A recommender system for behavioral change in 60-70-year-old adults

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Abstract

Early old age (60-70 years old) is a particular period of life when possible habit modifications may occur, often related to job retirement. While taking up a more sedentary lifestyle may be pernicious for health, changing behavior by introducing simple exercises within daily life routines can effectively prevent age-related functional decline.

This article presents the Profiling Tool, a system that provides 60-70-year-old adults with personalized recommendations to integrate simple activities, promoting balance, strength, and physical activity into their daily life. Its first implementation has been designed on information from literature, data from previously available longitudinal datasets, and experts' opinions. It has been deployed within a randomized controlled trial. Strategies for its update are based on model-based reinforcement learning approaches.

Keywords 1

Ageing, functional decline, prevention, recommender system, behavioral change

1. Introduction

Population aging is one of the major issues of our present world. Developing preventive interventions is one of the keys to tackling this issue, and Artificial Intelligence (AI) can enable these interventions and make them more effective and efficient.

Early old age (60-70 years old) is thought to be the right window of opportunity for prevention. In this period of life, habit modifications may take place, often related to job retirement. While taking up a more sedentary lifestyle may be pernicious for health, changing behavior by introducing simple exercises within daily life routines can effectively prevent age-related functional decline.

Different mobile applications for healthy lifestyle promotion have been developed using behavioral change theories, and some of them have been tested within randomized controlled trials [1]–[3]. However, no design principle for using users' data to issue optimal recommendations has been ideated and put in place. Within this work, we present the Profiling Tool, a tool developed within the PreventIT project [4] that provides personalized recommendations to 60-70-year-old adults on strength, balance, and physical activities to integrate into daily life routines. Its ideation and design are based on psychological theories and techniques of behavioral change [5] and AI solutions for recommender systems [6].

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In the following sections, we overview the PreventIT project and IT ecosystem and describe the Profiling Tool, including its modeling, its first implementation and deployment within a randomized control trial, and strategies for its update.

2. PreventIT and the iPAS

PreventIT stands for 'Early risk detection and prevention in aging people by self-administered ICT-supported assessment and a behavioral change intervention, delivered by use of smartphones and smartwatches.' It is a European Horizon 2020 project carried out from January 2016 to March 2019 [4]. The project aimed to develop a proof-of-concept, unobtrusive mobile health system based on a personalized behavior change intervention on balance, strength, and physical activity. The intervention is designed for young older adults (adults between 60 and 70 years old) to prevent accelerated functional decline at an older age.

The PreventIT ICT based Personalized Activity System (iPAS) is a mobile health system delivering the intervention on smartphones and smartwatches. It includes a smartphone and smartwatch app as frontend and a risk model for functional decline [7], [8], the eLiFE intervention program, a Profiling Tool for personalizing the intervention, and a behavior change theories-based motivational strategy running on a cloud-based backend (**Figure 1**).

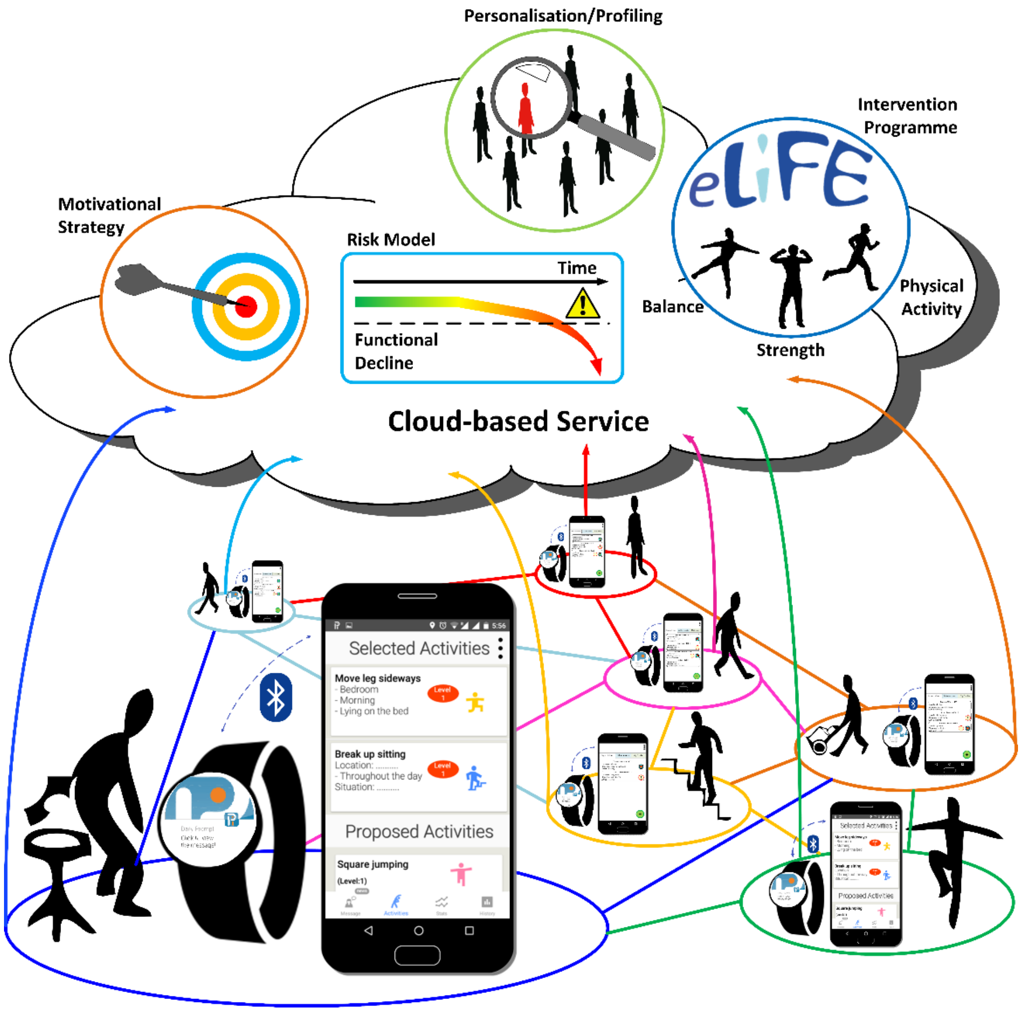

Figure 1. The PreventIT mobile health system's architecture, including risk screening for functional decline, profiling for personalizing the intervention, the eLiFE intervention program with balance, strength, physical activity integrated into daily life, and individual feedback on behavior aimed at increasing motivation for behavior change. A smartphone and a smartwatch are used to monitor behavior, deliver the intervention, and give individualized feedback on behavior.

The PreventIT intervention program is based on the Lifestyle-integrated Exercise (LiFE) approach [9]. In LiFE, rather than using a prescribed set of exercises, activities are performed whenever the opportunity arises during the day. The LiFE approach allows personalizing and integrating exercise in daily life, and it was found to significantly reduce falls, improve physical function, decrease disability and improve adherence, compared with a traditional exercise program and a sham intervention [10]. In PreventIT, the original LiFE was adapted (aLiFE, adapted LiFE, [11]) to the needs of 60-70-year-old adults to make activities challenging and complex enough for a younger target population. The integration of the aLiFE program into the PreventIT iPAS is named eLiFE (enhanced LiFE, [12]).

Since the LiFE program relies on users embedding balance, strength, and physical activities into their everyday life, it can only be successful if they change their behavior. The original LiFE concept is underpinned by the behavioral change concepts of habit formation, self-efficacy, skills training, and outcomes gained. The motivational strategy in PreventIT is based on the extension of the behavioral change framework supporting the intervention [5].

3. Profiling Tool

The Profiling Tool is a tool for personalized recommendations on activities to be integrated into seniors' daily life routines.

The Profiling Tool takes as input an individual's health state, a list of potential activities and difficulty levels, an estimate of their expected impact on the individual's health state, and contextual information, including the individual's preferences for the activities. On this knowledge basis, the Profiling Tool provides recommendations to the individual on which activities best fit their needs and the appropriate difficulty level for each activity.

There are 21 types of activities in the eLiFE program with up to four difficulty levels for each activity, grouped into three domains:

1. Strength domain: squatting, lunging, walking on toes, walking on heels, stair climbing, sit-to-stand, move legs sideways, tighten muscles;
2. Balance domain: tandem stand, one-leg stand, tandem walk, side-to-side leaning, forward-backward leaning, stepping over objects, stepping and changing direction, square stepping and hopping, square jumping;
3. Physical activity domain: walk longer, walk faster, sit less, break-up sitting.

These same three domains describe the individual's health state.

An expected benefit is calculated for every single eLiFE activity on the specific user profile. Recommendations are provided to the individual, accompanied by motivational messages, designed according to theoretical constructs of behavioral change (e.g., the Health Action Process Approach) [5].

Each day the subject selects a list of activities he/she will perform during the day and confirms the actually-performed activities at the end of the day. After every six months, the subject is assessed for his/her health state (**Figure 2**A). All this information about the interactions between the Profiling Tool and the individual and their effects is recorded by the iPAS and used by the Profiling Tool for its update.

In the following, we give a modeling description of the Profiling Tool and its interactions with the user, describe the implementation of its first version within the PreventIT project, and present an updating strategy.

4. Models

To appropriately design the Profiling Tool, including its recommendation policy and updating strategy, we characterize the interactions between the Profiling Tool and the user in terms of two models, describing the preferences of the individual for the activities and the benefit of these activities on the health state respectively.

4.1. Preference model

We define the preference model as the model that describes the activities that an individual with specific characteristics would perform when given personalized recommendations.

We use the subscript t to indicate the t-th six-month time period and the subscript $t \cdot i$ to indicate the i-th day of the t-th six-month period.

We call x_t the vector of subject's features – including their health state, $d_t = d(x_t)$ the personalized recommendations issued by the Profiling Tool, and $z_{t \cdot i} = \left(z_{t \cdot i,1}, z_{t \cdot i,2}, \dots, z_{t \cdot i,K}\right)'$ the vector expressing the $K = 21$ activities performed by the individual. In particular, $z_{t \cdot i,k}$ is the number of times the subject has performed activity k during day $t \cdot i$. We call z_t the vector expressing the number of times the individual has performed each activity during six months

$$z_t = \sum_{i=0}^{179} z_{t \cdot i} \tag{1}$$

Thus, the preference model that relates the cumulative selections z_t with the suggestions d_t can be expressed as

$$p(z_t | x_t, d_t) \tag{2}$$

Within the first version of the Profiling Tool, recommendations d_t were given in the form of an ordered list of potential activities, sorted according to their expected benefit on the individual's health state. Other choices are also possible to express more quantitatively the strength of recommendation for each activity. For example, $d_t = \left(d_{t,1}, d_{t,2}, \dots, d_{t,K}\right)$ could be a vector of such degrees of recommendation for each activity, under constrains

$$d_{t,k} \geq 0 \tag{3}$$

$$\sum_{k=1}^{K} d_{t,k} = 1 \tag{4}$$

A simple parametric form for the preference model (2) is

$$z_t = \delta_0 + \delta_1' d_t + \varepsilon_{z,t} \tag{5}$$

where δ_0 encodes personal preferences, $\delta_1' d_t$ encodes the influence of the recommendations, and $\varepsilon_{z,t}$ is an error term.

For recommendations that vary every day, the preference model can be expressed by

$$p(z_{t \cdot i} | x_t, d_{t \cdot i}) \tag{6}$$

and the linear model (5) could be replaced by a logistic or Poisson model over $z_{t \cdot i,k}$. We note that the features of the individual x_t do not change every day, as the health state is assessed once every six months.

Other forms for the preference model can be borrowed by the rich literature on choice modeling, and random utility theory [13], and models can easily be tested on data, as quantities x, d, and z are all observed and recorded in the iPAS system.

4.2. Health effect model

We define the health effect model as the model that describes the future health state x_{t+1}, based on the current health state x_t and the activities z_t performed by the individual

$$p(x_{t+1} | x_t, z_t) \tag{7}$$

Within the feature vector x, one variable y can be chosen as the primary outcome. A simple parametric form of the health effect model restricted to this outcome is

$$y_{t+1} = y_t + \alpha + \beta' z_t + \gamma' x_t + z_t' \theta x_t + \varepsilon_{y,t} \tag{8}$$

where α, β, and γ are vector parameters, θ is a matrix parameter, and $\varepsilon_{y,t}$ is an error term.

According to this model for the outcome, replacing z_t with a vector having 1 in the k-th component and zero otherwise, we get the expected health benefit on the outcome of one unit of activity k as

$$\beta_k + \sum_j \theta_{kj} x_j \qquad (9)$$

where β_k is the k-th component of vector β and θ_{kj} is the entry in position (k, j) of matrix θ.

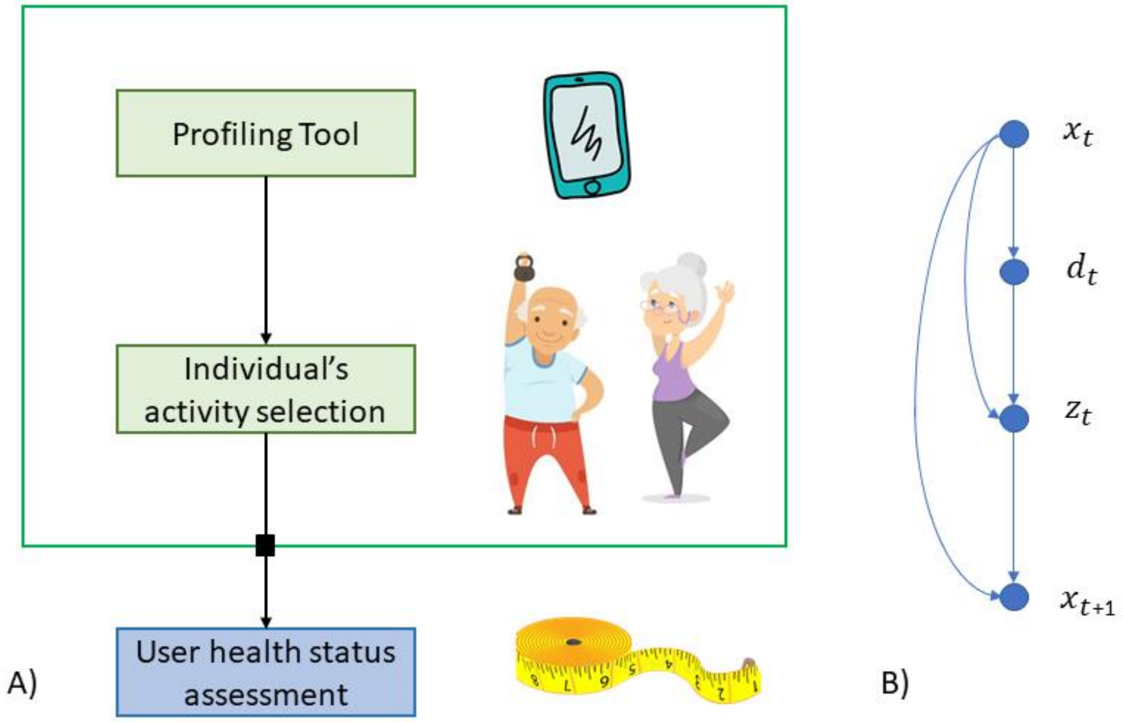

Figure 2: Activity selection and health effects. Panel A: The green rectangle represents a six-month cycle. Panel B: direct acyclic graph (DAG) [14] for the Bayesian network of health states x_t and x_{t+1}, recommendation d_t, and performed activities z_t. It encodes the conditional independence between x_{t+1} and d_t, given x_t and z_t.

As it is reasonable, we assume that the future health state x_{t+1} is independent of the recommendation d_t, conditional on the current health state x_t and the performed activities z_t (**Figure 2**B)

$$x_{t+1} \perp d_t \mid x_t, z_t \qquad (10)$$

Under this assumption, the transition probability $p(x_{t+1}|x_t, d_t)$ can be expressed as

$$p(x_{t+1}|x_t, d_t) = \int_z p(x_{t+1}|x_t, z_t)\, p(z_t|x_t, d_t) dz_t \qquad (11)$$

where we recognize the product of the preference and health effect models within the integral.

5. The first version of the Profiling Tool

The first version of the Profiling Tool was developed on knowledge from the literature, data from population studies on aging, and opinions from experts. It was tested in a feasibility randomized controlled trial (RCT) within the PreventIT study.

5.1. Design

This version for activity recommendation was based on four rules.

First, the feature vector at baseline x_0 was the three-score individual profile

$$x_0 = (s_1, s_2, s_3) \quad (12)$$

each score s_i ranging from 0 to 5 and expressing the prioritization of exercise on balance, strength, and physical activity domains. Each s_j was derived comparing measures of physical performance against cut-offs derived from the literature [15]–[19] and data of 60-70-year-old individuals pooled from three longitudinal studies on aging (ActiFE Ulm [20], InCHIANTI [21], LASA [22]). More in particular, for each domain, we considered two-to-three variables and created categories on these variables using cut-off values found in the literature. After applying these categories on the pooled cohort, if a prevalence of at least 10% was found in each category, the cut-off was retained valid. Otherwise, the cut-off was derived from the tertiles of the variable on the pooled cohort. Table 1 reports cut-offs, scores, and summary statistics on participants of the PreventIT study.

Table 1

Prevalence of categories of the individual profile of the Profiling Tool version 1 in participants in the feasibility RCT (n=189)

Assessment	Cut-off scores (males/females)	Profiling score	Prevalence in males (n=90)	Prevalence in females (n=99)
Balance				
Tandem stance (eyes open)	Unable or 0-9.99 s	2	24 (26.7%)	34 (34.3%)
	Able to hold for ≥10s	0	66 (73.3%)	65 (65.7%)
Tandem stance (eyes closed)	Unable or 0-9.99 s	2	76 (84.4%)	80 (80.8%)
	Able to hold for ≥10s	0	14 (15.6%)	19 (19.2%)
One leg stance (eyes open)	Unable or 0-9.99 s	1	38 (42.2%)	41 (41.4%)
	Able to hold for ≥10s	0	52 (57.8%)	58 (58.6%)
s_1: total score Balance median (IQR)		Range 0-5	2 (2-4)	2 (2-4)
Strength				
Handgrip strength (max. of one hand)	≤40.0 kg/ ≤23.0 kg	2	23 (25.8%)	25 (25.3%)
	40.0-47.0 kg/ 23.1-28.0kg	1	41 (46.1%)	35 (35.4%)
	>47.0 kg/ >28.0 kg	0	25 (28.1%)	39 (39.4%)
Chair stand test (five times)	Unable or ≥13 s/ ≥14.1 s	3	14 (15.6%)	10 (10.2%)
	10.8-12.9 s/ 11.5-14.0 s	2	18 (20%)	19 (19.4%)
	≤10.7 s/ ≤11.4 s	0	58 (64.4%)	69 (70.4%)
s_2: total score Strength median (IQR)		Range 0-5	2 (1-3)	1 (0-3)
Physical activity				
Gait speed	<1.0 m/s	2	1 (1.1%)	3 (3%)
	≥1.0 m/s	0	89 (98.9%)	96 (97%)
Moderate/vigorous activity per week	<150 minutes	1	30 (33.7%)	30 (31.2%)
	≥150 minutes	0	59 (66.3%)	66 (68.8%)
Step count	<7,499 steps/day	2	10 (11.2%)	6 (6.2%)
	7,500-9,999 steps/day	1	13 (14.6%)	17 (17.7%)
	≥ 10,000 steps/day	0	66 (74.2%)	73 (76%)

s_3: total score Physical activity median (IQR)	Range 0-5	1 (0-1)	1 (0-1)
Total score user profile, median (IQR)		5 (4-7)	5 (3-7)

Values are n (%) unless otherwise indicated.

Second, suggested activities were taken from a list of 21 activities, grouped according to three domains. Each activity was made of up to five difficulty levels, for a total of 89 exercises. The expected health impact of each activity was estimated from equation (9). In particular, the offsets β_k were set to zero, and matrix θ for the impact of each activity on each domain was filled by expert judgments with scores from 0 to 5.

Third, activities marked as not pleasant by the individual were dropped off the list of recommendations for the following days.

Fourth, for each suggested activity, its starting difficulty level was determined based on the individual's abilities assessed at the beginning of using the Profiling Tool by a trainer. The individual could decide at any time to downgrade the difficulty level of an activity, but they needed to train long enough to upgrade it.

Resulting recommendations $d_0 = d(x_0)$ were given in the form of a list of activities, sorted in descending order according to their expected health benefit.

The activities $z_{t \cdot i}$ performed each day were registered by the iPAS system, integrating feedback provided by the individual at the end of the day and recordings from global positioning system (GPS) and inertial measurement units (IMU) sensors embedded in the mobile phone.

A demo of this first version of the Profiling Tool is available on the Internet (http://taxonomy.disi.unibo.it/TaskRecommenderDemo/) [23].

5.2. Deployment

The Profiling Tool was tested within the three-arm PreventIT feasibility RCT (n=180) on three clinical centers in Trondheim, Stuttgart, and Amsterdam. One arm was assigned to the iPAS system and the Profiling Tool (eLiFE), one was given a booklet with recommendations by a trainer on activities to integrate into daily life (aLiFE). At the same time, participants of the control group were provided general physical activity recommendations. The primary outcome y was taken to be the Late-Life Function and Disability Instrument (LLFDI) [24], [25]. A detailed description of the trial protocol is available at [4].

The scoring system for the individual profile showed to be appropriate in stratifying the target population on domains of balance and strength, whereas, in the physical activity domain, too few participants (< 10%) fell on the lowest categories defined on gait speed and step count (Table 1).

On the participants of the eLiFE intervention arm that used the Profiling Tool (n=50), we evaluated with the iPAS system whether the ranking that was suggested by the Profiling Tool $d(x_0)$ was actually selected by the participants. In Table 2, it can be seen that there is not a clear association between the ranking of activities by the Profiling Tool and the actual choice of participants from the 21 activities. Activities ranked higher by the Profiling Tool, such as 'Square stepping and hopping' and 'Square jumping,' were not more frequently selected by participants to incorporate in their intervention regime. The only activities that showed a significant association ($p<0.05$) were 'Stepping over objects,' 'Stepping and changing direction,' and 'Lunging,' but there is not a clear pattern in the data to explain these associations.

The first evidence also shows that changes in health outcomes were modest over the RCT participants, making health effect models challenging to fit (data not shown).

Table 2

Frequency of activities ranked in the top 7 with Profiling Tool version 1 and that were actually selected by eLiFE participants (n=50).

Activities	Most frequent ranking profiling tool	In top 7 based on profiling tool	Actually selected by participants	Chi-square test ranking vs. selected p-value
Domain 1: Balance				
Tandem stand	21	-	25 (50.0%)	0.848
One leg stand	10	-	34 (68.0%)	0.083
Tandem walk	11	10 (20.0%)	24 (48.0%)	0.153
Side-to-Side leaning	7	13 (26.0%)	9 (14.0%)	0.609
Forwards and backwards leaning	3	23 (46.0%)	11 (22.0%)	0.685
Stepping over objects	8	2 (4.0%)	5 (10.0%)	0.009
Stepping and changing direction	9	9 (18.0%)	8 (16.0%)	0.039
Square stepping and hopping	2	40 (80.0%)	3 (6.0%)	0.869
Square jumping	1	48 (96.0%)	3 (6.0%)	0.060
Domain 2: Strength				
Squatting	15	8 (16.0%)	26 (52.0%)	0.251
Lunging	4	41 (82.0%)	27 (54.0%)	0.023
Walking on toes	5	39 (78.0%)	22 (44.0%)	0.247
Walking on heels	6	37 (74.0%)	11 (22.0%)	0.214
Stair climbing	17	24 (48.0%)	29 (58.0%)	0.064
Sit to stand	13	32 (64.0%)	26 (52.0%)	0.150
Move leg sideways	20	11 (22.0%)	10 (20.0%)	0.072
Tighten muscles	21	2 (4.0%)	11 (22.0%)	0.104
Domain 3: Physical activity				
Walk longer	18	-	9 (18.0%)	0.948
Walk faster	15	2 (4.0%)	5 (10.0%)	0.927
Sit less	19	-	17 (34.0%)	0.498
Break up sitting	12	9 (18.0%)	24 (48.0%)	0.387

Values are n (%).

6. Updating strategy

Data collected from the iPAS (either in the above-mentioned feasibility RCT or its continuous usage) may refine the Profiling Tool and make it more effective. To this end, we model the interactions between the Profiling Tool and the subject with a Markov Decision Process (MDP) [26]

$$MDP = \{T, X, \mathfrak{D}, p(x_{t+1}|x_t, d_t), r(x_t, d_t)\} \tag{13}$$

where:

- T is an ordered set of time points;
- X is the set of features characterizing the individuals;
- $\mathfrak{D}$ is the set of recommendations that the Profiling Tool can issue;
- $p(x_{t+1}|x_t, d_t)$ is the transition probability between state $x_t \in X$ at time $t \in T$ to state $x_{t+1} \in X$ at time $t+1 \in T$, when the Profiling Tool has issued the recommendation $d_t \in \mathfrak{D}$;
- $r(x_t, d_t)$ is the reward of being in the state x_t and issuing recommendation d_t.

We assume that issuing different recommendations has the same cost and thus the reward $r(x_t, d_t)$ is a function of the sole health state x_{t+1}. In particular, we pose a reward equal to the primary outcome:

$$r(x_t, d_t) = y_{t+1}. \tag{14}$$

Considering to use the data collected during the PreventIT feasibility trial to develop a second version of the Profiling Tool (**Figure 3**A), the Markov decision problem is defined over only one period ($T = \{0,1\}$) and is stated as follow

$$\max_{d_1:X\to\mathfrak{D}} E[r(x_1)|x_1,d_1] = \max_{d_1:X\to\mathfrak{D}} E[y_2|x_1,d_1] \tag{15}$$

$$= \max_{d_1:X\to\mathfrak{D}} \int_z E[y_2|x_1,d_1,z_1]p(z_1|x_1,d_1)dz_1$$

$$= \max_{d_1:X\to\mathfrak{D}} \int_z E[y_2|x_1,z_1]p(z_1|x_1,d_1)dz_1$$

Using the linear outcome model for $E[y_2|x_1,z_1]$ as in equation (8), and the preference selection model in equations (3-5), the problem (15) becomes:

maximize

$$d_1{}'\delta_1(\beta+\theta x_1) \tag{16}$$

subject to

$$d_{1,k} \geq 0\ \forall k \tag{17}$$

$$\sum_{k=1}^{K} d_{1,k} = 1 \tag{18}$$

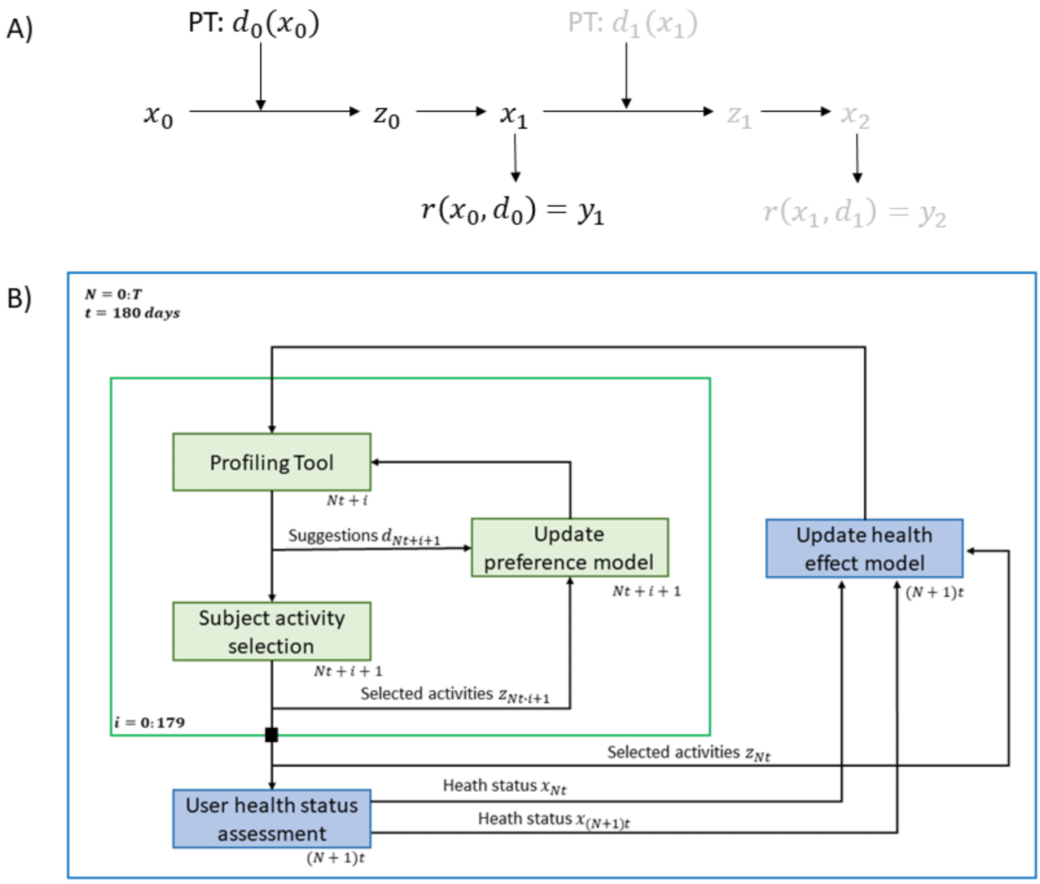

Figure 3: Update of the Profiling Tool (PT). Panel A. Quantities in black are those already collected with the first experimentation of the PT in PreventIT; quantities in grey are those relative to a second version of the PT. Panel B. Iterative updating strategy of the PT's preference and outcome models, in the case of iterative deployment. The inner green rectangle represents a six-month cycle with a time unit equal to one day, while the outer blue rectangle represents a cycle over repetitions of six-month cycles (i=0:179).

Given x_1 and having estimated the parameters δ_1, β, and θ from the data, the problem (16-18) is a simple linear program in the canonical form. Calling a the vector $\delta_1(\beta+\theta x_1)$, and provided that a has at least one positive component, the problem is solved by the sparse vector $d^* = (d_k^*)$, so that $d_k^* = 1$

for $k = arg \max_k a_k$, and $d_j^* = 0$ for all others $j \neq k$. We note that replacing constraint (3) with one over the L2 norm of d_t, makes the solution non-sparse.

Model parameters (e.g. $\delta_0, \delta_1, \alpha, \beta, \ldots$) could be derived for a) the whole population or sets of users, b) in a subject-specific manner, or c) combining both approaches with mixed-effect models. We judged that data from the PreventIT feasibility trial are insufficient to estimate all model parameters with appropriate precision and robustness. Hence, model fitting can proceed according to Bayesian estimation using parameter values of the first version to construct prior parameter distributions. Otherwise, data-driven recommendations can be combined heuristically with recommendations coming from the first version.

Figure 3B further shows a schema for updating the Profiling Tool beyond the second version, upon consecutive deployments over a time horizon T. The Profiling Tool is foreseen to evolve as more data accrue and update the preference and health effect models. The preference model can be updated every day since performed activities $z_{t \cdot i}$ are recorded daily, while the health effect model is updated with a six-month periodicity.

Focusing on the slower update periodicity and following the conceptual framework usually employed with MDPs, we define a cumulative reward

$$R(x_0) = E\left[\sum_{t=0}^{T} r(x_t, a_t) \mid x_0\right] = E\left[\sum_{t=1}^{T} y_t \mid x_0\right] \tag{19}$$

Considering the recommendation function

$$d_t : X \rightarrow \mathfrak{D} \tag{20}$$

that possibly changes with time as the Profiling Tool is updated, we aim to find a recommendation policy

$$\pi = (d_0, d_1, \ldots, d_T) \tag{21}$$

that maximizes $R(x_0)$.

Upon knowledge of the preference and health effect models, the transition probability is known and the Markov decision problem to find the optimal policy π^* can be solved with linear programming techniques (e.g., backward induction, value iteration, or policy iteration algorithms). However, in the more general case, both the transition probability and the recommendation policy have to be learned on data, as long as they accrue. Reinforcement learning heuristics serve this case [27], balancing the tradeoff between exploiting the likely most effective recommendations and exploring others' effectiveness.

7. Discussion

We have presented the Profiling Tool's design and first deployment, a recommender system for behavioral change of 60-70-year-old adults.

Its design was inspired by and based on psychological theories and techniques of behavioral change [5] and AI solutions for recommender systems [6]. Its first version was designed on information from the literature, data from cohorts of epidemiological studies on aging, and experts' opinions. The mathematical models that describe its interactions with the user serve to analyze its functioning and plan updating strategies as more data get available. To the best of our knowledge, their employment is new in the applicative field of mobile applications for prevention.

Analyses from its first deployment within the PreventIT feasibility RCT have provided insights. First of all, the individual profile scoring was shown to be satisfactory, distinguishing distribution of scores on the domains of balance and strength, but not on the physical activity domain, in our cohort of people aged 60-70 years old.

Secondly, recommendations are only loosely associated with actually-selected activities. In the PreventIT feasibility RCT, the intervention regime was put together by the participants themselves, in consultation with the trainer. This might have affected the decisions of participants and could have overruled the ranking by the Profiling Tool. Another possible cause behind this lack of correspondence between recommendations and user selection of activities may lie in the form the recommendations were provided. More specifically, recommendations were ordered list of activities without any indication of the strength of recommendation associated with each activity. For future developments, we could test whether recommendations become more convincing by expressing the strength of recommendation more quantitatively or by presenting a limited number (e.g., only the top 7 rankings) of activities. It is further suggested to explore different strategies for planning the intervention regime and sending motivational messages accompanying the recommendations.

Preliminary analyses have also shown that health changes could be small over six months for a highly functional target population, making health effect models challenging to estimate. This issue could be solved by deploying the tool on a population which is broader and more heterogeneous.

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9. References

[1] S. Mehra *et al.*, "Translating behavior change principles into a blended exercise intervention for older adults: Design study," *J. Med. Internet Res.*, vol. 20, no. 5, May 2018, doi: 10.2196/resprot.9244.

[2] A. C. King *et al.*, "Effects of Three Motivationally Targeted Mobile Device Applications on Initial Physical Activity and Sedentary Behavior Change in Midlife and Older Adults: A Randomized Trial," *PLoS One*, vol. 11, no. 6, p. e0156370, Jun. 2016, doi: 10.1371/journal.pone.0156370.

[3] L. Paul *et al.*, "Increasing physical activity in older adults using STARFISH, an interactive smartphone application (app); a pilot study," *J. Rehabil. Assist. Technol. Eng.*, vol. 4, p. 205566831769623, Jan. 2017, doi: 10.1177/2055668317696236.

[4] K. Taraldsen *et al.*, "Protocol for the PreventIT feasibility randomised controlled trial of a lifestyle-integrated exercise intervention in young older adults.," *BMJ Open*, vol. 9, no. 3, p. e023526, Mar. 2019, doi: 10.1136/bmjopen-2018-023526.

[5] E. Boulton *et al.*, "Implementing behaviour change theory and techniques to increase physical activity and prevent functional decline among adults aged 61–70: The PreventIT project," *Progress in Cardiovascular Diseases*, vol. 62, no. 2. W.B. Saunders, pp. 147–156, 01-Mar-2019, doi: 10.1016/j.pcad.2019.01.003.

[6] F. Ricci, L. Rokach, and B. Shapira, Eds., *Recommender systems handbook*, Second Edi. New York: Springer, 2015.

[7] N. H. Jonkman *et al.*, "Predicting Trajectories of Functional Decline in 60- to 70-Year-Old People," *Gerontology*, vol. 64, no. 3, pp. 212–221, Mar. 2018, doi: 10.1159/000485135.

[8] N. H. Jonkman *et al.*, "Development of a clinical prediction model for the onset of functional decline in people aged 65-75 years: Pooled analysis of four European cohort studies," *BMC Geriatr.*, vol. 19, no. 1, Jun. 2019, doi: 10.1186/s12877-019-1192-1.

[9] L. Clemson *et al.*, "LiFE Pilot Study: A randomised trial of balance and strength training embedded in daily life activity to reduce falls in older adults.," *Aust. Occup. Ther. J.*, vol. 57, no. 1, pp. 42–50, Feb. 2010, doi: 10.1111/j.1440-1630.2009.00848.x.

[10] L. Clemson *et al.*, "Integration of balance and strength training into daily life activity to reduce rate of falls in older people (the LiFE study): randomised parallel trial.," *BMJ*, vol. 345, no. aug07_1, p. e4547, Jan. 2012, doi: 10.1136/bmj.e4547.

[11] M. Schwenk *et al.*, "The adapted lifestyle-integrated functional exercise program for preventing functional decline in young seniors: Development and initial evaluation," *Gerontology*, vol. 65, no. 4, pp. 362–374, Jul. 2019, doi: 10.1159/000499962.

[12] J. L. Helbostad *et al.*, "Mobile health applications to promote active and healthy ageing," *Sensors (Switzerland)*, vol. 17, no. 3. MDPI AG, 18-Mar-2017, doi: 10.3390/s17030622.

[13] H. A. Soufiani, D. C. Parkes, and L. Xia, "Random utility theory for social choice," *Adv. Neural Inf. Process. Syst.*, vol. 1, no. 1, pp. 126–134, 2012.

[14] K. J. Rothman, S. Greenland, and T. L. Lash, *Modern epidemiology*, Third edit. Lippincott Williams and Wilkins, 2008.

[15] J. M. Guralnik, L. Ferrucci, E. M. Simonsick, M. E. Salive, and R. B. Wallace, "Lower-extremity function in persons over the age of 70 years as a predictor of subsequent disability.," *N. Engl. J. Med.*, vol. 332, no. 9, pp. 556–61, Mar. 1995, doi: 10.1056/NEJM199503023320902.

[16] F. Lauretani *et al.*, "Age-associated changes in skeletal muscles and their effect on mobility: An operational diagnosis of sarcopenia," *J. Appl. Physiol.*, vol. 95, no. 5, pp. 1851–1860, 2003, doi: 10.1152/japplphysiol.00246.2003.

[17] M. Cesari *et al.*, "Prognostic value of usual gait speed in well-functioning older people - Results from the health, aging and body composition study," *J. Am. Geriatr. Soc.*, vol. 53, no. 10, pp. 1675–1680, Oct. 2005, doi: 10.1111/j.1532-5415.2005.53501.x.

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

[19] C. Tudor-Locke and D. R. Bassett, "How Many Steps/Day Are Enough? Preliminary Pedometer Indices for Public Health," *Sports Medicine*, vol. 34, no. 1. Sports Med, pp. 1–8, 2004, doi: 10.2165/00007256-200434010-00001.

[20] M. D. Denkinger *et al.*, "Accelerometer-based physical activity in a large observational cohort--study protocol and design of the activity and function of the elderly in Ulm (ActiFE Ulm) study.," *BMC Geriatr.*, vol. 10, no. 1, p. 50, Jan. 2010, doi: 10.1186/1471-2318-10-50.

[21] L. Ferrucci *et al.*, "Subsystems contributing to the decline in ability to walk: bridging the gap between epidemiology and geriatric practice in the InCHIANTI study.," *J. Am. Geriatr. Soc.*, vol. 48, no. 12, pp. 1618–25, Dec. 2000.

[22] M. Huisman *et al.*, "Cohort profile: the Longitudinal Aging Study Amsterdam.," *Int. J. Epidemiol.*, vol. 40, no. 4, pp. 868–76, Aug. 2011, doi: 10.1093/ije/dyq219.

[23] University of Bologna - AI Group, “PreventIT Profiling Tool,” 2017. [Online]. Available: http://taxonomy.disi.unibo.it/TaskRecommenderDemo/. [Accessed: 14-Sep-2020].

[24] A. M. Jette *et al.*, "Late life function and disability instrument: I. Development and evaluation of the disability component.," *J. Gerontol. A. Biol. Sci. Med. Sci.*, vol. 57, no. 4, pp. M209-16, Apr. 2002.

[25] S. M. Haley *et al.*, "Late Life Function and Disability Instrument: II. Development and evaluation of the function component.," *J. Gerontol. A. Biol. Sci. Med. Sci.*, vol. 57, no. 4, pp. M217-22, Apr. 2002.

[26] M. L. Puterman, *Markov Decision Processes. Discrete Stochastic Dynamic Programming*. Hoboken, New Jersey: John Wiley & Sons, Inc., 2005.

[27] R. S. Sutton and A. G. Barto, *Reinforcement learning. An introduction*, Second ed. Cambridge, Massachusetts, USA: MIT Press, 2018.