual steps* ( $r_s = 0,87$ ). This result shows that users had a basic awareness of the steps they walk (see figures 3-5). Moreover, P2 and P3 improved moderately in estimating their step counts, while P1 did not (see table 1). The most active participant, P2, also improved the most in estimating his steps over the study period. His estimation error (difference between estimated and actual steps) averaged over the first five days ( $\emptyset=5748,2$ ) declined by 3865,7 steps compared to the last five days ( $\emptyset=1882.5$ ). P1 offered an explanation for the lack of improvement: *"I think it didn't get better because my days turned out to be very different. When you do completely different activities you can't really transfer it."* All participants stated that it was always difficult to estimate the step count in the evening. P1's approach to overcome this difficulty was to assign and memorize step counts to

routine behaviors: *"When I had to estimate my step count in the evening, I thought of my day in intervals, for example, going to the shop in the morning, then going to work, then going to university."*

Despite the limited improvements in estimating step counts, participants expressed that they learned from wearing the step tracker: For example P2 and P3 learned in what range their daily activity varies (P2,P3); P2 learned how few steps he walked on work days; and P3 learned that delivering newspapers boosts one's step count remarkably.

### Discussion

Two out of three participants in our pilot study indeed got better in estimating their steps counts. However, further research is necessary to investigate if and when exactly users abandon tracking technology because they have "learned enough" as suggested by recent research [3,4]. Therefore, we plan to repeat the presented study with more participants and a refined study design capturing not only step estimation but also other learnings that users might have. As an initial framework, we derived the following four levels of learning from our interview data and previous research (from general, high-level learnings to specific, low-level learnings):

#### Problem-screening Level

With problem-screening level, we refer to yes/no-questions similar to the diagnosis of a doctor, e.g., Does my average step count roughly reach the recommended 10,000? Is daily physical activity something I need to worry about? For some users simply knowing that they reach the recommended step count might be having "learned enough".

<sup>1</sup> Interview questions and participants' quotes have been translated from German.

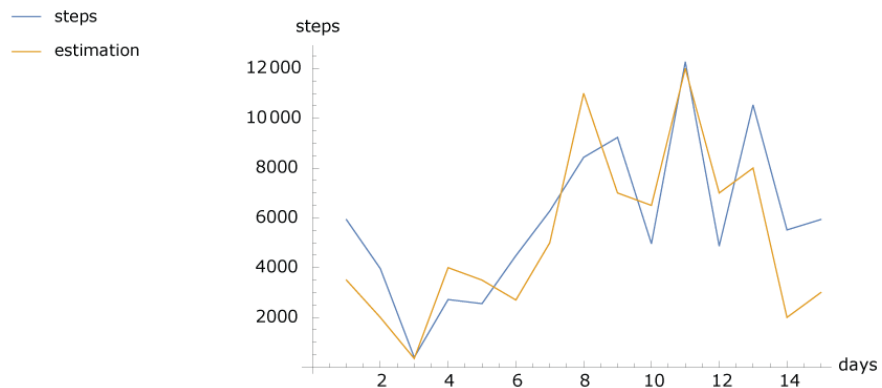


Figure 3 Actual steps and step estimation (in the evening) over the fifteen-day pilot study period of P1.

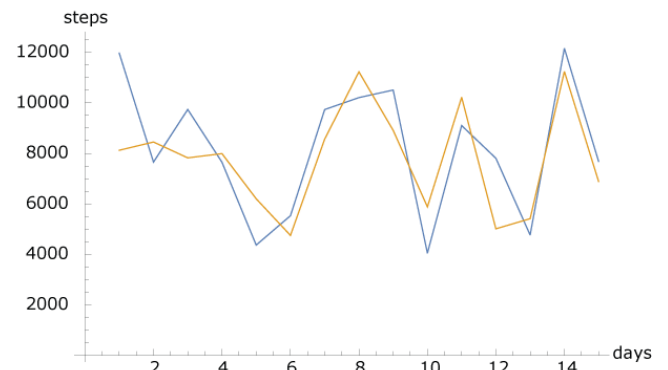


Figure 5 Actual steps and step estimation (in the evening) over the fifteen-day pilot study period of P3.

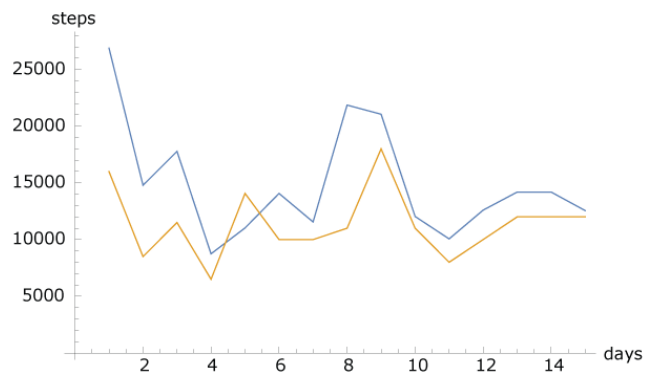


Figure 4 Actual steps and step estimation (in the evening) over the fifteen-day pilot study period of P2.

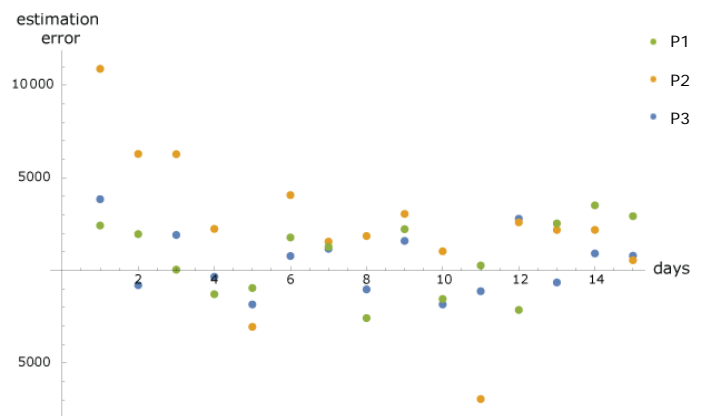


Figure 6 Difference between estimated and actual steps over the fifteen-day pilot study period for all participants (indicated by colors, see legend on the sidebar).

### *Routine Level*

In our pilot study participants mainly memorized the step counts of routine behaviors, but were not able to transfer that knowledge to other activities. We describe this kind of insight as learning about one's own routines, e.g., the impact of delivering newspapers on one's step count.

### *Correlational Level*

Going beyond understanding past and routine behavior, technology can help users to understand the causes and effects of their behavior. For example, in Health MashUp, Bentley et al.[2] enabled insights, such as "when I sleep more and eat healthy, I'm usually more physically active", by mining different streams of health and wellbeing data. We did not observe any learning on this level in our data.

### *Data Level*

In our pilot study, we attempted to capture whether users get better in estimating their daily step count, just as users of the belt feelSpace got better in navigating intuitively. In our study, two of three participants moderately improved in estimating their step counts. Whether and how learning on this level takes place with step trackers might be influenced, e.g., by the users' knowledge, motivation, and awareness, the frequency of feedback exposure (home-screen, ambient display, on-device,...), and the format of feedback (haptic feedback, counts, graphs, stylized displays).

### **Conclusion**

This paper presents a pilot study about learning through self-tracking, in which two out of three participants improved in estimating their step counts. All participants, moreover, expressed to have learned from using the step tracker on other levels as well. We, hence, considered four different levels of learning, namely data, routine, correlational, and problem-screening level.

We plan to conduct a follow-up study with more participants and additional means of data collection to capture all kinds of learnings that happen with step trackers, including but not limited to learnings on the four presented levels. Additional research questions, we aim to address, concern the impact of the format of feedback, the knowledge necessary to make effective use of the data level, and the durability of the improved ability after abandonment of the technology. We hope that future work in this area will help to judge when, for whom, and for how long self-tracking technology is most valuable, in which cases abandonment indicates success, how technology could be designed to better foster self-knowledge, and how learning that happens with alternative approaches such as technology for embodied discovery [1] is different than learning with traditional Personal Informatics tools.

### **Acknowledgements**

I'd like to thank Robert Mueller, who provided assistance with the pilot study; Andreas Butz, Julie Wagner, and Daniel Buschek for valuable discussions about the ideas presented in this paper; as well as Fabius Steinberger and Kilian Moser for their valuable comments on this manuscript.

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