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Multimodal hybrid reasoning methodology for personalized wellbeing services

Rahman Ali [a], Muhammad Afzal [a], Maqbool Hussain [a], Maqbool Ali [a], Muhammad Hameed Siddiqi [a], Sungyoung Lee [a,*], Byeong Ho Kang [b]

[a] Department of Computer Engineering, Kyung Hee University, Seocheon-dong, Giheung-gu, Yongin-si 446-701, Gyeonggi-do, Republic of Korea
[b] Department of Computing and Information Systems, University of Tasmania, Hobart, Tasmania 7005, Australia

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ABSTRACT

A wellness system provides wellbeing recommendations to support experts in promoting a healthier lifestyle and inducing individuals to adopt healthy habits. Adopting physical activity effectively promotes a healthier lifestyle. A physical activity recommendation system assists users to adopt daily routines to form a best practice of life by involving themselves in healthy physical activities. Traditional physical activity recommendation systems focus on general recommendations applicable to a community of users rather than specific individuals. These recommendations are general in nature and are fit for the community at a certain level, but they are not relevant to every individual based on specific requirements and personal interests. To cover this aspect, we propose a multimodal hybrid reasoning methodology (*HRM*) that generates personalized physical activity recommendations according to the user's specific needs and personal interests. The methodology integrates the rule-based reasoning (*RBR*), case-based reasoning (*CBR*), and preference-based reasoning (*PBR*) approaches in a linear combination that enables personalization of recommendations. *RBR* uses explicit knowledge rules from physical activity guidelines, *CBR* uses implicit knowledge from experts' past experiences, and *PBR* uses users' personal interests and preferences. To validate the methodology, a weight management scenario is considered and experimented with. The *RBR* part of the methodology generates goal, weight status, and plan recommendations, the *CBR* part suggests the top three relevant physical activities for executing the recommended plan, and the *PBR* part filters out irrelevant recommendations from the suggested ones using the user's personal preferences and interests. To evaluate the methodology, a *baseline-RBR* system is developed, which is improved first using ranged rules and ultimately using a *hybrid-CBR*. A comparison of the results of these systems shows that *hybrid-CBR* outperforms the *modified-RBR* and *baseline-RBR* systems. *Hybrid-CBR* yields a 0.94% recall, a 0.97% precision, a 0.95% *f*-score, and low *Type I* and *Type II* errors.

1. Introduction

An individual's healthy lifestyle impacts the overall health of a population and results in a healthier society [1]. Without a healthy lifestyle, *i.e.*, proper diet, exercise, and controlled body mass index, individuals are prone to various diseases [2] that include lifestyle as an important cofactor [3]. Adopting physical activity is one of the key responses of individuals that helps in promoting a healthier lifestyle [4]. Similarly, wellness guidelines and automatic wellness recommendation systems play roles in public health promotion. These systems provide support for wellness experts in recommending the appropriate physical activity to individuals according to their personal requirements [5]. A healthier lifestyle involves a balanced combination of physical activity, mental behavior, and social interaction with other community members [6–8]. In this study, we focus on the physical activity aspect of a healthier lifestyle. We also focus on the development of a physical activity recommendation system to motivate users to keep their life active by involving themselves in various types of physical activities. Traditional physical activity recommendation systems provide general guidelines in the form of recommendations, which do not provide user-centric recommendations. To fulfill the

* Corresponding author. Tel.: +82 1073451441; fax: +82 31 202 2520.
E-mail addresses: rahmanali@oslab.khu.ac.kr (R. Ali), muhammad.afzal@oslab.khu.ac.kr (M. Afzal), maqbool.hussain@oslab.khu.ac.kr (M. Hussain), maqbool.ali@oslab.khu.ac.kr (M. Ali), siddiqi@oslab.khu.ac.kr (M.H. Siddiqi), sylee@oslab.khu.ac.kr (S. Lee), byeong.kang@utas.edu.au (B. Ho Kang).

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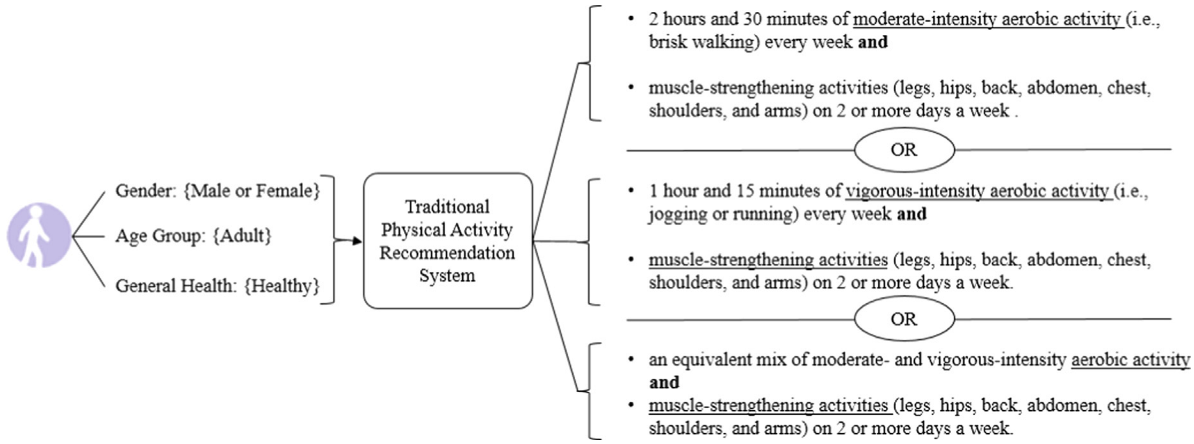

Fig. 1. General physical activity recommendations adopted from the Center for Disease Control and Prevention (CDC) guidelines [9].

personal needs of different users, a personalized physical activity recommendation system is required.

We illustrate the concept of personalized physical activity recommendation using an example in which an overweight, 30-year-old person affected with asthma is interested in personalized physical activity recommendation. The goal is to recommend an appropriate physical activity to this person according to his health needs as well as personal interests. If the recommended activity reflects his requirements, then it will be accepted; otherwise, it will be rejected. Existing physical activity recommendations, proposed by *CDC* [9], *WHO* [10], *AHA* [7], among others, recommend general physical activity for the whole community of users. These recommendations are abstract and exploit limited personal information of the users. An example of the *CDC* recommendations is shown in Fig. 1.

Fig. 1 shows that gender, age and health conditions are taken into consideration while suggesting options of physical activities. The following important questions arise:

A. Are the suggested recommendations appropriate for the person considered in the example?
B. Are the provided recommendations based on the user personal information (*e.g., BMI*), health, physical activities routines and preference list?

The answers to these questions are 'no', which mean that the system provides general guidelines and the user has to look into his personal information, daily routines, and preferences and choose appropriate physical activity for himself. Generally, this should not be the case and the recommendations shall reflect the person's specific needs. The system needs to be intelligent enough to first reason on the user personal profile information and calculate the user's weight status, target weight (goal status), and plan to achieve the goal. Based on these assessments, appropriate physical activity should be recommended according to the user current and past routines of activities and preference list.

To achieve the above stated goal, we are working on a personalized wellness platform called Mining Minds[1] [11] (see Section 3). Mining Minds is a collection of services, tools, and techniques for collaboratively investigating and analyzing the user's personal profile and daily routines for providing personalized wellbeing services. These services are generated by executing knowledge rules using the Mining Minds (*MM*) reasoning engine. This study focuses on the reasoning methodology adopted by the reasoning engine to generate daily physical activity recommendations. A multimodal hybrid reasoning methodology (*HRM*) is proposed, which plays an important role in interpreting the user's profile, physical activity routines, and personal preferences for generating personalized physical activity recommendations. *HRM* integrates the rule-based reasoning (*RBR*), case-based reasoning (*CBR*), and preference-based reasoning (*PBR*) methodologies for enabling the reasoning engine to personalize the recommendations. *RBR* of the proposed *HRM* exploits domain knowledge rules extracted from guidelines, *CBR* exploits implicit knowledge obtained from experts' past experience (successful cases), and *PBR* exploits users' personal preferences and interests to ensure accurate and personalized recommendations. The key ideas of *HRM* include the following: (i) exploitation of the diverse knowledge sources for personalized wellbeing recommendations using the integration of multiple reasoning methodologies, such as *RBR*, *CBR* and *PBR* in a linear combination to form *HRM*, (ii) reducing the bottlenecks of traditional single reasoning methodologies, which exploit only single knowledge sources for generating a single service at a time and (iii) enabling the generation of specific, relevant and personalized physical activity recommendations according to the user's specific requirements.

To validate the proposed *HRM*, a weight management scenario is considered, and a set of experiments are performed. The use of *HRM* for weight management is an innovative idea that guarantees specific and precise personalized physical activity recommendations. It is important to mention that our prescription of physical activities only focuses on healthy adults and not on people with disabilities, women who are pregnant and people who have medical complications.

The rest of the paper is structured as follows. Previous research is summarized in Section 2. In Section 3, an overview of the *MM* platform is provided. In Section 4, the proposed *HRM* is discussed from architectural, knowledge acquisition and reasoning perspectives. In Section 5, the experiments are performed, and the system is evaluated based on a weight management scenario. In Section 6, a discussion on the methodological aspects of the paper, different challenges faced and limitations of the approach is provided. Section 7 concludes the work performed and outlines some possible future extensions. Section 8 acknowledges the contributors and financial sponsors.

2. Related work

Human experts are limited in number and expensive in terms of healthcare and wellness services provided. Healthcare decision

[1] http://www.miningminds.re.kr/

support systems play effective roles in overcoming the shortage of human experts and improving quality of life with better services [12]. Decision support systems rely on automatic reasoning methodology for their decisions. Most of these systems are based on a single methodology for reasoning, such as *CBR* or *RBR* [13], among others. Nevertheless, a few use multiple reasoning approaches with a certain integration strategy. The integration of multiple reasoning methodologies in a single system has attracted increased attention in the research community due to the improved performance with respect to accuracy. The analogy of integration of reasoning methodologies is adopted from the decisions made by domain experts, who rely on multiple knowledge sources rather than a single source. Domain experts use information from general guidelines, clinical trials, and past successful cases to arrive at a final decision. In automatic reasoning systems, the concept of multimodal reasoning methodology evolved from the use of heterogeneous knowledge sources to generate the final decision [13]. The knowledge source, such as guidelines and past successful cases are modeled as knowledge rules and case bases that require *RBR* and *CBR* for their executions.

The integration of reasoning approaches can follow any set of strategies, such as *RBR* followed by *CBR*, *CBR* followed by *RBR* and *RBR* and *CBR* in parallel [13,14]. In the first strategy, *RBR* is used as the main methodology for making the decision. If *RBR* fails, CBR is used [15]. In the second strategy, *CBR* is used for the master reasoning process and *RBR* is used to refine the decision [16]. An example of this strategy is reasoning system for diabetes management [17]. The *CBR* refines the rules for the final outcome, specific to the patient's requirements. In other combinations, *CBR* and *RBR* are used in parallel, where either both outcomes are simply displayed or the best one is displayed based on some criteria. An example of parallel integration is the *WHAT* system [18,19], which is used for training beginning sports medicine students to design exercise regimens for patients with cardiac or pulmonary disorders. The regimens are produced by *RBR* and *CBR* in parallel and presented to the experts for choosing the best one. Other methodologies exist that closely cooperate with each other for generating final decisions [20,21]. Apart from *RBR* and *CBR*, filtration-based approaches, such as content-based filtration [22] and collaborative filtration [23,24] are also popular in the area of recommender systems for online shopping, product selection, and healthcare services. Preference-based recommender systems are used in e-applications such as e-commerce to offer alternative or cross-selling products to customers [25].

In the healthcare domain, hybrid reasoning approaches have been frequently used. In treatment planning for adolescent early intervention, hybrid *CBR* that uses *RBR* and fuzzy theory has been implemented [26]. For supporting physicians for the management of diabetes mellitus, integration of *CBR*, *RBR* and model-based reasoning (*MBR*)[27] and web-based *CBR* [28] has been proposed. For cancer decision support services, *CBR* has been integrated with *RBR*. The *CBR* part is used to adapt the production rules for decision making [21]. A recent study [29] integrates rough set theory and correlation analysis in a hybrid model, called *H2RM*, that predicts the diabetes type and manages patient observations for future trend analyses. Other similar studies can be found that focus on heart disease [12] and oncology [13], among others.

In the wellness field, the knowledge acquisition and reasoning engine (*KARE*) [5] is used in activity awareness for human-engaged wellness applications (*ATHENA*) [6] to promote active lifestyles. *KARE* uses the hybrid reasoning methodology by integrating the Random Forest, Naïve Bayes, and IB1 approaches. *KARE* generates food, physical activity, and music therapy recommendations for *ATHENA* users. For the elderly, an intelligent personalized exercise recommendations system is proposed [30] that utilizes the user's health status, goals and preference information. Similarly, a hybrid *CBR*/*RBR* approach has successfully been used for designing nutritional menus [31].

All of these methodologies have the common basis of being used in an exclusive manner. They do not guarantee a minimization of the shortcomings of *RBR* and *CBR*, which are discussed as follows:

- Conventional *RBR* systems lack the capability of specializing recommendations for individuals. In general, to deal with specific requirements of users and provide user-centric specialized recommendations, it is necessary to gradually increase the number of rules in the knowledge base. This approach not only results in knowledge base intractability problem, but also causes maintenance and combinatorial explosion issues [32].
- Standard *CBR* systems provide solutions for new problems using a large and unbiased case base as implicit knowledge. However, the requirement of a large case base is a difficult task and associated with a number of other issues, such as physical storage, proper indexing and computational complexities [33]. The preparation of the query cases to feed the *CBR* cycle for generating physical activity recommendations is a challenging task.
- There have been significant improvements in the integration of these methodologies in hybrid systems [34]; however, a number of challenging issues still need to be resolved for applying integration in the wellness domain.

The proposed *HRM* mitigates these problems by integrating *RBR*, *CBR*, and *PBR* in a sequential manner that exploits guideline rules, past successful experience cases and the personal preferences of users to enable personalization of recommendations.

3. Overview of the Mining Minds platform

Advancement in technology greatly impacts the means of service provisioning to the community by employing innovative and state-of-the-art techniques. This includes handling real-time data streaming by utilizing a big data infrastructure with cloud data storage and processing abilities. Our indigenously developed *MM* platform [11,35] provides a comprehensive picture of the usage of these technologies for monitoring users and collecting information that can facilitate the use of healthcare applications on a global scale. An abstract design view of the *MM* healthcare platform is shown in Fig. 2.

The overall *MM* platform is divided into four layers: *data curation layer (DCL), information curation layer (ICL), service curation layer (SCL)* and *supporting layer (SL)*. The *DCL* is responsible for curating the data. It consists of different modules for data streaming and communication, data representation and mapping and big data storage in a *Hadoop Distributed File System (HDFS). HDFS* addresses the volume, velocity and variety aspects of raw sensory data acquired using mobile sensors. The accelerometer raw data for low-level activities (*i.e.,* sitting, standing, moving in a bus, moving in a subway, walking, running, and cycling) are transferred to the *DCL* virtual machine, which is transformed to have a structured format and stored in a relational data model on the *DCL* server machine. The mobile device used in this case works as a gateway to connect to the *DCL* cloud server over the Internet. The stored data are fed to the *ICL* for activity recognition that leads to context formulation and behavior analysis of the users' daily activities. The information is stored back in the *HDFS* logs of the *DCL*. The processed activities, context, behavior information, and personal profile information are utilized by the *SCL* for reasoning and providing personalized physical activity recommendations. In *SCL*, knowledge bases are created by domain experts based on the online guidelines and experts' past experiences. This enables the process of provisioning personalized recommendations to users

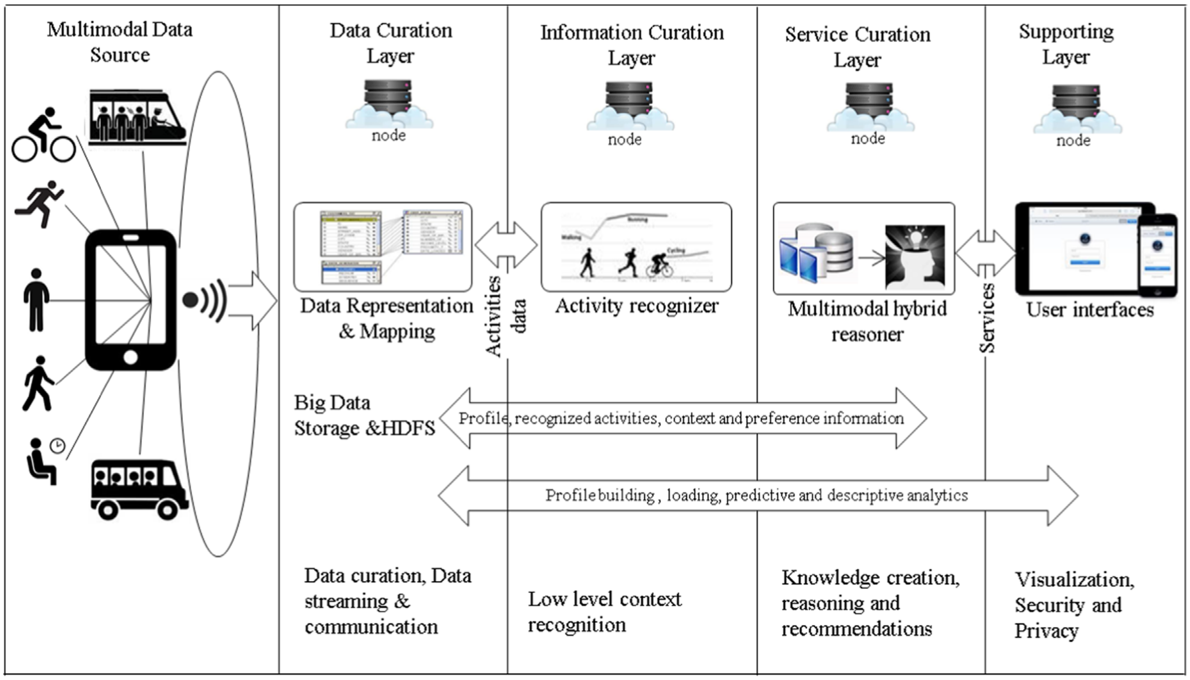

Fig. 2. Overview of the Mining Minds healthcare and wellness platform.

based on their needs, preferences, and interests. SL facilitates other layers by providing security, privacy, visualization and user interfaces. The user's personal profile information is collected using a mobile application and stored on the *DCL* server in a relational data model.

A multimodal hybrid reasoner is a key component of *MM* and plays the role of an intelligent service provisioning agent. It performs execution on the server side of the *SCL* and enables personalization of physical activity recommendations by integrating data and knowledge from diverse sources. The focus of this paper is on the reasoning methodology and its usefulness in *MM* for generating personalized physical activity recommendations.

4. Multimodal hybrid reasoning methodology (*HRM*)

For building an intelligent physical activity recommendation system, we moved beyond the traditional single reasoning methodology systems to a multiple reasoning methodology system. Our work integrates *RBR* and *CBR* with *PBR* into a single methodology called *multimodal hybrid reasoning methodology (HRM)*. *HRM* forms the basis of multimodal hybrid reasoner for the *MM* platform, which is the focus of this study. In *HRM*, these methodologies can be integrated in any of the following design strategies, shown in Fig. 3.

In Fig. 3(a–c), the sequence of the design strategy of *baseline-RBR* is as follows: level-1 *RBR* is followed by level-2 *RBR*, which is followed by level-3 *RBR* and *PBR*. The design strategy of the *modified-RBR* follows the same strategy as the *baseline-RBR*, except for the ranged-*METs*[2] rules, which are used at the level-3 *RBR*. The strategy of *hybrid-CBR* differs from those of the first two strategies at level-3, where *CBR* is used instead of *RBR*. In our study, we use the first strategy for building a baseline system to compare the results of the other strategies. The second strategy is the improved version of strategy 1, which is implemented in *MM* system (v1.0) but has its own limitations. To eradicate the shortcomings of the first two strategies, the third strategy of *hybrid-CBR* is used, which integrates *RBR*, *CBR,* and *PBR*. This strategy is experimented and realized outside the *MM* platform on a local set up in our lab.

Based on the idea illustrated above, we have defined the core components of the proposed multimodal hybrid reasoner and depicted them in the functional flow diagram shown in Fig. 4.

Fig. 4 shows high-level interactions of the different components of the reasoner along with the methodology used in each component. Like any other reasoning system, the core components of the proposed reasoner include the following: input/output interfaces, input data sources, knowledge bases, reasoning methodology and outputs. They are explained below as follows.

- *Input/output interfaces*: user's smart phone that runs the *MM* application works as the input/output interface for the reasoner.
- *Input data sources*: inputs of the reasoner include user requests, personal profile data, and daily physical activity data. The input data, except for the user requests, are stored in an intermediate database. The request for recommendation is received from the user's mobile application.
- *Knowledge base*: knowledge of the reasoner is composed of rules created from physical activity guidelines and past successful cases obtained from the implicit experience of the domain experts. The rules are stored in the rule base, while the past successful cases (*METs* index) are stored in the *METs case base (METCB).*
- *Reasoning methodology*: the reasoning methodologies include *RBR*, *CBR*, and *PBR*, which are integrated in a linear combination. The *RBR* methodology is applied at multiple levels: level-1, level-2, and level-3. At level-3, *RBR* is either used with distinct-*METs* rules or with ranged-*METs* rules. At the same level, *CBR* can also be used (using *METs* cases) as a counterpart of *RBR* for improved services. At the end, the multi-level filtration mechanism is applied in *PBR* to filter out irrelevant recommendations by utilizing the user's preferences and interests.
- *Outputs*: outputs of the reasoner include wellbeing recommendations for users, weight status, weight management plans, personalized physical activity recommendations and personalized filtered physical activity recommendations. These

[2] A metabolic equivalent, or *METs*, is a unit used to describe the energy expenditure of a specific physical activity. A *METs* is the ratio of the rate of energy expended during an activity to the rate of energy expended at rest (2008 Physical Activity Guidelines for Americans).

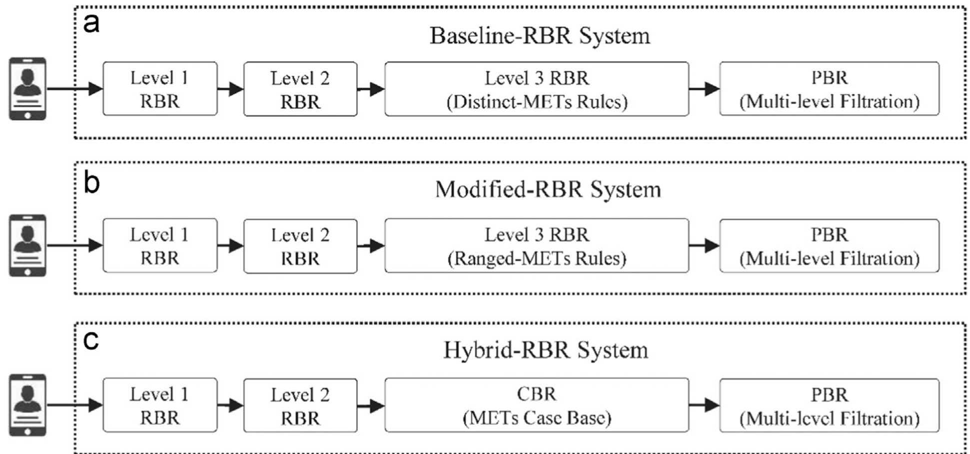

Fig. 3. Multiple design views of the proposed hybrid reasoning methodology on the basis of integration of different reasoning methodologies.

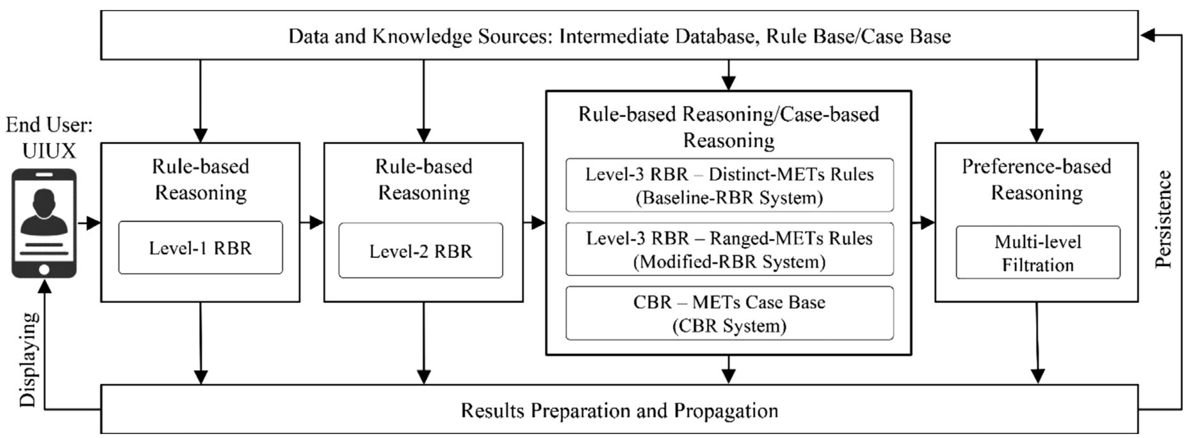

Fig. 4. Functional flow diagram of the proposed multimodal hybrid reasoning engine.

recommendations are aggregated and prepared by *Results Propagator* and then delivered to the end user and intermediate database. In the intermediate database, it is stored for future use as a successful case.

In the subsequent sub-sections, a detailed description of the architectural design of the proposed *HRM* is provided (Section 4.1), and then, the process of knowledge creation is discussed (Section 4.2); finally, the reasoning methodology is described in detail (Section 4.3).

4.1. Architectural design and workflow

A detailed data flow diagram of the multimodal hybrid reasoning engine illustrating communication is shown in Fig. 5.

The key components of the *HRM* are *service request handler (SRH), data loader and manipulator (DLM), knowledge base (KB), knowledge loader (KL), hybrid reasoner (HR)* and *result preparator and propagator (RP)*. The hybrid reasoner consists of *RBR*, *CBR*, and *PBR* modules along with the *PR* module. The *RBR*, *CBR*, and *PBR* modules work cooperatively in a linear combination for enhancing recommendations. *CBR* is the key reasoning methodology that is activated by the output of *RBR*. The output of *CBR* in turn activates the *PBR* methodology to personalize the recommended physical activity.

From the service execution perspective, when a user requests service, the *SRH* analyzes the request and activates the appropriate module of the reasoner. *SRH* supports the *MM* platform for multiple service generation. *SRH* forwards the request to *HR*, where the *RBR* (level-1, level-2), level-3 *RBR/CBR*, and *PBR* methodologies are sequentially executed. Outputs of the *HR* are forwarded to the *RP* module for final preparation and forwarded to the user mobile application interface (*UIUX*) for being displayed to the users.

For the weight management scenario, the multimodal hybrid reasoning methodology operates in the following flow.

- First, level-1 *RBR* is applied, which loads the *weight status rules (WSR)* (see Section 4.2) from the *KB* and the required personal profile data from the *intermediate database (IDB)* using the *data loader (DL)* component. The necessary computation on the personal data, *e.g., BMI* calculation from height and weight information, is performed using the *data manipulator (DM)* and passed to the level-1 *RBR*. The level-1 *RBR* uses *RBR* methodology to recommend weight status recommendations (normal, overweight, underweight) as a service to the user and to level-2 *RBR* for further processing.
- Level-2 *RBR* receives the output of the level-1 *RBR* as input and performs the same reasoning procedure as level-1 *RBR* for recommending the goal state and associated calorie consumption plan and weight management plans. The level-2 *RBR* uses the *goal* and *plan recommendation rules (GPR)* loaded by *KL* from the *KB* and the personal profile data loaded by the *DL* from the *IDB*. The purpose is to generate goal and plan recommendations, which are provided to the users as a service and to level-3 *RBR/CBR* for further processing.
- Level-3 *RBR/CBR* receives the output of the level-2 *RBR* as input and further generates physical activity recommendations. Level-3

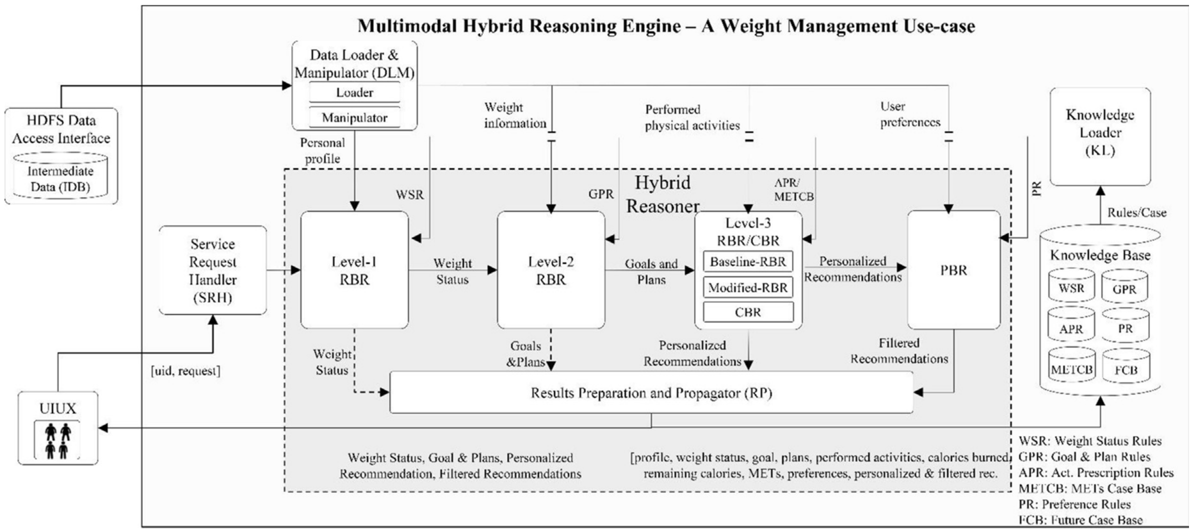

Fig. 5. Detailed data flow diagram of the proposed multimodal hybrid reasoning engine.

RBR/CBR supports both the *RBR* and *CBR* methodologies. The *RBR* results in *baseline-RBR* and *modified-RBR* systems. The *baseline-RBR* uses distinct-*METs* rules, while the *modified-RBR* uses ranged-*METs* rules that are loaded from the *KB* during the activity recommendation generation. The *CBR* methodology uses the *METCB* of the historical successful physical activity recommendations. In our case, we use the 2011 compendium of physical activity guidelines [36] as our key physical activity case base, which has physical activity recommendations associated with *METs* values. In either case (*i.e., baseline-RBR*, *modified-RBR* or *hybrid-CBR*), the list of all of the performed physical activities is loaded from the *IDB* and commutated for the duration, amount of consumed calories, remaining calories and corresponding metabolic equivalent (*METs*) value. The corresponding physical activities for the *METs* value are recommended and provided to the users. These physical activities are not filtered according to the preferences and interests of the users; therefore, they are forwarded to the *PBR* module for further personalization.

- *PBR* first receives the physical activities recommended by level-3 *RBR/CBR* and then loads the personal preferences and interests information from the *IDB*. The associated *preference-based rules (PR)* are loaded from the *KB* to apply multi-level filtration for filtering out irrelevant recommendations. The final filtered recommendations are personalized according to the user's personal preferences.
- The personalized recommendations are passed to the *RP* for proper preparation and packaging to be forwarded to the user application to be displayed on the user's mobile application.
- The user query, intermediate recommendations, and final personalized recommendations are stored in the *future case base (FCB)* for future use.

4.2. Knowledge acquisition

Knowledge is one of the most important ingredients of a reasoning system. This section describes how the knowledge used by the *HRM* is created. The key methodologies of *HRM* are *RBR* and *CBR*; therefore, we first need to create knowledge in the form of rules and cases. The process of knowledge acquisition is discussed below.

4.2.1. Rules base creation: translating guidelines

Wellness guidelines are the key source of information for improving the quality of life. Translating guidelines into computer-processable rules is a challenging task because it requires the involvement of knowledge engineers and domain experts [37]. In our study, knowledge from the unstructured guidelines of a weight management scenario is translated to rules with the help of *three* knowledge engineers and *two* domain experts. Based on the design of our study, the knowledge engineers first studied the weight management scenario, surveyed the weight management guidelines, indexed them, and categorized them into two groups: (a) standard equations to compute standard values and (b) indexes to be used in rule creation. An example of the first category is the calculation of calories burned/day, while an example of the second category is the *BMI* index. These rules are used by the *RBR* to generate physical activity recommendations. The process of guideline translation is described below.

4.2.1.1. Personal profile assessment. To classify users into underweight, normal or overweight states, personal profile assessment based on the standard *BMI* index is required [38]. The *BMI* index and personal profile information are combined together to form rules, which are shown in Table 1. For the *BMI* calculation, the standard *BMI* formula is used.

These rules are applicable for adults and used by level-1 *RBR* (see Section 4.3.1) for finding the weight status of the users.

4.2.1.2. Goal setting and plan management. A weight management system requires goals and the associated plans to achieve the goals. A goal can be either a local goal or global goal (*gloGoal*). A global goal is the final objective of the user to be achieved, while the local goal refers to a set of sub-goals to reach the global goal. For example, the total weight to be lost is considered a global goal, while weekly targets are considered local goals. To set a global goal in the context of the weight management scenario, first, an estimation of the ideal body weight (*idlWgt*) is required, which can be obtained using the Robinson JD [39] equation. The difference between the current weight (*curWgt*) and ideal weight

Table 1
Weight status rules (*WSR*) based on the standard Body Mass Index (*BMI*).

Gender	Age	*BMI* value	Weight status
M or F	>20	<18.5 kg/m^2	Underweight
M or F	>20	>18.5 and <25 kg/m^2	Normal
M or F	>20	>25 and <30 kg/m^2	Overweight

Table 2
Goals and weight management Plan Rules (GPR) for recommending the goal status and an appropriate plan.

Gender Male (M)/Female (F)	**Global Goal (gloGoal) - kg**	**Weight status (WS)**	**Plan prescription (PP)**
M or F	>0 (+ive)	Normal or Overweight	Weight Loss Plan (WLP): lose gloGoal(kg)
M or F	$=0$ (neutral)	Normal	Weight Maintenance Plan (WMP): motivational statements
M or F	<0 (−ive)	Underweight	Weight Gain Plan (WGP): gain gloGoal(kg)

yields the best estimation for the target goal in terms of the number of kg to be lost. The ideal body weight and global goal are computed using Eqs. 1 and 2.

$$idlWgt = 51.65\ kg + 1.85\ kg/inch\ over\ 5\ feet \quad (man)$$
$$idlWgt = 48.67\ kg + 1.65\ kg/inch\ over\ 5\ feet \quad (woman) \tag{1}$$

The ideal body weight is a debatable topic but has successfully been used in healthcare systems, such as drug dosage estimation [39] and cell transplantation [40]. Therefore, we have adopted it for the estimation of the global goal in our study.

$$gloGoal(kg) = curWgt(kg) - idlWgt(kg) \tag{2}$$

In our system, *gloGoal* by itself is a user service, but it is aimed towards devising plans for achieving the global goal. The rules defined for identifying appropriate plans, such as a weight loss plan, weight gain plan and weight maintenance plan *(GPR)*, are shown in Table 2.

In Table 2, we only focus on the first two cases.

Details of the suggested plan, *i.e.,* duration for achieving the global goal, can be computed using Eq. 3.

$$wghRedPlan(days) = roundup\left(\frac{7(days) * gloGoal(Kg)}{0.5(Kg)}\right) \tag{3}$$

In Eq. 3, a constant value of 0.5 represents the weight to be lost during one week. From this equation, local goals for weeks and months can be determined by subtracting a weight of 0.5 kg from the weight of the previous week (weekly plan). These plans can also be estimated in terms of the calories burnt (per day, per week, per month, *etc.*) using Eq. 4.

$$calToBurDay = \frac{gloGoal(kg) * Cal(1kgfat)}{wghRedPlan(days)} \tag{4}$$

In Eq. 4, *Cal* represents the number of calories equivalent to burning 1 kg of body fat.

All of these rules are used for setting the goal, devising plans, and managing weight and are used by level-2 *RBR*.

4.2.1.3. Physical activities assessment. Once a weight management plan is assessed, monitoring and recognition of the user's physical activities are required. Based on monitoring the previous day's activities, using the accelerometer sensor of the smartphone, the next day recommendations are planned. This process is performed in terms of the duration spent in each activity and the estimated amount of calories burnt. The amount of each activity (*amtAct*) is calculated by taking sum of all of the time slots (*timSlot*) during which the user performed that activity (*Act*), computed using Eq. 5.

$$amtAct_i = \sum_{j=1}^{t} Act_i.timSlot_j \tag{5}$$

The estimation of calories (*Cal*) for a specific activity (Act_i) in a specific time duration, $amtAct_i$, can be estimated by the product of the *METs* of that activity with the amount of activity and current weight of the subject. This calculation is shown in Eq. 6, which is adapted from the compendium of physical activities [36].

$$Act_i.Cal = Act_i.METs * amtAct_i(h) * weight(kg) \tag{6}$$

METs estimates the capacity and tolerance level of an individual to exercise in which he/she may participate safely without hurting him/herself [41]. We use it in our system to estimate calories from the physical activities and vice versa. In our calorie estimation process, we use the average *METs* rather than the exact value. The average *METs* for an activity (*e.g.,* walking) is calculated by considering all types of walking included in the *METs* guidelines [36] and taking the average. The same procedure is used for other activities that we consider (i.e., running, jogging, transportation, sitting, and standing). The rationale behind the average *METs* is the limitation of our current activity recognition system in recognizing the exact intensity of every sub-type of activity, for example, walking.

After applying Eq. 6, for all of the activities, Eq. 7 is used to sum all of the estimated calories.

$$totalBurnedCal = \sum_{i=1}^{a} Act_i.Cal \tag{7}$$

The remaining calories (*remCalToBurn*) for the rest of the day (in a daily calorie consumption plan) are computed using Eq. 8.

$$remCalToBurn = calToBurDay - totalBurnedCal \tag{8}$$

The aim of estimating the remaining calories is to recommend the appropriate physical activity using our reasoning system to meet the goals of the day. This recommendation requires the *METs* value computed from the *remCalToBurn* using Eq. 9 [36].

$$METs = \frac{remCalToBurn}{(amtAct = 1h) * weight(kg)} \tag{9}$$

We use the METs *value in both* RBR *and* CBR *to recommend the appropriate physical activity. For* RBR, *rules need to be created using the user's personal information and the required* METs *value. For* CBR, *a case base is to be prepared.*

4.2.1.4. Rules creations. Based on the estimated *METs* value and the user's personal information (*e.g.,* age), two types of rules are created. The first type is based on distinct-*METs* values, and the second type is based on ranged-*METs* value. The distinct-*METs* rules are used to build the *baseline-RBR* system, while the ranged-*METs* rules are used for building the *modified-RBR* system. When we considered distinct-*METs* and age together, we created a total of 122 rules for the 48 distinct-*METs* values. The distribution of the rules is as follows: 22 rules belong to the *Young* age group, 33 rules belong to the *Older Adults* group, and 47 belong to the *Adults* group. In the context of physical activity recommendation, age plays an important role; therefore, it is considered an essential

Table 3
Distinct-*METs* rules for recommending physical activity in the baseline rule-based reasoning system (*baseline-RBR*).

Rule ID	Age group	METs value	Activity prescription
R#1	Young	2	Walking, household
R#2	Older adults	6.5	Climbing hills with 0–9 lb load; Race walking; rock or mountain climbing
R#3	Young	7.8	Backpacking; hiking or organized walking with a daypack
–	–	–	–
R#122	Adult	15	Running; stairs up

Table 4
Ranged-METs rules for recommending personalized physical activity.

Rule ID	Age group	METs value	Activity prescription
R#1	Young, Adults, Older adults	< 3	Light activity
R#2	Adults	≤ 23	Moderate – vigorous-intensity
R#3	Older adults	≤ 10.25	Moderate – vigorous (lower intensity level)
R#4	Young	≤ 7	Moderate

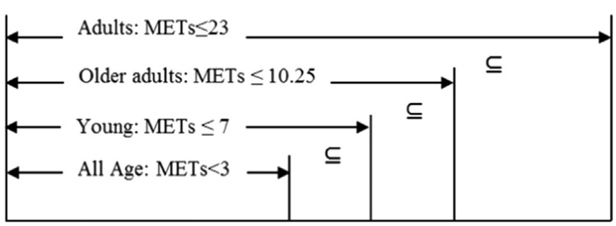

Fig. 6. Distribution of the subjects on the basis of age and intensity level of physical activities (*i.e., METs*).

part of the rules. The transformation of age to different age groups is supported by the guidelines from *WHO* [10] and *UK* [42]. These guidelines categorize users into three major age groups: *Young* (age 5–17), *Adults* (age 18–64), and *Older Adults* (age ≥ 65). A partial list of the distinct-*METs* rules is shown in Table 3.

In the *MM* implementation, we use ranged-*METs* rules; therefore, we first define ranges for the *METs* values used in these rules. According to the well-known physical activity guidelines from the center for disease control and prevention (*CDC*), American College of Sports Medicine (*ACSM*) [7], *WHO* [10], *US* [43] and *UK* [42], physical activities can be grouped into three categories: light (< 3.0 *METs*), moderate (3.0–6.0 *METs*) and vigorous (> 6.0 *METs*). According to these guidelines, moderate to vigorous-intensity physical activities are recommended to *Young*, *Adults* and *Older Adults*, but with slightly changed doses and patterns. For example, the *Young* group is recommended a physical activity of *METs* ≥ 3–7, and the *Adults* and *Older Adults* groups are recommended a physical activity of *METs* ≥ 3. However, the *Older Adults* group is recommended the same physical activities in the range of *METs* values for the *Adult* group but with lower intensity and dose due to their lower capabilities for exercise and physical activities. We have formulated these guidelines by considering the threshold value of *METs* ≤ 10.25 for *Older Adults*, *METs* ≤ 7 for *Young* and *METs* ≤ 23 for *Adults*. The light-intensity activities (*i.e., METs* < 3) are appropriate for all age groups because they do not lead to injuries. Based on this grouping of the *METs* values by the age groups, the ranged-*METs* rules are defined and summarized in Table 4.

Table 5
Case base structure of the metabolic equivalent of tasks (*METs*) values by physical activities.

Attribute	Data type	Possible value	Description
Age group	Symbol	{All age, Young, Adults, Older adults}	Age of the subject
METs	Float	Min = 1.3, Max = 23.0	Metabolic Equivalents of Tasks one hour
Recommendations	String	Physical activities {running, walking, cycling, traveling-bus and subways, standing, sitting}	Physical activities

4.2.1.5. Case base creation. The *CBR* part of *HRM* operates based on well-established past successful cases to generate physical activity recommendations. The cases in the case base are adapted from the 2011 compendium of physical activity guidelines [36]. These guidelines contain a list of physical activities associated with *METs* values. We used the *METs* values and the associated physical activities as the two key attributes of our case base. We named this case base the *METs* case base *(METCB)*. Based on the discussion made in Section 4.2.1.4, we extended the number of attributes of the *METCB* to include an additional attribute, *age group*. The relationship between *age group* and *METs* ranges is represented in Eq. 10 and depicted in Fig. 6.

$$AgeGroup = AllAge \subseteq Young \subseteq OlderAdults \subseteq Adults \tag{10}$$

In the above Eq. 10 and Fig. 6, it can be seen that we have added a fourth age group named *'All Age'* (*METs* < 3). It is a subset of all of the other age groups because activities of this intensity are not injurious and can equally be recommended to any *age group*. The current *METCB* contains 119 instances, which may increase in the future. Table 5 presents the detailed characteristics of the *METCB*.

4.3. Hybrid reasoning

Hybrid reasoning is the key methodology implemented in the proposed reasoning engine that generates personalized physical activity recommendations in the *MM* system. It is composed of *RBR*, *CBR*, and *PBR* and is discussed in the subsequent sub-sections.

4.3.1. Multi-level rule-based reasoning (Multi-level-RBR)

In *HRM*, the *RBR* methodology works at three levels (level-1, level-2, and level-3). Its objectives include the following: (1) assessment of personal information and recommendation for weight status, (2) assessment of the ideal body weight and recommendations for goals and plans and (3) assessment of the performed physical activities and recommendations for appropriate physical activity. The recommendations of each level are provided to the user, on one end, and to the next level, on the other. For example, the first level of recommendations is provided to the user and to the level-2 *RBR*. This process involves a sequential flow, and finally, recommendations are generated, which are provided to the users on their mobile applications. The idea of provisioning intermediate results to the users is motivated from the fact that *MM* system supports the PULL service model, where users can subscribe either to a single service or a combination of services. Using this approach, some of the users subscribe only for *weight status recommendations*, while others subscribe for *goal and plan recommendations* and *physical activity recommendations*. If the MM system is constrained only to support the PUSH service model, then it may be enough for the users who require services on the subscription basis but will not support users who require customized subscription-based services.

4.3.1.1. Level-1 RBR. Once the user query arrives at the *HRM*, level-1 *RBR* gets activated, loads personal profile information, performs the necessary computations, retrieves the *WSR* (Table 1) and starts the rule-based reasoning process [44]. The outputs are provided to the end user and to the level-2 *RBR*. The steps of the level-1 *RBR* are listed in Algorithm 1.

Algorithm 1. Rule-based reasoning for the recommendations of weight status.

```
Input: UID:uid
Output: Weight Status (WS): List <Weight Status>
Begin
Let SID:sid = Weight Status Service Id
WSR: Set of Weight Status Rules, WSR = ∅
KB: Knowledge Base
1. Foreach RULE R in KB
     If (R ∈ sid)
       WSR:=WSR ∪ R;
     End If
   End for
2. Foreach RULE R in WSR
     WS := ExecuteWSRule(R, uid)
     IfWS ≠ "Underweight"
       PropgatWSResultsToUIUX(uid, WS);
       InvokeLevel2RBR(uid, WS); // See Algorithm 2
       Go to step 3
     Else
       PropgatWSResultsToUIUX(uid, educational &
       motivational statments for Weight Gain)
       Go to step 3;
     End If
   End for
3. FCB:=AddWStatus(uid, WS); // See discussion
4. Exit;
End
```

In first step of Algorithm 1, *WSR* are loaded from the knowledge base using an iterative loop process. The design of the knowledge base is based on the types of services, and rules are stored accordingly. Therefore, the type of service identifies the type of rules to be loaded. The type of service can be identified by the service Id (*sid,* in this case). Once the rules are loaded, the execution commences. The definition of *ExecuteSWRule*() is given in Function 1, and it loads the personal profile data of the user from the *IDB* and performs the necessary computations. The data loading process of the *IDB* uses a simple object access protocol (*SOAP*)-based service, defined in the *SCL*. Finally, the pattern matching process starts, and when a rule is matched, it is fired, and its corresponding weight status recommendations are generated. The results of this function are returned to Algorithm 1 for further processing.

Function 1. Rules execution for the weight status recommendations.

```
ExecuteWSRule(RULER, UIDuid)
Let WS = Weight Status, showing BMI status of the user
IDB: Intermediate Database
PPROF: Personal Profile
BMI: Body Mass Index
RHS: Right Hand Side
LHS: Left Hand Side
1. Load PPROF of uid from IDB;
2. Compute BMI;
3. IfR.LHS.values = (PPROF and BMI)
     WS:=RHS of R;
     EndIf
4. Return(WS)
```

When the weight status recommendations are received by Algorithm 1, they are forwarded to the user mobile application interface (*UIUX*) and to the level-2 *RBR*. The function *PropgatWSResultsToUIUX*() is responsible for providing the recommendations to the user while the function *InvokeLevel2RBR*() is used to invoke the level-2 *RBR*. The propagation function first communicates with the user's mobile application and then provides the generated intermediate recommendations along with some metadata for display purposes. In case the intermediate result of the level-1 *RBR* is the *underweight* status, then the system propagates motivational and educational statements using the *PropgatWSResultsToUIUX*() function (see Section 6).

4.3.1.2. Level-2 RBR. Level-2 *RBR* is activated by level-1 *RBR* for setting goals and prescribing the associated weight loss and calorie consumption plan recommendations. In level-2 *RBR*, the goal and plan rules (*GPR*) specified in Table 2 are used along with Eqs. 1–4. The algorithmic steps of level-2 *RBR* are given in Algorithm 2.

Algorithm 2. Rule-based reasoning algorithm for goals and plans prescription recommendations.

```
Input: UID:uid, WS
Output: Weight Loss Plan (WLP)
Begin
Let SID:sid = Weight Loss Service Id
GPR: Goal and Plan Rules, GPR = ∅
PP: Plan Prescription
1. Foreach RULE R in KB // KB: Knowledge Base
     If (R ∈ sid)
       GPR:= GPR ∪ R;
     End If
   End for
2. Foreach RULE R in GPR
     PP:=ExecuteGPRRule (RULE R,UID uid)
       If PP="WLP"
         Let wlPlan:= List <WLPlan>;
       wl Plan=ComputeWLPlansInKgAndCalories(); // use
   Eq. 3 and 4
         PropgatWLPResultsToUIUX (uid,wlPlan);
         FCB:=AddRecommendedPlan (uid,wlPlan); // See
   discussion
         InvokeLevel3RBR-CBR (uid,wlPlan ["caloriesPlan"]); //
   See Algorithm 3
         Go to step 3;
     Else
         PropgatWMPResultsToUIUX(uid, educational & motiva-
   tional statments for Weight Maintenance)
         Go to step 3;
       End if
     End for
3. Exit;
End
```

In Algorithm 2, the rules are loaded from the *KB* on the basis of service type (*sid*). The service is goal and plan recommendations, and the associated rules are the *GPR*. After the rules are loaded, Algorithm 2 executes *ExecuteGPRRule*() to generate the plan prescription (*PP*) recommendations. The definition of this function is shown in Function 2, which takes each rule from the *GPR* and retrieves the required personal profile data from *IDB* and computes the ideal body weight (*idlWgt*) and global goal (*gloGoal*). The pattern matching process then starts, and each attribute of the left hand side (*LHS*) of the rule *R* is checked against the loaded and computed values. When a match is found, rule *R* is fired, and its right hand side (*RHS*) is provided as the *PP* recommendation. These recommendations are returned to Algorithm 2 for further processing.

Function 2. Execution of the goal and plan rules for goal and plan recommendations.

ExecuteWMPPlanRule(RULER, UIDuid)
Let IDB: Intermediate Database
gloGoal: global Goal
idlWgt: ideal Weight
PPROF: Personal Profile
LHS: Left Hand Side
RHS: Right Hand Side
PP: Plan Prescription
1. Load PPROF of uid from IDB;
2. ComputeIdealWeight(idlWgt); //use Eq. 1
3. ComputeGlobalGoal(gloGoal); //use Eq. 2
4. **If** R.LHS.values = (PPROF, gloGoal)
 PP:=RHS of R;
 End if
5. Return (PP);

If the output retained in *PP* is weight loss plan (*WLP*), then the *Compute WL plans in kg and calories*() function is activated for computing daily, weekly, and monthly plans in terms of the number kg to lose and the associated calorie consumption plans. These plans are forwarded to the users and are displayed on their mobile application interface (*UIUX*) and are also forwarded to level-3 *RBR–CBR*. The functions responsible for these tasks are *Propgat WLP Results To UIUX*() and *Invoke Level* $2RBR-CBR$(), respectively. In case the *PP* value is the weight maintenance plan (*WMP*), then educational and motivational statements are provided to the users using the *PropgatWMPResultsToUIUX*() function (see Section 6).

4.3.1.3. Level-3 RBR–CBR. In *HRM*, level-3 *RBR–CBR* uses either *baseline-RBR* or *modified-RBR* or *CBR* methodology. For these methodologies, an assessment of the performed physical activities is required in terms of the burned calories, remaining calories, and equivalent *METs* value. This assessment and the computations are performed using Eqs. 5–9. In the *baseline-RBR*, distinct-*METs* rules (Table 3) are used, while in the *modified-RBR*, ranged-*METs* rules (Table 4) are used to generate personalized physical activity recommendations. The algorithmic steps for both the *baseline-RBR* and *modified-RBR* are given in Algorithm 3 and are the same from the methodology perspective but different based on the nature of rules they use (for the level-3 *CBR*, see Section 4.3.2).

Algorithm 3. Assessment of physical activities and prescription of physical activity recommendations using rule-based reasoning.

Input: UID:uid, wlPlan
Output: Personalized Physical Activity Recommendations (PAR): List < Recommendations >
Begin
Let SID:sid = Personalized Physical Activity Recommendation Service APR : activity prescription rules and APR = ∅
1. **Foreach** RULE R in KB // KB: Knowledge Base
 If (R ∈ sid)
 APR: = APR ∪ R;
 End if
 End for
2. **Foreach** RULE R in APR
 PAR : = ExecuteActPrescRule(RULER, UIDuid)
 If PAR ≠ ∅
 Break;
 End If
3. **End for**
4. PropgatPARResultsToUIUX(uid, PAR);
5. *FCB*:=Add*RBR*PAR(uid, PAR); // See discussion
6. Invoke*PBR*(uid, PAR); // See Algorithm 5
7. Exit;
End

Algorithm 3 first loads the activity prescription rules (*ARP*) from the *KB* based on the service id, specified in the service request. For generating appropriate personalized physical activity recommendations (*PAR*), the *ExecuteActPrescRule*() function is used, the details of which are given in Function 3. The physical activities are recommended on the basis of the final computed *METs* values and the user's personal profile information. The *METs* value represents the intensity level of a physical activity. Within the same physical activity type, for example, walking, different intensity values exist that range from a *METs* value of 2.3 to a *METs* value of 12 [36]. Similar ranges exist for other activities as well, such as running, cycling, transportation, standing, and sitting. In the *METs* guidelines, a large number of distinct *METs* values are available, which makes it hard to define distinct *METs* rules. One of the solutions to this issue is to define range-based *METs* rules. In the *MM* implementation for the weight management scenario, *METs* range-based rules are used.

Function 3. Execution of distinct-*METs* and ranged-*METs* rules for physical activity recommendations.

ExecuteActPrescRule(RULER, UIDuid)
Let IDB: Intermediate Database
METs: Metabolic Equivalent of Task
PPROF: Personal Profile
AMTACT: Amount of Physical Activity Performed
PAR: Personalized Physical Activity Recommendations: List < Recommendations >
LHS: Left Hand Side
RHS: Right Hand Side
1. Load PPROF, AMTACT of uid from IDB;
2. Compute AMOUNT OF PHYSICAL ACTIVITY performed so far; //use Eq. 5
3. Compute CALORIES for each ACTIVITY; //use Eq. 6
4. Compute TOTAL BURNED CALORIES; //use Eq. 7
5. Compute REMAINING CALORIES; //use Eq. 8
6. Compute METs value; //use Eq. 9
7. **If** R.LHS.values = (PPROF, METs)
 PAR:=RHS of RULE;
 End if
8. Return(PAR)

Once *PAR* are generated, they are provided to the end users on their mobile application interface (*UIUX*) using the *Propgat PAR Results To UIUX*() function. The output of Algorithm 3 can be a list of physical activities that are generated either on the basis of ranged-*METs* rules or multiple physical activities against a single *METs* value in a rule. To filter this list of recommendations and personalize them to another level, they are provided to the

Table 6
Local similarity values of the attribute '*age group*' in the form of similarity matrix.

Age group	All age	Young	Older adults	Adults
All age	1	1	1	1
Young	1	1	0	0
Older adults	1	1	1	0
Adults	1	1	1	1

PBR methodology by using the *Invoke PBR*() function call of Algorithm 3 (see Section 4.3.3 for the *PBR* functionality).

4.3.2. Case-based reasoning (CBR)

To overcome the limitations of level-3 *RBR* implemented in the *MM* platform, we use *CBR* for generating more personalized recommendations. The *CBR* implementation is performed outside the *MM* implementation in our lab with the aim of enhancing the performance of *HRM*. The *CBR* methodology helps in recommending specific physical activity to users based on their gender information and required intensity for physical activity *i.e., METs* value. The *CBR* methodology is selected due to its capabilities of (1) recommending specific and precise physical activities to the user, (2) providing a list of top relevant physical activities as recommendations (*e.g.*, walking) with multiple similar alternatives (*e.g.,* running or cycling) and (3) refining the suggested recommendations based on the user's feedback for enhancing recommendation accuracy and specificity. *CBR* execution follows the standard *CBR* cycle (*retrieve, reuse, revise* and *retain*) to complete the process of suggesting and refining recommendations along with an incremental learning approach. In our study, we are unable to perform the *revise* step in *HRM* due to the limitation of the *MM* system in being unable to handle user feedback. This phase is left as future work.

4.3.2.1. Retrieve and reuse steps. In our *CBR* model, the case query contains two attributes, *age group* and *METs* value. The age value is retrieved from the personal profile of the user, which is transformed to the predefined *age group*. The value of the *METs* attribute is computed from the user's personal profile information and the physical activities the user performed so far. For this purpose, steps 1–6 of Function 3 are used. These values are provided to the *retrieve* step of the *CBR*, which starts retrieving similar cases from the *METCB.* For the retrieval of *age group* and *METs* values, two local similarity functions are defined, which are shown in Eqs. 11 and 12.

$$METSim_l(nC, eC) = \frac{d_g(Max_{MET}, Min_{MET}) - d_l(nC_{MET}, eC_{MET}) - 1}{d_g(Max_{MET}, Min_{MET})} \tag{11}$$

Here, $METSim_l$ calculates the similarity of the *METs* between the *new query case* (nC) and *existing cases* (eC) in the *METCB*. Similarly, d_g is the global distance function that calculates the distance between Max_{MET} (maximum *METs* value in the *METCB*, *i.e*., 23 for running) and Min_{MET} (minimum *METs* value in the *METCB*, *i.e.,* 1.3 for resting). Here, d_l is the most important local similarity function that computes the distance between the *METs* values of nC and eC.

$$AGSim_l(nC, eC) = \left\{ \begin{array}{ll} AG_{ij} = 1 & for \forall (i \geq j) \text{ OR } (i = 0 \text{ OR } \; j = 1) \\ 0 & otherwise \end{array} \right\} \tag{12}$$

In Eq. 12, $AGSim_l$ is the local similarity function that matches the *METs* values of eC with nC. The similarity criterion used in the equation is the exact match, which is denoted as value 1. The interpretation of this value is that if the age group of the query case is similar to that of the existing case (*i.e.,*$AG_{nC} = AG_{eC}$), then this value will be 1; otherwise, it will be 0. The symmetric view of the local similarity function of this attribute is represented in a confusion matrix shown in Table 6.

In the above confusion matrix, the diagonal value of each age group is equal to 1, which shows the exact match relationship of each age group with itself. The age group, labeled as *All Age*, represents the list of *METs* values (less than 3) that can be equally recommended to the rest of the age groups; therefore its value is 1 for all of the other age groups. Similarly, the *METs* values of the age group *Young* (less or equal to 7) are also a subset of the *METs* values of the *Older Adults* and *Adults* age groups; therefore its value is 1 for all these age groups. This makes both the columns identical in the similarity matrix table.

After computing the local similarities, we use the weighted sum global similarity function, Sim_g**,** to compute the global distance between nC and eC, as shown in Eq. 13.

$$Sim_g(nC, eC) = \beta(AGSim_l(nC, eC)) + \gamma(METSim_l(nC, eC)) \tag{13}$$

Here, β denotes the weight value assigned to the attribute *age group* and γ denotes the weight value assigned to the *METs* attribute. The value of β is 0.1 (*i.e.,* $\beta = 0.1$), and the value of γ is 0.9 (*i.e.,* $\gamma = 0.9$). The higher value of γ represents the importance and contribution of the *METs* attribute in the final decision. For the selection of similar cases, we use k-NN [45] with k=3 to select the top three similar cases and reuse them as the suggested recommendations. In the *MM* system, the selection of the top three cases provides choices to the users for following any of the proposed recommendations based on their personal preferences and interests. The top recommended activities are of the same intensity or close to each other in intensity and have similar impacts on an individual's health. The acceptance of the top three recommendations is based on the threshold value (confidence), denoted by symbol μ. We set the threshold value to be greater than or equal to 95 (*i.e.,* $\mu \geq 95$). If a single case satisfies the threshold, only one recommendation is provided as the final physical activity recommendation. If more than 1 case is retrieved, then *PBR* is activated for further filtration and personalization of the suggested physical activity recommendations (see Section 4.3.3). The confidence value for the acceptance of recommendations is the threshold value, which is computed using Eq. 13. It is the aggregate score obtained from the local similarity values of Eqs. 11 and 12. The method used for aggregation is the weighted sum, which has a higher weight $\gamma = 0.9$ for the *METs* attribute and lower weight $\beta = 0.1$ for the *Age Group* attribute. To set the confidence/threshold value as $\mu \geq 95$(0.05threshhold), we were motivated by the well-known work [46–48] in the statistical community. The authors considered a 95% confidence interval or 0.05 threshold value as the acceptable value for accepting a hypothesis. The detailed working methodology of the proposed *CBR* is presented in Algorithm 4.

Algorithm 4. Case-based reasoning methodology for generating personalized physical activity recommendations.

Input: UID:uid, METCBurl, nC:= new Case, where $nC \in$ PPROF, METs and nC is computed using Eqs. 5–9

Output: Personalized Physical Activity Recommendations (PAR)): List < Recommendations >
Begin
Let PAR: = A set of top 3 relevant existing cases as the proposed recommendations
Sim_g[]: = Array of global similarities of existing cases
1. $METCB_r$: = ReteriveCaseBaseFromKB(METCBurl), Where $METCB_r$ is the matrix $eC_m \times A_n$, eC_m is the set of existing cases, i.e., $eC = eC_1, eC_2, eC_3, \ldots, eC_m$. Similarly, A_n is the set of attributes, i.e., $A_n = A_1, A_2, A_3, \ldots, A_n$
2. **For** $i = 1$ to SizeOfCases($METCB_r$)
   Let Sim_l []: = Array of local similarities of attributes of individual cases
   For $j = 1$ to SizeOfAttributes($METCB_r$)
   Sim_l [A_j]: = ComputeLocSim(nC.A_j,$METCB_r$ [i,j]); // use Eqs. 11 and 12
   End for
   $\mathbf{Sim_g}$ [eC_i]: = ComputeGlobSim ($\mathbf{Sim_l}$); // weighted sum method (Eq. 13)
3. End for
4. PAR: = ApplyKNN(Sim_g]); //where k = 3
5. PropgateCBRResultsToUIUX(uid,PAR);
6. FCB:=RetainCBRPAR(uid,PAR); // See discussion
7. InvokePBR(uid,PAR); //See Algorithm 5
8. Exit;

End

Algorithm 4 begins execution when nC is input to the *CBR* algorithm. In the first step, the *ReteriveCaseBaseFromKB*() function is used to load the existing cases from *KB* to the $METCB_r$. For this purpose, the *URL* of *METCB*, *METCBurl,* is used. Each *eC* is matched against *nC*, and the distance is calculated using the local and global similarity functions (*i.e.*, Eqs. 11 and 12). *k-NN* with $k = 3$ is used to obtain the top three similar cases as the suggested physical activity recommendations. These recommendations are specific and precise compared with the results of the *baseline-RBR* and *modified-RBR* systems. The retrieved case(s) is/are passed to the end users as the proposed personalized physical activity recommendations with the help of the *PropgateCBRResults*() function. Similarly, this/these recommendations(s) is/are also forwarded to *PBR* using the *InvokePBR*() function to filter them according to the user's preferences and interests.

4.3.2.2. Retain steps. Once the *reuse* step suggests recommendation(s), the whole case needs to be retained in the case base as a new case. In the proposed *HRM*, we add this new case to a data store, called the future case base (*FCB*). If the *retrieve* step ends with a single recommendation, the whole case, including the user's personal profile and suggested activity, is stored in the *FCB*. However, if more recommendations are generated, the new case is stored in the *FCB* after applying the *PBR* methodology (see Section 4.3.3).

4.3.3. Preference-based reasoning (PBR)

The recommendations generated by the *RBR* and *CBR* methodologies are based on the knowledge created based on general guidelines, which are unable to reflect the user's personal interests and preferences. These recommendations are not personalized from the perspective of the user's personal interests and preferences; to satisfy them, another level of refinement and filtration of the suggested recommendations is required that is performed by the *PBR* methodology. The *PBR* mechanism exploits the user model, built on top of the user profile. A user model contains the user's personalized requirements, such as preferences and interests. This information is initially acquired from the user, during the registration process and updated thereafter. The recommendations provided by the *RBR* and *CBR* exploit data only from the user's personal profile and physical activity behaviors and do not take into account the preferences. When recommendations are provided on the basis of these methodologies, multiple interpretations can be made. For example, consider a scenario where a user *U* requires *X METs* of physical activity to burn an amount *Y* of calories. The *RBR* or *CBR* can generate the following set of recommendations for the mentioned scenario.

- Walking *M1* minutes OR Running *M2* minutes OR Cycling *M3* minutes OR Hiking *M4* minutes, *etc.*

These recommendations are equivalent and can meet the user's requirement mentioned in the scenario' however some of them may not fit the user's personal interests and preferences adequately. It may be that the user is interested in walking and cycling but not in running and hiking. Therefore, the final recommendations should only include walking and cycling.

To obtain the user's final preference-based personalized recommendations, we propose a multi-filter approach implemented as part of the *PBR*. According to this approach, filtered personalized physical activity recommendations (*FPAR*) are obtained from the list of generated personalized physical activity recommendations using the user preferences (UPrefrences). This process of filtration is shown in Algorithm 5.

Algorithm 5. Filtration of the personalized physical activity recommendations using user preferences.
Input: UID: uid, PAR
Output: Filtered Personalized Physical Activity Recommendations(FPAR): List < filteredRecommendations >
Begin
Let UPrefrences[] = List of user preferences
FCB: = Future Case Base
FPAR : = ∅
1. UPrefrences[] = loadUserPrefences(uid);//Load user presences from user profile in IDB
2. **Foreach** Recommendation Rec in PAR
   If (Rec ∈ UPrefrences)
   FPAR: = FPAR ∪ Rec;
   End if
   End for
3. PropgatFilteredPARToUIUX(uid, FPAR);
4. *FCB*:=AddFPAR(uid, FPAR); // see discussion
5. Exit

End

The process of preference-based reasoning starts by loading the user's list of preferences, denoted by *UPrefrences*, from the intermediate database. The filtration process is performed in step 2 by taking each recommendation from the *PAR* and checking it against the preference list of the user. If the recommendation does not satisfy the user's preference, it is filtered out; otherwise, it is added to the filtered list *FPAR*. This process is continued till all of the recommendations in *PAR* are checked. Finally, the filtered personalized recommendations are provided to the user on his mobile application interface using the PropgatFilteredPARToUIUX() function. At the same time, the final *FPAR* are retained in the *FCB* as the recommended physical activity. This incrementally grows the *FCB*, which can be best used in future for successful cases of physical activity recommendations.

Table 7
Personal profile information of the volunteers, *WHO* participated in the evaluation of Mining Minds platform.

User ID	**Gender:** Male (M), Female (F)	**Age** (Years)	**Height** (Feet)	**Weight** (Kg)	**Preferred activities**
1	M	26	6.2	84.5	Running, walking
2	M	28	5.7	72.5	Running, walking, cycling
3	M	28	5.8	70.1	Walking
4	M	31	5.4	68	Running, cycling
5	M	31	5.6	71.9	Walking, traveling
6	M	32	6	85.9	Running
7	F	32	5.2	65	Walking, jogging
8	M	37	5.8	75	Walking, cycling
9	F	30	5.2	75	Walking running, cycling
10	M	38	5.8	71	Running, cycling

Table 8
Distribution of the physical activities in the *METs Case Base.*

S.No	**Type of activity**	**Distribution**
1	Running	25
2	Walking	56
3	Cycling	18
4	Standing	5
5	Sitting	4
6	Transportation	4
7	Volunteer	7
Total instances		119

5. Experiments and evaluation

For evaluating the performance of the proposed *HRM*, we performed the following set of tasks. Initially, we defined a weight management scenario, then set up a set of experiments, and finally performed the experiments and analyzed the results.

5.1. Case-study: weight management

We considered and implemented a weight management scenario for healthy individuals who are overweight or tend to overweight. After implementation of the methodology, we asked ten volunteers (ages 26–38 years) to use the system for a couple of weeks. The basic personal information of these individuals is shown in Table 7.

The individuals were asked to use the application during the specified period of time and follow the recommendations provided. During the user's physical activity, the mobile application collected the user's daily physical activity data using the accelerometer sensor of the smartphone. These activities included sitting, standing, moving in a bus, moving in a subway, walking, running and cycling, which are recognized by the *activity recognizer* module (in the *ICL*) of the Mining Minds platform (Fig. 2). For the detailed methodological process of recognition of these activities and the support of *ICL*, refer to the work of Han et al. [49], and Banos et al., [50]. The data are stored in the *DCL*, from where they are recognized by the *ICL* and provided to the *SCL* for recommending the appropriate physical activity for the remaining targets.

5.2. Experimental setup

To perform the experiments, we first set up the required environment, then specified the data and knowledge used for the experiments and finally defined the evaluation criteria.

5.2.1. Environment

The implementation of *HRM* was performed on a distributed framework in the Microsoft Azure public cloud environment. As described in Section 3, the *MM* platform is composed of four layers, and each layer is deployed on an individual virtual instance. The proposed *HRM* is part of *SCL*, which was hosted on a standard *A3 MS* Azure instance with Microsoft Windows Server 2012 *R2* as the guest Operating System (*OS*). *HRM* communicates with *DCL* and *SL* and communicates with *DCL* to load data for reasoning and storing final recommendations. With *SL*, *HRM* provides a recommendation service on the request and response model. The services in *SCL* are implemented as *SOAP*-based web services, and their accessibility is defined using service contracts between layers. Web services are implemented in Java and deployed on Glassfish server on virtual machine (*VM*).

For implementation of the third experiment, *hybrid-CBR*, which operates on *METCB*, we used myCBR[3], which is an open-source similarity-based retrieval tool. We used the Windows environment on a *PC* with an Intel Pentium Dual-CoreTM (2.5 GHz) with 4 GB of memory.

5.2.2. Data and knowledge (rules/case base)

As we evaluate our proposed *hybrid-CBR* methodology in terms of the performance of the *baseline-RBR* and *modified-RBR* systems, we therefore require data and knowledge on all of these systems. For the *baseline-RBR* and *modified-RBR* experiments, we used the user's personal profile, physical activity data and knowledge rules created based on the guidelines (Tables 3 and 4). For the *hybrid-CBR* experiments, we use *METCB*, prepared from *METs* guidelines [36]. The size of our '*METCB*' is 119 instances. It contains the activities we focus on in the *MM* platform. The distribution of these activities in *METCB* is shown in Table 8.

In the compendium of physical activity guidelines [36], "standing" and "sitting" are the sub-categories of volunteer physical activity. More details on the structure of *METCB* are given in Table 5. For the offline testing and evaluation of the methodology, we designed a *Test Case Base (TCB)* that contains 64 test instances. We prepared these test cases from the original *METCB*. The method used for defining the value of the *METs* attribute of the *TCB* was random value computation. The random value is computed from the *METs* attribute of the original *METCB* using Microsoft Excel [51]. The function used for the random value generation is shown in Eq. 14.

$$METs.value = randbetween(bottom, top) \tag{14}$$

Here, *bottom* represents the minimum value of the *METs* and *top* represents the maximum value of *METs* for the new test cases. We used $bottom = 1.3$ and $top = 23$. The values 1.3 and 23 are the

[3] http://mycbr-project.net/index.html

Table 9
Weight status and goal and plan recommendations generated by level-1- and level-2 rule-based reasoning of the proposed multimodal reasoning methodology.

User ID	Level-1 *RBR* (Algorithm 1) Results		Level-2 *RBR* (Algorithm 2) results				
	BMI	**Weight status**	**Ideal body weight** (Kg)	**Goal** (# of Kg to lose)	**Weight management plan**	**Duration plan** (weeks)	**Calories burning plan** (daily)
1	23.9	Normal	78.0	6.5	weight loss	13	550
2	25.02	Overweight	64.8	7.7	weight loss	15	550
3	23.5	Normal	66.6	3.5	weight loss	7	550
4	25.7	Overweight	59.1	8.9	weight loss	18	550
5	25.8	Overweight	62.9	9.0	weight loss	18	550
6	25.7	Overweight	74.2	11.7	weight loss	23	550
7	26.2	Overweight	52.0	13.0	weight loss	26	550
8	25.14	Overweight	66.6	8.4	weight loss	17	550
9	30.24	Obese	52.0	23.0	weight loss	46	550
10	23.8	Normal	62.1	8.9	weight loss	18	550

minimum and maximum values, respectively, of the *METs* attribute in the original *METCB*.

5.2.3. Evaluation criteria

To evaluate the proposed reasoning methodology, a group of system-centric evaluation criteria are used [52]. We evaluated the system using *Type I* (False positive-FP) and *Type II* (False negative-FN) errors, precision, recall, accuracy, and *f*-score criteria. We do not focus on a user-centric evaluation that addresses the user's satisfaction because in the current implementation, only a prototype of the *MM* platform is implemented. The *hybrid-CBR* experiments were performed in a closed environment in our lab; therefore, we leave user-centric evaluation as future work when the *MM* platform will be fully implemented with the feedback mechanism.

5.3. Experiments and analysis of the results

As the design of *HRM* is based on *RBR*-first followed by the *CBR* strategy, we therefore first evaluate the *RBR* and then tailor its results to *CBR*. During the *RBR* execution, the level-1 *RBR* is first executed for reasoning the weight status of all of the subjects using Algorithm 1 and presenting the output as recommendations to the users, as shown in Table 9. If the weight status is not underweight, the output is fed to level-2 *RBR* for setting goals and recommending weight loss and calorie consumption plans using Algorithm 2. The resulting recommendations of the level-2 *RBR* are also shown in Table 9.

These recommendations include the goal in terms of kg to lose, weight management plan, number of weeks to successfully execute the plan and daily calorie consumption plan. The volunteers were asked to follow these plan recommendations. The objective of *HRM* is to recommend appropriate physical activities for these plans. The *HRM* estimates *METs* values to materialize the plans. The *METs* estimation is required in two cases:

- At the start of plan, when *HRM* initially recommends the physical activity for starting the plan.
- During the plan, *i.e.*, the subject follows the plan and the system makes further recommendations.

In the first case, the *METs* estimation is performed only for the recommended 'daily calorie consumption plan', which is the output of the level-2 *RBR*. In the second case, the *METs* estimation is based on the remaining calories (see Eq. 8). Once the *METs* value is computed, the corresponding physical activity recommendations are generated. These recommendations can be generated using the *baseline-RBR, modified-RBR* and *hybrid-CBR* systems; therefore, we perform three different sets of experiments, which are discussed below.

Table 10
Physical activity recommendations generated by the baseline rule-based reasoning system.

User ID	METs	Personalized physical activity recommendations
1	6.5	i. Climbing hills with 0–9 lb load. ii. Race walking; rock or mountain climbing
2	7.6	X
3	7.8	i. backpacking; hiking or organized walking with a daypack
4	8.1	X
5	7.6	X
6	6.4	X
7	8.5	i. bicycling; BMX ii. bicycling; mountain; general iii. bicycling; 12 mph; seated; hands on brake hoods or bar drops; 80 rpm
8	7.3	i. climbing hills with 10–20 lb load
9	7.3	i. climbing hills with 10–20 lb load
10	7.7	X

5.3.1. Experiment 1: baseline-RBR system

The purpose of this experiment is to build the initial *baseline-RBR* system for comparing the results of the systems. The results of this experiment were generated prior to the implementation of the proposed idea in the *MM* platform. In level-3 *RBR*, distinct-*METs* rules, shown in Table 3, are used to generate physical activity recommendations using Algorithm 3 with exact match criteria. A few examples of the prescribed recommendations are shown in Table 10. These are based on the initial calorie consumption plan of the 10 volunteers.

While generating these recommendations, the first *METs* values for all volunteers are computed based on their calorie plans and then combined with the attribute *age group* to prepare the data for the rules. The symbol 'X' in Table 10 denotes that no recommendation is generated for these query cases. From Table 10, it is clear that five out of ten queries cases are unsuccessful and that recommendations could not be generated for them. These include the queries of users 2, 4, 5, 6 and 10. The reasons for the empty recommendations are that these queries do not match any rule described in Table 3. The distinct rules used in this experiment use *METs* values adopted from the *METs* guideline for physical activity, which does not include the values 7.6, 8.1, 7.6, 6.4, and 7.7. Therefore, no rule with these values exists in Table 3, and hence, no match is found during the reasoning process for the specified input query cases. For the detailed evaluation of the *baseline-RBR* system, the whole '*TCB*' is used as a test case. The results are calculated and presented in Figs. 7 and 8, which show that the recall

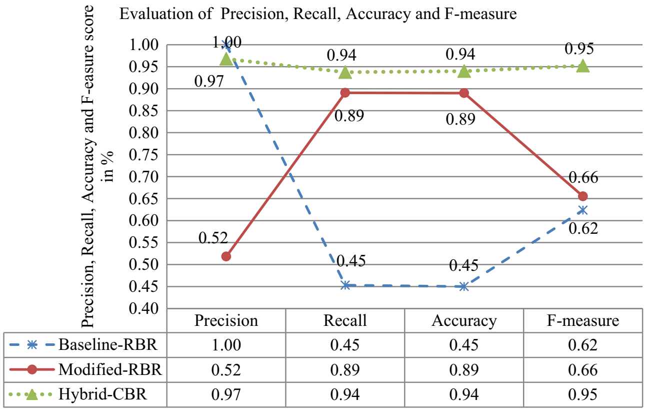

Fig. 7. Comparison of baseline-*RBR*, *modified-RBR* and *hybrid-CBR* system on the basis of precision, recall, accuracy, and *f*-measure.

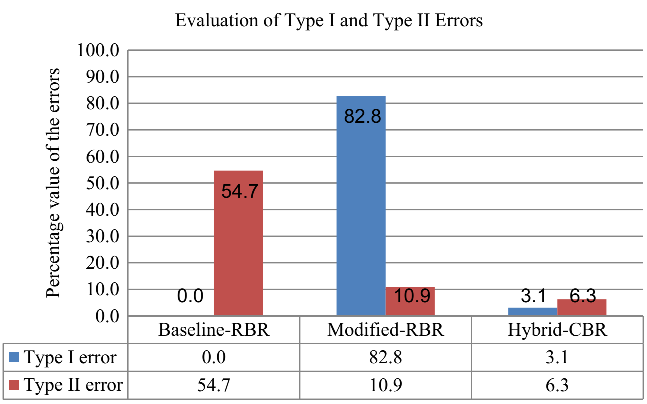

Fig. 8. Comparison of baseline-*RBR*, *modified-RBR* and *hybrid-CBR* for *Type I* and *Type II* errors.

of the *baseline-RBR* is very low (45%) and that the *Type II* errors are very high (54.5%). The limitations of this experiment are summarized as follows: (1) creation of distinct rules for each value of *METs* is a difficult task that results in a rule intractability problem, (2) the closest similar recommendations are overlooked if an exact match is not found, and (3) a high *Type II* error rate is observed.

5.3.2. Experiment 2: modified-RBR system

Based on the lesson learnt from the *baseline-RBR* system, level-3 *RBR* is implemented with *ranged-METs* rules (Table 4) in the *MM* platform. Algorithm 3 is used to execute these rules. To demonstrate the effectiveness of this experiment, we consider an example query for volunteer 4 (Table 7) with *age group* = *adults* and *METs* = 8.1 (see Table 10). The *modified-RBR* generates multiple recommendations for this query, though *baseline-RBR* fails to do so. To fully evaluate Algorithm 3, the whole '*TCB*' is applied, and the results produced are shown in Figs. 7 and 8. The recall and accuracy are increased from 0.45 to 0.89 and the *f*-score is increased from 0.62 to 0.66, while the Type II error rate is reduced from 54.7 to 10.9. The advantage of the *modified-RBR* system is that all queries are served and no query is returned with empty recommendation results. For example, when the query case with '*age group*' = *All Age* and *METs* = 2.7 is processed, a total of 17 recommendations are generated, as shown in Table 11. When the *baseline-RBR* is used for this query, no recommendation is generated because the *METs* value of the query case has no match with the *METs* values of the distinct rules. However, in the *modified-RBR*, the ranged-*METs* rule with a *METs* value less than 3 is satisfied, and hence, all of the associated recommendations are generated.

Table 11
Physical activity recommendations generated for a single query case using the modified rule-based reasoning system

Recommendation #	METs	Suggested physical activity recommendations
1	1.3	Riding in a car or truck
2	1.3	Riding in a bus or train
3	1.5	Sitting; meeting; general; and/or with talking involved
4	1.5	Sitting; light office work; in general
5	2.0	Walking; household
6	2.0	Walking; less than 2.0 mph; level; strolling; very slow
7	2	Sitting; child care; only active periods
8	2	Walking; less than 2.0 mph; very slow
9	2.3	Carrying 15 lb child; slow walking
10	2.3	Standing; light work (filing; talking; assembling)
11	2.5	Bird watching; slow walk
12	2.5	Walking from house to car or bus; from car or bus to go places; from car or bus to and from the worksite
13	2.5	Walking to neighbor's house or family's house for social reasons
14	2.5	Walking; to and from an outhouse
15	2.5	Sitting; moderate work
16	2.5	Automobile or light truck (not a semi) driving
17	2.8	Walking; 2.0 mph; level; slow pace; firm surface

Similarly, all of the queries yields results, and no query is unsuccessful.

The limitation of the system is its high *False Alarm* rate (*i.e., Type I* error), as shown in Table 11. From this table, we see that a list of 17) recommendations is generated for a single query. On average, 52 options of physical activities are provided as recommendations for each query, which is problematic. A summary of the *Type I error* for this experiment is shown in Fig. 8. The high *False Alarm* rate results in a wide scope of recommendations that may not fit well with the user's required physical activity. This effect is normalized in *PBR* when multiple filters are applied for filtering unnecessary and irrelevant recommendations.

5.3.3. Experiment 3: CBR system

The objective of using *CBR* is to minimize limitations of the *baseline-RBR* and *modified-RBR* systems. To overcome these problems, we performed the *CBR* experiment in a local set up without involving the *MM* setup. The outputs of level-1 *RBR* and level-2 *RBR* and the estimated *METs* value generate a query case for the *CBR* methodology. Algorithm 4 uses the local similarity function, global similarity function, k-NN with $k=3$ and a threshold $\mu>=95$ to generate appropriate physical activity recommendations. The *CBR* methodology has significantly improved *Type I* and *Type II* errors, as shown in Fig. 8. *CBR* offers the following advantages:

- *Type I* errors are reduced – k-NN with $k=3$ retrieves the top cases that are most relevant to the query case and specific to the user's requirement. Hence, the *False Alarm* rate is significantly reduced.
- *Type II* errors are reduced and recall is improved – the global similarity function of *CBR* with threshold $\mu>=95$ has reduced *Type II* errors. The retrieval of most similar recommendations minimized the *False Negative* cases and improved recall.
- Relevant and specific recommendations – the retrieve phase of *CBR* retrieves the top three recommendations that are either exactly the same as required by the user or close to the user's specific requirements for physical activity. Hence, the number of recommendations is reduced to an optimum level on the one hand and is closer to the user's specific requirements on the other.

Table 12
Physical activity recommendations generated using case-based reasoning methodology.

User ID	New case (METs value)	Retrieved cases (METs value)	Suggested physical activity recommendations
1	6.5	6.5	i. climbing hills with 0–9 lb load.
		6.5	ii. race walking; rock or mountain climbing
		6.3	iii. climbing hills; no load
2	7.6	7.3	i. climbing hills with 10–20 lb load
		7.5	ii. bicycling; general
		7.8	iii. backpacking; hiking or organized walking with a daypack
3	7.8	7.8	i. backpacking; hiking or organized walking with a daypack
		8	ii. running; training; pushing a wheelchair or baby carrier
		8	iii. running; marathon
4	8.1	8	i. running; training; pushing a wheelchair or baby carrier
		8	ii. running; marathon
		8	iii. carrying 25 to 49 lb load; upstairs
5	7.6	7.3	i. climbing hills with 10 to 20 lb load
		7.5	ii. bicycling; general
		7.8	iii. backpacking; hiking or organized walking with a daypack
6	6.4	6.3	i. climbing hills; no load
		6.5	ii. climbing hills with 0–9 lb load
		6.5	iii. race walking; rock or mountain climbing
7	8.5	8.5	i. bicycling;
		8.5	ii. bicycling; mountain; general
		8.5	iii. bicycling; 12 mph; seated; hands on brake hoods or bar drops; 80 rpm
8	7.3	7	i. walking; 4.5 mph; level; firm surface; very; very brisk
		7.3	ii. climbing hills with 10–20 lb load
		7.5	iii. bicycling; general
9	7.3	7	i. walking; 4.5 mph; level; firm surface; very; very brisk
		7.3	ii. climbing hills with 10–20 lb load
		7.5	iii. bicycling; general
10	7.7	7.5	i. bicycling; general
		7.8	ii. backpacking; hiking or organized walking with a daypack
		8	iii. bicycling; 12–13.9 mph; leisure; moderate effort

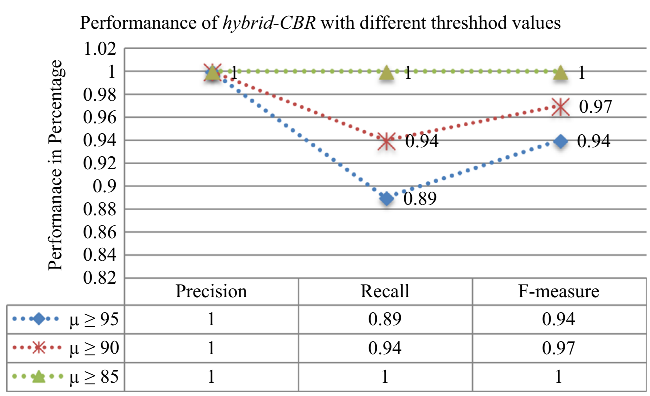

Fig. 9. Performance of basline-*RBR*, *modified-RBR* and *hybrid-CBR* with different threshold values.

To demonstrate the effectiveness of the *CBR* methodology for these objectives, we consider the case of 10 volunteers of the *MM* evaluation team and their estimated *METs* values (Table 10). The initial recommendations for the calculated *METs* values and *age group*=*adults* are shown in Table 12.

Table 12 shows that for each query case, the top three most relevant physical activity recommendations are provided, which fulfills the user's specific requirements. For the query *age group* = *Adults* and *METs* = 8.1, *baseline-RBR* failed to generate recommendations (see Table 10) and *modified-RBR* produced 59 possible recommendation options, but *CBR* produced only three recommendations (Table 12). The difference between the required *METs* values of the query case and the one using the rules is only 0.1, which is negligible; however, *baseline-RBR* fails to generate recommendations. This clearly shows the effectiveness of the proposed *CBR* methodology in *HRM*.

Moreover, to fully evaluate the *CBR* methodology, we apply the whole *'TCB'* to generate recommendations. The results are shown in Figs. 7 and 8. These results are significantly improved compared with those of the *baseline-RBR* and *modified-RBR* methodologies.

The green line at the top of the graph in Fig. 7 shows the performance of *hybrid-CBR*, which is superior to the other two approaches.

Fig. 8 pictorially shows that hybrid *RBR*/*CBR* has improved *Type I* and *Type II* error results compared with the other experiments. To present the results of *hybrid-CBR* with different threshold values i.e., $\mu \geq$ 95, $\mu \geq$ 90 and $\mu \geq$ 85, we applied the '*TCB*' and calculated the results, which are shown in Fig. 9.

Fig. 9 shows that the proposed *hybrid-CBR* model produces 100% results for precision, recall, and *F*-score when the threshold μ is taken as 85.

Table 13
Physical activity recommendations for volunteer no. 8, generated using hybrid case-based reasoning methodology

User ID	Physical activity recommendations based on *hybrid-CBR*
8	i. walking; 4.5 mph; level; firm surface; very; very brisk ii. climbing hills with 10–20 lb load iii. bicycling; general

Table 14
Personalized filtered recommendations refined using the user's personal preferences.

User ID	Personalized filtered recommendations
8	i. To be healthy with normal body weight, you can take a *very brisk walk on firm surface with a speed of* 4.5 mph ii. To achieve today's goal for your required calories consumption, you can perform *physical activity of bicycling*

5.3.4. PBR (preference-based reasoning) results

We evaluated the *PBR* methodology results using an example and examined the filtration process, which filters the physical activity recommendations generated by level-3 *RBR*/*CBR*. Consider the physical activity recommendations, shown in Table 13, for volunteer no. 8.

As the preferences of volunteer no. 8 are walking and cycling (Table 7), *PBR* filters out the *climbing hills* recommendation. Similarly, all recommendations are filtered one by one, and the final filtered recommendations are sent to the *result propagator,* which forwards the recommendations in descriptive form to the end user. Table 14 shows the filtered recommendations in descriptive form.

6. Discussion

Physical activity recommendations help users adopt an active pattern of life. In this regard, the 2011 compendium of physical activities guidelines [36] suggests a wide range of activities with different intensity levels that are measured in terms of *METs* values. The study has described a hybrid multimodal reasoning methodology that has integrated *RBR, CBR,* and *PBR*. The *RBR* methodology is based on domain expert knowledge created from online guidelines for generating intermediate recommendations of goal setting, weight status and goal achieving plans that serve *CBR* to generate final physical activity recommendations. The goal of hybrid reasoning methodology is to ensure accurate and precise personalization of physical activity recommendations. A number of experiments are performed to demonstrate that the methodology achieves this goal. The results shows that the *hybrid-CBR* system outperformed the *baseline-RBR* and *modified-RBR* systems and had significantly improved precision, recall, accuracy, f-measure, and *Type I* and *Type II* errors. The *baseline-RBR* system was tested with 122 distinct-*METs* rules, and it exhibited specificity with exact match criteria, but suffered from a high *False Negative* rate, low accuracy and the rule intractability problem. The *modified-RBR* system was tested with a reduced number of ranged-*METs* rules and implemented in the MM platform and exhibited improved accuracy, but at the cost of low precision. A large number of recommendations were generated, with the majority being irrelevant to the user requirements. In the results, the correctness of recommendations was compromised by the *False Alarm* rate, which is generally unsuitable in the context of a personalized recommendation system. For minimizing the *Type I* and *Type II* errors and increasing the accuracy, *hybrid-CBR* was tested, and it outperformed the other two systems.

The challenging issue associated with *hybrid-CBR* was the design and preparation of the case base. We resolved this issue by creating a case base, *METCB,* from the compendium of physical activities guidelines [36], user personal profile information and general guidelines of physical activities from different organizations, such as *WHO*, *UK* and *CDC*. A *CBR* methodology has a complete cycle starting from *retrieval* to *reuse, revise* and *retain*; however, we did not focus on the *revise* step. The rational is that *revise* should be activated once any of the following conditions are obtained: (1) no existing case with confidence (nC, rC) ≥ 95 is found in *METCB* or (2) the *MM* feedback mechanism returns user remarks indicating dissatisfaction. As the *MM* feedback mechanism is not yet built, we did not focus on these options and have planned them for future work. Furthermore, the current '*METCB*' consists of only three attributes: age group, required *METs* value and recommended physical activity. This imposes the constraint of using multi-level *RBR* prior to applying *CBR*. The *RBR* refines the required high-level information from the basic profile and physical activity information to serve the *CBR* cycle for generating personalized physical activity recommendations. The *RBR* part of this methodology can be excluded and the complexity can be reduced if a case base with all of the required data, starting from the user's personal profile to the intermediate recommendations and final physical activity recommendations, are prepared and stored in a single case base. This case base will contain the user's personal profile, weight status, recommended plans for weight loss, required *METs* value, list of recommended physical activities, personal preference list and final filtered list of physical activities. To obtain a case base with the specified schema, we created a case base, named *FCB*, which incrementally adds new solved cases as successful cases for future use. For this purpose, in Algorithms 1–4, we added a statement that populates the respective attributes in the *FCB*. In the future, this case base will help in directly generating personalized physical activity recommendations. It will also help in validating results of other similar systems.

Regarding the scope of this study, using the weight management scenario, we only focused on a weight loss plan and did not address underweight and normal body weight cases. Therefore, the focus of recommendations is on *weight loss plan* rather than *weight gain plan* and *weight maintenance plan*. To smoothly tackle underweight and normal body weight cases, in Algorithm 1 and Algorithm 1, we display messages describing educational and motivational statements. However, we have not added details of these educational and motivational statements. In this study, we simply provide statements such as "eat high-fat foods or use protein powders to intake more calories", "maintain a reasonable amount of the exercise routine", and "you are doing good, keep it up" Furthermore, we also provide links to known online resources to educate the user about weight gain and weight maintenance.

We have partially implemented *PBR* with only a preference-based reasoning technique. The personalized recommendations are filtered one by one on the basis of the user's personal preferences and interests. A *PBR* system can provide more features; however, our interest lay only in filtering out irrelevant and unnecessary recommendations, and we therefore partially implemented the system in *HRM*. In the future, a complete user model may add more features to the system in terms of more personalized recommendations.

In the current technologically advanced era, a number of technologies (such as *CCTV* cameras etc.) can be used to monitor individuals' behaviors, specifically those of the elderly, to provide surveillance services [53]. This reduces the risk of a number of unobserved incidents that mostly occur among the elderly. The traditional surveillance mechanism can be avoided if "personal big data" are introduced to record the recognized daily physical activities of individuals and if analysis operations are enabled for them.

7. Conclusion and future work

This paper has presented *HRM* that effectively integrates multiple reasoning methodologies, such as *RBR, CBR,* and *PBR*, facilitating adoption and extension for different wellness services. The *hybrid-CBR* methodology achieves the objective of precise and specific personalized recommendation generation according to the user's specific needs. The application of *HRM* in a weight management scenario has proved that the precision, recall, accuracy, and f-score of personalized physical activity recommendations can be significantly improved if the integration of these methodologies is performed correctly. *Hybrid-CBR* achieves 0.97% precision, 0.94% recall, 0.94% accuracy, and a 0.95% f-score on the *TCB* with 64 test instance cases. Similarly, the *Type I* and *Type II* errors are significantly reduced. The significance of the proposed methodology is its preciseness in the recommendations made, which ensures personalization. Furthermore, the proposed methodology can be easily extended to other application areas, which will increase its worth.

In future, we plan to design and prepare an extended case base to host all the relevant information required for generation of personalized recommendations. This will enhance performance of *CBR* and *RBR* in *HRM*. Furthermore, it will reduce the complexity of the *HRM*. Moreover, the current personalized recommendations are merely based on *mode* and *intensity* features that lake '*amount*' and '*frequency*' characteristics. Hence, we plan to include these aspects in the future extensions. We also plan to extend *HRM* for recommending physical activity plans in dynamic way, using the user calendar and personal schedule information. Finally, we also plan to extend *PBR* part of the model by exploiting user model in comprehensive way to ensure more personalization.

Conflict of interest statement

Authors have no conflict of interests.

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Rahman Ali is a Ph.D. student in Ubiquitous Computing Laboratory (UCLab), Department of Computer Engineering, Kyung Hee University, South Korea. He got his M.Phil Degree in Computer Science from Department of Computer Science, University of Peshawar, Pakistan in 2009. He secured his M.Sc Degree (in Computer Science) from Hazara University, Mansehra, Pakistan in 2005 and Bachelor Degree from Govt. Jahanzeb College Saidu Sharif, Swat, Pakistan back in 2002. He has been a lecturer in Computer Science at University of Peshawar since 2009. He also served IIT, University of Science and Technology, Bannu as a lecturer in computer science and the Laboratoire d'Informatique de l'Universit du Maine, France as a research assistant. His current research includes Artificial Intelligence, Machine Learning, Knowledge Acquisition and Reasoning.

Muhammad Afzal is a Ph.D. student in Ubiquitous Computing Laboratory (UCLab), Department of Computer Engineering, Kyung Hee University, South Korea. He got his M.S Degree in Information Technology from School of Electrical Engineering and Computer Science, National University of Sciences and Technology (NUST), Pakistan in 2009. He secured his B.S degree in Computer Science from Kohat University of Science and Technology (KUST). He has been serving as proctor of HL7 International for conducting HL7 Standard Certification Exams in Pakistan since 2010. His current research includes Evidence-based Knowledge Acquisition and Systems, Applications of Machine Learning, Text Processing, and Information Extraction.

Maqbool Hussain received his M.S. degree from the School of Electrical Engineering and Computer Science, National University of Sciences and Technology, Pakistan in 2009. He is now enrolled in Ph.D. program in the Department of Computer Engineering of Kyung Hee University, Republic of Korea. His research interest includes Artificial Intelligence, Healthcare Interoperability Standards and Clinical Decision Support Systems.

Maqbool Ali received his M.Sc. and M.S. degrees with distinctions in computer science from the University of Agriculture, Faisalabad, and NUST, Islamabad, Pakistan, in 2001 and 2013, respectively. From 2002 to 2005, he served as an instructor in the field of computer science and from 2005 to 2014, he has been a researcher in the same field. Since March, 2014, he has joined Ubiquitous Computing Lab. to start his Ph.D. at the Dept. of Computer Engineering, Kyung Hee University, Republic of Korea. His research interests include data mining, machine learning, and natural language processing.

Muhammad Hameed Siddiqi is Ph.D. student in Ubiquitous Computing (UC) Lab, Department of Computer Engineering, Kyung Hee University, South Korea. He did his Master of Engineering from the Department of Computer Engineering, Kyung Hee University, South Korea in 2012, and Bachelor of Computer Science (Hons) from Islamia College University of Peshawar, N-W.F.P, Pakistan in 2007. He was a Graduate Assistant at Universiti Teknologi PETRONAS, Malaysia from 2008 to 2009. His research interest focuses on Image Processing, Pattern Recognition, Machine Intelligence, Activity Recognition, and Facial Expression Recognition.

Byeong Ho Kang is an Associate Professor of Computing and Information Systems at the University of Tasmania, Australia. He received his Ph.D. degree from the University of New South Wales, Sydney, in 1996. His research interest includes Artificial Intelligence, Expert System, Knowledge Acquisition and Internet Applications.

Sungyoung Lee received his B.S. from Korea University, Seoul, Korea. He got his M.S. and Ph.D. degrees in Computer Science from Illinois Institute of Technology (IIT), Chicago, USA in 1987 and 1991 respectively. He has been a professor in the department of Computer Engineering, Kyung Hee University, Korea since 1993. He is a founding director of the Ubiquitous Computing Laboratory, and has been affiliated with a director of Neo Medical ubiquitous-Life Care Information Technology Research Center, Kyung Hee University since 2006. Before joining Kyung Hee University, he was an assistant professor in the Department of Computer Science, Governors State University, llinois, USA from 1992 to 1993. His current research focuses on Ubiquitous Computing and Applications, Wireless Ad-hoc and Sensor Networks, Context-aware Middleware, Sensor Operating Systems, Real-Time Systems and Embedded Systems, Activity and Emotion Recognition. He is a member of ACM and IEEE.