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Tailoring mHealth Apps on Users to Support Behavior Change Interventions: Conceptual and Computational Considerations

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Abstract: Personalization is an important factor to increase the user experience (UX) and effectiveness of mHealth solutions. In this paper, we present an innovative approach to the personalization of mHealth apps. A profiling function has been developed based on the physical and psychological characteristics of users, with the final aim to cluster them acting as a guideline to the design and implementation of new functionalities to improve the overall acceptance degree of the app. A preliminary analysis case study has been proposed to evaluate the impact on user experience according to the state of the art to draw useful lessons for future works.

1. Introduction

Wearable expert systems [1] (WES) and wearable environments [2] have been recently introduced as methodological frameworks for developing recommendation systems tailored to user characteristics, thanks to the effective integration of wearable devices and knowledge-based methods. Indeed, one of the most challenging fields of application is mHealth, concerning the exploitation of mobile computing and communication technologies in health care and public health [3], as witnessed by the recent development of many similar applications in the field (see, e.g., [4–6]).

Modern Smartphones and wearable devices have many interesting features that can be useful to design and implement mHealth applications; the integration of behavior change theories (BCT) [7] in wearable expert systems is a promising approach from this point of view, in particular for WES devoted to goal-setting or self-monitoring of users' behavior [8]. Smartphones and wearable devices contribute to filling the gap between health monitoring and decision-making processes, empowering both patients and professionals. The role of the former is crucial, looking for more and more engaging user experiences during the applications use; positive experiences can support to influence health behaviors, which in turn can impact desirable health outcomes expected by professionals. Analyzing mHealth apps from the UX perspective is a good opportunity to formulate new theories and practices, as well as develop new successful technologies.

In this context, the MoveUp module of the PERCIVAL project [9] has been designed and implemented to support a risky population, i.e., people in the range 35–45 years with a sedentary lifestyle, to change their behavior by making the recommended amount of weekly physical activity (PA). The system deliberations are tailored to the physical and psychological characteristics of users. Personalization, meant as the incorporation of recognizable aspects of a person into tailored content [10], is a key aspect to be incorporated into mHealth solutions to promote behavioral change [11] and positive UX. In [12], the authors conducted an interesting review of literature pointing out how personalization is considered the most important feature for increasing the UX feeling in mobile health app development, with respect to other characteristics, like reinforcement, navigation, message

presentation, interface aesthetic, credibility, and communication. The authors defined personalization as a design feature that makes mobile technology act in a particular way depending on user preferences, composed of three elements, namely *assessment*, *feedback*, and *manipulation*. About the first point, users expect to be assessed with metrics pertaining to the health problem that was the focus of the intervention in as much detail as possible to create an *accurate profile*. About the second point, it is highlighted that users quickly lost interest when they did not receive feedback that was customized; they prefer mobile devices providing personalized information, including tailored intervention content matched to their basic characteristics, and feedback on continuous monitoring data, for example, their health and behavior progress over time, predicted possible causes and consequences of a health problem and advice on the behavior under investigation, possibly presented in graphical or tabular form. Finally, users wanted to be able to customize the mHealth intervention themselves, choose when and how they receive reminders, set goals for the future use of the tool, and so on. As reported in [13], the profile of users is a crucial dimension for personalization of mHealth intervention, as well as the customization of apps, enabling the user to state interests and preferences explicitly using a direct configuration of human–computer interfaces or system's options [14].

In this paper, we reflect on these issues by presenting a recent extension of MoveUp that bridges these two dimensions of mHealth personalization: A *user profiling* functionality has been added to MoveUp to estimate which is the overall level of physical and psychological well-being at the end of a week, and this function has been exploited to increase the overall performance of the app from the UX perspective. A preliminary evaluation of these functionalities is also included in the paper to address future developments based on user feelings.

The rest of the paper is organized as follows: Section 2 provides a brief literature review about the use of wearable technologies in the mHealth domain from the user experience point of view; Section 3 presents the main conceptual and computational aspect of the MoveUp module in terms of underlying *core model* (see Section 3.1) and *experimental setup* to increase personalization (see Section 3.2); Sections 4 and 5 describe the new method to profile users in MoveUp from the design and implementation perspectives, respectively; Section 6 presents the results of a test conducted to evaluate the user experience perception of the solution proposed. Finally, Section 7 briefly ends the paper by addressing future research based on previous content.

2. Related Work

The term *user experience* was introduced in 1995 [15]; the original idea behind its definition was to reflect the experience between a human and a system in terms of many aspects that go beyond the human interface or usability. According to the authors, the understanding of users' needs is the crucial issue that should guide UX; such needs should be met by designers providing users with positive feelings when using applications. Another relevant definition of UX was given by *the International Standard on Ergonomics of Human-System Interaction* (ISO 9241-210) as *a person's perceptions and responses that result from the use or anticipated use of a product, system, or service* [16].

Anyway, a shared definition of UX is not available: as user experience is subjective by nature and related to an individual's perception (i.e., products or services) they interact with [17], characterizing it to understand if a given application will be acceptable is not simple.

A recent work [18] has produced a very relevant review of the literature with the final purpose to propose a framework for classifying the different characteristics and approaches to UX developed over the last decades. They have classified UX typologies as follows:

- *Ergonomic*: the UX is focused on the human–system interaction from the usability, performance, affordances, effectiveness, and user's behavior;
- *Cognitive*: the UX focus is on the system perception and understanding by humans, in particular from the functional and aesthetic points of view;

- *Emotions*: the UX concerns how the users feel, in terms of pleasure, empathy, hedonistic values, social values, affection, and so on.

With respect to the mHealth domain, it is known that the acceptance level is low [19]. *Care for the elderly* is one of the most important fields. Wearable devices can be useful to monitor aged people living in critical conditions [20], increasing their autonomy level and supporting them to delay the negative effects of aging [21]. Wearing a device that monitors and tracks movements encourages the user to be more proactive in increasing their activity level [21]. Despite these great opportunities, wearables services are still behind elderly expectations [19]. The main reason for this is the objective difficulty in designing applications capable of meeting the elderly needs due to their low ICT literacy and adoption [22]. Many researchers, such as [23] have demonstrated how the inclusion of personalization aspects in the design and implementation of mobile health applications can have a positive impact on the involvement of older adults, with great benefits on the quality of life of caregivers too.

Wearable devices have been demonstrating their usefulness in the management of chronic diseases too. People at higher levels of risk can be continuously monitored at home. Patients suffering from heart diseases, diabetes, and so on can collect data about their conditions and interact with doctors at a distance [24,25]. They can wear sophisticated glucose monitors to check their status continuously [26,27]. Psychological support is really important in the treatment of chronic patients [28]. Their motivation to follow therapies and good lifestyles must be continuously monitored and stimulated [29]. The proper support of caregivers is even more crucial: many studies, such as [30] point out the extremely heavy burden suffered by relatives of the patient, especially in the early stages of a chronic disease: the adoption of sensors and wearable devices can significantly decrease their burden, especially when chronic conditions are paired with aging and related complications [31]. As reported in [32], wearable devices are mandatory to implement personalization in healthcare and, consequently, to improve UX feelings; moreover, efficient and effective services must be designed to tailor the more and more sophisticated and powerful available technologies for the user needs. In [33], a very detailed and extensive categorization of mobile apps on the market has been proposed, grouping them into 18 clusters. Among them, two categories concern data management and communication, nine on monitoring and tracking a patient's health conditions, five on the treatment of specific diseases (including compliance), and two on the support of doctors in analyzing data and reasoning.

Many WES-like applications have been recently developed that can be classified accordingly. In [34], an expert system based on the *wireless sensor networks* paradigm is presented for supporting aged people at home, customized to the specific needs of the elderly. In [35], a new methodology is designed for objective evaluation and automatic scoring of bradykinesia in repetitive finger-tapping movements for patients with idiopathic Parkinson's disease and atypical parkinsonism. In [36], a web-based remote human pulse monitoring application with intelligent data analysis is presented, based on physiological sensors, wireless communication, and intelligent data analysis technologies, for home health care in daily lives. A pulmonary disease management system with on-body and near-body sensors is described in [37]; fall detection is the main goal of applications in [38–40], where different kinds of reasoning techniques are combined with data detection from sensors to obtain personalized alarms about fall risk for elderly people.

Successful use of mHealth apps can potentially provide information and support diagnosis. Such tools can increase communication levels among the roles involved in disease management, i.e., patients, professionals, and caregivers, as highlighted in [41]. In [42], correspondence, competence, and relevance are indicated as the most valuable characteristics of an mHealth service to be fully accepted. Correspondence concerns the trade-off between the functionalities of the service and the needs perceived by the user. Competence regards the psychological effort the user requires during the interaction with the service. Relevance is a measure of the user's personal understanding of a service.

Some researchers [43] focus on trust dimensions too, like privacy and security. Indeed, it is necessary to keep the user involvement high on a long-term horizon [44], developing apps that consider user experience to promote their long term use to reach effective behavior change of the users, with benefits from the reduction of health risks perspective [45].

User experience depends on the emotional state of the user, that could change during and after the interaction with a product or service [46]. According to [47], UX aspects having influence on the relationship between the user and a product are privacy, context, emotional state, functionality, infrastructure, service response time, and visual attractiveness. Given that user experience is context-dependent, mHealth apps should export different characteristics of user experience, like ubiquity, interactivity, personalization, and context sensitivity [48]. Moreover, patient history, clear instructions, and feedback are key features that mHealth apps should include based on users' needs [49].

3. Materials and Methods

The PERCIVAL project [9] has been launched as an example of a wearable expert system to offer a treatment of chronic diseases tailored to the physical and psychological characteristics of users. Physical activity is one of the most important factors to prevent or mitigate chronic diseases; the MoveUp module of PERCIVAL has been designed and implemented to support a risky population, i.e., people in the range 35–45 years with a sedentary lifestyle, to change its behavior making the recommended amount of weekly physical activity. The MoveUp module proposes a personalized plan evaluating the physical and psychological conditions of the person through quantitative and qualitative variables. By doing so, the wearable expert system can promote a *behavior change intervention*, collecting data that can be easily analyzed by human experts too. The final aim of the app is to support the user to reach (and maintain) the amount of 600 MET of PA per week prescribed by WHO guidelines [50].

3.1. The Core of a Wearable Expert System

Metabolic equivalent of task (*MET*) variable is adopted to evaluate the amount and intensity of PA accomplished; moreover, the MoveUp module estimates users' *self-efficacy* (*SE*) at the end of each training session. *MET* calculus is based on the relationships between *MET* and *heart beat rate* (HBR) [51]:

$$MET = 4 \times Time^{MPA} + 8 \times Time^{VPA} \tag{1}$$

where $Time^{MPA}$ and $Time^{VPA}$ are the periods of time the subject performs *moderate* and *vigorous* physical activity, measured in minutes. A PA session is defined *moderate* if the registered HBR values are in the range $[\frac{6 \times MHR}{10}, \frac{7 \times MHR}{10}]$, with $MHR = 220 - age$ is the subject *maximum heart rate*, depending on his/her *age*. A PA session is defined *vigorous* if the registered HBR values are in the range $(\frac{7 \times MHR}{10}, \frac{8 \times MHR}{10}]$. Two PA sessions per week must be accomplished by the user.

Self-efficacy variable [52] has been considered to estimate psychological conditions. SE, also referred to as *personal efficacy*, is evaluated through a collection of questions about the positive or negative conduction of training sessions:

$$SE_{day_i} = \frac{\sum_{j=1}^{n} answer_j}{n} \tag{2}$$

where $day_i, i \in [1, 2]$ identifies the current day of physical activity, n is the number of questions posed to the user, and $answer_j$ is the value given by the user, usually an integer value in the range [1...4]. Currently, two questions are posed to the user for self-efficacy estimation: *How much do you feel able to do similar training next week, despite its duration? How much do you feel able to do similar training next week, despite its intensity?* The sum of SE_{day_i} values returns the whole self-efficacy on a week (thus, $2 \leq SE_{week} \leq 8$). A user could not answer too: in this case, their SE_{week} would be set to 1 by default.

The reasoning process is implemented as a rule-based system to link physical and psychological variables obtaining suggestions for the next week, i.e., *increase by 120 MET*, *maintain*, or *decrease by 120 MET*.

3.2. Personalization Level Improvement in MoveUp

The MoveUp module has been tested in a real experiment, during which 60 users were monitored for eight weeks in performing PA tasks suggested by the system. The starting point for each user was 120 MET per week (equivalent to 30 min of moderate physical activity). The wearable device to get heartbeat rate was a $PulseOn^T M$ smartwatch. The users were 25 female and 35 male subjects in the 35–45 age range. A profile for each of them was developed, combining eight values of PA (numeric values from $MET_{min} \in [120, 240, 360, 480, 600]$) and SE (numeric integer values in the range [2, 8] obtained during the test, for a total of 16 features.

These features have been analyzed with experts [53] to define groups of people according to the comparison with an *optimal profile* exploiting the case-based reasoning (CBR) paradigm [54]. Such a profile characterizes a user capable of increasing their goal every week, thanks to the highest levels of both *MET* and *SE* variables. Such user would reach the maximum amount of MET, i.e., 600, at the 5th week of training, maintaining the goal for the last three weeks. Four classes have been determined based on the similarity percentage to the optimal profile, which are summarized in Figure 1.
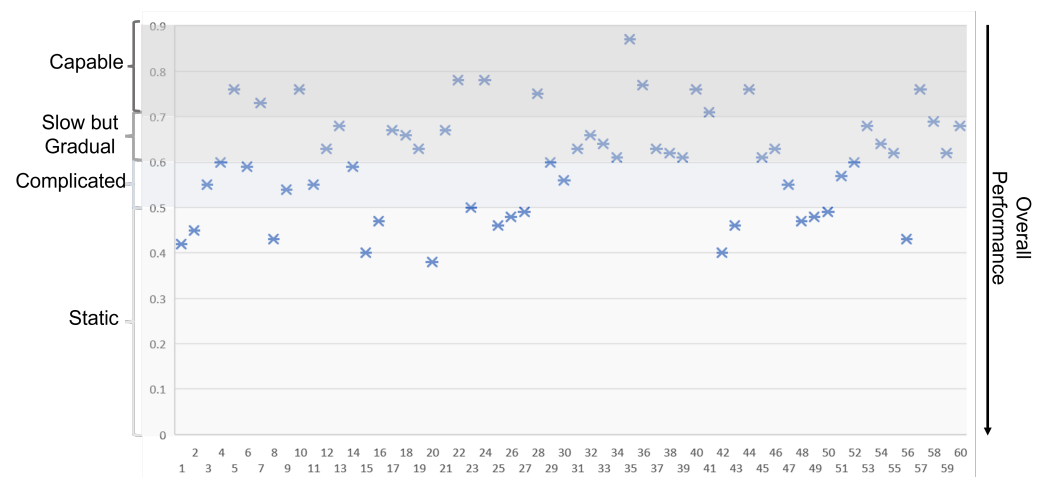

Figure 1. Users' profiling based on the comparison with an optimal profile.

Further details about the conceptual model of MoveUp are out of paper scope; they can be found in [9]. Here, the challenge is understanding how results obtained from the study can address useful extensions of MoveUp from the mHealth standpoint. The main idea is to exploit user profiling to increase the acceptance level of the app using new functionalities tailored to user characteristics. The CBR method adopted in the analysis described so far allowed us to identify four classes of users, characterized by different levels of performance, decreasing from *capable* to *static*. Anyway, some crucial issues can be identified that do not make CBR the best choice to develop a profiling function in MoveUp:

- some cases are not clearly attributable to a specific class;
- classes numerosity could diverge in case of different case characterization.

Regarding the first point, let's consider, for example, the case numbers 29 and 6, depicted in Table 1. Case 29 has a similarity value of 60% with the optimal case, thus, it has been attributed to *Slow but gradual* set. Case 6 is 59% similar to the optimal case, thus, it has been categorized as *Complicated*. Looking at their concrete MET and *SE* values, they are equal from the physical point of view, both reaching one week the maximum amount of 600 MET per week and very similar from the *SE* perspective (user #29 overperforms user #6 one week more). Indeed, this different classification can be acceptable, and CBR can

be considered a good method to cluster MoveUp users, but borderline situations like the one described so far are difficult to manage. About the second point, the current model of MoveUp reasoning strategies does not consider real physical performance obtained by people. The system is interested in *MET* values included in the [120, 240, 360, 480, 600] set, with possible variations of 120 MET per week, according to the experts' knowledge. This means that in case a user would accomplish 387 MET of PA at the end of a given week, the system will not record that value, being only interested to understand if the user will reach the prescribed amount of PA (i.e., 360 MET or less) or not (i.e., 480 or 600 MET) that week. If this strategy changed in future implementations, CBR would not probably be able to give a good clustering of users because the identification of clusters would be problematic and the graphical distribution of cases similarity with respect to the optimal profile will be more sparse.

Table 1. Comparison between borderline profiles in MoveUp.

User	MET								SE							
29	120	240	360	360	480	480	600	480	7	7	3	8	2	6	2	4
6	120	240	360	480	360	480	480	600	6	6	6	2	6	4	8	4
$\Delta(29,6)$	=	=	=	−	+	=	+	−	+	+	−	+	−	+	−	=

For these reasons, we have decided to exploit CBR as a method to specify possible classes of users in MoveUp, but we moved to different choices for effective profiling implementation.

4. A New Approach

The profiling functions provided by CBR have been exploited to derive a computational algorithm from being implemented into the MoveUp application. As suggested by the experiences above, to build up a reliable description of a user, three kinds of attitudes should be taken into account:

$$index_{TOT} = \frac{a \times index_{goal} + b \times index_{MET} + c \times index_{SE}}{a + b + c} \tag{3}$$

with $index_{TOT} \in [0, 1]$. Currently, weights $a = b = c = 1$.

4.1. Goal Index

The first index involved in the profiling function of MoveUp users in $index_{GOAL}$, whose aim is quantifying how much a person is capable of reaching prescribed targets. First of all, the target number of *MET* a user must reach at the end of a training week is defined as follows:

$$MET_{OB_{WEEK}} = \sum_{i=1}^{j} MET_{OB_{day_i}} \tag{4}$$

where $j \in 2, 3$ is the number of training sessions per week chosen by the user and $MET_{OB_{day_i}}$ is the amount of *MET* the user must accomplish at the end of a given training session.

According to the prescriptions suggested by MoveUp, this amount of *MET* should be in the [120, ..., 600] range, depending on the overall physical and psychological conditions of the current user. The conceptual model above has shown us that an ideal *optimal user* should be capable of constantly improving their performance week by week, reaching the upper bound of 600 MET at the 5th training week and maintaining them till the end of the training period. We can exploit this information to derive a relationship between the ideal performance of an optimal profile and the data about real performance obtained by *current user* to profile as follows:

$$index_{GOAL} = 1 - \frac{\sum_{i=1}^{n}(MET_{OB_{WEEK_i^{OU}}} - MET_{OB_{WEEK_i^{CU}}})}{\sum_{i=1}^{n} MET_{OB_{WEEK_i^{OU}}}} \tag{5}$$

where $MET_{OB_{WEEK_i^{OU}}}$ and $MET_{OB_{WEEK_i^{CU}}}$ are the instances of Equation (4) $\forall i \in [1,8]$ for *optimal user* and *current user* respectively.

The main rationale of Equation (5) is building up a numeric value in the (0, 1] range by penalizing the current user according to their distance from the optimal one with respect to the capability to reach the objectives prescribed by the application. It is important to notice that the maximum value of 1 can be reached iff $CU \equiv OU$, while the minimum value of 0 is unreachable, given that the lower amount of *MET* suggested by MoveUp is 120; thus, the numerator and denominator of the ratio will ever differ. To take care of a user who systematically fails the proposed activity plan every week, i.e., $MET_{OB_{WEEK_i^{CU}}} = 120$, $\forall i \in [1,8]$, $index_{GOAL}$ will be put to 0 by default.

4.2. Physical Activity Index

The second index considers how many *MET*s the user has accomplished during the week regardless of the goal they had to reach. By doing so, it is possible to reduce the bias deriving from profiling user performance from the physical perspective based only on weekly goals satisfaction. First of all, the following formula

$$MET_{EFF_{WEEK}} = \sum_{i=1}^{j} MET_{EFF_{day_i}} \tag{6}$$

returns the effective amount of *MET* per week made by the user, with $j \in [2,3]$ the number of training sessions per week chosen by them. Then, the arithmetic mean of $MET_{EFF_{WEEK}}$ values on a n weeks time horizon can be considered:

$$V_{\overline{MET}} = \frac{\sum_{i=1}^{n} MET_{EFF_{WEEK_i}}}{n} \tag{7}$$

where $n \in [1,8]$ in our case study. Finally, remembering that the maximum value $V_{\overline{MET}_{max}}$ of significant *MET* in our case study is 600:

$$index_{MET} = \frac{V_{\overline{MET}}}{V_{\overline{MET}_{max}}} \tag{8}$$

with $index_{MET} \in [0,1]$.

4.3. Psychological Index

The last part of the profiling function we defined above is the psychological index based on self-efficacy evaluation. We proceed similarly to $index_{GOAL}$, penalizing the maximum possible value by a ratio taking care of answers given by the user with respect to lower and upper bounds of self-efficacy estimation. We start by defining the following equation:

$$SE_{WEEK} = \sum_{i=1}^{j} SE_i \tag{9}$$

where $j \in 2,3$ is the number of training sessions per week chosen by the user and $SE_i \in 1,2,3,4$ in our model. Then, we can obtain the following three values:

$$V_{SE} = \sum_{i=1}^{n} SE_{WEEK_i}$$

$$V_{SE_{MAX}} = n \times SE_{WEEK_{MAX}}$$

$$V_{SE_{MIN}} = n \times SE_{WEEK_{MIN}}$$

where $n \in [1, 8]$ in our case study and $V_{SE_{MAX}}$ and $V_{SE_{MIN}}$ represent the upper and lower bounds, respectively for the V_{SE} variable, that is the overall value of SE specified by the user over the n weeks time horizon. Finally, the psychological index is defined as follows:

$$index_{SE} = 1 - \frac{|V_{SE_{MAX}} - V_{SE}|}{|V_{SE_{MAX}} - V_{SE_{MIN}}|} \tag{10}$$

4.4. An Example

In this section, we present an example of the profiling function defined by Equation (3) works. Table 2 presents data about four users extracted from the case study presented in Section 6, grouped on the basis of their role in the calculus of Equations (5), (8), and (10) respectively. The same boundaries proposed [53] have been maintained:

- a user CU is considered *capable* iff $index_{TOT}^{CU} \geq 0.70$;
- a user CU is considered *slow but gradual* iff $0.60 \geq index_{TOT}^{CU} < 0.70$;
- a user CU is considered *complicated* iff $0.50 \geq index_{TOT}^{CU} < 0.60$;
- a user CU is considered *staticl* iff $index_{TOT}^{CU} < 0.50$.

Table 2. Samples of input values for profiling users according to Equation (3).

	Index Goal Characterization based on Equation (5)							
	$MET_{OB_{WEEK_1}^{CU}}$	$MET_{OB_{WEEK_2}^{CU}}$	$MET_{OB_{WEEK_3}^{CU}}$	$MET_{OB_{WEEK_4}^{CU}}$	$MET_{OB_{WEEK_5}^{CU}}$	$MET_{OB_{WEEK_6}^{CU}}$	$MET_{OB_{WEEK_7}^{CU}}$	$MET_{OB_{WEEK_8}^{CU}}$
A	120	240	360	480	360	480	480	600
B	120	240	360	360	360	480	480	360
C	120	240	240	240	360	480	360	240
D	120	120	240	120	120	240	120	120
	Physical Activity Characterization based on Equation (8)							
	$MET_{EFF_{WEEK_1}}$	$MET_{EFF_{WEEK_2}}$	$MET_{EFF_{WEEK_3}}$	$MET_{EFF_{WEEK_4}}$	$MET_{EFF_{WEEK_5}}$	$MET_{EFF_{WEEK_6}}$	$MET_{EFF_{WEEK_7}}$	$MET_{EFF_{WEEK_8}}$
A	251	278	385	388	520	515	535	498
B	282	293	389	392	402	496	378	320
C	187	251	262	305	310	382	405	310
D	110	140	125	115	125	134	116	115
	Psychological index characterization based on Equation (10)							
	SE_{WEEK_1}	SE_{WEEK_2}	SE_{WEEK_3}	SE_{WEEK_4}	SE_{WEEK_5}	SE_{WEEK_6}	SE_{WEEK_7}	SE_{WEEK_8}
A	6	6	6	2	6	4	8	4
B	6	5	4	4	6	4	4	4
C	6	4	4	6	6	4	4	4
D	6	6	2	2	7	2	2	2

First of all, let's make some considerations common to all the users A, B, C, and D:

- The denominator of Equation (5) is equal to 3600 MET;
- the denominator of Equation (8) is equal to 600 MET;
- the denominator of Equation (10) is equal to 48, being $V_{SE_{MAX}} = 8 \times 8 = 64$ and $V_{SE_{MIN}} = 8 \times 2 = 16$, given that in our case study $n = 8$ and $j = 2$, thus the maximum and minimum value for weekly SE are 8 and 2, respectively.

About user A, we obtain the following value for $index_{TOT}$:

$$index_{TOT}^A = \frac{1 - \frac{480}{3600} + \frac{421.25}{600} + 1 - \frac{22}{48}}{3} = 0.703472222$$

User A can be classified as *capable*, according to the clusters created by the CBR method. They demonstrated excellent physical performance, while their personal motivations showed some problems. The overall index seems able to capture these peculiarities, posing user A at the lower bound of the capable region proposed in Figure 1.

The calculus of $index_{TOT}$ for user B is as follows:

$$index_{TOT}^B = \frac{1 - \frac{840}{3600} + \frac{369}{600} + 1 - \frac{37}{48}}{3} = 0.606388889$$

User B presents very good physical attitudes, lacking in motivation: this is main reason why the app suggests them to maintain of reduce training goals when needed. Thus, the profile evaluation for this person is *slow but gradual*.

User C is characterized on the basis of the following calculus:

$$index_{TOT}^{C} = \frac{1 - \frac{1320}{3600} + \frac{301.5}{600} + 1 - \frac{38}{48}}{3} = 0.531388889$$

Physical performance decreases significantly with respect to previous users, both form the goal and the effective met points of view. From the psychological standpoint, the self-efficacy estimation maintains good standards, which is slightly higher than user B. This profile can be clustered as *complicated*, and the final value of the overall index confirms this opinion.

Finally, user D is characterized by the following formula:

$$index_{TOT}^{D} = \frac{1 - \frac{2400}{3600} + \frac{122.5}{600} + 1 - \frac{29}{48}}{3} = 0.269444444$$

User D shows significant physical and psychological problems; the overall performance is characterized by many failures and few successes, as pointed out by the very low value of the overall index variable. Moreover, in this case, we can conclude that user D has been correctly profiled as *static*.

5. Implementation and Use in MoveUp

Figure 2 shows a sketch of the classes developed to implement user profiling in MoveUp. The `UserRating` class is the heart of this functionality, that dialogues with application storage to read/write useful information when necessary through the `DBReadWritePoint` class services. In particular, two queries are accomplished to extract *MET* and *SE* values from database tables and calculate their upper and lower bounds necessary to the calculus of indexes by the equations above. Figure 3 shows this code and a sketch of the database table on which it works. For the sake of clarity, only one week is shown in the figure, codified as number 64 and characterized by two training days. The *blue information flow* concerns Equation (8), as the average value of *MET* accomplished by the user over a given time horizon of n weeks is returned; the *green path* leads to the solution of Equation (5), focusing on the global amount of MET objectives proposed by the app to the user over the same time horizon; finally, the *orange line* allows to extract useful data about *SE* for solving Equation (10).

The user profiling function has been integrated within MoveUp to enable new functionalities. First of all, it has been exploited to give immediate feedback to the user about their performance: the top part of the Figure 4 shows the dedicated GUI.

The user can select his/her expected level of performance, choosing it among *Turtle*, the avatar of the *static* profile, *Cat*, a representation of *complicated* profile, *Leveret*, associated to the *slow but gradual* profile, and *Cheetah*, related to the *capable* profile. At the end of the session, the user can ask the system to show them the profile modification according to the real physical and psychological data: this is optional as the possible decrease with respect to user expectations could negatively impact the behavior change plan.

Second, the profiling model has allowed to include *social* issues, considering *group physical activities*, which is an important research topic for the mHealth field. For example, group physical activity is more effective than individual to reduce fatigue in patients who have breast cancer; although the comparison with peers can be negatively perceived [55]; it seems to allow aged people [56] to overcome barriers, such as living in not safe neighborhoods and positively impacting on patients with schizophrenia [57]. To promote group PA, a calendar of activities shared among groups of users has been developed in MoveUp: bottom part of Figure 4 shows a sketch of the graphical user interface. First, the user can plan new PA sessions as they prefer, in terms of activity type (e.g., running) and scheduling during the week. Then, they can decide to maintain the activity *private* or publicize it over the shared calendar to invite others to join the session: *red activities* in the figure are

private training sessions, while *green ones* are public. Others will see green sessions on their calendars; moreover, they will be able to subscribe to one or more of them (see right part of the figure), receiving information about weather condition forecasts and the group participants' profile (*leveret* in the figure), to decide if participating or not.
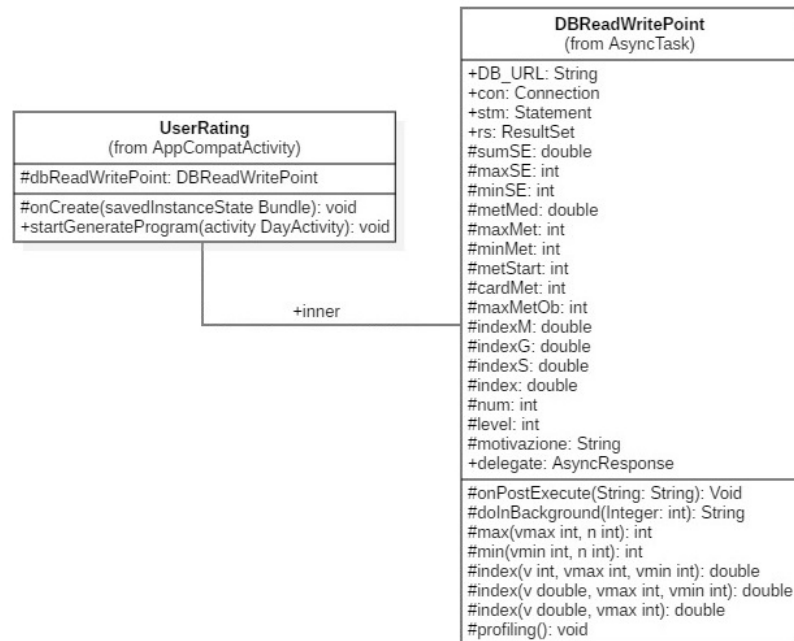

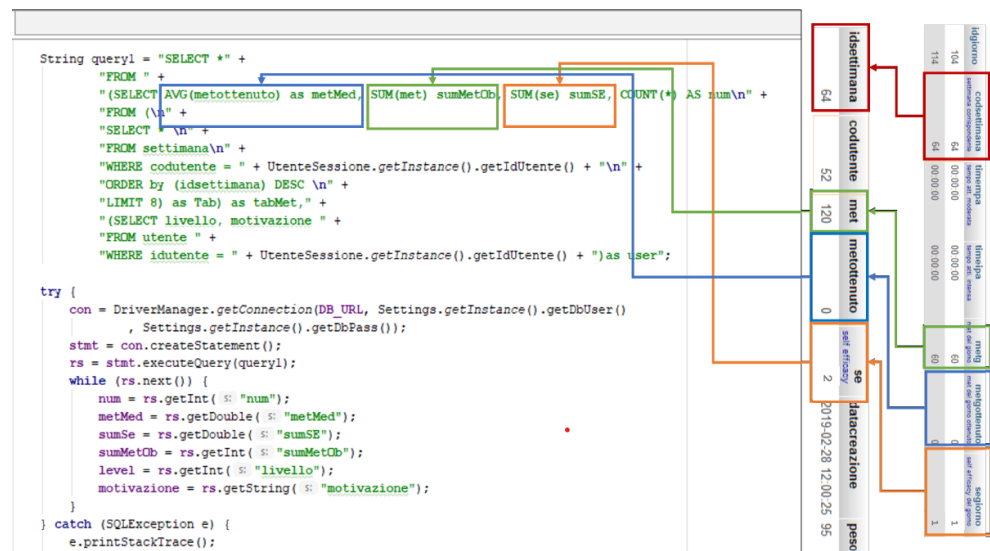**Figure 2.** Classes added the MoveUp UML diagram to deal with profiling.

Figure 3. The query is exploited by the UserRating class to extract necessary information from MoveUp database.
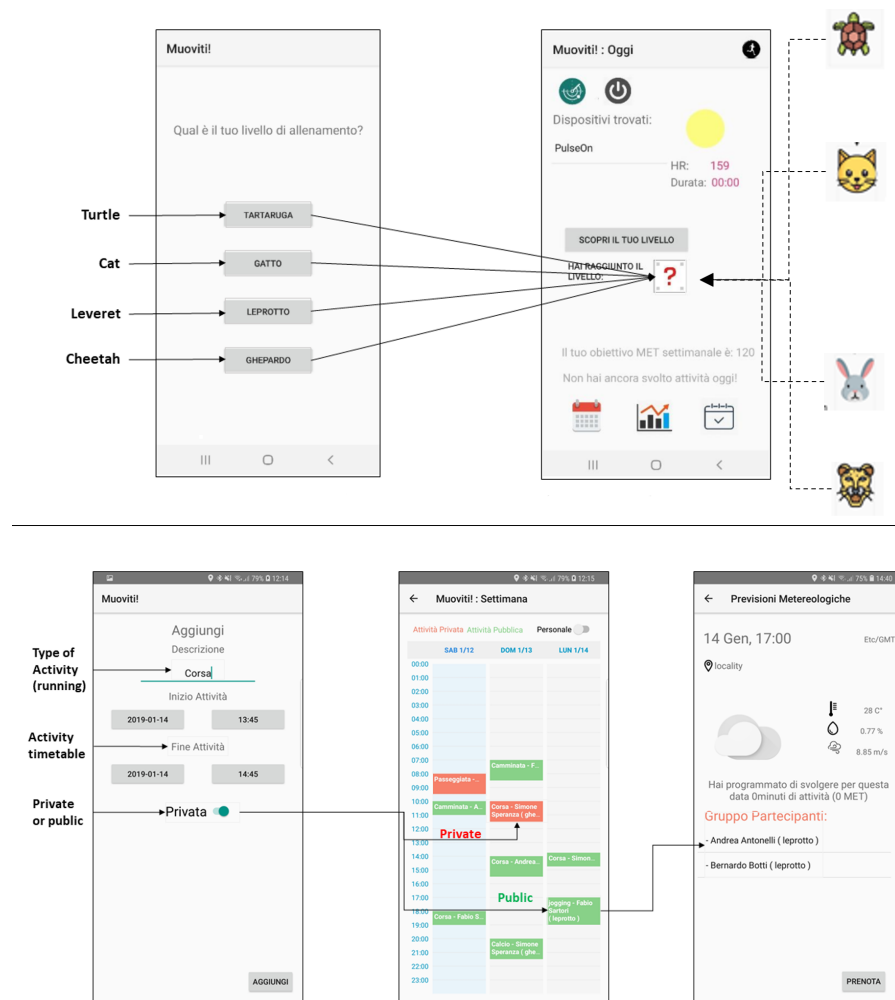
Figure 4. On the **top**, the GUI for self and automatic assessment of user profile; on the **bottom**, the calendar function developed in MoveUp.

6. User Experience Evaluation

Data collection about user experience with MoveUp was based on the questionnaire proposed in [58]; the authors elaborated this questionnaire to obtain an overall impression of the long-term user experience with mHealth apps. To this aim, their set of questions was grouped in a *before use* and an *after use* parts. Due to Covid restrictions, we could not organize a data collection phase over a long period of time. Thus, we focused our questions on evaluating the user experience after one or two PA sessions, as shown in Table 3. Questions Q8–Q11 were added to evaluate the acceptance level of social functionalities.

The questionnaire was submitted in paper form to some volunteers we selected among runners at the North Park in Milan. We asked them to make a brief PA session, possibly replicating it in a couple of days. Thirteen people accepted, and six of them replicated the experience of completing a training week. Each of them was equipped with a smartphone with MoveUp installed and a $PulseOn^{TM}$ watch connected to it. The smartphone and the watch were sanitized after each use. Results are presented in Table 4, which shows for each participant the profile at the end of each session (*none* if not performed, *undefined* if data were not sufficient), and the sequence of 11 answers to the questions, possibly replicated if the user completed the two training sessions.

Table 3. Questionnaire for user experience evaluation inspired by [58].

Question	Aspect/Category	Possible Answers
Q1: Did the app live up to your expectations?	Development process/Satisfaction	Yes/Somewhat/No
Q2: Was the information provided by the app useful to you?	Functionality/Useful information	Yes/Somewhat/No
Q3: What do you think about the app icons and images?	Aesthetics/Images	Good/Fair/Bad
Q4: What would you change in the app?	Infrastructure/Modifications	GUI/Suggestions/ Entertainment
Q5: Would you keep using the app?	Everyday operations/Keep using	Yes/Somewhat/No
Q6: Would you recommend this app to others?	Trustworthiness/Recommendation	Yes/Somewhat/No
Q7: Did you like the app methods?	Method/Assessment	Yes/Somewhat/No
Q8: Do you feel better performing suggested physical activity in a group or alone?	Method/Assessment	Group/Alone
Q9: If you have performed the last physical activity session alone, do you feel ready to do it in a group next time?	Emotional/Feeling	Yes/Somewhat/No
Q10: If you have performed the last physical activity session in a group, do you think you will continue next time?	Emotional/Feeling	Yes/Somewhat/No
Q11: If you have performed the last physical activity session in a group, do you feel able to join a group with a profile higher than yours?	Emotional/Feeling	Yes/Somewhat/No

Table 4. Results of data collection.

Participant	$Profile_1$	$Profile_2$	Answers to Questions in Table 3
$Participant_1$	Leveret	None	Y/S/G/S/Y/Y/S/A/N/-/-
$Participant_2$	Leveret	Leveret	Y/Y/F/GS/S/Y/Y/A/Y/-/- Y/Y/F/GS/Y/Y/Y/G/-/Y/S
$Participant_3$	Cheetah	Cheetah	S/S/F/GSE/Y/Y/Y/A/N/-/- S/S/F/GSE/Y/Y/Y/A/N/-/-
$Participant_4$	Undefined	None	N/S/F/GSE/N/N/S/G/-/Y/S
$Participant_5$	Turtle	None	Y/Y/B/G/S/S/S/G/-/Y/Y
$Participant_6$	Undefined	None	No answers given
$Participant_7$	Leveret	Cat	Y/Y/G/E/Y/Y/Y/A/Y/-/- Y/Y/F/GE/Y/Y/Y/G/-/Y/N
$Participant_8$	Leveret	None	No answers given
$Participant_9$	Cheetah	Cheetah	Y/S/G/S/Y/Y/S/A/Y/-/- Y/S/F/GS/Y/Y/S/G/-/Y/Y
$Participant_{10}$	Cat	None	N/N/F/S/N/N/N/A/N/-/-
$Participant_{11}$	Leveret	Leveret	Y/S/G/SE/S/S/S/G/-/Y/N Y/S/G/SE/S/S/S/G/-/Y/S
$Participant_{12}$	Leveret	Cheetah	S/Y/F/S/S/S/S/A/N/-/- S/S/F/S/N/N/N/A/N/-/-
$Participant_{13}$	Cheetah	None	N/N/B/GSE/N/N/Y/A/S/-/-

6.1. Involvement Evaluation

Only 6 of 13 participants have completed the one-week evaluation. This is coherent with literature about the mHealth acceptance by target users [59]. It is important to notice that the MoveUp module is thought for a particular category of users; thus, most of its functionalities could be considered too low a level by runners. Looking at the personal evaluation made by those who did not replicate the PA session (i.e., 1, 4, 5, 6, 8, 10, 13), three of them chose Leveret or Cheetah avatars, two Turtle or Cat, and two did not specify any initial profile. $Participant_4$, $Participant_{10}$, and $Participant_{13}$ explicitly declare the app is not suitable for their scopes, suggesting revising it from every point of view. $Participant_6$ and $Participant_8$ did not provide answers. Six users were fully convinced that the app was useful. Among them, some participants pointed out the information provided was partially important; they suggested improving the GUI of the app (for example, to include cartography and maps or extend the set of avatars), the suggestions returned by the app (e.g., they would be interested in different kinds of activity to accomplish, not only running) and the entertainment functionalities perspective (e.g., the indication of points of interest to visit during the PA session). Group physical activity is considered a good option to improve the overall performance, despite some participants (i.e., 10, 12, 13) excluded this possibility. From this point of view, the most interesting answers have been given by $Participant_2$ and $Participant_9$, who accomplished the first PA session alone and the second one in the group, specifying that continuing group PA is preferable. An interesting outcome is about the last question: only $Participant_5$ and $Participant_9$ declare they are ready to make PA with more active peers; participants 2, 4, and 11 put some constraints such as the possibility to leave the group in case of too evident differences with respect the buddies or difficulties in establishing a good relationship with them.

6.2. Computational Model Evaluation

$Profile_1$ column in Table 3 concerns self-assessments made by users at the beginning of the first PA session; $Profile_2$ column shows values assigned by MoveUp at the end of the session, based on a week by week model. Four of six profiles, i.e., 2, 3, 9, and 11, were confirmed. Users were characterized by good physical conditions and high levels of self-efficacy. The computational model has captured such characteristics. About the two discording profiles, we can state that $Participant_7$ has been underestimated due to difficulties to follow GUI indications (the user was not able to run in the required HBR range), while $Participant_{12}$ demonstrated better physical and psychological conditions than they thought. Thus, we can reasonably suppose the model will work fine in real case studies with a higher number of people involved. Anyway, many technical limitations must be solved to make MoveUp an effective mHealth app capable of fully meeting user requirements. Some participants (i.e., 2, 3, 4, 7, 11, and 13) highlighted that the app is not usable with their own smartphones and wearable device. The reason for this is that the pairing between the smartphone running MoveUp and the wearable device is via BLE^{TM} technology. Many devices do not implement standard BLE, thus their sensors are not readable without an opportune API, that must be provided by the device manufacturer. We have discussed this issue in [2], where the *wearable environment* architecture has been developed to overcome this problem on a larger scale. Anyway, this is not sufficient to delete this limitation on the target user, who must use an ad-hoc configured environment. Indeed, this issue negatively impacted the overall UX perception of some participants and will be solved in the future implementation of MoveUp.

6.3. Discussion

The proposed study has many limitations due to the very low number of users involved. Being developed under the COVID-19 restrictions, it has not been possible to organize it on a larger scale. To this aim, one of the most important future works is to organize a more robust data collection campaign, possibly involving people attending gyms as previously done. In doing so, we hope to develop new solutions to solve the

technical problems introduced above as well as to test new features we are going to design based on the integration of *virtual reality*.

Anyway, we can draw some interesting conclusions since our goal was to collect an initial set of data to understand if our research goal could be reached in the future. In this sense, we can say that the user's answers are encouraging: the profiling function based on the adoption of avatars we developed in MoveUp and the shared calendar functionality we have integrated into the app to promote group PA among users are the most important contributions of our approach to the research in the field, being capable to influence positively the user engagement in the app.

This is not trivial according to existing literature. In a recent paper [60] the authors applied an extended *Unified Theory of Acceptance and Use of Technology* to evaluate different parameters concerning the acceptance of mHealth applications on a set of 165 users. This study was very interesting as it compared the same population using both a fitness and a medical app. They were analyzed based on *performance expectancy*, *effort expectancy*, *social influence*, and *facilitating conditions*, which are the features typical of the traditional UTAUT model [61], plus *privacy concerns*. Social influence was originally defined as the *degree to which an individual perceives that important others believe they should use the new system*. In the MoveUp context, *important others* are identified by

- users profiled by the system proposing a group PA session on the shared calendar;
- users profiled by the systems who accept joining a group PA session on a shared calendar proposed by peers.

The relevant element of discontinuity with respect to the past is that social influence has been positively evaluated by users involved in the MoveUp study: in [60] the users involved in the fitness app acceptance evaluation rejected social influence, due to their adversion in sharing personal data with peers. Similar findings were obtained by [62], who pointed out that, although motivation to physical activity might increase thanks to the achievement of milestones, sharing performance data from a wearable device is not favored either.

Moreover, the implementation of social support features in MoveUp is a significant improvement with respect to similar apps like [63], where this crucial persuasive feature was not considered, given that primary task support, computer-human dialog support, and system credibility support were already satisfied in MoveUp, thanks to the existing architectural choices [9].

The profiling function of MoveUp is a sample of application for real-time classification of user behavior. The developed model developed does not aim to discover the lifestyle of a person, like in [64]; its main goal is obtaining a synthetic schema of real-time data of a user characterized by sedentary lifestyle, to guide them towards a behavior change thanks to the comparison with others. Analyzing both quantitative and qualitative variables about, respectively, physiological and psychological well-being is the most important innovation of the approach with respect to the existing literature. According to [65], *tactic* is a set of generic actions to describe how persuasion can be delivered to users. Profiling of users in MoveUp has allowed us to consider tactical aspects of the mHealth app: the comparison with peers could be a way to increase the interest of a user in modifying their own lifestyle.

Finally, some consideration can be made on policy implications for future research on mHealth apps. To this aim, it could be useful to come back to the personalization perspective discussing its features with reference to dimensions proposed in [13], namely *Users*, *System functionalities*, *Information*, and *App properties*. The first dimension is composed of

- *Personality*, which should be measured in terms of the so-called *Big Five* model [66];
- Profile, which is used to define the type of user according to different scales;
- Need for cognition, which describes users based on their differences in *motivation to engage in effortful cognitive endeavors*;
- Perception of the social norm, referring to the *perceived social pressure to perform or not to perform a given behavior*;

User dimension features stated by our approach are *user profile* and *perception of social norm*. While the first one is quite clear, given the goal of profiling function, the second feature is related to the suggested amount of *MET* compared to the peers. Indeed, *personality* could be a good indicator to be included in an mHealth app: the Big Five model suggests describing it by means of five factor, namely *neuroticism*, *openness*, *conscientiousness*, *altruism*, and *extroversion*, that could be useful to extend the psychological characterization of $index_{TOT}$. Moreover, the *need for cognition* dimension is not supported at the moment but should be considered in future developments of the mHealth app based on our approach, for example including a *mental state* evaluation.

The second dimension is made of:

- *App functionalities*, which refers to the services provided by the application to the user, such as reminders or self-monitoring;
- *Gamification*, concerning gaming features that can be personalized, like goal settings or progressions.

System functionalities features are both satisfied, thanks to the adoption of messages and warning about the PA to perform, the avatars the user merits at the end of each training week and the calendar of activities shared with peers. Indeed, thanks to the suggestion of users, many improvements can be made in order include more gamification features in the mHealth app exploiting opportune conceptual and computational models compatible with the WES framework [67,68].

About the third dimension, it is constituted of knowledge and information to be transmitted to expert as well as feedbacks to users. It is possible to say that the user profiling elaborated by MoveUp can provide useful information and feedback not only to the user but also to other roles possibly involved in their support, like caregivers, doctors, and other professionals. a possible development, according to what presented in this paper, could be the implementation of *comparative feedbacks*, based on the results obtained by the user with respect to the plethora of peers with the same profile, for example. In this way, *users* and *information* dimensions could be overlapped, generating possible, interesting new areas of research in the mHealth domain.

Finally, the fourth dimension includes aesthetic and customization features. About that, the adoption of avatars, calendar and graphical representation of user's profile has increased the app properties level from the aesthetics point of view. Anyway, many developments can be thought, especially to improve the UX from the customization perspective. According to the vision of [13], customization of mHealth apps must be meant as *the explicitation of the user's interests and preferences using the direct configuration of human-computer interfaces*. In this sense, the integration of *virtual and augmented reality* can provide the user of mHealth apps with the necessary tools to extend the functionalities from this point of view.

7. Conclusions

Positive user experience is critical to motivate users of mobile health applications over time, especially when they are characterized by intrinsic physical and psychological frailties. As highlighted in [58], if users report a satisfactory UX and rate the functionality and content as useful, then they will be inclined to use the application for a longer period. When developing mHealth apps, personalization aspects must be then taken into consideration to increase the overall user experience feeling and the acceptance level by people as a consequence.

In this paper, we have reflected about these points, presenting the design choices behind the implementation of new functionalities in MoveUp, a mHealth app to support frail people in achieving and maintaining satisfying levels of PA. A method to group users according to their performance has been proposed, to be exploited for the promotion of collective training sessions among peers. Although profiling users is going to gain a negative connotation, being the term "profiling" often associated with an unwanted breach of privacy, we think that our proposal is respectful of individuals, being based on a neutral

evaluation of their physical and psychological performance with the final goal to improve their global satisfaction when accomplishing PA by comparison with peers.

Indeed, the most important contribution of our approach has been the definition of a profiling function through which new services can be incorporated into mHealth apps to increase their acceptance level by users; a preliminary evaluation of user experience has been made, which has revealed us some weaknesses of our approach that negatively impact on user experience perception. This lesson learned will be useful in the process of the development of more refined and usable prototypes of MoveUp.

In particular, we are currently working on the incorporation of virtual reality aspects within MoveUp. The main rationale behind this development would be the support of users in lower categories from the motivational point of view, i.e., *static* and *complicated* ones, allowing them to follow the app suggestions at home, by means of different kinds of wearable devices, like 3D-glasses, and different kinds of services, like the possibility to make PA exploiting virtual environments rather than concrete ones, overcoming traditional barriers affecting frail people.

Another interesting future work is to exploit the lessons learned from the improvement of UX perspective in developing other modules of PERCIVAL systems. As reported in [9], one of the new modules to be added is the *diet* one (see Figure 5), that aims at integrating information about the amount of accomplished PA registered by MoveUp (i.e., the *red flow* in the figure) with suggestions about the meals eaten during the day (i.e., the *blue flow* in the figure) to build up a more reliable behavior change plan for the user. The module exploits the relationship between *MET* and calories burned to build up a balance with calories assumed through the meals. Future works are devoted to understand how to exploit the suggestions coming from the diet module to define a fourth component of $index_{TOT}$, possibly identifying new classes of users and new social functionalities (e.g., social dinners among peers or joint sessions of physical activity and food education) to improve the overall perception of UX and maximize the benefits of behavior changes interventions.
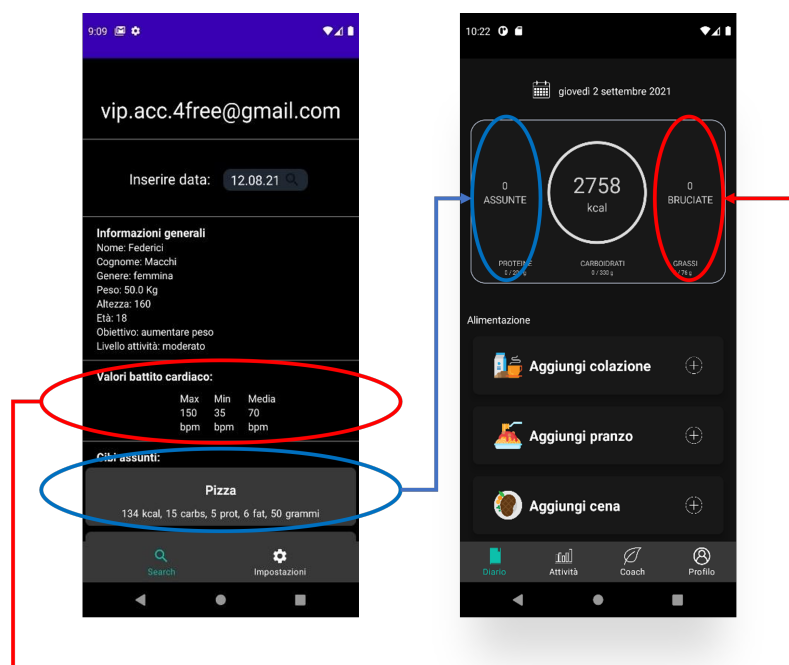

Figure 5. The GUI of the diet module of the PERCIVAL project.

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