Expert Systems With Applications 96 (2018) 506–521

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Personalization of wellness recommendations using contextual interpretation

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ARTICLE INFO

Article history:
Received 13 June 2017
Revised 1 November 2017
Accepted 2 November 2017
Available online 8 November 2017

Keywords:
Context-aware recommendation
Physical activity recommendation system
Personalized recommendation
Precise recommendation
Knowledge-based system

ABSTRACT

A huge array of personalized healthcare and wellness systems are introduced into the portfolio of digital health and quantified-self movement in recent years. These systems share common capabilities including self-tracking/monitoring and self-quantifications, based on the raw sensory data. These capabilities provide solid ground for the users to be more aware of their health; however, such measures are inefficient for changing the unhealthy habits of the users. In order to induce healthy habits in the users, a system must be capable of generating context-aware personalized recommendations. The main obstacle in this regard is the contextual interpretation of recommendations based on user's current context and contextual preferences. To resolve these issues, we propose a methodology of cross-context interpretation of recommendations (CCIR) for personalized health and wellness services. The CCIR method adds additional capabilities to the traditional reasoning methods and builds advanced form of the reasoning with the incorporation of contextual factors in the process of interpretations of the recommendations. With CCIR, the self-quantification systems can be enhanced to generate personalized recommendations in addition to tracking, quantifying, and monitoring user activities. In order to validate the proposed CCIR methodology, a set of 40 contextual scenarios and corresponding recommendations are presented for the evaluation collected from 40 different end users and 10 domain experts. Using chi-square test evaluation, the results demonstrated acceptable "goodness of fit" indices for the system developed on proposed CCIR methodology with respect to the end users' opinion. Also from the statistical observation, it is found that there exists a higher level agreement towards the system between the participants of both end users and experts.

1. Introduction

The number of applications and systems for personalized healthcare and wellness management have rapidly grown during the recent years due to the increase in wearable and mobile technologies (Adomavicius & Tuzhilin, 2011; Agu & Claypool, 2016; Charles, Stanley, & Agbaeze, 2013; Dharia et al., 2016; Donciu, Ionita, Dascalu, & Trausan-Matu, 2011; Lim, Husain, & Zakaria, 2013; Powell et al., 2014; Verbert, Manouselis, & Ochoa, 2012; Wuttidittachotti, 2015). These systems and applications have augmented the portfolio of digital health and quantified-self movement. With advances in self-quantification applications, capturing and recording data of human health and fitness is now possible. With the availability of this data, systems and applications provide better understanding of users' health status and their relationship to the world around them (Zammit, 2013). Self-quantification systems and applications are of high importance to educate users of their health status; however, they solely cannot be considered sufficient to change unhealthy habits in the users. Changing unhealthy habits of the users, demands actionable recommendations. Existing systems such as Fitbit Flex ("Fitbit," 2017), Jawbone Up (AliphCom dba Jawbone., 2014), and Misfit Shine ("Misfit: Fitness Trackers & Wearable Technology - Misfit.com," 2016) are few examples of providing some basic recommendations based on the measured steps and slept hours. Samsung S Health (Samsung, 2015) and Google Fit (Google Inc., 2016) are working as personal fitness coach and health-tracking platform respectively

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https://doi.org/10.1016/j.eswa.2017.11.006
0957-4174/

on the basis of capturing user steps counting. A large set of work exists in literature in the area of agent-based and social interactive healthcare monitoring and recommendations for aged population (Chan, Ray, & Parameswaran, 2008; Barrué, Cortés, Moreno, Pérez-Pasalodos, & Cortés, 2015; Gómez-Sebastià & Moreno, 2016); however, the scope of our study is focused on middle-aged adults' health and wellbeing recommendation services.

According to the research, contextual information such as location, time, activity, physical conditions, social interaction etc. are very important to generate trustworthy and accurate recommendations (Asabere, 2013). In traditional recommender systems only two types of entities; users and items, are utilized to provide recommendations (Adomavicius & Tuzhilin, 2005; Asabere, 2013). However, accurate recommendations certainly depend upon the degree to which the recommender system has incorporated the relevant contextual information into the recommendations' generation method (Adomavicius & Tuzhilin, 2015). Interpretations of context may not be dealt equally in the approaches of different recommender systems. For instance, contextual modeling approach uses contextual information as an explicit predictor directly in the recommendation function; while in contextual pre-filtering approaches, information about the current context is used for the recommendation (Adomavicius, Sankaranarayanan, & Sen, 2005). On the contrary, contextual post-filtering algorithm initially ignores the contextual information for the recommendation generation, then the resulting set of recommendations is refined for each user based on the contextual information (Adomavicius & Tuzhilin, 2005, 2015). These three types of contextual approaches (context modeling, pre-filtering, and post-filtering) provide the opportunities to use contextual information in different kinds of recommender systems; collaborative, content-, and knowledge-based recommender systems. In literature, different combinations of these approaches are associated with different types of recommender systems (Herlocker, Konstan, Terveen, & Riedl, 2004; Martinez, Arias, Vilas, Duque, & Nores, 2009; Su & Khoshgoftaar, 2009). Regardless of the recommender systems' types and algorithmic approaches, involving context in recommendation poses a number of challenges:

A. How is the contextual knowledge acquired and represented in the system?
B. How is the context processed to evaluate the suitability of recommendations' forwardness?
C. How are the contextual preferences processed to evaluate the recommendations that are qualified in original or alternative form?

To cope with these challenges, we previously proposed an innovative digital health framework called Mining Minds (Banos et al., 2016) for personalized healthcare and wellness support. It provides personalized recommendations on the basis of expert knowledge and domain guidelines. In current status, the Mining Minds recommendations are generated based on the user's profile information and it does not handle to account for the user's current context, preferences, and environmental variables.

By not handling the contextual factors, the users of the Mining Minds are unable to get the final personalized recommendation services. The main objective of the proposed work is to solve the above mentioned problem by adding the capability to the existing system to exploit not only the users' profile information but also their current context, preferences, and the environmental variables.

To achieve this objective, we proposed a cross-context interpretation of recommendations (CCIR) methodology to interpret the recommendations based on the user's contexts: physical context (low level and high level contexts), environmental variables (weather), and preferences and interests. This method provides more insight about user's situation with respect to context and preferences thus leading to a higher level of personalization in health and wellness recommendations. The key contributions in this paper to achieve the intended objectives are listed below.

- Mechanisms for contextual knowledge acquisition and representation.
- A rule-based matching method for context interpretation method to determine appropriateness of recommendation to be forwarded to the user.
- A contextual matrix aggregation method for contextual preference interpretation of recommendations.

For the evaluations of the proposed CCIR, a user-centric approach is followed to assess the validity of the methodology and acceptability of the system developed over CCIR methodology. All the experiments are performed on the basis of personalized physical activity recommendations. The rest of the paper is structured as follows.

Section 2 provides explanation of related work and their difference with proposed work. Section 3 provides an overview of Mining Minds platform that provides a baseline for the proposed work. Section 4 describes the proposed CCIR methodology with technical details. Section 5 presents the experimental evaluation of the system (recommendation interpreter) that is developed based on the proposed CCIR methodology. Section 6 discusses the significance of the work and limitations. Section 7 concludes the work and provides a roadmap for the future work.

2. Related work

Recommender systems as an area of inquiry have been extensively researched in the past decade in a wide array of domains including healthcare and wellness promotion (Verbert et al., 2012). In this regard, key categorization of recommender systems include content-based filtering, collaborative filtering, knowledge-based filtering and their hybridizations (Verbert et al., 2012). Over the years research interest has pivoted towards context-aware recommender systems (Adomavicius & Tuzhilin, 2011). These systems are capable of adapting to different situational needs of a user. Traditional recommender systems employed simple user models e.g., vector of item ratings. Later on, these models were extended to accommodate user preferences as well. But still earlier systems lacked the notion of "situated actions" (Adomavicius & Tuzhilin, 2011). Physical activity based recommender systems belong to the category of systems which require adequate contextual information in order to provide reasonable recommendations to a user (Faiz, Mukhtar, & Khan, 2014). In healthcare and wellness domain cross-context information plays an important role where multiple contexts are aggregated to provide a holistic situational context. Most prevalent contextual factors considered in research literature include information such as time, location, current physical activity, weather, etc. Adomavicius and Tuzhilin (2011) further categorized contextual factors into static and dynamic based on change over time. Most of the contexts in the purview of physical activity belong to dynamic contexts such as location, where new locations may be added later on. Following are some of the proposed recommender systems in the domain of healthcare and wellness promotion.

A physical activity recommender system designed by Sami, Nagatomi, and Terabe (2008) provides leisure-time physical activity to adults based on user with similar lifestyle and preferences. Moreover, ontologies are created to find distance among different physical activities. This system is lacking mechanism to dynamically evaluate user's current context to provide the most relevant recommendation at the given moment.

A mHealth application is proposed by Wuttidittachotti (2015). This system uses Body Mass Index, Basal Metabolic Rate, and required energy for performing pre-defined set of activities. This system also lacks mechanism to user's contextual information in order to provide more amenable set of recommendations based on the given situational settings.

Cypress (Agu & Claypool, 2016) is a cyber-physical recommender system which is designed to discover smartphone exergame enjoyment. The key intent of this system is to induce healthy behavior by promoting exergames. The proposed system uses smart phone sensing capabilities in order to learn game preferences for a given user; moreover, the system can recommend similar games once the user's engagement level is reduced. This system is not geared to physical activity based recommendations such as jogging, walking, swimming, stretching, etc.

A personalized therapy based recommender system is proposed by Lim et al. (2013). A hybrid case-based reasoning technique is used to address user's current wellness problems by inferring information from past relevant cases. This system is primarily designed for general therapy recommendations and no such mechanisms are developed to address different contextual factors related to the user such as user's location.

A web-based wellness management system is proposed by Omar and Wahlqvist (2005). This system caters for both physical activity and dietary requirements of a user. System is evaluated through the technology acceptance model at the end of a six-week longitudinal study. The proposed system lacks capabilities to acquire and process contextual information about the user. Wahidah Husain and Lim Thean Pheng developed a personalized wellness therapy recommender system using hybrid case-based reasoning (Husain & Pheng, 2010). This system also lacks capabilities for handling multiple contextual factors.

Faiz et al. (2014) proposed an integrated approach of diet and exercise recommendation for diabetes patients. It is an ontology based solution which integrates knowledge from different domains in order to provide a comprehensive recommendation.

The proposed solution lacks capabilities to adapt to the changing user's context; hence, user has to sift through different recommendations to select the appropriate one.

A knowledge-based diet and physical exercise advisory system is developed by Charles et al. (2013). It is a web based solution for diet and exercise recommendation based on expert system framework. This system employs information such as users' demographical data, religious information, health conditions, etc. Consequently, a set of recommendations are provided. Since, no sensory data is used; therefore, the proposed system is not capable of adapting to the contextual factors of the users.

PRO-Fit is a personalized fitness assistant framework which provides workout session recommendations (Dharia et al., 2016). It collects data from accelerometer and synchronizes it with the user's calendar in order to recommend personalized workout sessions. The proposed system also lacks capabilities of handling multi-context information.

The Runner (Donciu et al., 2011) is a comprehensive recommender system for runners. It provides workout and nutrition recommendations to the users. Although the proposed system can process contextual information but its recommendations are limited to a single activity, i.e., running. Therefore, the system lacks mechanism for handling a wide array of popular physical activities such as stretching, cycling, dancing, etc.

Aforementioned are some of the recommendation systems in the domain of healthcare and wellness. Most of these systems are capable of handling static contextual factors but lack capabilities for adapting to changing user's contexts. Weather context is one the important contexts for outdoor physical activity yet none of the aforementioned systems considered it. Moreover, a higher level comparison of these systems with our system that is built on CCIR methodology is provided in Table 1.

3. Mining minds platform

Mining Minds platform consists of an array of innovative services, tools, and techniques, working collaboratively to investigate human's daily life data, generated from heterogeneous resources, for personalized health and wellness support (Banos et al., 2016). It orchestrates the whole function into a layered approach to provide the personalized digital health and wellbeing services. As shown in Fig. 1, there are five autonomous layers including data curation layer (DCL), information curation layer (ICL), knowledge curation layer (KCL), service curation layer (SCL), and supporting layer (SL).

In a brief, DCL provides the support to acquire, curate, and persist the data obtained from multimodal data sources (MDS) so it can be processed for higher level understanding (Amin et al., 2016). The intermediate database stores the lifelog and user profile data used by the upper layer for their processing. DCL forwards the curated data to ICL in order to determine low-level and high-level contexts.

ICL (Banos et al., 2016) is responsible for the inference and modeling of the user context and it is composed of two main modules, namely, low-level context awareness (LLCA) and high-level context awareness (HLCA). LLCA recognizes the low-level contexts on the basis of trained machine learning models. HLCA performs semantic reasoning over the low-level contexts and find outs the high-level context. The contexts modeled by this layer are used by the upper layers for different interpretations.

KCL is designed to enable the acquisition and maintenance of knowledge created either by the domain expert or knowledge engineer, by using expert- and data-driven approaches. The knowledge created by KCL is used by SCL to build knowledge-based recommendations.

SCL, which is the main subject of this paper, provides the means to transform the data, information, and knowledge curated by DCL, ICL, and KCL respectively into the final health and wellness support services; particularly, the personalized recommendation services.

Lastly, SL provides the support to enrich the overall Mining Minds functionalities through interactive and adaptive UI/UX (user interface/user experience) tool, implicit and explicit feedback analysis, advanced analytics, and adequate privacy and security mechanisms.

4. Cross-context interpretation of recommendations (CCIR) methodology

The main motivation to develop a method for cross-context interpretations is to evaluate the recommendations on the basis of user context and contextual preferences. In case, the system generated recommendations are forwarded directly to the user without interpreting the contextual information, it may increase the chance for the users to not follow the recommendations and eventually tend to drop its use. Our proposed CCIR methodology considers the user current context to determine the appropriateness of delivery time and contents of the recommendations in order to make them more personalized according to the user situation. The abstract flow of information and processing is depicted in Fig. 2, while in Fig. 3, the complete functional flow diagram of CCIR methodology is shown to represent the data input and output of each component contributing to the personalized recommendations.

Service orchestrator: Communication services are managed by the Service Orchestrator (SO). It takes care to handle the potential requests, invoking the necessary services, and coordinating the processes involved in the curation of the services. The requests may be of various types, i.e., scheduled on time (e.g., "every day at 8 am"), triggered by direct user queries ("suggest me an exercise plan for today's workout") or based on events (e.g., "sitting

Table 1
High level comparison of existing systems with proposed system.

System	Physiological factors	Rec. technique	Dynamic context*	Multi-activity recommendation	Preferences consideration
Sami et al. (2008)	Ailments, gender, activity level, blood pressure, protein in urine, blood in urine, sleeping habits, etc	Ontology	Static (In-door/out-door, aerobic/non-aerobic, group/individual, winter sport)	Bicycling, Running, Swimming, Aikido, Horse Riding, Polo	Yes
Wuttidittachotti (2015)	BMI, BMR, energy, ailments, age, gender, weight, height	MET, RDR-Tree	No	Jogging, Swimming, Tennis, Walking, etc	Yes
Agu and Claypool (2016)	Emotions	Regression and Classification	Dynamic (Game Enjoyment)	Exergame	Yes
Faiz et al. (2014)	BMI, BMR, age gender, weight, life style. ailments	MET, Ontology	Static (assumed user is available)	Run, Walk, Cycling	Yes
Charles et al. (2013)	Ailments, pregnancy status, body stature	Goal-driven backward chaining	Static	Brisk walk, Jogging, Running, Swimming	Yes
Dharia et al. (2016)	Life style, age, weight, fitness level	Content-based and User-Similarity	Dynamic (location and time-aware)	Yoga, Jogging	Yes
Donciu et al. (2011)	ailments	Ontology	Dynamic (runner type, surfaces, race types)	Running Only	Yes
Proposed	BMI, age, gender, weight, life style, ailments, height	MET, Content-based Contextual Matrix	Dynamic (Location, High-level activity, Weather, Emotions)	Hiking, Running, Sitting, Stretching, Cycling, Walking	Yes

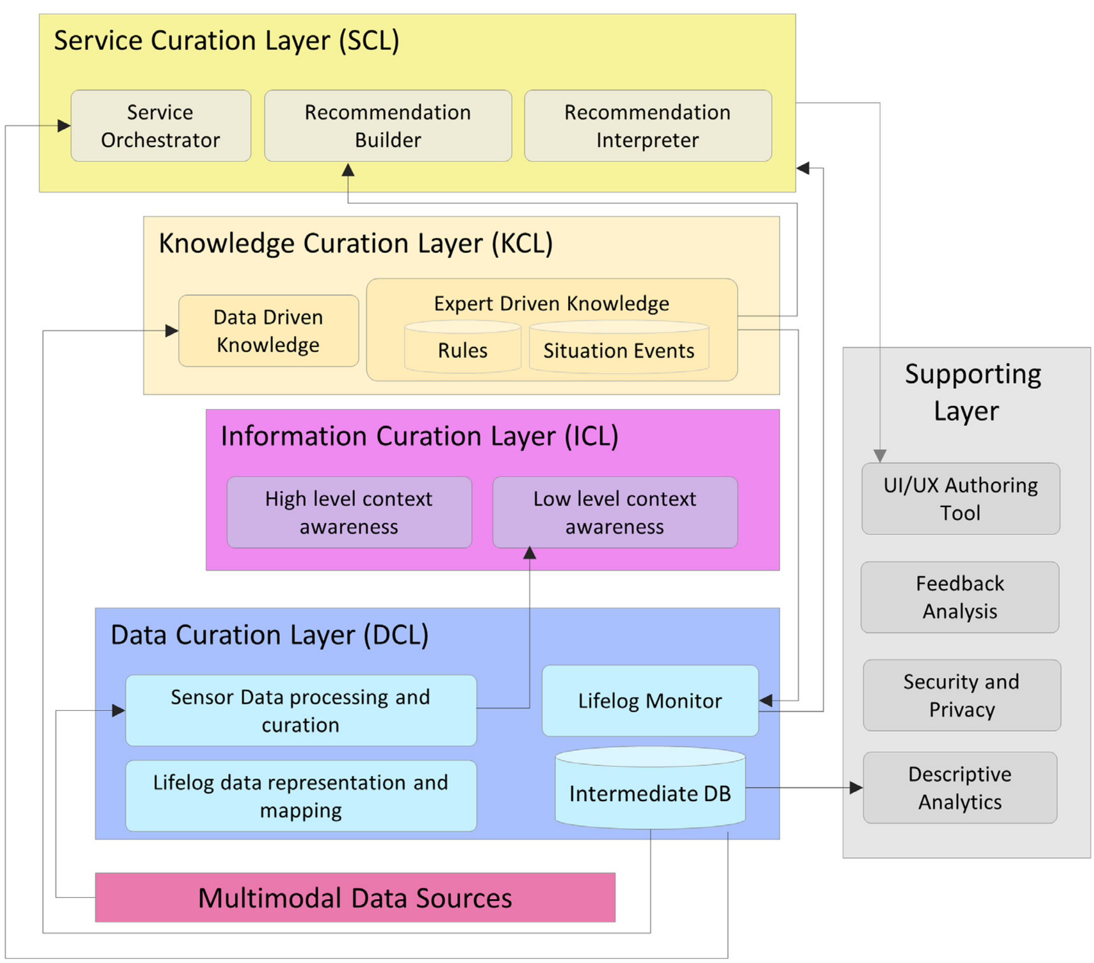


Fig. 1. Miningminds platform abstract view.

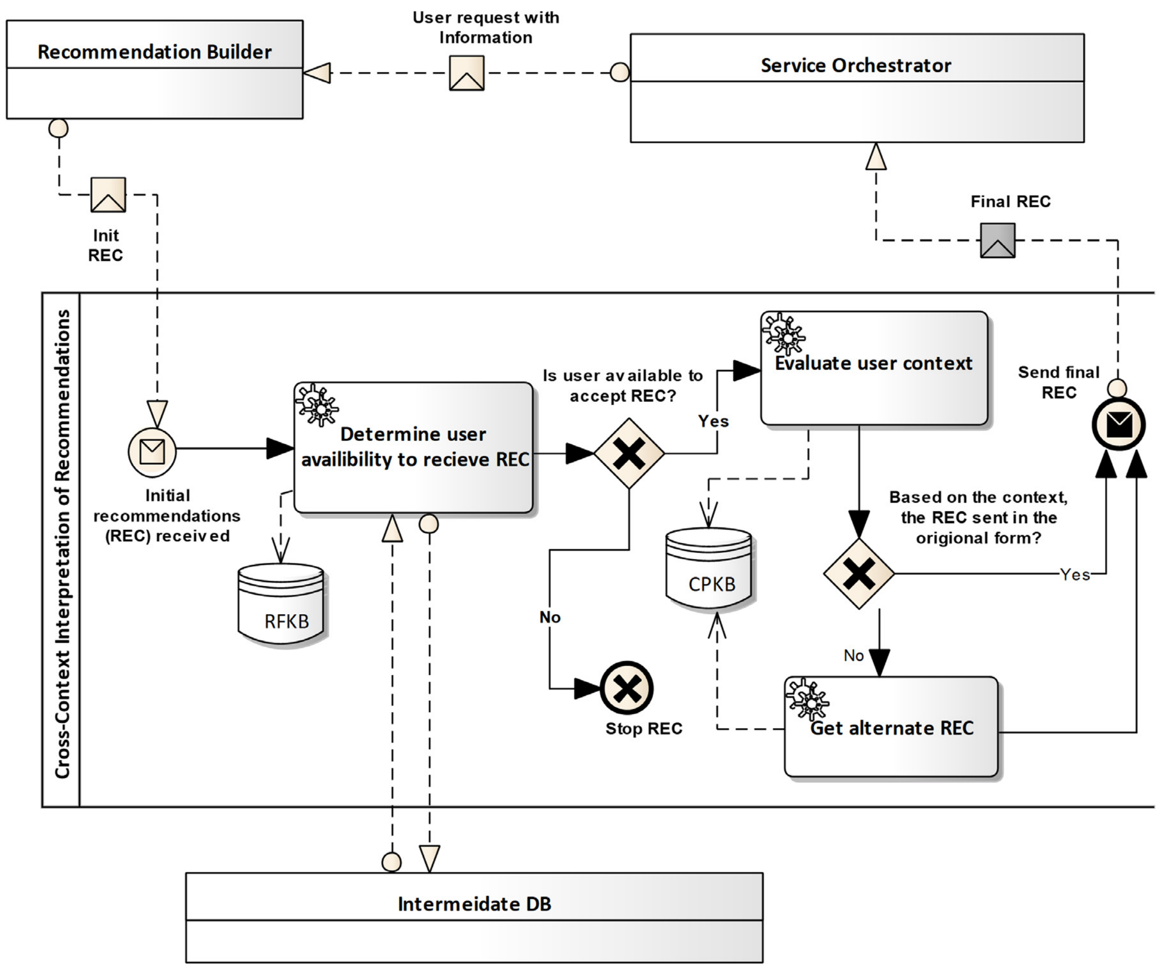


Fig. 2. CCIR Methodology abstract flow of information and processing.

one hour"). In addition to service invocation, it handles the data requirements by communicating with data sources in other layers of the Mining Minds.

Recommendation builder: Generalized recommendations are generated by the Recommendation Builder (RB) component through reasoning on the user profile and lifelog data provided by DCL, and the knowledge facilitated by KCL for the specific domain of the service. RB works on multimodal hybrid reasoning methodology expressed in our recent work (Ali et al., 2016). RB follows a multimodal hybrid reasoning methodology which generates physical activity recommendations. This methodology integrates Rule-based Reasoning (RBR), Case-based Reasoning (CBR), and Preference-based Reasoning (PBR) in a linear combination which enables the system to generate personalized recommendations. The RBR part of the system uses explicit knowledge rules from physical activity guidelines and prepares new cases for the CBR methodology, whereas the CBR itself uses implicit knowledge in the form of physical activity guidelines as successful cases from expert's past experiences. The suggested recommendations of CBR methodology are either exactly similar to the requirements of the user's current situation or closed to the requirement. In case the recommendations are more than a preliminary level, personalization is implemented in the form of PBR which uses user's personal interests and preferences. However, the level of personalization achieved is trivial and cannot handle the user contextual situation; such as, what recommendation is more suitable in a particular location context, weather context, and other high-level activity contexts? Thus, RB provided recommendations are considered as an initial recommendation because of the fact that the recommendations are yet to be interpreted from the user's contextual perspective. These may result in forwarding the initial recommendation as-is or transforming it to a more amenable form. Moreover, user's availability status is not yet taken into account.

Recommendation interpreter: In Recommendation Interpreter (RI), the recommendations received from RB undergo a series of steps for personalization. The main personalization objective is to provide such recommendations as to best suit the user's requirements, interests, and demands. For achieving this goal, the CCIR methodology is activated and operated at the backend. First step of CCIR methodology is to consider user's availability status. Once a user is deemed available to comply with the physical activity based recommendations, then current context of the user is evaluated. Current context of a user includes all the available contexts e.g., user's location, user's current activity, environmental conditions, and others. Moreover, user's preferences are incorporated on a priority basis by preference-based reasoner in the course of recommendation interpretation. There are two types of knowledge bases required for recommendation interpretations:

1. Recommendation Forward Knowledge Base (RFKB) is the knowledge base which consists of rules that account for user's context and specify the needed recommendations be forwarded based on current context of the user. For instance, the recommendations are not forwarded to the user if he/she is in the commuting context.
2. Contextual Preference Knowledge Base (CPKB) is the knowledge base that consists of rules for the evaluation of contextual

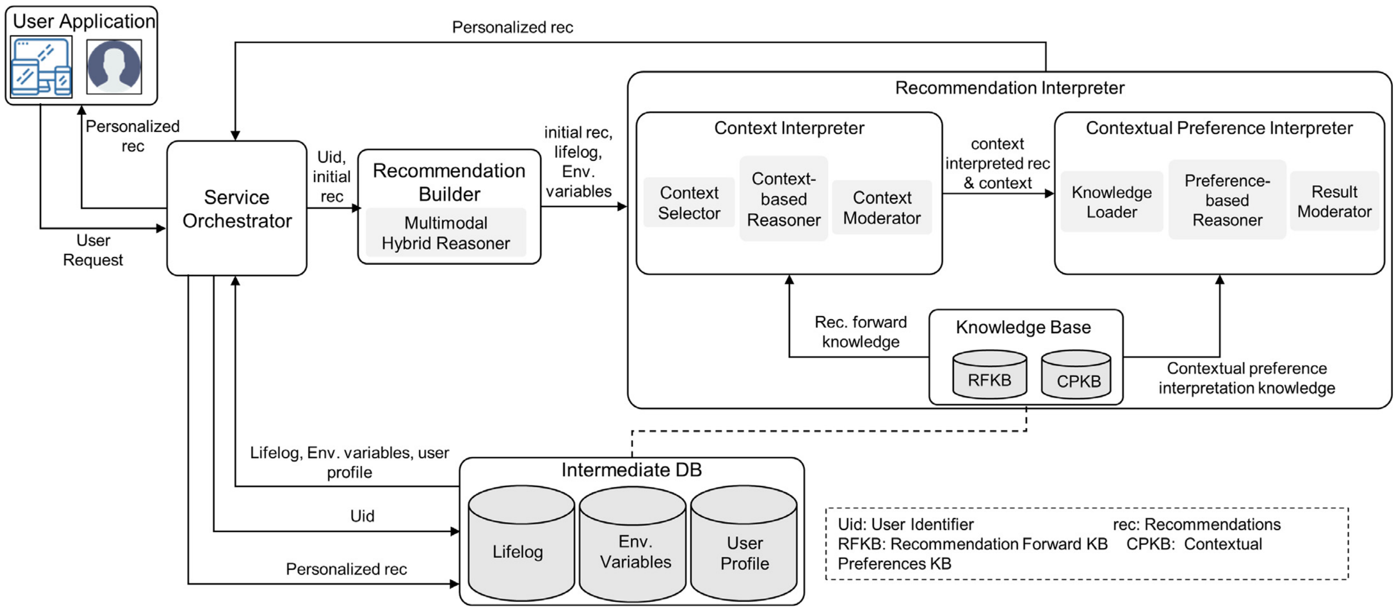


Fig. 3. Cross-context interpretation of recommendations (CCIR) functional workflow.

preferences. The decisions are made on given rules whether the recommendation is appropriate in the original form or it needs to be fine-tuned based on the user's current context. For instance, if it is raining outside and the system generates an activity-oriented recommendation to be conducted outside, then the recommendation is changed to an alternative indoor activity.

Intermediate database: The data collected from wearable sensors and smart phone is curated and persisted in the intermediate database (IDB) with a logical division of user profile data, lifelog data, and environmental data. The user profile data include user demographics (gender, age), physiological factors (height and weight), and preference data. Contextual data is categorized into two type of contexts: low-and high-level contexts. Low-level context includes location, emotion, and physical activities. High-level context includes more abstract representations of the user context which are determined from the low level context, such as office-works, commuting, eating, and others. Environmental variables include weather context as rainy, sunny, and others. All these contextual parameters are constantly monitored by the information curation layer (ICL) as described in Section 3 about Mining Minds.

4.1. Contextual knowledge acquisition

The mode of data acquisition for RFKB is questionnaire-based. The user is prompted to provide RFKB related information at the time of subscription to the Mining Minds services. Since this information is not incumbent on the user; therefore, he/she can opt out of this step. In which case, a survey is conducted to provide more common situations when a recommendation may be forwarded/blocked given different contexts. For example, as a default case when a user's location is "home" and high-level context is "sleeping", then any recommendation initiated by RB is stopped from being forwarded to the user. Hence, survey based data serves as a default case until user provides his/her information for a given context. From surveying 40 users, we identified the common situations, where majority of the users agree on recommendation to forward or not. A partial list of these non-forwarding rules are described in Table 2 which shows if any of these rules matches for a given a context, the recommendation will not be forwarded.

4.2. Contextual preferences interpretation knowledge acquisition

CPKB is yet another important piece of knowledge about users' contextual preferences. This knowledge is instrumental for the "contextual preferences interpretation" task; discussed in detail in the coming sections. Its mode of acquisition is similar to that of RFKB. A comprehensive questionnaire is devised to acquire knowledge for contextually preferred recommendations. Items in the questionnaire are developed for commonly used contexts in physical activity recommendation domain (Bull, Maslin, & Armstrong, 2009; Lin, Jessurun, de Vries, & Timmermans, 2011). Each item was of dichotomous answer format (suitable = 1, not suitable = 0). For instance, if (location = home), the value for recommendations such as hiking and running are not suitable. Overall 40 users participated in the survey and answered to the questions in questionnaire. For computationally viable representation, we formulate the knowledge in a two dimensional matrix for "contextually preferred recommendation" . A majority vote method is utilized to set the final contextual matrix. As an example, in Table 3 we represent the location context with respective recommendations.

Preference information is stored in a two-dimensional matrix. In Table 3, there are 7 different location based contexts including "Don't Care" as a default case. Each row is populated with 0 s and 1 s. For example, intersecting cell of "Gym" and "Hiking" contains 0. It means that "Hiking" cannot be performed while location is "Gym". In case of "Gym" and "Running" the cell contains 1 which allows this activity for the given context. This contextual data matrix is populated through information provided by the user at the time of subscription to the Mining Minds services. In the absence of user-specific data, a survey is conducted and majority vote is used to populate contextual matrices. Table 4 represents the majority vote results of a survey conducted from 40 different users for three different contexts (location, high level context, and weather).

4.3. Processing method of context interpretations

Processing of context interpretations play the key role in personalized recommendation. The rationale for the contextual interpretations is to model user's convenience and allow recommendations when user is in a more receptive mode. Current context of a user is required to model user's receptivity. Cur-

Table 2
Partial list of context interpretation knowledge rules.

Identifier	Rule Conditions
R1	If (Location = Transport && HLC = Commuting && Weather = Don't Care)
R2	If (Location = Restaurant && HLC = HavingMeal && Weather = Don't Care)
R3	If (If (Location = Home && HLC = Sleeping && Weather = Don't Care))
…	…
Rn	If (If (Location = Office && HLC = OfficeWork && Weather = Don't Care))

Table 3
Location context applicability with respect to recommended activity.

Location context	Recommendations					
	Hiking	*Running*	*Sitting*	*Stretching*	*Cycling*	*Walking*
Gym	0	1	1	1	1	0
Home	0	1	1	1	0	1
Office	0	0	0	1	0	1
Transport	0	1	1	0	1	0
Outdoors	1	1	0	1	0	1
Don't Care	0	1	0	1	0	1

rent context includes location information, high-level context and weather information; which is provided by *Service Orchestrator*. Moreover, user provided contextual knowledge is acquired through RFKB. RFKB stores user's information which accounts for his/her inclinations to receive physical activity based recommendations. Knowledge stored in RFKB is in the form of production rules i.e., {Location = *Transport*, HLC = *Commuting*, Weather = *Don't Care*} → *Recommendation Not Forwarded*. RFKB only stores rules for blocking scenarios. As stated before, these blocking scenarios are provided either by the user or through a generalized survey-based response. RFKB can vary for different users as per their varied inclinations for receiving recommendations in different contexts. The working of context interpreter component is depicted in Fig. 4. Once a recommendation is generated by RB, it is received by *Context Selector* along with user_id. Based on the user_id, *Context Selector* fetches current context of the user from intermediate database (IDB) hosted in DCL. The recommendations along with the current context of the user are forwarded to the context based reasoner for contextual interpretation. For this interpretation, the context-based reasoning requires rules, that are fetched from the RFKB. These rules specify such scenarios in which user is deemed unreceptive for a physical activity based recommendation. Current context is evaluated/reasoned against the rules, using the rule-based reasoning approach with exact match strategy.

If current context matches to any of the rules then initial recommendation, generated by RB, is blocked for further processing. Alternatively, initial recommendation along with the user_id and current context are forwarded to *Contextual Preference Interpreter* to assess the suitability of the recommendation within the scope of user's preferences.

4.4. Processing method of contextual preference interpretations

The main objective of contextual preference interpretations (CPI) is to evaluate the initial recommendation proposed by RB against user contextual preferences. There are three sub-components of CPI namely knowledge loader and preference-based reasoner, and result moderator (Fig. 4). The *knowledge loader* acquires relevant knowledge from CPKB, while the *preference-based reasoner* performs reasoning on the user's specific preference-based data against the recommendations. *Result moderator* delivers the results to target entities. When context interpreter allows the initial recommendation to be further processed, then *contextual preference interpreter* is invoked. It receives the user_id, initial

Table 4
Knowledge for contextually preferred recommendations.

What recommendation do you think is more appropriate to be acted upon at which location point?

Location Context	**Recommendations**					
	Hiking	*Running*	*Sitting*	*Stretching*	*Cycling*	*Walking*
Gym	0	1	1	1	1	0
Home	0	1	1	1	0	1
Office	0	0	0	1	0	1
Transport	0	1	1	0	1	0
Outdoors	1	1	0	1	0	1
Don't Care	0	1	0	1	0	1

What recommendation do you think is more appropriate to be acted upon at which situation (high level context)?

HLC Context	**Recommendations**					
	Hiking	*Running*	*Sitting*	*Stretching*	*Cycling*	*Walking*
Amusement	0	1	1	1	1	0
Commuting	0	0	1	1	0	1
Exercising	1	1	0	1	1	1
Gardening	0	0	1	0	1	0
HavingMeal	0	1	0	1	1	1
Inactivity	1	1	0	1	1	1
Don't Care	1	1	1	1	1	1

What recommendation do you think is more appropriate to be acted upon in which weather condition?

Weather Contextual Matrix

Weather Context	**Recommendations**					
	Hiking	*Running*	*Sitting*	*Stretching*	*Cycling*	*Walking*
Rainy	0	1	1	1	0	1
Sunny	0	0	1	1	0	1
Windy	1	1	0	1	1	1
Cloudy	0	0	1	1	0	0
Don't Care	1	1	1	1	1	1

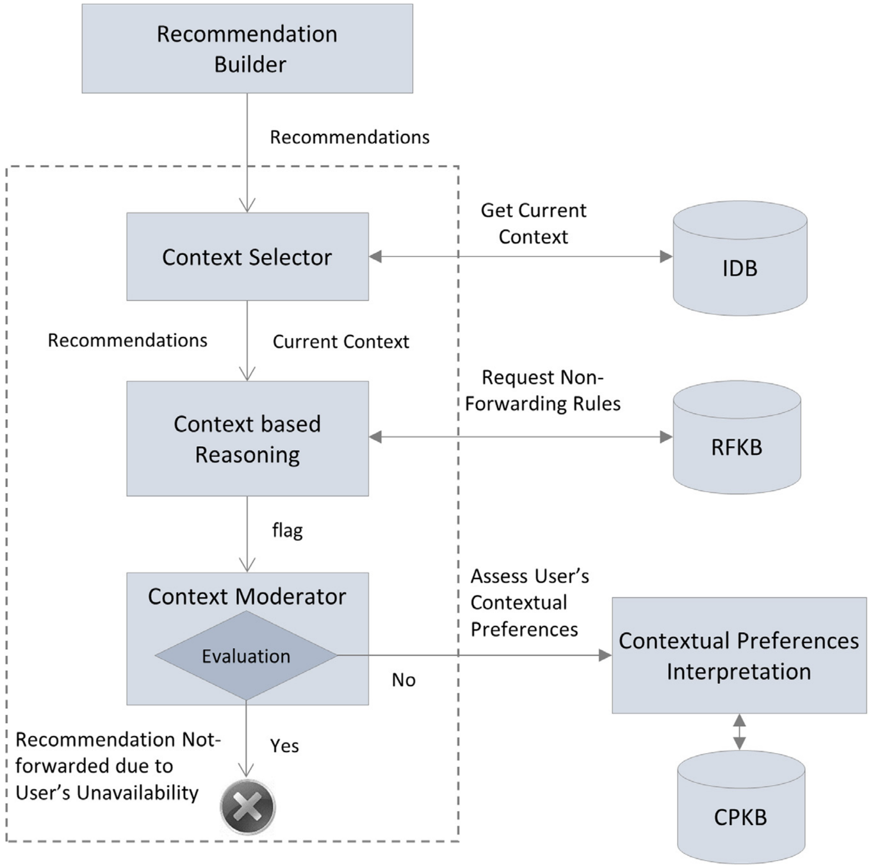


Fig. 4. Working scenario of recommendation interpreter component.

recommendations, and current context of the user from *Context Interpreter*. Based on the user_id, relevant contextual data is fetched from IDB through service orchestrator. CPKB stores users' physical activity preferences against different contexts, i.e., location, high level context and weather. If user has not provided his/her preferences, then CPKB is populated through generalized behavior patterns conducted on a public survey. Once user relevant context data is prepared then it is consolidated into contextual matrices similar in structure as shown in Fig. 5.

In Fig. 5, the two-dimensional contextual matrix stores user's preferences for physical activities against different contexts. For example, a case is depicted in Fig. 5, i.e., a user is in his/her office, in an inactivity mode, and weather is rainy outside. All this information is combined by taking the complete row of each occurring context and put it into the aggregate contextual matrix. This aggregate contextual matrix may have different values for another user based on his/her preferences. Once matrix is generated an aggregate vector is computed to summarize matrix results. The aggregate vector is computed by taking an "AND" operation on each column of the aggregate contextual matrix, i.e., putting the resultant bit 1, if all the bit values are 1 in a given column, 0 otherwise.

Preference-based reasoner first interprets the aggregate vector. Each bit in the vector represents a physical activity in a pre-specified order e.g., first bit represents "Hiking", second bit represents "Running", and so on. The activities that are marked 1 are applicable given the current context of the user, while others are not applicable. Hence, in the aforementioned case only Stretching and Walking are applicable recommendations in the given user context. The contextual interpretations of original recommendations on the basis of contextual preferences are given in Algorithm 1.

Algorithm 1 requires two inputs; original recommendation and current context of the user. Original recommendation is received from context interpreter component. Current context is comprised of three sub-contexts. Location and high-level context are provided by the user lifelog while weather related information is provided by environmental variables. LoadCurrentContext function takes userID and returns current location, high-level context and weather conditions in the vicinity of the user. This information is temporarily stored in cContext for further processing. It iterates over all the original recommendations oRec and for each recommendation r in oRec all the contexts are evaluated to generate context evaluation vector contextEvalVector. In Fig. 4, for instance, there is value 1 for "stretching" recommendation against office location in the Location Contextual Matrix, in this case, 1 value is picked up and added at the corresponding index of context evaluation vector (contextEvalVector). Each contextEvalVector is added to the list of context evaluation vectors (contextEvalVectorList). On the basis of context evaluation vectors, an aggregate vector (aggregateVector) is computed with computeAggregateValues. Aggregate values computation is described in Algorithm 2.

Algorithm 2 receives the list of context evaluation vectors (contextEvalVectorList) as an input and returns the aggregate vector as an output. Each of vectors in the list is processed through logical AND operation. Logical_Anding_Operation function applies logical AND operation to all the elements of a vector and assigns the resulting value in aggregateVector list. Hence, first element of aggregateVector corresponds to the first vector in contextEvalVectorList, and so on. As shown in Fig. 4, there are six context evaluation vectors corresponding to each recommendation namely, hiking, running, stretching, sitting, cycling, and walking. Each of these vectors are evaluated with logical_Anding_Operation in order to generate

Location	**Recommendations**					
Context	*Hiking*	*Running*	*Sitting*	*Stretching*	*Cycling*	*Walking*
Gym	0	1	1	1	1	0
Home	0	1	1	1	0	1
Office	0	0	0	1	0	1
Transport	0	1	1	0	1	0
Outdoors	1	1	0	1	0	1
Don't Care	0	1	0	1	0	1

HLC	**Recommendations**					
Context	Hiking	Jogging	Sitting	Stretching	Cyclng	Walking
Amusement	0	1	1	1	1	0
Commuting	0	0	1	1	0	1
Exercising	1	1	0	1	1	1
Gardening	0	0	1	0	1	0
HavingMeal	0	1	0	1	1	1
Inactivity	1	1	0	1	1	1
Don't Care	1	1	1	1	1	1

Weather	**Recommendations**					
Context	Hiking	Jogging	Sitting	Stretching	Cyclng	Walking
Rainy	**0**	**1**	**1**	**1**	**0**	**1**
Sunny	0	0	1	1	0	1
Windy	1	1	0	1	1	1
Cloudy	0	0	1	0	1	0
Don't Care	1	1	1	1	1	1

Aggregate Contextual Matrix						
Context/Rec	*Hiking*	*Running*	*Sitting*	*Stretching*	*Cycling*	*Walking*
Location= Office	0	0	0	1	0	0
HLC= Inactivity	1	1	0	1	1	1
Weather= Rainy	0	1	1	1	0	1

Fig. 5. Aggregate contextual matrix preparation.

Algorithm 1 Contextual interpretations of recommendations.

```
Input:
   oRec = {r1, r2, …, rn} //list of original recommendations
   cContext = {c1, c2, …, cn} //list of current context
   userID;
Output:
   iRec = {ir1, ir2, …, irn} // list of interpreted recommendations
Let;
   contextEvalVector = {v1, v2, …, vn} // list of values (0, 1)
   contextEvalVectorList = {cv1, cv2, …, cvn}
   aggregateVector = {v1, v2, …, vn} // list of values (0, 1)
1. Start
2.   cContext = loadCurrentContext(userID)
3.   foreach r in oRec
4.   Begin
5.      foreach c in cContext
6.      Begin
7.         contextValue = evaluateContext(r, c);
8.         AddContextValue(contextEvalVector, contextValue);
9.      End
10.          contextEvalVectorList.add(contextEvalVector);
11.      aggregateVector = computeAggregateValues(contextEvalVectorList);//Algorithm 2
12.   End
13.   foreach v in aggregateVector
14.   Begin
15.      if (!(v) == 0)
16.      Begin
17.         AddRecommendation(iRec, r); // add original recommendation r to iRec list
18.      End
19.   End
20.   if (isEmpty(iRec))
21.   Begin
22.      iRec = Contextual Evaluation of Alternative Recommendations; //Algorithm 3
23.   End
24.   return iRec;
25. Stop
```

true (1) or false (0) value. For instance, the hiking context evaluation vector consists of 1, 1, and 0 values. When these valued are ANDed, we get false (0) value and it is added to the aggregate vector at first index. Similarly, running context evaluation vector is composed by 0, 1, and 1 values, when they are ANDed, they yield false (0) value and it is added to the aggregate vector at index 2. The process continues till the end of the context evaluation vector list and the resultant values of logical_Anding_Operation are added to the corresponding indexes of aggregateVector.

Aggregate vector is composed of 0 s and 1 s, since it is computed by bitwise ANDing operation. It checks each index value (0, 1), if the index value in the vector is 1, it means the corresponding original recommendation is in compliance with the current context of the user and the recommendation is added to the list of interpreted recommendations iRec. In case all the values are returned as 0 means false value, the algorithm will check for the possibilities of alternative recommendations.

Algorithm 2 Aggregate values computation.

```
Input:
  contextEvalVectorList //list of context evaluation vectors
Output:
  aggregateVector // list of values [0,1]
Start
  foreach vector in contextEvalVectorList
  Begin
      result = logical_Anding_Operation(vector)
      AddAggregateVector(aggregateVector, result)
  End
  return aggregateVector
Stop
```

Definition 1. Alternative Recommendations
Let Rec be the set of all recommendations in the scope, and oRec be the set of original recommendations where, oRec ⊆ Rec; and
iRec is the set of alternative recommendations where, altRec = Rec − oRec

The algorithm for contextual evaluation of alternative recommendations is similar to evaluations of original recommendations in Algorithm 1 with the exception that the input is the list of alternative recommendations rather the original recommendations. The definition of Alternative recommendation is given in Definition 1.

5. Experimental evaluation

5.1. Knowledge acquisition case study

For evaluation, we use a weight management scenario implemented in Mining Minds for healthy individuals, who live sedentary life. Sedentary lifestyle refers to one of these situations; either no physical activity, or with irregular pattern, or in an insufficient amount (Thorp, Owen, Neuhaus, & Dunstan, 2011). It includes the activities such as; sitting, reading, watching television, playing video games, and computer use for much of the day with little or no vigorous physical exercise (Owen, Healy, Matthews, & Dunstan, 2010).

5.1.1. Sedentary behaviors' recommendations translated from guidelines

Based on the monitoring capabilities of Mining Minds, we choose recommendations generated against multiple sedentary situations categorized in three categories; prolong sitting, prolong standing, and prolong lying down. In Table 5, a list of respective recommendations for selected sedentary situations is provided.

5.1.2. User current context collection

In Mining Minds, different type of context is recognized including low-level (LLC) & high-level context (HLC), location context (LC), emotion context (EC), weather context (WC), and others. The LLC, EC, and LC are used to identify the HLC using ontological reasoning using context ontology (Villalonga, Banos, Khan, & Ali, 2015). In Table 6, a partial list of different contexts is represented.

5.1.3. Knowledge rules for contextual interpretations

As mentioned previously, every recommendation that is generated by RB may not be appropriate for forwarding to the user unless contextual information is not aptly considered. From surveying users, we identified the common situations where majority of the users agree on recommendation to forward or not. A partial list of these non-forwarding rules are described in Table 2 that shows if any of these rules matches for a given context, the recommendation will not be forwarded.

5.1.4. Knowledge rules for contextual interpretations

In order to interpret the appropriateness of recommendations to be forwarded in their original state or in the alternative form, we investigate to find the knowledge for contextually preferred recommendations. This knowledge is collected through questionnaires composed of items related to three contexts: LC, HLC, and WC. Responses of surveyed users are recorded through the questionnaire. Through majority voting mechanism as explained in Section 3, the final answers are populated in a two dimensional matrix for each context, as shown in Table 3.

5.2. Implementation scenario

A prototype implementation of the proposed CCIR method is implemented as a part of Mining Minds. Mining Minds is a distributed platform where the implementation is deployed over a hybrid cloud combining Microsoft Azure public cloud environment (Banos et al., 2016; Microsoft, 2016). All of the layers of Mining Minds work independently, however, they are interrelated for the data and knowledge communication in order to perform their tasks. SCL layer is dependent on DCL for data communication while on KCL for knowledge communication. The resulting recommendations are communicated to SL layer for presentation. This communication is implemented by establishing service contracts among the layers, which communicate by means of RESTful web services (Richardson & Ruby, 2008). Mining Minds source code is available on the open source GitHub repository and can be downloaded from the link.[1] In the same repository, the proposed work on recommendation interpreter can be found on the link.[2]

5.2.1. Implementation workflow

The implementation diagram shown in Fig. 6, describes the communication pattern between different layers and components. First, the recommendation request is received to SCL service orchestrator (SO) components either through user directly or from DCL. Service orchestrator passes the request to recommendation builder (RB). RB connects to KCL in order to find the rules against the triggered situation event. KCL returns all the candidates knowledge rules to take part in recommendation generation. RB determines the data requirement from the rules and make a data request to SO. SO connects to DCL's intermediate database and fetches all the required data (user profile data) for recommendations and forward to RB. In RB, multimodal hybrid reasoner performs reasoning over the rules and data, and builds the initial set of recommendations which is then passed to recommendation interpreter (RI). The recommendation received to RI from RB in JSON format have two parts: structured and unstructured. The structured part is for the computer interpretability while the unstructured part is for the explanation purpose. RI interprets the structured part according to the algorithms discussed in Section 3 of this paper. The final contextualized recommendations are first sent to DCL to persist in the life-log of the user and then sent to the SL for the user presentations.

5.2.2. End-to-end example scenario

Consider "John" as a user of the CCIR system with his current context described as follows. On a busy working day, John stays for longer hours in his office in an inactive state while the outside weather is sunny. In this scenario, location is office, high-level context is inactivity, and weather is sunny. The CCIR component receives original recommendation as input for the stated context

[1] https://github.com/ubiquitous-computing-lab/Mining-Minds.
[2] https://github.com/ubiquitous-computing-lab/Mining-Minds/tree/master/service-curation-layer.

Table 5
Partial list of recommendations for prolong sitting, standing and lying down.

Sedentary behavior	Criterion	Recommendations	Identifier	Reference
Prolonged Sitting	15–20 m sitting	TAKE A BREAK! Get out of your chair or couch every 15 min and merely stand up and then sit back down, Or do some stretching for 20–30 s.	Rec1	Fitness Peak (Mercola, 2014)
	1 h sitting in chair for non-obese adults	Take a five-minute walk for every hour you spend in your chair	Rec2	Thosar, Bielko, Mather, Johnston, and Wallace (2015)
Prolonged Standing	2 h standing in workplace	TAKE A SITTING BREAK! Have a rest of 4–5 min, 2–3 times per hour of standing.	Rec3	Gregory and Callaghan (2008)
	1 h standing for males	PERFORM PREVENTATIVE STRETCHING! Relax your legs every after 30 min	Rec4	Standing on the Job (Preventing Work-related Injuries: Standing on the Job., 2016)
Prolonged Lying Down	1 h lying down as a bed rest	BODIES ARE MADE TO MOVE! Please have a walk of 5 min, 2–3 times every after 1 h of inactive lying down period	Rec5	Convertino, Bloomfield, and Greenleaf (1997)

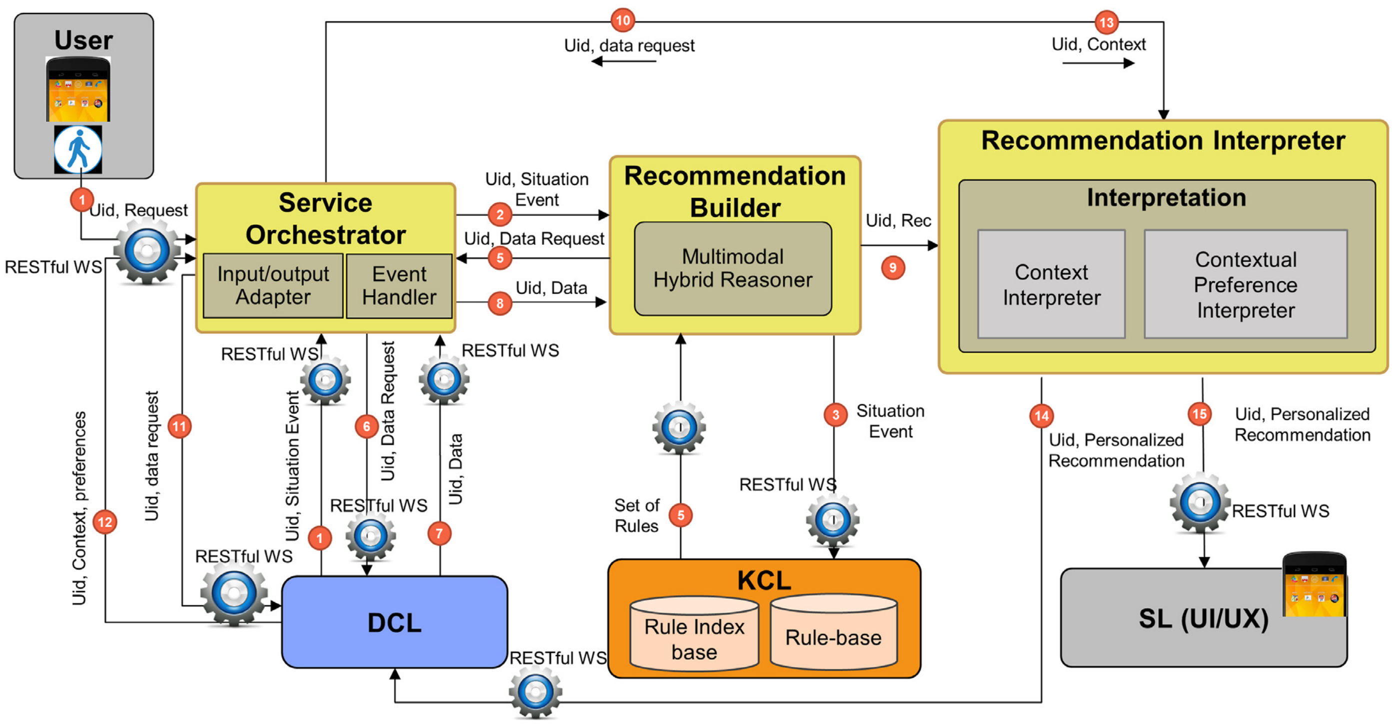


Fig. 6. Intra and inter layer communications of CCIR of service curation layer with components and layers of mining minds.

Table 6
Partial list of contextual scenarios consist of location, high level, and weather context.

Context				Identifier
LLC	LC	HCL	WC	
Sitting	Home	Inactivity	Sunny	S1
Standing	Home	Inactivity	Sunny	S2
Stretching	Office	Officework	Windy	S3
Walking	Office	Exercising	Windy	S4
.	…	…	…	…
…	…	…	…	…
…	…	…	…	…
Sweeping	Outdoor	UnIdentifiedHLC	Rainy	S39
Running	Outdoor	Exercising	Rainy	S40

as "running". To generate interpreted recommendation for this scenario, the step-wise CCIR methodology is described as follows.

Step 1: *Recommendation Interpreter* (RI) receives "running" recommendation and user identifier (user_id) from *recommendation builder* (RB).

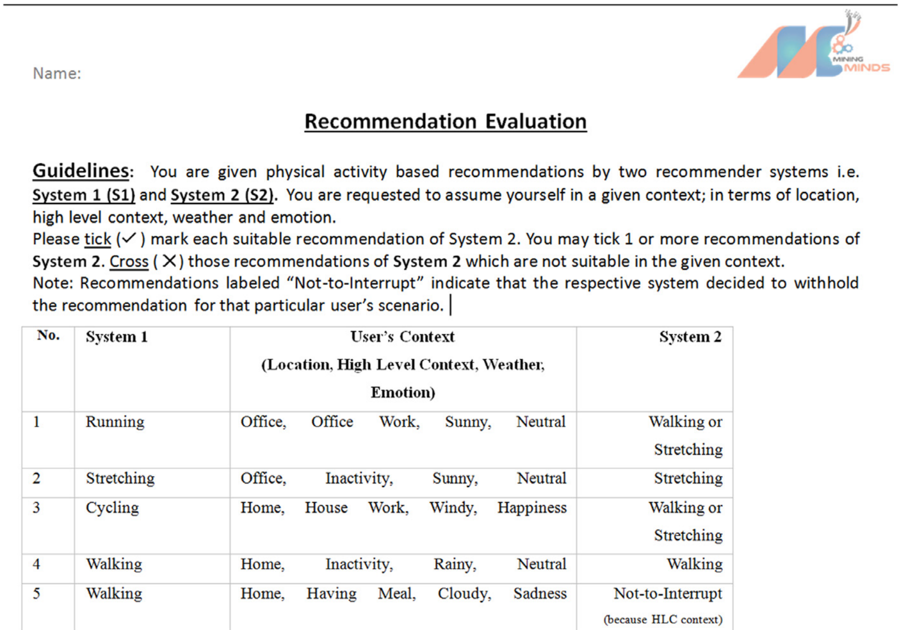
Step 2: RI fetches the current context (office, inactivity, and sunny) from the lifelog through *service orchestrator*.

Step 3: RI loads the rules of RFKB to check the appropriateness of user current context to determine whether the recommendation should be allowed and forwarded or stopped at this stage. Since John is "inactive" in office, so the system allows the recommendation to be forwarded because no such rule is available (see Table 2) to stop the recommendation.

Step 4: RI checks the recommendation "running" is applicable in the given context or not. Using the knowledge in contextual preference knowledge base (CPKB), RI finds that "running" recommendation is not applicable because of the "office" context.

Step 5: As recommendation "running" is blocked; therefore, RI searches for alternative recommendations to replace the "running" recommendation. We can see from the aggregate matrix (Fig. 4), two alternative recommendations are applicable i.e., "walking" and "stretching".

Step 6: Finally, recommendation "walking/stretching" is forwarded to the user to follow and break the inactive state of the day.



Name:

Recommendation Evaluation

Guidelines: You are given physical activity based recommendations by two recommender systems i.e. **System 1 (S1)** and **System 2 (S2)**. You are requested to assume yourself in a given context; in terms of location, high level context, weather and emotion.
Please tick (✓) mark each suitable recommendation of System 2. You may tick 1 or more recommendations of **System 2**. Cross (✕) those recommendations of **System 2** which are not suitable in the given context.
Note: Recommendations labeled "Not-to-Interrupt" indicate that the respective system decided to withhold the recommendation for that particular user's scenario.

No.	System 1	User's Context (Location, High Level Context, Weather, Emotion)	System 2
1	Running	Office, Office Work, Sunny, Neutral	Walking or Stretching
2	Stretching	Office, Inactivity, Sunny, Neutral	Stretching
3	Cycling	Home, House Work, Windy, Happiness	Walking or Stretching
4	Walking	Home, Inactivity, Rainy, Neutral	Walking
5	Walking	Home, Having Meal, Cloudy, Sadness	Not-to-Interrupt (because HLC context)

Fig. 7. Questionnaire for recommendation evaluation.

5.3. Experimental setup

In order to assess the effectiveness of the proposed system developed on CCIR methodology, we have conducted a questionnaire based evaluation. A questionnaire is prepared with 40 scenario items collected in a week long activities of different users. Each scenario item has a context and a recommendation from two systems. A snapshot of the questionnaire is depicted in Fig. 7 where System 1 and System 2 denote recommendation builder (RB) and recommendation interpreter (RI) respectively. Context and recommendation values are taken from the lifelog of the users stored in IDB. Because of the relational structure of lifelog, each recommendation is easily back tracked to corresponding contextual information. It is pertinent to mention here that the recommendations are generated on the basis of the contextual preferences stored initially in CPKB because none of the user provide their preferences during subscription time. As we mentioned in section 3.2, CPKB is considered as a default if user fails to provide his/her preferences during subscription time.

Questionnaire is distributed among 50 participants to observe the given context and respond to the recommendations. Among 50 participants, 40 were end users and 10 were domain experts who were having certain level of knowledge of the wellness domain and recommender systems. The portfolio of the end user participants includes 30 males and 10 females in the middle-aged group (25–49 years). These participants belong to 10 different nationalities including South Korea, Pakistan, Vietnam, Spain, Myanmar, Ecuador, India, China, Bangladesh, and Uzbekistan. The distribution of participants based on gender and ethnicity are shown in Table 7.

While, the expert users were belonging from South Korea (3), Pakistan (2), Bangladesh (1), Iran (2), and Vietnam (2) in the range of middle-age (25–49 years). There are few assumptions which were considered for the proposed system evaluations.

- User's current context is available and is accurate.
- Acquired general activity preference trend from a user base (through a questionnaire) is representative of the target population.
- User is physically able to perform recommended activities.

Table 7
Gender and Ethnicity wise participant distribution.

Ethnicity	Gender		Total
	Male	Female	
South Korea	9	1	10
Pakistan	8	1	9
Vietnam	3	2	5
India	1	1	2
China	2	0	2
Spain	1	1	2
Uzbekistan	0	2	2
Yemen	2	0	2
Ecuador	0	2	2
Bangladesh	4	0	4
Total	30	10	40

5.4. Evaluation of the system

All the results of the study are collected and analyzed in a tabular form. In case of multiple physical activity recommendations, if one of the physical activities is deemed appropriate then the entire recommendation is considered reasonable. Appropriate recommendations are labelled "Yes" while inappropriate recommendations are labelled "No". If a participant selects RI's results as more reasonable than RB's results will be deemed inappropriate.

Three kinds of analysis are performed on the data acquired from end users and expert users. Firstly, each user response is evaluated to find out the "goodness of fit" of the system. Secondly, statistical observations are recorded on the collected data using descriptive statistical analysis parameters including mean, standard deviation, and skewness. Thirdly, a comparison graph is drawn of end users and experts to find out mutual relationship in their response to the system.

5.4.1. Chi-Square goodness of fit test

We calculated the Chi-Square (χ^2) value using Eq. (1) to check the "goodness of fit" of the system on the basis of end user's observation and expected values as shown in Table 8. In Eq. (1), O represents the observed value and E represents the expected value.

Table 8
Essential values for chi-square (x^2) test.

Scenarios	Observed values		Total	Expected values		Chi Stat (X^2)	
	Yes	No		Yes	No	Yes	No
S1	38	2	40	34.675	5.325	0.319	2.076
S2	37	3	40	34.675	5.325	0.156	1.015
S3	38	2	40	34.675	5.325	0.319	2.076
S4	25	15	40	34.675	5.325	2.700	17.579
S5	33	7	40	34.675	5.325	0.081	0.527
S6	33	7	40	34.675	5.325	0.081	0.527
S7	35	5	40	34.675	5.325	0.003	0.020
S8	36	4	40	34.675	5.325	0.051	0.330
S9	38	2	40	34.675	5.325	0.319	2.076
S10	27	13	40	34.675	5.325	1.699	11.062
S11	36	4	40	34.675	5.325	0.051	0.330
S12	32	8	40	34.675	5.325	0.206	1.344
S13	38	2	40	34.675	5.325	0.319	2.076
S14	33	7	40	34.675	5.325	0.081	0.527
S15	36	4	40	34.675	5.325	0.051	0.330
S16	37	3	40	34.675	5.325	0.156	1.015
S17	37	3	40	34.675	5.325	0.156	1.015
S18	37	3	40	34.675	5.325	0.156	1.015
S19	36	4	40	34.675	5.325	0.051	0.330
S20	36	4	40	34.675	5.325	0.051	0.330
S21	37	3	40	34.675	5.325	0.156	1.015
S22	38	2	40	34.675	5.325	0.319	2.076
S23	28	12	40	34.675	5.325	1.285	8.367
S24	37	3	40	34.675	5.325	0.156	1.015
S25	36	4	40	34.675	5.325	0.051	0.330
S26	34	6	40	34.675	5.325	0.013	0.086
S27	35	5	40	34.675	5.325	0.003	0.020
S28	36	4	40	34.675	5.325	0.051	0.330
S29	35	5	40	34.675	5.325	0.003	0.020
S30	34	6	40	34.675	5.325	0.013	0.086
S31	36	4	40	34.675	5.325	0.051	0.330
S32	24	16	40	34.675	5.325	3.286	21.400
S33	33	7	40	34.675	5.325	0.081	0.527
S34	37	3	40	34.675	5.325	0.156	1.015
S35	37	3	40	34.675	5.325	0.156	1.015
S36	38	2	40	34.675	5.325	0.319	2.076
S37	38	2	40	34.675	5.325	0.319	2.076
S38	32	8	40	34.675	5.325	0.206	1.344
S39	32	8	40	34.675	5.325	0.206	1.344
S40	32	8	40	34.675	5.325	0.206	1.344

$$x^2 = \sum_{i=1}^{n} \frac{(O_i - E_i)^2}{E_i} \quad (1)$$

For our experiment, the null and alternative hypothesis are set as follows:

Null Hypothesis (H_0): There is no significant difference between the observed and expected values.

Alternative Hypothesis (H_1): There is a significant difference between the observed and expected values.

Based on the essential values as described in Table 8, we calculated the value of x^2 (105.491) with a degree of freedom value 39 [(r −1) (c-1) = (40–1) (2–1)]. The x^2 value is tested against the chi-square distribution for the standard level $\alpha = 0.05$ to find the critical (chi crit) value (54.572). Since the calculated chi-stat value is greater than the standard chi-crit value; thus, we reject the null hypothesis H0, and accept the alternative hypothesis H1. It shows that there exists significant difference between the observed values and the expected values regarding the system that is developed on the basis of our proposed CCIR methodology.

5.4.2. Statistical observations

We compared the results of opinions by the experts and users for the 40 context scenarios using the descriptive statistics. We performed a statistical analysis to examine factors using the SPSS Windows program (Ferguson, 1959; George & Mallery, 2016). Using descriptive statistics, the arithmetic mean (M), standard deviation (SD), and skewness were calculated for both datasets of users and experts to observe their response's tendencies. The descriptive statistics are illustrated in Table 9, where the higher M value 34.625 shows that the majority of end users agree with the recommendations generated based on the given context scenarios. Similarly, the standard deviation 3.533 infers that the end users have very small deviation in their agreement on different context scenarios. The skewness value −1.58 is acceptable for a normal distribution, because most of the values are in an acceptable range (between + 2 and −2) (George & Mallery, 2016). On the other hand, the standard deviation of the expert users has even a smaller deviation of 1.145 in their agreement on different scenarios. Also, the experts' skewness value −1.419 is in the range of acceptable values. From these statistical analysis, we infer that the participants of both the groups are in agreement and have a higher level of central tendency and a lesser level of variability in their responses to the system.

Table 9
Mean, standard deviation, and skewness.

Metric\User type	User	Expert
Arithmetic mean	34.675	8.850
Standard deviation	3.533	1.145
Skewness	−1.586	−1.419

Table 10
Comparison of participantss' response to the system.

Scenarios	Observed values		Observed values (%)	
	Users	Expert	Users	Expert
S1	38	10	95	100
S2	37	8	92.5	80
S3	38	9	95	90
.	.	.	.	.
.	.	.	.	.
S38	32	9	80	90
S39	32	10	80	100
S40	32	10	80	100

5.4.3. Participants' response to the system

Finally, we record the response from both end-users and experts to find out the mutual relationships in their responses. Because of the unequal number of participants in each group, we converted the response values to the percentage response values as shown in Table 10. The average value (%) for the end-users is recorded as 86.688, which is very close to the average value (%) 88.500 of the expert users, means the participants of both the groups have almost similar opinion about the system. Also, a value-by-value comparison of the values in Table 10 is depicted in Fig. 8. It can be seen from the figure that there exists a very close relationship in the response of the participants from both the groups. It leads us to the conclusion that both the groups are agreed in their opinion with respect to the positive response, thus the system is considered to be acceptable.

In order to segregate the contexts, we have selected 34 (user) and 8.5 (expert) as a cutoff point. Hence cutoff point of 34 and 8.5 indicates that a particular context has gained over 85% acceptance from the participants. These contexts are a subset of daily activities performed by a user. Since the Mining Minds platform recognizes contexts such as location, high-level context, weather, and emotion, therefore selected scenarios belong to these particular contexts only. The main purpose of the aforementioned experimenta-

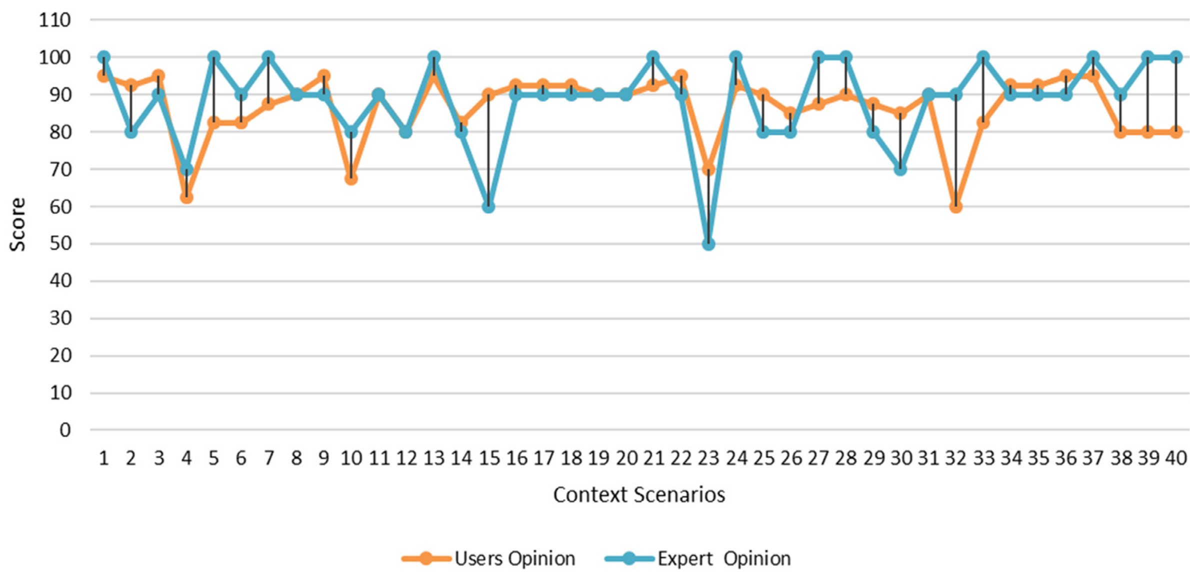


Fig. 8. Score for different context scenarios showing opinion of experts and users about the system.

Table 11
Contexts with score less than the cutoff point.

S. No.	Scenario item	Contexts (Location, HLC, Weather, Emotion)	RB	RI
1	4	Home, Inactivity, Rainy, Neutral	Walking	Walking
2	5	Home, HavingMeal, Cloudy, Sadness	Walking	N/I
3	6	Home, Sleeping, Windy, Neutral	Stretching	N/I
4	10	Outdoors, Commuting, Cloudy, Neutral	Walking	N/I
5	12	Gym, Exercising, Cloudy, Neutral	Running	Running
6	14	Mall, UnidentifiedHLC, UnidentifiedWeather, Sadness	Running	Walking
7	23	UnidentifiedLocation, Anger, Rainy, Inactivity	Cycling	Walking
8	26	Gym, Sleeping, UnidentifiedWeather, Neutral	Running	N/I
9	31	Restaurant, Sleeping, Windy, Sadness	Running	N/I
10	32	Home, Inactivity, Rainy, Sadness	Cycling	Walking
11	33	Yard, Sleeping, Sunny, Happiness	Walking	N/I
12	38	Office, OfficeWork, Sunny, Neutral	Walking / Running	Walking
13	39	Yard, UnidentifiedHLC, Cloudy, Sadness	Running /Stretching	Walking/Cycling
14	40	Home, Exercising, Sunny, UnidentifiedEmotion	Walking	Walking

tion is to evaluate participants' response variability against different contexts and cross validation from the expert users. Analysis of participants' response helped us categorized these contexts in two clusters, i.e., acceptable performance and non-acceptable performance scenarios.

For end users, a total of 14 such contexts are identified which scored less than the cutoff point. These contexts are listed in Table 11. Both RB and RI have same recommendations for 4 out of 14 aforementioned contexts. Hence, in only 10 out of 14 contexts most participants marked RI's recommendations "unreasonable". Varied personal preferences could be one of the reasons since some of these contexts are rather rare e.g. "outdoors, commuting", "gym, sleeping", and "yard, sleeping", etc. This analysis necessitates acquiring of personal preferences of the user.

Two ways to address the issue of infrequent scenarios where the user have marked RI recommendations unreasonable: (i) Through acquiring user specific preferences data from the users themselves through a feedback mechanism, (ii) revising the validity of the contexts recognized by the system as it seems that some of the recognized contexts are not valid thus lead to generate unreasonable recommendations.

6. Discussion

Recommendation systems tend to be very complex. These systems not only perform information filtering but also take into account different preferences of the users. Task of the recommender systems becomes more challenging in the wake of scarcity of the data. One of the main problems in recommendation systems is the cold start which is pertinent to mention along with the interpretation of recommendation with respect to user preferences. Cold start problem occurs in most of the systems that requires data to draw any inferences for users or items about which sufficient amount of information is not yet gathered. Therefore, system is unable to provide any useful recommendations to the user in the wake of cold start problem. In order to circumvent this issue, we have relied on a questionnaire based data gathering technique which provides sufficient data to extract general patterns of human behavior under different conditions. These global patterns of human behavior are used to make initial recommendations to the user. These resulting patterns are stored in CPKB for each user and a generic level of personalization is achieved. This approach is evaluated with an experiment which examined the users with 40 different everyday scenarios and assess the viability of recommendations for each case. As per the experiment results most of the users showed inclination towards the provided recommendations. Their generalized response is depicted in Fig. 7. It indicates that our system, in its early stages, is able to handle most of the everyday scenarios and successfully avoid cold start problem. But these generic patterns may not capture idiosyncrasies of different users. Hence, inferring preferences of users on the basis of general patterns can be very tricky. Therefore, in order to avoid such issues, each user is prompted to provide his/her preferences across multiple contexts customization of the recommender system.

Another important aspect of this experiment is to assess behavior of the recommender for infrequent scenarios. Since the proposed method is able to respond to different everyday scenarios, it is interesting to study its recommendations for rare events. Fig. 8 provides item scores across different users. Each item denotes a specific scenario. Most of the scenarios capture everyday aspects while in some of the items rare or infrequent contexts are also incorporated. It is observed that the system's response to such events as rare or infrequent is not adequate. Some of these events are highlighted in Table 11. For infrequent events survey participants had provided varied responses and to approximate a generalized response required a much greater number of survey participants. In this regard a small subset of the users may be affected by the imprecise approximation of our system. In order to address the issue, more data is required for such cases to pinpoint a response which is applicable to a greater population. Moreover, this issue will not hinder those users who would have provided their preferences, explicitly.

With all positives, the proposed methodology has a room to improve by address the following major limitations.

- Contextual matrices are composed of binary values which may further be enhanced to reflect probabilistic decisions
- Current system lacks a feedback process which may enable the system to fine tune its recommendations

7. Conclusion

In recent years personalized healthcare and wellness systems have acquired a pivotal role in the quantified self-movement. These systems share some common characteristics such as self-tracking, self-monitoring, and self-quantification. In order to perform these tasks raw sensory data is acquired and processed for providing intelligent recommendations to the users. Most of these systems focus on valid recommendations, i.e., recommendations which are consistent with domain knowledge or guidelines. While contextual information about the user is not fully exploited. We have proposed cross-context interpretation of recommendation (CCIR), a mechanism in which contextual information about the user is seamlessly incorporated with the knowledge-based recommendation system. The key assertion of the proposed system is that contextual information should also be taken into account along with domain relevant recommendations. An empirical study is performed which validated our assertion and most of the users preferred context interpreted recommendations. Proposed system produced encouraging results in terms of user's acceptability. This system is in its early stages therefore more research is required in terms of identifying key contexts for user behavior modeling, ethnicity traits, and reduction the chances of infrequent scenarios. It will require to consider either increasing number of surveyed members for knowledge acquisition or explicitly obtained user preferences from the users themselves.

As a future work, we intend to incorporate the feedback mechanism for improving the quality of personalized recommendations. We also plan to investigate implicit and explicit data gathering mechanism for user experience quantification. This will enable us to measure the user satisfaction level for modifications in the services provision. Lastly, continuously evolution of knowledge bases (using expert and data driven approaches) will result in adapting recommendations that takes into account the trends as well.

Acknowledgments

This research was supported by the (i) MSIT(Ministry of Science and ICT), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2017-0-01629) supervised by the IITP (Institute for Information & communications Technology Promotion)," (ii) Industrial Core Technology Development Program (10049079, Development of mining core technology exploiting personal big data) funded by the Ministry of Trade, Industry and Energy (MOTIE, Korea)," (iii) Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT & Future Planning (2011-0030079), " and (iv) Korea Research Fellowship Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (NRF-2016H1D3A1938039) and (NRF-2016K1A3A7A03951968), and (v) Institute for Information & communications Technology Promotion (IITP) grant funded by the Korea government (MSIT) (No. 2017-0-00655).

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