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Research Article

Improving Physical Activity mHealth Interventions: Development of a Computational Model of Self-Efficacy Theory to Define Adaptive Goals for Exercise Promotion

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The practice of regular physical exercise is a protective factor against noncommunicable diseases and premature mortality. In spite of that, large part of the population does not meet physical activity guidelines and many individuals live a sedentary life. Recent technological progresses and the widespread adoption of mobile technology, such as smartphone and wearables, have opened the way to the development of digital behaviour change interventions targeting physical activity promotion. Such interventions would greatly benefit from the inclusion of computational models framed on behaviour change theories and model-based reasoning. However, research on these topics is still at its infancy. The current paper presents a smartphone application and wearable device system called *Muoviti!* that targets physical activity promotion among adults not meeting the recommended physical activity guidelines. Specifically, we propose a computational model of behaviour change, grounded on the social cognitive theory of self-efficacy. The purpose of the computational model is to dynamically integrate information referring to individuals' self-efficacy beliefs and physical activity behaviour in order to define exercising goals that adapt to individuals' changes over time. The paper presents (i) the theoretical constructs that informed the development of the computational model, (ii) an overview of *Muoviti!* describing the system dynamics, the graphical user interface, the adopted measures and the intervention design, and (iii) the computational model based on Dynamic Decision Network. We conclude by presenting early results from an experimental study.

1. Introduction

Noncommunicable diseases such as cardiovascular and respiratory diseases, cancer, diabetes, and obesity are the main cause of mortality in Western countries and cause unimaginable costs for public health [1]. Although physical activity constitutes an important protective factor against such diseases [2], large part of the population does not respect the recommended physical activity guidelines and lives a sedentary life [3]. Hence, there is the need to find new, effective, and large-scale solutions to promote behaviour change in the direction of a higher physical activity.

Recent availability of effective and inexpensive sensors, generally embedded into commercial devices, such as wearables and smartphones, has opened the way to the development of smartphone applications (apps) oriented to promote health behaviour change [4]. Healthcare apps are becoming one of the most important and promising tools for delivering behaviour change interventions [5, 6]. With regards to physical activity (PA) behaviour, mobile sensors can perform direct, intense, and longitudinal measurements of physical parameters (e.g., the heartbeat) and may produce detailed records of the individual behaviour (e.g., exercise) that are immediately available for analysis [7]. Thanks to such opportunities for data collection, new technologies can rapidly manage and combine different input datasets, provide accurate predictions about the influence pattern among interested variables (e.g., behavioural, psychological), and deliver behaviour change interventions that are adaptive to individual and context changes over time [8]. For these reasons, mobile technology has been hypothesized to support the science of behaviour change and it constitutes a preferential tool both for modeling behaviour change theories and for testing them in real world settings [4, 9, 10]. In spite of that, existing PA apps are characterized by a lack of adherence to behaviour change theories [11] and relatively little attention has been paid to the adoption of specific computational models grounded in behaviour change theories [12]. More specifically, even though digital interventions that made extensive use of behaviour change theories produce larger effects on behaviour [13], Cowan and colleagues [11] evidenced that *Health & Fitness* apps mostly included only minimal theoretical content.

Self-efficacy theory [14, 15] is one of the most prominent psychological theories about behaviour change and it lays its foundations on the construct of self-efficacy. Self-efficacy (SE) has been defined as the beliefs in one's capabilities to organize and execute the courses of action required to produce given attainments [14]. Such beliefs affect several areas of human endeavor [15] and these effects are particularly relevant with regards to health-related behaviours [16–18]. More specifically, it has been consistently shown that self-efficacy is a key determinant for the adoption and maintenance of PA behaviour [17, 19, 20], as well as a mediator of the effects of interventions on physical activity [21–24].

Self-efficacy beliefs develop as a consequence of four sources of information: enactive mastery experience, vicarious experience, verbal persuasion, and physiological or affective states management [15]. Among them, mastery experience has been shown to be the most potent source of self-efficacy in different domains and populations [15, 25–27]. It refers to the direct experience of performing a specific task and, hence, it represents an authentic indicator of the individual ability to accomplish similar tasks in the future. Indeed, when people engage in tasks and activities, they interpret the results of their actions and they use such interpretations to develop beliefs about their capability and to subsequently act according with the created beliefs. Experiences interpreted as successful generally increase confidence while experiences interpreted as unsuccessful generally undermine it [15]. As a consequence, in light of the reciprocal influence between self-efficacy and behavior, the selection of any specific behavioral goal should be set with the aim to gradually support both the achievement of successful experiences and the increasing of self-efficacy. For this purpose, goals should be (i) doable in order to permit individuals to master successful experiences and (ii) challenging in order to adequately reinforce self-efficacy beliefs once the goal has been achieved [15, 28].

In recent years, we assisted the first attempts of developing computational models based on self-efficacy theory in order to promote PA [29, 30]. Self-efficacy theory is particularly suitable to be modeled because of its nature that is explicitly *dynamic* (i.e., it takes into account time-varying information such as individual achievements, self-efficacy beliefs and expectations) and, thus, permits adapting the intervention to the individual over the course of the intervention itself [12]. The advantages of developing a computational model based on a behaviour change theory, such as self-efficacy theory, mainly rely on the capacity of predicting directionality and magnitude of effects among variables (e.g., target behaviour and its psychological determinants),and simulating and testing how they change and influence each other across contexts and over time [31].

First computational models of self-efficacy focused on different approaches and frameworks. Pirolli [30] proposed a computational model, called ACT-R-DStress, aiming to (i) model interactions among behavioral goals, memories of past experiences, and behavioral performance, and (ii) explains and predict both the dynamics of self-efficacy and the individual performance in an exercise program. For these purposes the ACT-R-DStress exploited the computational neurocognitive architecture that characterizes the ACT-R theory's simulation environment [32]. Differently, Martin et al. [29] developed a dynamical model of social cognitive theory adopting principles from control system engineering with a focus on system identification methodologies. Specifically, *system identification* compares what happens in different states and contexts of the person over time to what was predicted by a precise mathematical model of a given theory. Such methods have been applied to PA promotion and to generate dynamical models for future predictions to be tested against social cognitive theory (for an overview see [33]).

The current paper presents an innovative computational model that is conceptually framed in self-efficacy theory with a particular emphasis on self-efficacy beliefs and goal setting constructs. The computational model is embedded in a digital behaviour change intervention delivered by *Muoviti!*, a mobile app and heart rate monitor system that aims at the promotion and maintenance of PA among adults not meeting the recommended PA guidelines. The main contribution of the current work is twofold: (i) generating a computational model that combines input data collected through mobile technology (i.e., amount of PA collected through a heart rate monitor, SE assessed through ecological momentary assessment) in order to set PA goals that are dynamically adapted to each individual's achievement and changes in SE over time and (ii) tuning the proposed computational model according to early empirical findings from real case studies.

2. Materials and Methods

2.1. Overview of Muoviti!

2.1.1. The Experimental System. The experimental system that constitutes *Muoviti!* is made of three key components (see Figure 1):

(i) A heart rate (HR) wristband needed to measure the amount of PA performed. More specifically, two commercial, low-cost and reliable HR monitors (i.e., MioAlpha, PulseON) have been tested. Such devices nonetheless provide an estimate of the relevant physiological parameters which is precise and reliable enough for our purposes [34, 35].

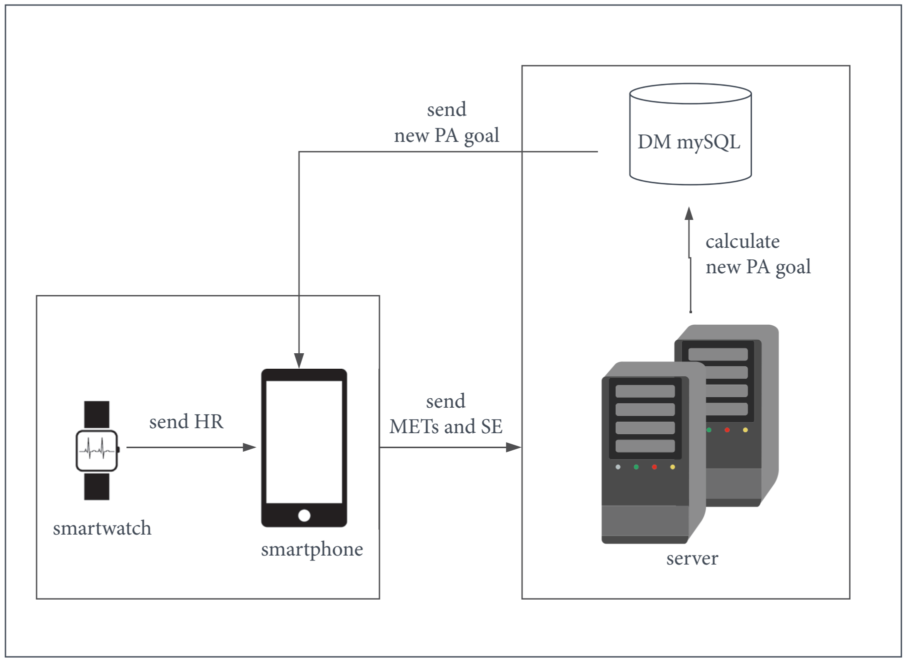
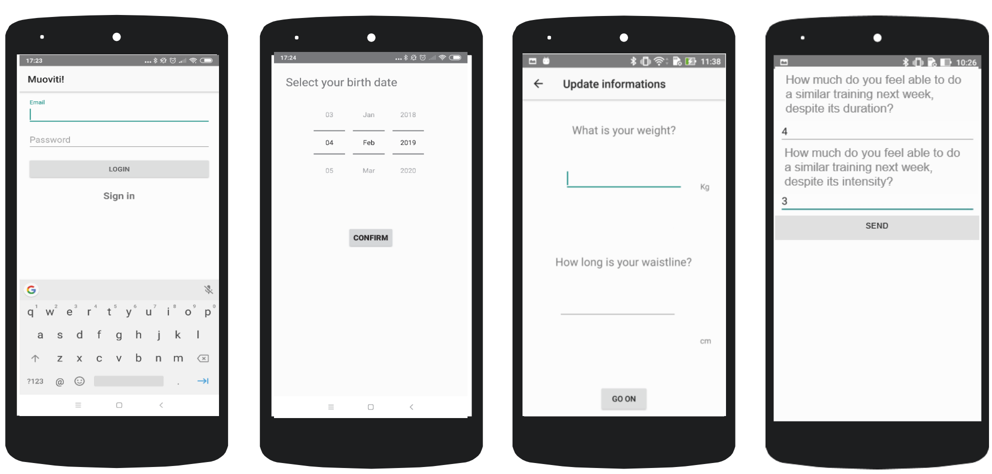


Figure 1: The general architecture of Muoviti!



1. Login phase 2. Age statement 3. Physical parameters detection 4. Self-Efficacy statement

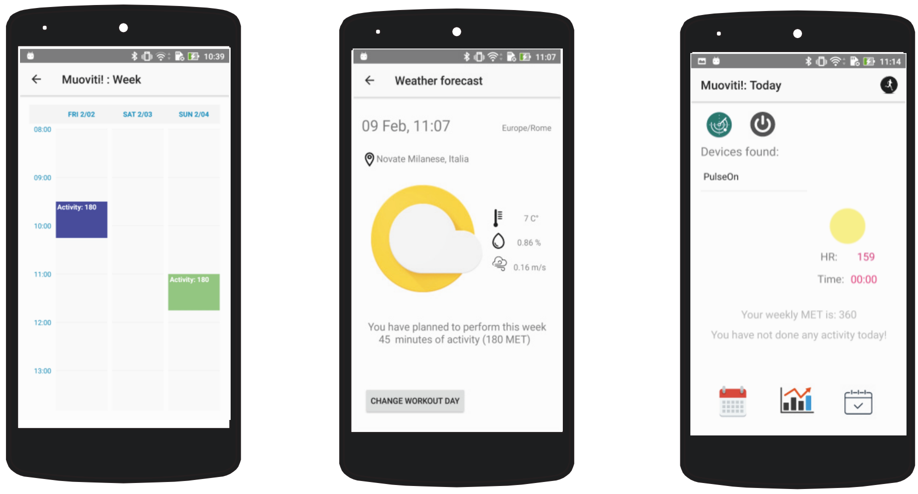
Figure 2: Screenshots from the Graphical User Interface (GUI) of the Muoviti! App.

(ii) A smartphone app which (i) handles the user interface, (ii) ecologically assesses SE through an *ad hoc* short questionnaire, (iii) collects information from the heart rate monitor, and (iv) transfers information to/from the back office.

(iii) A back office with a server that stores the data relative to each person and executes the modeling algorithm, thus formulating tailored PA suggestions for the next training period.

Muoviti! operates as follows. At the beginning of each weekly training period, a suggested PA goal for the week is generated on the basis of two different input data: (i) goal achievement during the previous week and (ii) SE beliefs in doing physical activity during the previous week. Finally, *Muoviti!* splits the weekly PA goal into daily short-term goals, translates them into concrete PA tasks (e.g., minutes of running, or fast walking), and presents them to the user (see below in the 'Computational model' paragraph).

2.1.2. Graphical User Interface. Figures 2 and 3 illustrate the main components of *Muoviti!*'s graphical user interface. During the login process, users are asked to specify the login credentials (Figure 2.1), their age (Figure 2.2), and other



1. Activity calendar
2. Training session information
3. Training session execution

Figure 3: Screenshots from the GUI of the Muoviti! App.

parameters like weight and waistline (Figure 2.3) that are useful to evaluate possible benefits or drawbacks emerging from exercising. Furthermore, the figure shows the interface for the collection of values to assess users' self-efficacy after a physical activity session (Figure 2.4). Each week the training sessions calendar is automatically updated on the basis of previous training sessions results (Figure 3.1). The user can manually place the activities suggested by the system to fit better with other duties (e.g., working hours). The calendar provides the patient with important information about the training event (Figure 3.2), like the weather forecasting, the duration and intensity of the activity to do, with the possibility for the user to change the position of the activity in the agenda. Finally, the system supports the user in self-monitoring and collecting significant data when the activity is accomplished (Figure 3.3), in particular the heart-beat rate, a visual warning about the correct execution of the activity, and the shortcuts to statistics and graphs about the results obtained.

Finally, Figure 4 illustrates how the individual performance has varied over the time, to provide people with an immediate feedback about the results obtained day by day and week by week. *Muoviti!* currently allows visualizing the heart-beat rate graph of the last training session, the curves of weight and waistline variations week by week, the burned calories graph, session by session, and the percentage of vigorous activity with respect to moderate activity.

2.2. Measures

2.2.1. Physical Activity. The computation of the PA goal for the new training period (i.e., output data) is expressed in terms of METs (Metabolic Equivalent of Task) that is a measure of the amount and quality of performed PA normalized to the physical characteristics and age of the individuals. Specifically, it METs represent the ratio of the metabolic rate (the rate of energy consumption) during a specific exercise to a reference metabolic rate:

$$1MET = \frac{kcal}{kg} * h \quad (1)$$

MET is used as a mean of expressing the intensity and energy expenditure of activities in a way comparable among persons of different weight. Actual energy expenditure (e.g., in calories or joules) during an activity depends on the person's body mass; therefore, the energy cost of the same activity will be different for persons of different weight. When the subject begins performing a PA training session, she/he asks the app to start the collection of PA data through the Bluetooth connection with the wristband. The app translates the HR collected by the wristband into the equivalent energy expenditure (METs), given by the following formula [36]:

$$MET\ minutes = 4 * Time^{MPA} + 8 * Time^{MPA} \quad (2)$$

where $\mathrm{Time}^{\mathrm{MPA}}$ and $\mathrm{Time}^{\mathrm{VPA}}$ are the periods of time the subject is involved in moderate physical activity (MPA) and vigorous physical activity (VPA) and parameters 4 and 8 represent the corresponding MET expenditure per minute. A PA session is defined as moderate if the registered HR values are in the range $[6 * MHR/10, 7 * MHR/10]$, while it defined as vigorous if the registered HR values are in the range $[7 * MHR/10, 8 * MHR/10]$. MHR represent the maximum heart rate depending on the subject age and it is calculated by subtracting *age* to a standard value (i.e., 220 – *age*).

2.2.2. Self-Efficacy Beliefs. SE beliefs are ecologically assessed at the end of each training session, through a set of questions to the person, each concerning a specific aspect of the physical activity. Currently, two questions are proposed to the user to evaluate the self-efficacy beliefs referring to the PA they have just performed:

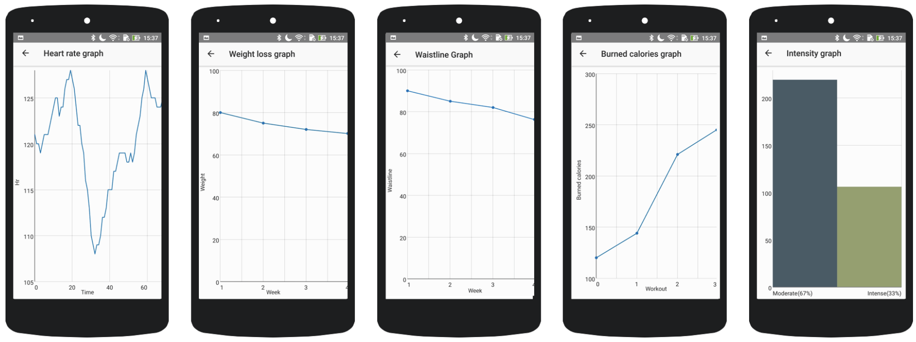


FIGURE 4: Screenshots from the GUI of the Muoviti! App.

(i) *How much do you feel able to do a similar training next week, despite its duration?*

(ii) *How much do you feel able to do a similar training next week, despite its intensity?*

The SE score is given by the arithmetic mean of the provided answers:

$$SE_i = \frac{\sum_{i=1}^{n} answer_i}{n} \quad (3)$$

where n is the number of questions posed to the user and $answer_i$ is the value given by the user on a 4-point Likert scale, ranging from 1 (not able at all) to 4 (absolutely able). The advantages of assessing SE through digital ecological momentary assessment rely on the opportunity to minimize recall bias, maximize ecological validity, and better understand behaviour in real-world contexts [37].

2.3. Intervention Design. *Muoviti!* aims to homogeneously merge physical and psychological variables into a unique conceptual framework, in order to build up tailored PA goals. For this purpose, at the end of the weekly period, the app interacts with the user by notifying the degree of accomplishment of the weekly goal and sends the recorded data to the back office. *Muoviti!*'s back office aggregates PA accomplishments and SE scores from each single training session in order to get a global evaluation of the users' PA accomplishments and SE beliefs over the week. The global evaluation of PA achievements and SE beliefs over the weekly period may assume the following facets and codes:

(i) Physical activity:

(a) The weekly PA goal was achieved (PA+);

(b) The weekly PA goal was not achieved (PA-);

(ii) Self-efficacy:

(a) The weekly PA self-efficacy was high – average SE equal or higher than 2.5 (SE+);

(b) The weekly PA self-efficacy was low – average SE lower than 2.5 (SE-).

After this assessment is made, the PA goal for the next week is proposed. Table 1 shows the decision rules about how global evaluations of PA and SE are combined in order to set new goals.

Finally, according to the user preferences, the PA goal for the next training period is successively split in daily short-term goals in order to support an effective action planning. The goal setting strategies at each period are taken with the aim of obtaining a successful result in a long-term perspective that is determined according to the general guidelines for PA promotion, which state that a person should perform 600 METs per week of PA [3].

2.4. Computational Modeling. The developed computational model combines knowledge about the PA performed, measured through the data collected by the wearables and an ecological momentary assessment of self-efficacy beliefs. The model was employed to define and dynamically adapt, a PA plan consisting of suggestions about the PA goal to be carried out every week, with the aim of maximizing the probability of bringing the person to the recommended PA level at the end of the long-term training period. The mathematical model adopted is a Dynamic Decision Network (DDN), a sequence of simple Bayesian Networks (BN), each representing the person's situation at a specific training period (i.e., one week). Figure 5 shows the current decisional model in *Muoviti!* (Part (a)) and the future one (Part (b)). The basic BN embodies variables which represent the physical activity performed, the estimated self-efficacy of the period, and the possible external factors (e.g., weather) influencing the performed activity. The DDN model includes decision variables at each training stage, which represent the PA goal proposed for the week, and a utility function on the final level of PA achieved. Moreover, the mathematical model of *Muoviti!* clearly combines self-efficacy with objective measurements of PA, being able to build up a personalized plan taking into account possible different trajectories towards the final goal.

The DDN model has been preferred to other approaches present in the literature (for instance, based on neurocognitive simulation [30] or on the theory of dynamic systems [29] because it represents with accuracy the sequence of decision points (the weekly PA suggestions) that we have envisioned in our approach. An explanation of the model can be given as follows: the NEW GOAL variable (on Figure 5, part (a))

Table 1: Decision rules and rationale for setting new weekly goals.

Condition	Goal for the new training period (*newGOAL*)	Rationale for the goal setting strategy based on the relevant literature [15, 28]
(PA+) & (SE+)	Increase PA goal	Setting a harder goal is challenging but doable for the person, because it is in line with the physical capabilities and supported by strong SE beliefs
(PA+) & (SE-)	Maintain the same PA goal	Maintaining the same goal is a strategy to reinforce the self-efficacy beliefs through the achievement of the same goal and thus trains the person for successive more difficult goals
(PA-) & (SE+)	Maintain the same PA goal	Maintaining the same goal is a strategy to avoid disappointing motivations and self-efficacy beliefs, thus provides the person with a further opportunity to achieve a goal corresponding to his/her SE beliefs
(PA-) & (SE-)	Decrease PA goal	Setting an easier goal is a strategy to allow the person to become familiar with the behaviour through an easier task and reinforce self-efficacy beliefs through more likely successful experiences

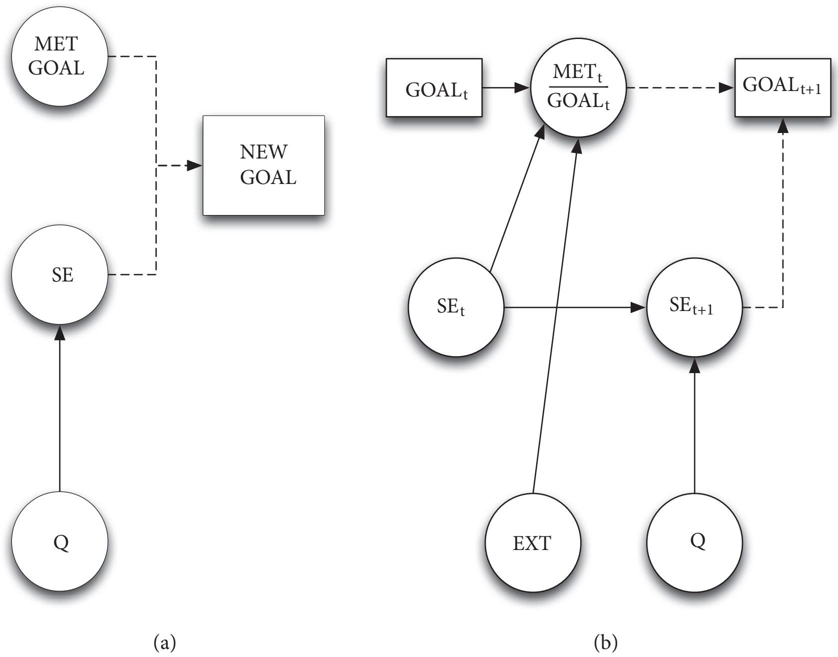


FIGURE 5: Part (a): the model basic decision step and Part (b): the relation between two consecutive “time slices” in the DDN model.

represents the decision to be taken at the beginning of each training period. It is influenced by the two basic variables describing the state of the subject: the SE and the level of success obtained in the preceding period, measured as the ratio of achieved METs with respect to the current GOAL. The achieved METs can be measured directly in our experimental system, and the SE can be evaluated from the result Q of a set of questions posed to the subject. Figure 5, Part (b) shows how the basic decision step is embedded in the sequence of time slices constituting the DDN. The structure of the model can be explained by considering its two main purposes:

(1) Providing an integrated estimation of SE on the basis of the self-report assessment of SE (i.e., Q) and SE autocorrelation in preceding periods. We consider that SE is a long-term developing psychological determinant of PA; therefore, its values in succeeding periods are correlated. The model conditions the SE_{t+1} value at the beginning of period t+1 to its preceding value SE_t, which has already shown its effects on the results (MET/GOAL) obtained in period t. We also introduced a variable EXT to explain away a decrease in SE when the observed PA shows a reduction due to factors external to the training (e.g., an illness or a period of bad weather).

(2) Providing planning decisions. The sequence of decisions represented by the $GOAL_t$ variables must lead the subject to achieve the desired PA level before the end of the program; the decision to be taken in each period must be compatible with this long-term target (i.e., 600 METs per week). We call the sequence of decisions from the present time until the end of the program a *strategy*. The overall objective is modeled by defining a utility function computed on the expected value assumed by the MET variable in a stable, long-term situation. The utility value distribution can be computed, for each strategy, on the basis of the present state assuming no external interference. In this way an updated assessment of the possible strategies can be carried out at each decision step.

The model tuning consists of the derivation of the conditional probability tables (CPT) from the experimental collection of data, as described in the next section.

3. Results

Muoviti!'s computational model represents a mathematical description of a behaviour change model based on self-efficacy theory that needs to be tuned according to real case studies. To this scope, we assume that potential users of *Muoviti!* can be classified into different basic profiles and that such profiles are represented by the different values in the CPTs present in the model. In this section we present early findings from a study based on real case data. For these purposes, we recruited 60 potential users of *Muoviti!*, chosen among people involved in indoor physical activity, mostly using treadmills. Participants (35 female, 25 male) were asked to use *Muoviti!* for a period of eight weeks, splitting the proposed amount of MET into two sessions, as suggested by the application. Each participant was in the 35-60 years old range, equipped with an Android smartphone and a wearable device capable to detect heart-beat rate, provided by us (i.e., PulseOn) or on their own. The study started with 120 MET as a goal to accomplish in the first week.

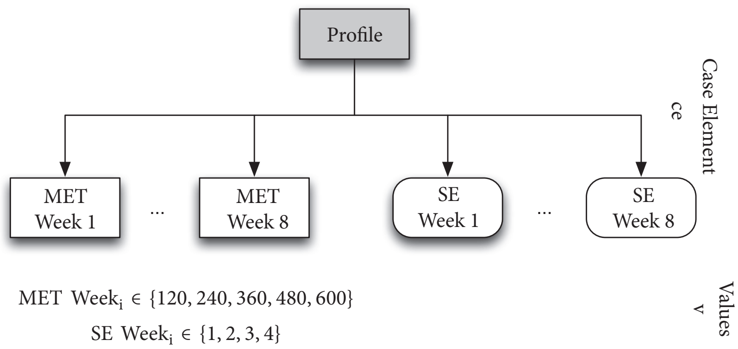


Figure 6: The case structure of our case study.

According to the results obtained, crossing self-efficacy and MET values obtained at the end of the week training session, the new goal could be increased or decreased by 120 MET with respect to the previous, or not modified, till a maximum value of 600 MET to reach. The collected data were used to build up a user profiling, suitable for the future set-up of the Dynamic Bayesian Network: each user was characterized by METs and SE values obtained in the eight weeks of the study, for a total of 16 descriptors. These descriptors were compared with an optimal user profile, exploiting the case-based reasoning paradigm and the CREPERIE platform [38, 39]. In CREPERIE, a case is a finite collection of pairs *(ce_i, v_i)*, i ∈ [1, ∞), where case elements *ce=(id, t, n)*, where *id* ∈ Z^+ - {0} is the case element identifier, t ∈ T identifies the range of values associated to ce (i.e., String, Integer, Double), and n ∈ String is the name of the case element; v ∈ t is the value associated to each ce. Case elements can be arranged into a vector or a tree. CREPERIE defines different kinds of similarity functions to use in the retrieval step, according to the nature of the case elements values. In particular, the following one has been adopted in our case study, given that the values are numbers:

$$sf(n, x\ y) = 1 - \frac{|v_{ce}(x) - v_{ce}(y)|}{\max - min} \quad (4)$$

where x and y are two cases, n is the attribute corresponding to ce(x) and ce(y), and max = $v_{ce}(n)$ ∈ x U y: $v_{ce}(n) \geq v_{ce}(m)$, for all $v_{ce}(m)$ ∈ x U y and min = $v_{ce}(k)$ ∈ x U y: $v_{ce}(k) \leq v_{ce}(j)$, for all $v_{ce}(j)$ ∈ x U y. In other words, max and min can be substituted by the extremes of the normalization interval if needed.

Once sf(n, x, y) has been calculated for all n in x and y, the similarity between case x and y is defined as follows:

$$sim(x, y) = \frac{\sum_{n \in D} sf(n, x, y)}{\sum_{n \in D} w_n} \quad (5)$$

where w_n ∈ [0, 1] is the weight of the attribute n, sim(x, y) is the local similarity between cases x and y, and D is the set of attributes in the cases.

Figure 6 shows the case structure adopted in our case study: the case elements were composed of 16 descriptors, eight met values reached during eight weeks of training and eight self-efficacy values calculated at the end of each week. The MET values are multiples of 120 in the range [120, 600], in accordance with the theoretical background of the model. The SE values are in the range [1, 4], according to (3). The denominator in the sf(n, x, y) calculus was equal to 480, given that the extremes of the met domain set were 120 and 600, respectively. Finally, we have considered w_n=1 for all n.

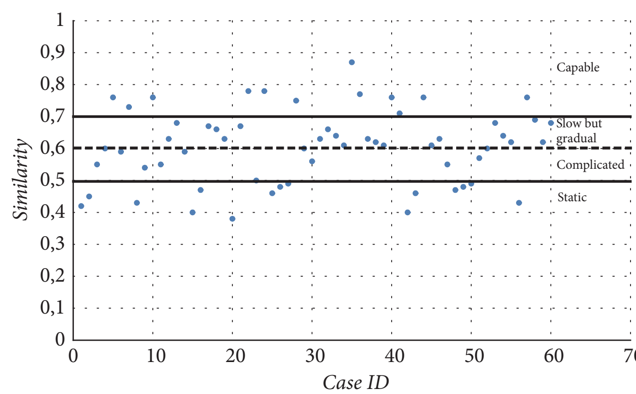


Figure 7: The profiling of Muoviti! app users according to the CREPERIE platform. Similarity values are on Y axis, while case element IDs are on the X axis.

Figure 7 shows the profiling of participants according to their similarity with the optimal profile. Four main clusters have been created: *static*, characterized by very low similarity degree with the optimal profile (less than 50%), *capable*, composed of profiles very similar to the optimal one (more than 70%), and a sort of "grey zone" with similarity between 50% and 70% where two subcategories can be identified, namely, *complicated* and *slow but gradual*. *Complicated* profiles are characterized by scarce physical performance and low self-efficacy, although they would potentially be able to reach proposed objectives; *slow but gradual* profiles are characterized by excellent physical performances, according to which they could be compared to optimal profile, but very low self-efficacy.

Table 2 shows some samples of users' data from the graph in Figure 7. The optimal profile data used in the case-based reasoning is shown at the end of the table.

Table 2: Samples of users' data referring to the current profiles emerged from the comparison with an optimal profile.

	Week							
	1st	2nd	3rd	4th	5th	6th	7th	8th
Profile 1–*Capable*								
Goal (METs)	120	240	360	480	360	480	480	600
Achievement	YES	YES	YES	NO	YES	YES	YES	NO
Self-Efficacy	HIGH	HIGH	HIGH	LOW	HIGH	LOW	HIGH	LOW
Profile 2–*Slow but gradual*								
Goal (METs)	120	240	360	360	360	480	480	360
Achievement	YES	YES	YES	YES	YES	YES	NO	NO
Self-Efficacy	HIGH	HIGH	LOW	LOW	HIGH	LOW	LOW	LOW
Profile 3–Complicated								
Goal (METs)	120	240	240	240	360	480	360	240
Achievement	YES	YES	YES	YES	YES	NO	NO	YES
Self-Efficacy	HIGH	LOW	LOW	HIGH	HIGH	HIGH	LOW	HIGH
Profile 4–*Static*								
Goal (METs)	120	120	240	120	120	240	120	120
Achievement	NO	YES	NO	NO	YES	NO	YES	YES
Self-Efficacy	HIGH	HIGH	LOW	HIGH	HIGH	LOW	LOW	LOW
Optimal Profile								
Goal (METs)	120	240	360	480	600	600	600	600
Achievement	YES	YES	YES	YES	YES	YES	YES	YES

4. Discussion and Conclusions

This paper presented an innovative approach to promote PA behaviour change among inactive adults. The approach is based on the development of a computational model grounded in self-efficacy theory and on the integration of mobile technologies and dynamic decision networks. The main aim of *Muoviti!* is to suggest personalized PA goals that adapt to individuals' changes in PA and self-efficacy over time. Early findings revealed the presence of four clusters of user profiles, reflecting the respective progression patterns towards the long-term goal. However, further research is needed to confirm such results by tuning the computational model around a greater number of real case studies. After having tuned the mathematical model in an experimental setting, *Muoviti!* will be tuned in real life contexts too. The purpose of this additional research phase is to develop a mathematical model that takes into account external (e.g., weather, time of the day, and day of the week), demographical (sex, age), and psychological (e.g., stress, outcome expectancies, and action control) factors that may influence the exercise behaviour. Furthermore, in the same vein, future research will aim to tune the current computational model in different populations (e.g., clinical populations) and contexts (e.g., rehabilitation settings) in order to validate its scalability. Finally, next works will be also devoted to develop an effective Android app for distribution: to this aim, many steps should be completed. In particular, the adherence of our approach to recent GDPR regulations must be implemented. At the current stage for development, personal data (like the heartbeat rate) of the users are stored inside their smartphones, while elaborations of the system are anonymized and stored in a cloud platform to be easily retrieved and used. Anyway, this is not sufficient to allow full sharing and downloading of the app through usual channels, like play-stores and websites. For this reason, at the end of this preliminary phase of analysis, where permissions to exploit user data have been only signed by the participants for research scopes, our strategy in future developments of the Muoviti! app will be completely revised.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

References

[1] A. Boutayeb and S. Boutayeb, "The burden of non communicable diseases in developing countries," *International Journal for Equity in Health*, 2005.

[2] B. K. Pedersen and B. Saltin, "Exercise as medicine - Evidence for prescribing exercise as therapy in 26 different chronic diseases," *Scandinavian Journal of Medicine and Science*, 2015.

[3] Who, *Global Recommendations on Physical Activity for Health*, World Health Organization, Geneva, Switzerland, 2010.

[4] K. Patrick, E. B. Hekler, D. Estrin et al., "The pace of technologic change: implications for digital health behavior intervention

research," *American Journal of Preventive Medicine*, vol. 51, no. 5, pp. 816–824, 2016.

[5] N. Lathia, V. Pejovic, K. K. Rachuri, C. Mascolo, M. Musolesi, and P. J. Rentfrow, "Smartphones for large-scale behavior change interventions," *IEEE Pervasive Computing*, 2013.

[6] S. Pagoto and G. G. Bennett, "How behavioral science can advance digital health," *Translational Behavioral Medicine*, 2013.

[7] E. B. Hekler, P. Klasnja, V. Traver, and M. Hendriks, "Realizing effective behavioral management of health: the metamorphosis of behavioral science methods," *IEEE Pulse*, Article ID 2271681, 2013.

[8] I. Nahum-Shani, S. N. Smith, B. J. Spring et al., "Just-in-time adaptive interventions (JITAIs) in mobile health: key components and design principles for ongoing health behavior support," in *Proceedings of the Annals of Behavioral Medicine*, 2016.

[9] W. J. Nilsen and M. Pavel, "Moving behavioral theories into the 21st century: technological advancements for improving quality of life," *IEEE Pulse*, Article ID 2271682, 2013.

[10] D. Spruijt-Metz, E. Hekler, N. Saranummi et al., "Building new computational models to support health behavior change and maintenance: new opportunities in behavioral research," *Translational Behavioral Medicine*, vol. 5, no. 3, pp. 335–346, 2015.

[11] L. T. Cowan, S. A. van Wagenen, B. A. Brown et al., "Apps of steel: are exercise apps providing consumers with realistic expectations?: a content analysis of exercise apps for presence of behavior change theory," *Health Education and Behavior*, 2013.

[12] W. T. Riley, D. E. Rivera, A. A. Atienza, W. Nilsen, S. M. Allison, and R. Mermelstein, "Health behavior models in the age of mobile interventions: Are our theories up to the task?" *Translational Behavioral Medicine*, 2011.

[13] T. L. Webb, J. Joseph, L. Yardley, and S. Michie, "Using the Internet to promote health behavior change: A systematic review and meta-analysis of the impact of theoretical basis, use of behavior change techniques, and mode of delivery on efficacy," *Journal of Medical Internet Research*, 2010.

[14] A. Bandura, "Self-efficacy: toward a unifying theory of behavioral change," *Psychological Review*, vol. 84, no. 2, pp. 191–215, 1977.

[15] A. Bandura, "Self Efficacy: the exercise of control," *American Journal Os Health Promotion*, 1997.

[16] A. Luszczynska and R. Schwarzer, "Social cognitive theory," in *Predicting Health Behaviour*, 2005.

[17] P. Steca, L. Pancani, F. Cesana et al., "Changes in physical activity among coronary and hypertensive patients: A longitudinal study using the Health Action Process Approach," *Psychology & Health*, vol. 32, no. 3, pp. 361–380, 2016.

[18] P. Steca, L. Pancani, A. Greco et al., "Changes in dietary behavior among coronary and hypertensive patients: a longitudinal investigation using the health action process approach," *Applied Psychology: Health and Well-Being*, vol. 7, no. 3, pp. 316–339, 2015.

[19] A. E. Bauman, R. S. Reis, J. F. Sallis, J. C. Wells, R. J. F. Loos, and B. W. Martin, "Correlates of physical activity: why are some people physically active and others not?" *The Lancet*, vol. 380, no. 9838, pp. 258–271, 2012.

[20] L. S. Rovniak, E. S. Anderson, R. A. Winett, and R. S. Stephens, "ocial cognitive determinants of physical activity in young adults: A prospective structural equation analysis," in *Proceedings of the Annals of Behavioral Medicine*, 2002.

[21] S. Ashford, J. Edmunds, and D. P. French, "What is the best way to change self-efficacy to promote lifestyle and recreational physical activity? A systematic review with meta-analysis," *British Journal of Health Psychology*, 2010.

[22] V. Burke, L. J. Beilin, H. E. Cutt, J. Mansour, and T. A. Mori, "Moderators and mediators of behaviour change in a lifestyle program for treated hypertensives: a randomized controlled trial (ADAPT)," *Health Education Research*, 2008.

[23] C. D. Darker, D. P. French, F. F. Eves, and F. F. Sniehotta, "An intervention to promote walking amongst the general population based on an "extended" theory of planned behaviour: a waiting list randomised controlled trial," *Psychology & Health*, 2010.

[24] G. R. Dutton, F. Tan, B. C. Provost, J. L. Sorenson, B. Allen, and D. Smith, "Relationship between self-efficacy and physical activity among patients with type 2 diabetes," *Journal of Behavioral Medicine*, 2009.

[25] S. L. Britner and F. Pajares, "Sources of science self-efficacy beliefs of middle school students," *Journal of Research in Science Teaching*, 2006.

[26] C. W. Loo and J. L. F. Choy, "Sources of self-efficacy influencing academic performance of engineering students," *American Journal of Educational Research*, 2013.

[27] L. M. Warner, B. Schüz, J. K. Wolff, L. Parschau, S. Wurm, and R. Schwarzer, "Sources of self-efficacy for physical activity," *Health Psychology*, 2014.

[28] E. A. Locke and G. P. Latham, "Building a practically useful theory of goal setting and task motivation: A 35-year odyssey," *American Psychologist*, 2002.

[29] C. A. Martin, S. Deshpande, E. B. Hekler, and D. E. Rivera, "A system identification approach for improving behavioral interventions based on Social Cognitive Theory," in *Proceedings of the American Control Conference*, 2015, https://doi.org/10.1109/https://doi.org/10.1109/ACC.2015.

[30] P. Pirolli, "A computational cognitive model of self-efficacy and daily adherence in mHealth," *Translational Behavioral Medicine*, vol. 6, no. 4, pp. 496–508, 2016.

[31] E. B. Hekler, S. Michie, M. Pavel et al., "Advancing models and theories for digital behavior change interventions," *American Journal of Preventive Medicine*, vol. 51, no. 5, pp. 825–832, 2016.

[32] J. R. Anderson, D. Bothell, M. D. Byrne, S. Douglass, C. Lebiere, and Y. Qin, "An integrated theory of the mind. Psychological Review," *Psychological Review*, 2004.

[33] E. B. Hekler, D. E. Rivera, C. A. Martin et al., "Tutorial for using control systems engineering to optimize adaptive mobile health interventions," *Journal of Medical Internet Research*, vol. 20, no. 6, p. e214, 2018.

[34] S. E. Stahl, H.-S. An, D. M. Dinkel, J. M. Noble, and J.-M. Lee, "How accurate are the wrist-based heart rate monitors during walking and running activities? Are they accurate enough?" *BMJ Open Sport & Exercise Medicine*, 2016.

[35] G. Valenti and K. R. Westerterp, "Optical heart rate monitoring module validation study," in *Proceedings of the Digest of Technical Papers - IEEE International Conference on Consumer Electronics*, 2013.

[36] T. Armstrong and F. Bull, "Development of the world health organization global physical activity questionnaire (GPAQ)," *Journal of Public Health*, 2006.

[37] S. Shiffman, A. A. Stone, and M. R. Hufford, "Ecological momentary assessment," in *Proceedings of the Annual Review of Clinical Psychology*, 2008.

[38] L. Manenti and F. Sartori, “etadata support to retrieve and revise solutions in case-based reasoning,” *International Journal of Metadata, Semantics and Ontologies*, 2011.

[39] F. Sartori, A. Mazzucchelli, and A. Di. Gregorio, “Bankruptcy forecasting using case-based reasoning: The CRePERIE approach,” *Expert Systems with Applications*, 2016.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