Anticipating Habit Formation: A Psychological Computing Approach to Behavior Change Support

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Abstract
Mobile computing systems hold the promise of becoming a cost-effective solution for supporting behavior change towards more healthy lifestyles. We present here an approach where the system implements a formal model of habit formation based on psychology theories, anticipates the behaviors and cognitive states of the users, and picks interventions based on model predictions. First, we discuss the motivation and system requirements for the approach. Next, we propose in detail an underlying computational model of habit formation which constitutes the key component of the system. Finally, future work and challenges will be discussed, focusing on the empirical validation of the model and the mapping between the model and intervention techniques.

Author Keywords
Behavior change; decision support; habit; mobile health intervention; psychological computing

ACM Classification Keywords
I.2.1 [Artificial Intelligence]: Applications and Expert Systems; I.6.5 [Simulation and Modeling]: Model Development; J.4 [Social and Behavioral Sciences]: Psychology

Introduction

Mobile computing systems have been proposed as promising tools to support behavior change towards more healthy lifestyles [14]. Such systems are supposed to collect diverse and vast amount of information from people's lives [13], to be context-aware, and to deliver interventions anywhere and at any time [8]. On top of these powerful capabilities, there is a recent trend of equipping the systems with an understanding of the behavioral and cognitive processes of users, to achieve more intelligent decision support [15, 16]. More specifically, psychological theories are translated into formal and dynamic models to be implemented in the system for prediction and anticipation [11, 15]. In this paper, we present a novel mobile computing approach that utilizes a computational model of habit formation to support the consolidation of healthy lifestyles.

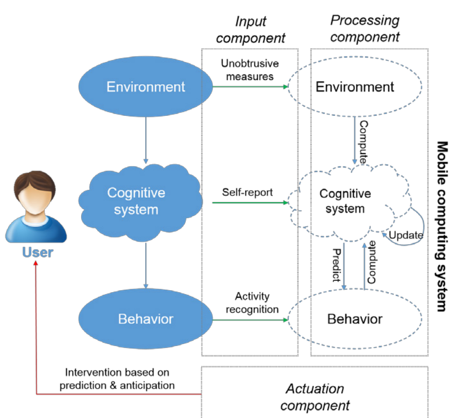

Figure 1: This picture illustrates the user model, the three components of the system, and their relations.

In terms of the stage model of behavior change [18], moving people from the action to the maintenance stage is often very challenging. In other words, even when the motivation and intention to change a behavior are there, it still takes a long and effortful process to fully acquire the behavior. This process can be referred to as habit formation because the hallmark of successful change is that performing the new behavior becomes habitual and effortless [21]. If a model of habit formation can be represented computationally by a mobile system, this challenging process can be facilitated in two ways. First, the system can present such information to the users as novel self-knowledge which they are not usually aware of, including, for instance, the current habit strength. A feeling of more control over the process may provide them with extra motivation to complete the change [2]. Second, and perhaps more importantly, the systems can use the model for prediction of user behaviors, anticipation of changes ahead, and basing decisions of interventions on the model. These are powerful functions that are largely unexplored. Consider a few examples of the questions such systems are able to answer:

- How far is the user away from forming the new habit? Will the behavior be maintained if the system stops coaching the user?
- How critical is it to perform the behavior today in order for the user to build up habit strength? Should the system intervene?
- How to estimate the degree of disruptions on habit formation caused by anticipated external constrains (e.g., bad weather preventing a user from exercising outside for a week), and what measures to take to put the user back on track?

Before focusing our discussion on the underlying computational model, we first describe how the system works and its required components.

System description and requirements

Figure 1 illustrates the key components of the system and their relations. The system consists of an input component for gathering necessary data, a processing component for turning the data to useful information based on the underlying model, and an actuation component to choose an intervention based on the information. On the user side, we adopt a classical cognitive view of behavior that any stimulus from the environment (including the system's intervention) can exert influence on the user's behavior through the mediation of a cognitive system. Below we discuss the I. INPUT COMPONENT

Monitoring actual behavior: The target behavior to be learned by the user is measured objectively by the sensors. This requires activity recognition (e.g., by accelerometer) in the context of learning a concrete behavior.

Sensing contextual variables: Contextual variables refer to potential determinants of the target behavior that change in different contexts. Both internal (e.g., mood, emotions) and external (e.g., weather, social environment) determinants are measured if unobtrusive measures (e.g., heart rate, microphone) can be obtained.

Measuring cognitive states: Users occasionally will be asked to report their cognitive states (e.g., attitude towards the target behavior). Additionally, cognitive states will be calculated if possible.

II. PROCESSING COMPONENT
Updating cognitive states: Because measuring cognitive states can often be difficult or burdensome to the users, some critical cognitive variables in the model will be computed based on their temporal dynamics informed by psychological theories. Objectively observed behaviors and the system's interventions are used as inputs for the computation.

Predicting the target behavior: The system uses the contextual variables and cognitive states measured or computed to predict behaviors at the next time step.

Anticipating the change process: When the contextual variables can be anticipated for some time in the future (e.g., weather and/or working agenda next week), the system simulates the dynamics of cognitive states and behaviors of the user in that future period.

III. ACTUATION COMPONENT
Model-based intervention: Given the model prediction and its mapping with intervention techniques, the system takes appropriate measures to influence the user's cognitive system, expecting a desirable change in the user's behavior. For example, if a prediction is made that the target behavior will likely be forgotten by the user, a reminder is sent to the user.

Theoretical basis and a conceptual model

To fully capitalize on the ubiquitous power of mobile computing systems, the theoretical framework should describe behavior at the same level of temporal granularity as the data collected [4]. Unfortunately, most behavior change theories are not developed for fine-grained temporal predictions [14]. The behavior to be predicted in many theories is conceptualized at an aggregated level (e.g., average frequency of physical exercise in a week), rather than the execution of behavior on each occasion. Empirical studies following these theories are exclusively cross-sectional or prospective (determinants are measured at a single time point to predict aggregate behavior over some future period), failing at telling stories about what happens in the process. Therefore, we propose a new conceptual model based on an extensive literature review of relevant theories in psychology, especially learning theories [1] and dual-processing models of decision-making [6]. The formation of a new habit is modeled at the level of each individual decision so that the dynamics of multiple decisions in time are also captured.

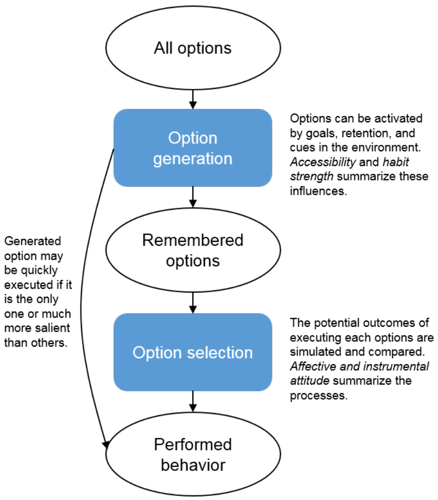

Figure 2: This picture illustrates the 2-stage model of decision-making on individual occasions.

Decision-making on individual occasions

In the domain of lifestyle behavior change, it is the repetitive "small" daily decisions that gradually lead to the formation of new habits and possibly better health. These decisions are modeled in two sequential processes: *option generation* and *option selection* (see Figure 2). Although option generation has only received some research interests recently, it is a prerequisite for choices in naturalistic decision-making [9]. Options are learned through operant conditioning [17], social observations [1], or direct instruction (e.g., a suggestion from a mobile app). At the moment of a decision, options can be activated from memory in three different ways: (1) effortful retention [20]; (2) activated by cues in the environment [21]; or (3) by a higher-level active goal [2]. The strongest activated option at a specific time can lead to automatic behavior execution, bypassing the option selection process.

When two or more options are equally salient and active, a second option selection stage is required to resolve the conflict. This is a slower and more deliberate process in which a person compares the options by simulating their potential outcomes [3]. Both instrumental values of the behavior outcomes to various personal goals and affective feelings are taken into account. At this stage, contextual variables can exert their influences on the final decision by changing the relative attractiveness of the options. For example, when choosing between office lunch and walking 10 minutes to eat at a canteen, bad weather may contribute to negative feelings towards the "walking" option, while a busy afternoon agenda may focus the comparison of options to their values to the work goal. Finally, the state of the individual, for example, fatigued or not, may also change the individual's tendency to rely more on feelings or goal values [7].

Temporal dynamics of decisions

In learning a new habit, the decisions on individual occasions are interconnected in time because each decision made exerts indirect effects on future decisions through its influences on cognitive states. The dynamics of three cognitive states are considered in this model.

- Accessibility: How accessible an option is from memory is crucial for option generation. When a person first form the intention to learn a new behavior, accessibility is high because the person would actively retain or rehearse the option in consciousness to ensure its activation at the moment of decision-making [20]. Accessibility naturally decays over time, but can be enhanced by external reminders and by performing the behavior.

- Habit strength: The strength of the association between cues and a behavior, commonly known as habit strength, increases when the behavior is repeatedly performed with the cues [21]. When a habit is strong, it becomes more likely that the behavioral option will be generated and even automatically executed just by perceiving the cues. Habit strength also decays slowly over time.

- Attitude: Attitude refers to the instrumental as well as affective evaluation of a behavior [20]. It is based on multiple beliefs about the outcomes of the behavior and can be shaped by the experienced outcomes on each occasion. Attitude may also be changed by persuasive interventions, for instance, those from a mobile system.

Computational implementation

In order to work with empirical data and to be used in a mobile computing system, the conceptual model needs to be implemented computationally. It should be noted that the conceptual model can be implemented in many different ways, depending on the different assumptions that are made and the specific behavior to be modelled. Here we present an example of the implementation where we focus on training people to increase the amount of time they are active, by walking to another building for lunch, instead of eating at office. Rationales and assumptions for the choices of mathematical formulas will be mentioned when applicable.

Prediction and anticipation of individual behaviors

This is the formal implementation of the 2-stage model of decision-making on individual occasions. First, in the case of lunch walk, we consider two options to simplify the discussion: having lunch in one's office while working, and walking 10 minutes to a canteen to eat. Second, we identify the typical contexts for this decision so that habit strength of the two options in each context can be defined. Assuming that weather (rainy, cloudy, and sunny), urgency of work (urgent, not urgent), and social companion (with colleagues, without colleagues) are the main contextual determinants, 12 different contexts can be distinguished.

The generation of each option *k* in a given context *C* at time *t* is affected by both the general accessibility of the option and the habitual responding in that context. The baseline activation of an option (AB_k^t) can be modeled as a stochastic process following a normal distribution with accessibility (ACC_k^t) as mean and a variance parameter, i.e., $AB_k^t \sim N(ACC_k^t, \sigma_{act}^2)$. Total activation ($AT_k^t$) in a given context is the sum of the baseline activation and habit strength, $HS_k^t(C)$. If one option is much more active than the other one (e.g., $AT_{k=1}^t - AT_{k=2}^t \geq W$), the corresponding behavior will be performed, bypassing option selection stage. Otherwise, the expected utilities of the two options (EU_k^t) are compared in the second stage.

Option selection is modeled based on utility calculations that are commonly used in travel behavior modeling (e.g., see [19]). Basically, the utility of each option is the weighted sum of the values x_{jn} of all attributes J in a given context *C* at time *t*. The option with the highest utility will be selected to execute.

$$EU_{i_k}^t = \sum_{j=1}^{Ji_k} \sum_{n=1}^{N_j} \beta_j \; x_{jn} \, P_{i_k j}^t \, (x_{jn} \mid c_t)$$

The two options can be compared on many attributes, for example, *benefit for work*, *health benefit*, *social benefit, enjoyment of walking outside*, and *discomfort*. Each user *i* holds a belief ($P_{i_k j}^t \, (x_{jn} \mid c_t)$) about each possible value x_{jn} of attribute *j* in context *C* at time *t*. Some beliefs differ greatly between people but is relatively stable across contexts, for example, the beliefs about the health benefits of lunch walk. On the contrary, the the distribution of the values of *enjoyment of waking outside* varies largely in different contexts (e.g., rainy or sunny). The β_j parameter in the formula represents individual decision weights on different attributes. For example, some users may weight *benefit for work* much more than *health benefit*

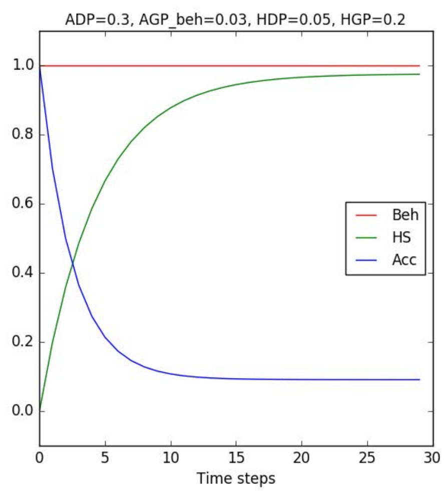

Figure 3: The picture shows the dynamics of accessibility and habit strength in a simple scenario – consistent behavior without reminders. Parameter values used are shown on top.

if work goal is much more important than health goal to them. The decision weights can be approximately measured by asking the users about the importance of different personal goals in their lives. Taking a different perspective, the total utility calculated can be understood as context-specific attitude since both are summarizations of behavioral beliefs.

Updating cognitive states
Three cognitive states that are impactful on decision-making, accessibility, habit strength, and attitude, require updates at each time step. Accessibility is modeled to be context-independent, decaying over time at a person-specific rate (ADP_i), while being enhanced by reminders from mobile systems (Rem) and by performing the behavior (Beh). The fomular is similar to the one used in Tobias [20].

$$ACC_{t+1} = ADP_i \times ACC_t + (1 - ACC_t) \times (AGP_{rem} \times Rem + AGP_{beh} \times Beh)$$

It is assumed that the accessibility of the intended behavior decays slower than knowledge in retrospective memory [20]. Individual's efforts of retention and rehearsal are not modeled explicitly but are reflected by the individual differences in ADP_i.

The dynamics of habit strength (HS) have been modeled mathematically by a number of researchers in different application domains [5, 10, 19, 20]. Despite some differences, the shared idea is that habit grows when the target behavior is performed in the presence of the cue(s), but decays slowly when the behavior is omitted. It is also commonly accepted that the growth of habit is faster in the beginning but slows down to reach a plateau, forming an asymptotic curve as shown in an empirical study [12]. We model habit strength to be context-dependent.

$$HS_{t+1}(C) = \begin{cases} HDP \times HS_t(C) + HGP_{c=1} \times (1 - HS_t(C)), \\ if\ Beh = 1\ and\ C = 1 \\ HDP \times HS_t(C) + HGP_{c=0} \times (1 - HS_t(C)), \\ if\ Beh = 1\ and\ C = 0 \\ HDP \times HS_t(C), \\ if\ Beh = 0 \end{cases}$$

There are a few assumptions and simplification made regarding this equation. First, the habit gain and decay parameters (HGP and HDP) are assumed to be the same for everyone. Second, habit strength for a given context increases the most when performing the behavior in that context, but also increase by a smaller amount when performing the behavior in a different context. Third, the reinforcement of habit by simply remembering the behavior is omitted.

Figure 3 illustrates the simulated dynamics of accessibility and habit strength when a behavior is consistently performed without any external reminders. As what would be predicted by dual-processing theories [6], accessibility gradually decrease to a very low level, meaning that conscious retention gives control to habitual responses [21].

Finally, the dynamics of affective and instrumental attitude can be modeled as the updates of beliefs towards the value distributions of attributes for different options, following principles of reinforcement learning [19]. Affective attitude is more variable in time because beliefs can be changed by concrete affective experiences. As health benefits of lunch walk are mostly in the long term, the lack of feedback for the users makes instrumental attitude to be more stable. However, as users are very uncertain about its values (very wide probability distribution), persuasion by mobile systems may greatly affect instrumental attitude.

Future work and challenges

We are currently in the phase of verifying the model. Agent-based simulations are running in R to check if the dynamics of cognitive states and behaviors generated by the model make sense based on existing empirical data of habit formation [12] and intuitive expectations. Working towards a mobile computing application, there are a number of steps to take in our future work. First, we will look for and collect appropriate dynamic field data to validate the usefulness of the model, and to calibrate the parameter values in the model. A currently considered study is to have people change their lunch habits with the support from a mobile app. Second, there will be a design phase where we map different ways of decision support (e.g., reminders, motivational messages, and timing of interventions) to the possible outputs of the model. Lastly, the usefulness of the model-based decision support will be tested in intervention trails and to be compared with benchmarks.

Besides the validation of the model, we are aware of several other challenges to our approach:

- Behavior recognition: Accurate recognition of the target behavior is still a nontrivial task for many behaviors. Not only the type of activity requires recognition (e.g., walking versus running), but also its meaning in the context (e.g., taking a walk after lunch).
- Higher-level cognition: Higher-level cognitive processes, such as goal-setting, self-reflection, planning, change of intentions, are not modeled. Modeling of these processes require computations at different temporal scales [15].
- Practical advantage: A simple but strong contender to our approach is to send reminders/motivational messages mindlessly without caring about the change process. As there is almost no financial cost for giving interventions, potential user-side costs (e.g., discarding the system due to annoyance) need to be defined for more meaningful comparison.

Conclusion

To promote healthy lifestyles, we propose here a novel conceptual theory of habit formation with an example of computationally implementation. Although empirical validation awaits, we believe that our approach can add new knowledge to the promising trend of model-based behavior change support.

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