Understanding Self-Efficacy and the Design of Personal Informatics Tools

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Abstract
The design of many personal informatics tools or approaches for behavior change can be influenced by Social Cognitive Theory, which suggests self-efficacy impacts ability to change. Self-efficacy is easy to measure and indicates adherence to behavioral strategies. This makes it an attractive construct for evaluation of PI technologies. In this workshop paper, we discuss what self-efficacy is, how to measure it, and three factors that impact the measurements.

Keywords
Social Cognitive Theory, behavior change, self-efficacy, personal informatics, mobile phone, health/wellness.

ACM Classification Keywords
H5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

General Terms
Measurement.

Introduction
One primary concern for the field of personal informatics (PI) is supporting people in making changes in their life. A driving philosophy is that an observed and measured life can lead to change. One theory that

frequently grounds this work is the Trans-Theoretical Model [7], which defines stages of change, how to evaluate which stage a person is in, and how to support that person, either within that stage or to move to the next stage.

Another relevant theory for PI designers and researchers is Social Cognitive Theory [1], which posits that a person's behavior, environment and inner qualities all contribute to how a person functions. This theory has been applied to understanding how people learn, how social environments impact what people do, and how people regulate their own behavior. A key component in this theory is self-efficacy (SE), which is summarized as a belief in one's abilities.

Now that we have introduced social cognitive theory and SE, the rest of this paper is organized as follows: First, we describe the traditional approach to measuring SE. Then we describe three factors that influence self-efficacy as it applies to PI tools, providing examples. Finally, we suggest some discussion points and areas for future work.

Measuring Self-Efficacy

SE is traditionally measured by self-report. To develop SE measurements for a particular domain, researchers use open-ended approaches to identify common challenges and barriers to the problem. They then develop a series of statements of the form "How confident are you that you can [achieve goal] even though [challenge]?" with a 4-unit response scale ranging from "Cannot do it" to "Highly certain can do". An example of a statement is "How confident are you that you can stick to a healthy eating plan after a long, tiring day at work?"

Research shows SE measures based on self-report indicate adherence to strategies to change behavior [6]. While short-term studies cannot prove behavior change, SE measures provides valuable feedback about whether an intervention is supporting adherence to behavior change strategies, and indicate whether participants complete the study with an intention to continue.

This is an important feature for PI researchers: we are familiar with a domain and common challenges, so can build the scales easily; we usually use short-term studies to indicate long-term impact; and properly designed scales can help us to discover where a PI tool breaks down.

Self-Efficacy Influencers

Now that we have described how SE can be measured and its relevance to PI researchers, it is important to acknowledge factors that may impact the measurements as applicable to PI tools.

Usability. Firstly, general usability is an important component to someone believing they can use a tool. Consumers have become increasingly savvy with their expectations of technology, and as researchers, we need to meet those expectations. While researchers may not have the resources to produce a tool that is as polished as a commercial tool, a well-designed tool impacts not just whether a person wants to use the tool, but whether they believe that it will work. We expect that many researchers and designers have experienced how usability or design problems have negatively impacted the ability and desire of people to use their tools, and we are simply acknowledging that general usability will impact a participant’s responses on a SE scale.

How well the tool matches the user’s goals. This refers to both a goal the user has and that the user has a belief in what they need to do in order to attain that goal. A user who is trying to lose weight may choose to focus on restricting caloric intake as well as increasing caloric expenditure, or choose to focus on only one of those areas. Social cognitive theory says these beliefs are based on what the user has observed amongst their peers, and how similar or different the user is from their peers.

We observed this in the BALANCE studies [2,3]. The goal of the BALANCE application consisted of a food diary to capture caloric intake, an automatic physical activity detection platform to measure caloric expenditure, and a visualization that provided real-time feedback of the person’s caloric intake/expenditure balance throughout the day, all on a mobile phone. The project included a series of 5 focus groups to inform the design of the food diary, and a validation phase with 24 people. In each phase, participants carried the phone and tracked their food intake for 3 days.

One recurring theme in the focus groups was that tracking food intake with such detail was too much work, and would only be worth it if they had a medical condition that made it very important to keep detailed records. However, some participants wanted to reflect on a higher level summary of their dietary intake for general health and disease prevention. In this case, we theorize that our participants would answer the question “How likely are you to improve your dietary intake with the BALANCE food diary?” with “Not likely”. We do not question that there are many ways to interpret this or to identify the source of the problem, we are merely observing that the issue of goal matching will impact SE measures.

Understanding the underlying technology. Another factor is how well the user understands the technology, or more specifically, how the technology may fail. Part of the BALANCE project was using sensors to identify and calculate calories expended via activity throughout an entire day. Other related tools are GPS-based run trackers that use GPS to track the location, duration and other metrics of the run. Technologies that use sensors to identify bouts of physical activity have some level of uncertainty associated with the recognition. This uncertainty comes from a variety of sources, such as parameters that reflect a tradeoff between power consumption and accuracy. GPS trace quality depends on terrain and location of satellites in the sky.

A recent New York Times article reflects the concern of GPS run tracker users [5]. Runners sometimes measure certified race courses, and report discrepancies to the organizers. These runners appear to trust the technology more than the organization. In the case of BALANCE (which exposes less detailed data about the calorie calculation and depends on more parameters), some users reported a feeling that the calculation “didn’t feel right”, but were unable to express how they thought it might be wrong. With both of these examples, the uncertainty with the technology could impact measures of SE. This raises the question of what other factors influence a person’s trust in the technology, as well as how SE may be impacted, and how it may vary from person to person.

Implications

In the field of PI, researchers face the challenge of trying to evaluate how well a tool could support behavior change without running the long-term study necessary to prove lasting change [4]. This is frequently addressed by providing "evidence of engagement", or measures that indicate a person is likely to continue using a tool. These more traditional measures of SE could contribute to evidence of engagement. Even more, SE measures can help researchers and designers better understand where an intervention or tool is succeeding or failing.

Finally, while SE measures are traditionally based on self-report, we as researchers may be able to identify quantitative measures that correlate with SE. For example, one could imagine that in the case of a food diary, we keep track of how many food entries are made while in social situations, or at locations not at home.

While our experience has been primarily in the domain of food and physical activity diaries, we believe that this issue is one that other researchers may have encountered and can provide enlightening insight about. Other domains such as sustainability depend on data sources that are faulty, and as such could both contribute to and benefit from such a discussion.

Future Work

In this paper, we described three items that can impact SE measures of personal informatics tools. We also introduce the idea of exploring how to collect objective data to indicate/measure SE, and how this could be useful for comparing PI research projects, particularly in similar domains. We hope to contribute these ideas to theoretical discussions at this workshop.

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