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ARTICLE

Knowledge-based reasoning and recommendation framework for intelligent decision making

Rahman Ali[1,2] | Muhammad Afzal[2,3] | Muhammad Sadiq[2] | Maqbool Hussain[2,3] | Taqdir Ali[2] | Sungyoung Lee[2] | Asad Masood Khattak[4]

[1] Quaid-e-Azam College of Commerce, University of Peshawar, Peshawar, Khyber Pakhtunkhwa, Pakistan

[2] Department of Computer Engineering, Kyung Hee University (Global Campus), Yongin, Gyeonggi, Republic of Korea

[3] College of Electronics and Information Engineering, Sejong University, Seoul, Korea

[4] College for Technological Innovation, Zayed University, Abu Dhabi, United Arab Emirates

Correspondence Sungyoung Lee, Department of Computer Engineering, Kyung Hee University (Global Campus), 1732, Deogyeong-daero, Giheung-gu, Yongin, Gyeonggi 17104, Republic of Korea.
Email: sylee@oslab.khu.ac.kr

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Abstract

A physical activity recommendation system promotes active lifestyles for users. Real-world reasoning and recommendation systems face the issues of data and knowledge integration, knowledge acquisition, and accurate recommendation generation. The knowledge-based reasoning and recommendation framework (KRF) proposed here, which accurately generates reliable recommendations and educational facts for users, could solve those issues. The KRF methodology focuses on integrating data with knowledge, rule-based reasoning, and conflict resolution. The integration issue is resolved using a semi-automatic mapping approach in which rule conditions are mapped to data schema. The rule-based reasoning methodology uses explicit rules with a maximum-specificity conflict resolution strategy to ensure the generation of appropriate and correct recommendations. The data used during the reasoning process are generated in real time from users' physical activities and personal profiles in order to personalize recommendations. The proposed KRF is part of a wellness and health care platform, Mining Minds, and has been tested in the Mining Minds integrated environment using a sedentary user behaviour scenario. To evaluate the KRF methodology, a stand-alone, open-source application (Version 1.0) was released and tested using a dataset of 10 volunteers with 40 different types of sedentary behaviours. The KRF performance was measured using average execution time and recommendation accuracy.

KEYWORDS

knowledge-based recommendation, physical activity recommendations, reasoning and recommendation framework, rule-based reasoning, sedentary behaviour

1 | INTRODUCTION

As ubiquitous computing technologies advance, people are increasingly interested in using sensing technology to monitor their daily routines and elevate their standard of life, especially in terms of active living. They want encouragement to live a healthier lifestyle and discouragement from sedentary behaviour through interventions such as appropriate physical activity recommendations (Lee et al., 2007). However, the generation of such recommendations in a real-world application is difficult because of several issues: creating credible knowledge rules, integrating real-world data with the rules, and generating accurate recommendations (Ali et al., 2016). In the literature, several studies focus on wellness and well-being applications in different domains, such as personalized wellness therapy (Lim, Husain, & Zakaria, 2013); promotion of the personal, physical, mental, and social health status of individuals (Fahim et al., 2014); personalized physical activity recommendations (Ali et al., 2016); promotion of active lifestyles (Ali, Siddiqi, Kang, & Lee, 2015); and personalized health care services for the normal activities of the elderly and their caregivers (Yuan & Herbert, 2014).

Apart from those applications, content-based filtering recommendation systems (Pazzani & Billsus, 2007; Van Meteren & Van Someren, 2000), collaborative filtering recommendation systems (Ekstrand, Riedl, & Konstan, 2011; Schafer, Frankowski, Herlocker, & Sen, 2007), knowledge-based recommendation systems (Bridge, Göker, McGinty, & Smyth, 2005; Trewin, 2000), and hybrid recommendation systems (Burke, 2002, 2007) have been widely adopted in various domains, such as entertainment (recommendation of movies and shows), e-commerce (recommendation of products), and services (recommendations for travel and houses to rent; Bobadilla, Ortega, Hernando, & Gutiérrez, 2013). Content-based recommendation systems begin with users' past ratings of items or services and recommend similar services to them and similar users (Pazzani & Billsus, 2007; Van Meteren & Van Someren, 2000). Collaborative recommendation systems use likes and dislikes from other users to make recommendations (Ekstrand et al., 2011; Schafer et al., 2007). In knowledge-based recommendation systems, explicit knowledge of the domain and user preferences are used to recommend services to end users (Bridge et al., 2005; Trewin, 2000). Hybrid recommendation systems use a combination of any of those methods to achieve the goal of generating accurate recommendations (Burke, 2002, 2007).

In health care and well-being applications, physical activity is a fuelling force for a healthy and active lifestyle and improves cardiorespiratory health, muscular fitness, bone health, and the risk of Type 2 diabetes (Haskell et al., 2007). The research community has approached those issues by developing physical activity recommendation systems (Ali et al., 2016; Blair, LaMonte, & Nichaman, 2004; Sparling, Howard, Dunstan, & Owen, 2015) to minimize the risks of those diseases. In this research work, we propose a knowledge-based recommendation framework (KRF) to support the development of knowledge-based recommendation systems. The framework is simulated using a real-world scenario of individuals who engage in prolonged inactivity.

The adaptability of the proposed KRF comes from its ability to generate reliable, trustworthy, and effective recommendations for high-risk health conditions, that is, an individual's sedentary behaviours (the proposed scenario). In the KRF, the source of each recommendation is essentially complete knowledge in the form of rules or cases generated from individuals' data or experts' past experiences, rather than the contents or ranks of others' preferences. Explicit knowledge is always trustworthy; therefore, that scenario is supported by the proposed KRF. The literature contains several knowledge-based frameworks (Shahar, 1997) and recommendation systems (Ali et al., 2016; Schmidt, Montani, Bellazzi, Portinale, & Gierl, 2001) that perform well in their respective domains and application areas.

The rationale behind our simulation of the proposed KRF is that physical inactivity (i.e., a sedentary lifestyle) has a major impact on public health (Blair et al., 2004) by exposing individuals to multiple diseases. A sedentary lifestyle has either no physical activity or activity in an irregular pattern or of an insufficient amount (Thorp, Owen, Neuhaus, & Dunstan, 2011). The research community defines inactivity or a sedentary lifestyle in different ways, such as activities with metabolic equivalent (MET) values below 1.5 (Tremblay, Colley, Saunders, Healy, & Owen, 2010); time spent sitting or lying down, other than sleeping (Franklin, Brinks, & Sternburgh, 2010); or a lack of moderate to vigorous physical activity (Marshall & Ramirez, 2011; Tremblay et al., 2010). The list of sedentary activities includes 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). Lack of physical activities adds to many preventable causes of death (Lopez, Mathers, Ezzati, Jamison, & Murray, 2006). According to World Health Organization (2011) estimates, physical inactivity is associated with 3.2 million deaths worldwide each year.

An individual who regularly follows the physical activity guidelines proposed by the American College of Sports Medicine (2015), Centers for Disease Control and Prevention (Pate et al., 1995), United Kingdom (Bull, 2010), Canada (Tremblay et al., 2011; Warburton, Charlesworth, Ivey, Nettlefold, & Bredin, 2010), and American Health Association (Haskell et al., 2007) but is mostly sedentary has high health risks. For example, individuals who sit for more than 4 hr/day have a 40% higher health risk than those who sit fewer than 4 hr/day. However, those who exercise at least 4 hr/week are as healthy as those who sit fewer than 4 hr/day (Dunstan & Owen, 2012; Han, 2012). Short breaks, such as simply standing up and walking at a normal pace for 2–5 min/hr, can work well to reduce health risks (Swartz, Squires, & Strath, 2011).

Proper interventions are required to reduce and break up sedentary behaviours among adults in domestic, workplace, and transportation environments (Nchpad, 2013). Australian guidelines for sedentary behaviour recommend minimizing the amount of prolonged sitting by adding more breaks (Australia's Physical Activity and Sedentary Behaviour Guidelines, 2014). Adults who frequently interrupt their sedentary time usually have better metabolic profiles than those who stay sedentary (Healy et al., 2008). The minimum number of beneficial interruptions and their duration is hard to determine; however, simple pose changing while working or changing from a seated to standing position is beneficial (Bey & Hamilton, 2003). To prevent hazards and risky sedentary situations, employers and researchers have begun equipping offices with technology to assist and promote an active lifestyle (Katzmarzyk, 2010; Salmon, 2010); however, this solution is not cost-effective for individuals or small organizations. Similarly, a recent study inducing an active lifestyle (Hussain & Lee, 2015) gave a surface-level idea of how to generate physical activity recommendations to interrupt prolonged sitting.

In the literature to date, researchers have focused on analysing the effects of prolonged sedentary behaviours on the general health conditions of individuals (Hamilton, Healy, Dunstan, Zderic, & Owen, 2008; Katzmarzyk, 2010) rather than on generating movement recommendations. The research community and organizations are focusing on preparing suitable physical activity guidelines for people who engage in prolonged sedentary behaviours and have to work together to develop automatic physical activity recommendation systems to induce sedentary persons to adopt an active lifestyle. However, to the best of our knowledge, little work has been done in the area of automatic physical activity recommendations for sedentary behaviour. Well-being recommendation systems, in the domain of physical activity recommendations, are usually based on users' predefined queries rather than the creation of an input query at run-time. Each input query contains the data required to match values in the rules. However, in real-world applications in which knowledge rules can be added in an incremental way and input queries are not prepared in advance, existing systems cannot work well due to their lack of automatic knowledge and data integration mechanisms. Apart from those issues, existing recommendation systems are generally domain specific and research oriented, rather than being in an open-source framework available to the general research community for other application domains.

To overcome those issues, we are working on an ongoing research project called Mining Minds (Banos et al., 2015, 2016), which examines human daily routines and provides personalized well-being recommendations. Those recommendations are generated by a KRF, which is the main focus of this study. The proposed KRF uses the rule-based reasoning methodology with data and knowledge integration; the Mining Minds system acquires knowledge rules from credible online guidelines for sedentary behaviour and data from users' daily routines. Our adoption of the knowledge-based recommendation approach is motivated by its reliability and high acceptance rate in real-world applications, which exceed those of collaborative and content-based filtering approaches (Felfernig et al., 2008). The abstract methodology of KRF can be described as follows: The Mining Minds platform continuously collects users' daily physical activities data using smartphones, wearable devices, and monitors. When prolonged sitting, standing, or lying down is recognized, the KRF generates appropriate recommendations and educational facts. The recommendations are provided to the end users via a mobile application.

The key contributions of this paper are as follows.

- The design and development of a flexible and adaptable KRF for intelligent decision making.
- Real-time data integration with knowledge rules using a semi-automatic approach to enable efficient decision making.
- The translation and transformation of implicit knowledge about sedentary behaviours from online guidelines into a classified and explicit knowledge model.
- The development of an intelligent conflict resolution strategy with a maximum specificity rule to pick accurate solution(s) from a set of multiple candidate decisions.
- The development of an adaptable, open-source, and stand-alone application that can easily be adapted and extended by the research community for other applications in different domains by simply changing the knowledge base.

The remainder of this paper is structured as follows. In Section 4, we provide an overview of the Mining Minds platform. Section 4.2 describes the proposed KRF from an architectural perspective, a knowledge and data integration perspective, and a reasoning and recommendation generation perspective. In Section 5, we describe the methodology of each of the key components of the KRF in detail. Section 6 considers a case study of sedentary behaviour to evaluate the proposed framework. In Section 6.2.3, we discuss the implementation of the KRF and describe experiments performed on a test dataset of 40 input cases of sedentary behaviour from 10 volunteers. The evaluation results are analysed and presented visually for better understanding. Section 7 discusses the significance, challenges, and limitations of the KRF, and Section 8 concludes the work with possible future directions.

2 | MINING MINDS OVERVIEW

In our lab, we have an ongoing research project called Mining Minds (Banos et al., 2015, 2016) that monitors users' daily life activities and generates personalized health care and well-being recommendations. The platform uses the concepts of data curation, information, knowledge, and services and implements the system as a five-layer platform, where the fifth layer is the supporting layer (SL) responsible for security, feedback, visualization, and analytics. The layers are thus named the data curation layer (DCL), information curation layer (ICL), knowledge curation layer (KCL), service curation layer (SCL), and SL, and they are interconnected as shown in Figure 1. The DCL performs sensory data acquisition, streaming and communication, lifelog data mapping and representation, and big data storage in a Hadoop Distributed File System. The acquired data are streamed to the ICL for low level context, such as activities (lying down, standing, sitting, walking, jogging, climbing stairs, riding an elevator, and stretching). The recognized activities are stored in the user's lifelog and big data storage. The lifelog storage is a relational data model used for real-time service generation for user requests using both push and pull service models. The ICL uses the low level context to recognize high level context using semantic reasoning approaches. The recognized low-level activities, high-level activities, user personal profile information, and other special conditions, such as risk factors and disease information, are used by domain experts in an offline environment to generate well-being rules for recommendations. Those rules are stored in the knowledge base for use in the SCL during the recommendation generation process. The SCL is the service provider layer of the Mining Minds system. It generates well-being recommendations upon user request. During service provision, the KRF combines the knowledge rules created by the KCL with the user requests. The KRF is the core execution engine of the Mining Minds platform; it enables intelligent decision making based on users' personal profile information, current activities recognized in the ICL, and knowledge rules provided by the KCL. Each user's personal profile information is collected and updated by the SL, which also holds users' personal preferences and special conditions.

The key focus of this study is the design and development of the KRF, specifically for the Mining Minds platform and generally for reuse in other knowledge-based decision-making systems. In the Mining Minds platform, the proposed KRF has its own knowledge integration and data integration interfaces to provide the rules and data for generating recommendations. The core of the KRF is the reasoning and recommendation module, which we emphasize in this paper. As a stand-alone application, the KRF depends on the knowledge rules and data or facts in user queries to generate recommendations. The KRF can be used in both a pull service model and a push service model depending on the query (generated by a user from the application side or by an automatic trigger in the system itself). In this study, we evaluate the proposed KRF in a pull service model scenario using a set of input cases created by the Mining Minds platform while monitoring users' daily sedentary behaviours.

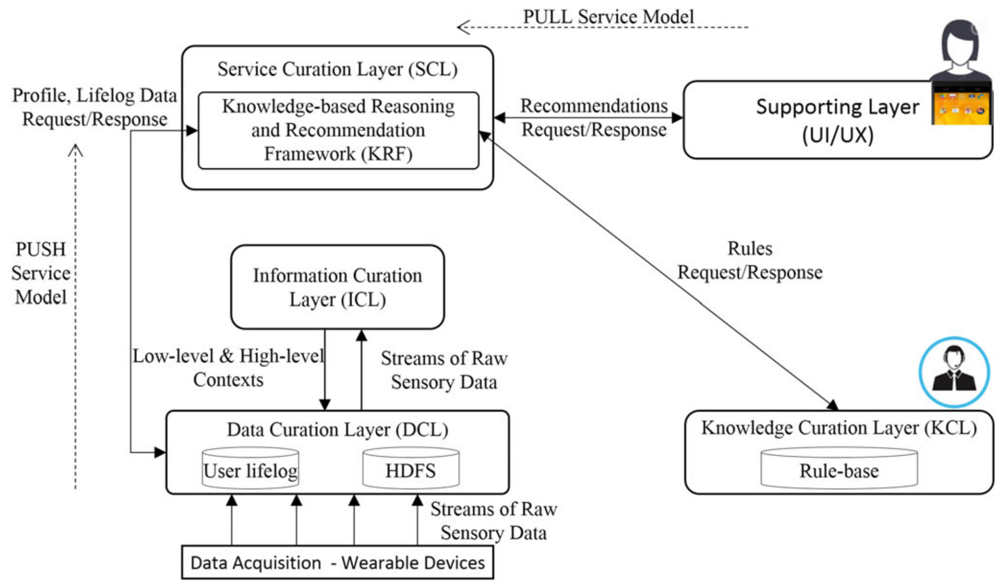

FIGURE 1 Mining Minds platform overview (Banos et al., 2015, 2016). HDFS = Hadoop Distributed File System; UI = User Interface; UX = User Experience

3 | KNOWLEDGE-BASED REASONING AND RECOMMENDATION FRAMEWORK

We propose the flexible KRF shown in Figure 2 to provide intelligent knowledge-based recommendations in the domain of physical activity. The framework is designed with flexibility to support its adoption in other domains of knowledge-based services. The key components of the framework and its working methodology are described briefly below.

- Knowledge integration (knowledge loading interface): In the knowledge integration module, the knowledge rules are loaded into the execution engine of the framework to generate recommendations. To enable this process, a knowledge loading interface performs two tasks: loading existing knowledge using the existing knowledge loader component and generating new rule notifications using the new knowledge notifier component. The new knowledge notifier is responsible for notifying the framework about any new rule added to the knowledge base and for which the framework should define a data integration service.
- Data integration (data loading interface): The data integration module establishes the association of rule conditions with data sources in users' lifelogs or any other data model. To do so, the data loading interface performs three tasks: data and knowledge integration, data transformation, and utility functions. Those tasks are performed by the knowledge and data mapper, data transformation, and utility library components, respectively.
- The knowledge and data mapper internally maintains associations between rule conditions and lifelog schema. The addresses of the schema are mapped against the rule conditions for quick data access.

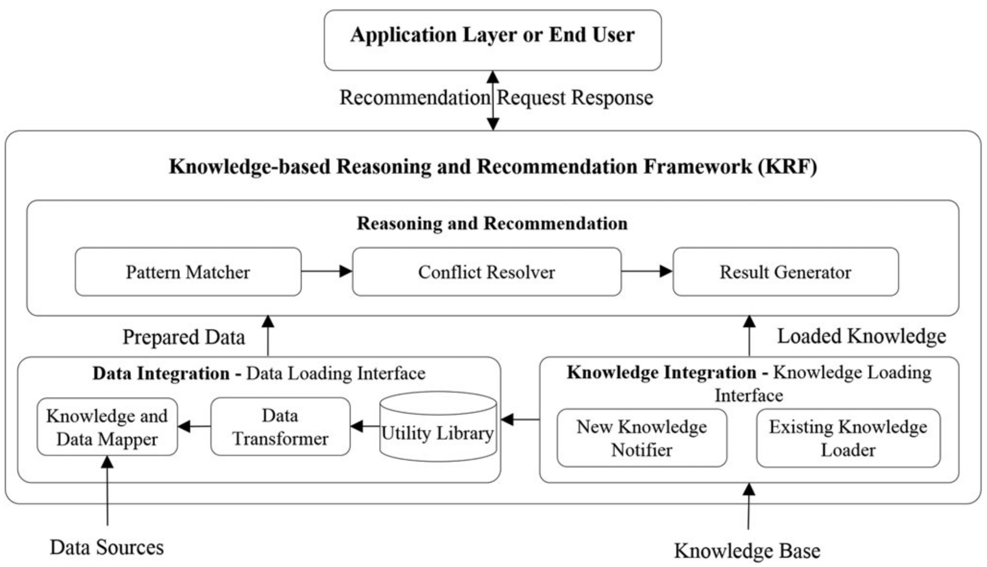

FIGURE 2 Knowledge-based reasoning and recommendation framework

- In the rules, conditions can be either atomic (e.g., age) or composite or abstracted (e.g., BMI). Composite conditions can be composed of multiple atomic conditions (e.g., height and weight for BMI). Calculating the aggregate values of abstracted conditions requires the transformation of constituent conditions. The data transformation component uses the utility functions for such conditions.
- The utility library is the repository of all of those functions. The library keeps a map between the schema and associated functions. During service execution, the data transformation component exploits the utility functions of the library and computes values for abstracted conditions.
- Reasoning and recommendation: This is the core execution engine of the proposed KRF. It consists of a set of intelligent techniques used to generate accurate recommendations upon user service requests. It uses data loaded and prepared by the data loading interface and knowledge loaded by the knowledge loading interface. The set of techniques implemented in the execution engine are pattern matching using the forward-chaining approach, conflict resolution using a maximum specificity strategy, and results generation using object-oriented modelling. The corresponding components of those tasks are the pattern matcher, conflict resolver, and results generator, respectively.

The operating mode of the proposed framework has two stages, the data and knowledge integration stage and the execution stage. The execution stage occurs online, and the data and knowledge integration stage occurs offline.

In the offline phase, the focus is on how the proposed framework will know about any new knowledge added to the knowledge base and how it will map the conditions of the rule to the data in the lifelog. When the knowledge loading interface receives a notification of new knowledge, it forwards the notification to the data integration module, where the knowledge and data mapper component starts registering the new conditions. Utility functions are defined for composite attributes and stored in the utility library. Those functions are also registered in the map files based on their items and corresponding utility functions.

In the online execution phase, a request for service (received from the application layer) is directed to the existing knowledge loader component of the knowledge loading interface to load relevant knowledge to the reasoning and recommendation module. In the reasoner, the conditions of each rule are first matched with each prepared data value using the pattern matcher component, which returns a list of all matched rules. If more than one rule matches, the conflict resolver component is activated to determine the final accurate rule(s). The final resolved rule(s) is or are passed to the results generator, where execution takes place, and the results are generated in the form of a Java object. This output is provided to the application layer as the final recommendation.

4 | METHODOLOGY

In this section, we describe in detail each module of the proposed reasoning and recommendation framework. The proposed framework is described in two dimensions: (a) interfaces for data and knowledge integration and (b) the intelligent decision making embedded in the reasoner in the form of intelligent algorithms.

4.1 | Interface for loading and integrating knowledge

In real-world knowledge-based decision support systems, integrating knowledge in a reasoning environment is a challenging task. A well-integrated knowledge base generates high performance results from the reasoning applications. Generally, knowledge can be either acquired from a large volume of data using automatic machine learning methods or created by domain experts using a knowledge-authoring environment. In both cases, the created knowledge must be embedded in the reasoning environment. However, knowledge acquisition is a continuous process, and rules are created and added to the system environment incrementally. Batch and incremental integration of knowledge rules in the reasoning environment requires an integration interface. In the proposed framework, knowledge integration is achieved through the knowledge loading interface, which performs two tasks: (a) loading existing knowledge from the knowledge base and (b) notifying the framework of new knowledge.

In the recommendation generation scenario, the knowledge rules are loaded to the reasoning and recommendation module by the existing knowledge loader component of the knowledge loading interface on the basis of users' service requests. Each service request is associated with at least one service, which determines the scope of the knowledge rules required. The specification of knowledge for the specific service is performed during service definition. The loaded knowledge is passed to the knowledge and data mapper component of the data loading interface to bind the data from their respective data sources with the conditions of the rules. If the rule has abstracted conditions, the data transformer takes control and calls the corresponding utility library functions to compute values for those attributes. Once all values have been computed and prepared, they are provided to the reasoning and recommendation module to generate recommendations.

In the new rule integration scenario, the proposed framework receives a new rule notification from the new knowledge notifier. Upon such notification, the new knowledge notifier forwards the new rule to the data integration module, where the knowledge and data mapper component starts working to register any new conditions introduced in the rule. For each new condition, the correct association with data in the lifelog is created in the map file. If the new condition is an abstracted one, for example, BMI, its items (i.e., height and weight) are specified, and a computational function is defined and added to the utility library. Mappings between computation functions and abstracted conditions are also created in the utility library.

In the Mining Minds platform, our proposed framework relies on the rules created by another layer, the KCL, which is external to our framework. The knowledge is represented in the form of procedural if-then rules using JavaScript Object Notation (JSON). An example rule in JSON format is shown in Figure 3.

The if part of the rule is labelled *conditionList* and contains condition attributes in object format with key–value pairs. The then part of the rules is labelled *ruleConclusion* and *conclusionList*, which hold the description of the recommendation and optional explanation in structured format, respectively. In the description of the ruleConclusion, we use #RECOM and #FACT tags specific to this study to indicate recommendation messages and educational fact messages for sedentary behaviour, respectively. The representation scheme used by our proposed framework is simple, straightforward, and generic, making it easily adaptable for others to use in their own domains. This increases the acceptability, adaptability, and extensibility of our proposed framework to every domain that expresses knowledge in the form of procedural rules. Moreover, to enhance the applicability of the proposed KRF, we plan to support other types of knowledge representation schemes in future versions.

4.2 | Interface for loading and integrating data

To support real-time services generation for user queries through the reasoning and recommendation system, the data integration module must possess the knowledge rules in advance. The conditions in the rules and the data labels in the schema of the data source must be compliant and mapped to one another for successful integration. For example, the condition BMI in a rule and its corresponding data label in the schema must comply and be linked to each other. In real-world applications for recommendation generation, especially in a distributed environment, those are the most challenging tasks. To generate service recommendations, the knowledge rules require satisfactory data mapping. If the data requirements or mapping for the conditions of the rules are not specified and well defined in advance, recommendation generation will fail.

To solve the data integration problem, we propose a semi-automatic knowledge-data-mapping mechanism that works during knowledge creation to map the conditions of the rules with their corresponding schema. This mapping is an offline process performed during the creation of knowledge rules, which are then sent to the reasoning framework for integration. The mapping process is performed in a semi-automatic manner, and the mappings are maintained in a map file, as shown in Table 1.

In Table 1, the mappings for the rule conditions (column 2) are maintained in columns 5 and 6. In column 5, mappings of the atomic conditions and ingredients of the composite conditions are maintained with the schema. Column 6 maintains the mappings of the composite conditions or attributes, which are merely the utility functions that produce the aggregate values for the composite attributes from their ingredients. The computation mechanism for abstracted conditions (i.e., composite conditions) is defined in the utility library; each composite condition is encoded in a utility function.

When a new rule is formed from the external knowledge base and the new knowledge notifier sends a notification, the knowledge and data mapper starts the mapping process by looking into the knowledge and data mapping file (Table 1) for each condition in the rule. If the conditions are already mapped in the file and their schemas are registered, they are ignored; otherwise, they are mapped in the file. The mappings are generated

```
[
  {
    "ruleConclusion": "#RECOM: Take a five-minute walk.
    #FACT: Taking five-minute walk for every hour of
    sitting can reduce heart disease risks. ",
    "conclusionList":
    [
      {
        "conclusionKey": "Recommended Activity",
        "conclusionValue": "Walking",
        "conclusionOperator": "=",
        "ruleID": 5,
        "conclusionID": 10173
      }
    ],
    "conditionList":
    [
      {
        "conditionKey": "Current Activity",
        "conditionValue": "Sitting",
        "conditionType": "String",
        "conditionValueOperator": "=",
        "conditionID": 1
      },
      { "conditionID": 2},
      { "conditionID": 3}
    ],
    "ruleID": 5
  }
]
```

FIGURE 3 Representation of the knowledge rule in JavaScript Object Notation format

TABLE 1 Data and knowledge integration in a knowledge and data mapping file

C. no.	Rules or conditions	Condition type	Ingredients	Mapping to schema	Mapping to utility library
1	Age	Atomic	Date of birth	Age	ageComputation (dateOfBirth, currentDate)
2	BMI	Composite or abstracted	Height Weight	Body height Body weight	BMIComputation (Height, Weight)
n	Gender	Atomic	Nil	Sex	Nil

Note. BMI = body mass index.

by registering the addresses of the schemas for each condition. For abstracted condition attributes, mappings are generated with the schema and utility functions in the utility library. This whole process is semi-automatic: the notification of a new rule and its conditions is generated automatically, and the remaining tasks, that is, map creation and utility function definition, are completed offline by a developer or administrator to keep the file up to date. The process of registering and mapping rule conditions with the schema and utility library is shown in Figure 4.

Consider a scenario in which our system receives a notification to integrate one rule *r* or a list of rules *R* into our reasoning environment. For their successful execution, those rules must be integrated with their corresponding data in the schema and utility functions in the utility library, which requires the sequential steps shown in Algorithm 1.

Algorithm 1. *Data and knowledge integration to enable reasoning and recommendations*

Begin
  inputs: $\boldsymbol{R} - \{r_1, r_2, \ldots, r_n\}$; //the list of *n* Rules
  output: ***mFile***; **//** mapping file for integrating ***c*** with schema
1. ***foreach*** *Rule* ***r*** *in* ***R***
2. mapFile **= updateMapFile**(mFile, r) // updateMapFile is a procedure defined below
3. *endfor*

End

Procedure updateMapFile(mFile, r)
Begin
  inputs: $\boldsymbol{C} - \{c_1, c_2, \ldots, c_c\}$; // the list of *c* conditions in a rule ***r***
  output: ***mFile***; **//** mapping file for integrating ***c*** with schema

1. ***foreach*** *Condition* ***c*** *in* ***r***
2. ***if c*** is mapped in **mFile** then // ***c*** is already integrated
3. ***goto*** step 1 // take next condition ***c***
4. ***elseif c*** is atomic then // ***c*** is atomic condition
5. map ***c*** in **mFile** // integrate condition ***c*** with schema
6. update **mFile**;
7. ***else*** // ***c*** is composite condition
8. map ingredients of ***c*** in **mFile;** // integrate ingredients of ***c*** with schema
9. define ***uFun*** for *c* in ***uLib***; // uFun is the utility function
10. // uLib is the utility library for uFuns
11. map ***uFun*** in **mFile** // create mapping for ***uFun***
12. update **mFile;**

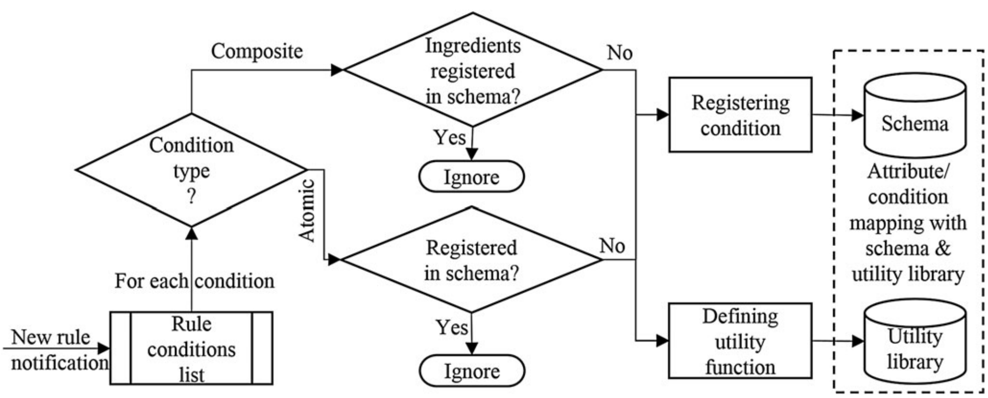

FIGURE 4 Flowchart of the mapping rule conditions with the schema and utility library

13. *endif*
14. *endif*
15. ***Endfor***
16. ***return mFile***

End

In Algorithm 1, the updateMapFile() function is used to register each new condition in the mapping file (and utility library if it is composite). The utility library is the continuously growing library of functions for new composite conditions. For example, in an activity recommendation service, the functions might not include food calorie computation, but a nutrition service will need the library to contain calorie computation functions. Two examples of utility functions used in both physical activity and nutrition recommendation services, ageComputation() and BMIComputation(), are shown in Table 1.

4.3 | Reasoning and recommendations

In knowledge-based recommendation systems, reasoners consume data in the form of new input cases and knowledge in the form of rules. Technically, rule-based reasoning systems use pattern matching, conflict resolution, and results generation to complete the whole cycle of recommendation generation. The execution of the reasoner starts when a service request is received in the form of a single-input case or batched-input cases. First, the KRF loads rules from the knowledge base using the existing knowledge loader component of the knowledge loading interface. The data loading interface loads the required data from the schema with the help of the map file. Both the loaded data and the knowledge rules are provided to the pattern matcher, conflict resolver, and results generator for further processing and final recommendation generation. Detailed descriptions of each component are given in the following subsections.

4.3.1 | Pattern matching using a data-driven approach

In rule-based systems, pattern matching can be either data driven (forward chaining) or goal driven (backward chaining; Brewka, 1991), depending on the availability of information about the goal state. In our case, we adopt the data-driven approach for matching rule conditions against the facts, which are provided as a new query case. We use the data-driven approach because we do not know the goal or conclusion in advance. The forward-chaining mechanism proceeds by taking one rule from the loaded set of rules and matching its conditions with the facts. If all conditions of a rule are matched, it is added to the list of matched rules, and the process continues until the list of rules is empty. The final list of matched rules is provided as the output of the pattern matcher to the next step of conflict resolution, as shown in Figure 2. The data-driven or forward-chaining process for matching rules is shown in Algorithm 2.

Algorithm 2. *Pattern matching with a forward-chaining strategy for matching rules to facts*

Begin

inputs: ***R*** – $\{r_1, r_2, \ldots, r_n\}$; //the list of *n* Rules

F – $\{f_1, f_2, \ldots, f_n\}$; // the list of *n* facts (loaded and prepared from schema as user query)

output: ***M***– $\{r_1, r_2, \ldots, r_m\}$; // the list of *m* matchedRules

1. ***foreach*** *Rule* ***r*** *in* ***R***
2. ***if*** **matchedRule**(F, r) then // matchedRule(F, r) is a procedure defined below
3. add ***r*** to ***M*** **//** add Rule ***r*** to the list of matchedRules ***M***
4. ***endif***
5. ***endfor***

End

Procedure matchedRule(F, r)

Begin

inputs: ***r*** //the single Rule, where ***r*** ∈ ***R***

K – $\{k_1, k_2, \ldots, k_k\}$; // the list of *k* ConditionKeys in each rule *r*

F – $\{f_1, f_2, \ldots, f_n\}$; // the list of *n* facts from user's query

output: ***boolean*** // returns true, if all conditionKeys(conditions) of a rule are matched, and false, otherwise

1. ***foreach*** *ConditionKey* ***k*** *in* ***r***
2. ***foreach*** Fact *f* in *F*
3. ***If k*** matched with *f* then
4. ***goto*** step 1 // condition_key ***k*** matched, take next condition_key ***k***
5. ***endif***
6. ***endfor***
7. ***return*** false // condition_key ***k*** not matched

8. ***endfor***
9. ***return*** true // all condition_keys of the Rule ***r*** are matched

End

In Algorithm 2, the key function, matchedRule(F, r), is fully defined in its procedure. It performs the task of matching facts F with the conditions C of each rule r. The matching technique used is an exact match, that is, a rule is declared to match the facts of the input case if all its conditions match. We do not use partial matches in our approach. The final output of the algorithm is the list of correctly matched rules against the facts of the user's query.

4.3.2 | Conflict resolution using the maximum specificity approach

The output of the pattern matcher can be that more than one rule satisfies all facts in the user query. All satisfied rules are syntactically correct; however, sometimes they are not semantically valid. One approach is to execute all matched and satisfied rules and generate their associated recommendations. However, the following situations require a resolution strategy: (a) when a more specific recommendation is essential and a candidate list of recommendations is unacceptable, (b) when many possible candidate solutions or recommendations are available, and (c) when personalized recommendations are required.

To fulfil those requirements, we use a *maximum specificity conflict resolution* mechanism, which chooses the matched rule with the maximum number of condition attributes as the appropriate rule for the recommendation. The rule with the maximum conditions satisfies the largest number of specific data points about the user, which ensures personalized recommendations. It is a general understanding that a rule with many conditions is more credible or knowledge-enriched than a rule with few conditions. Therefore, it is practical to select the matched rule with maximum conditions.

The maximum specificity conflict resolution algorithm is described in Algorithm 3.

Algorithm 3. *Maximum specificity conflict resolution strategy for selecting appropriate rule(s) from a set of candidates*

Begin

inputs: $\boldsymbol{M}$ – $\{r_1, r_2, \ldots, r_m\}$; //the list of m matchedRules

output: $\boldsymbol{F}$– $\{r_1, r_2, \ldots, r_k\}$; // the list of k finalResolvedRules, where $k \le m$ and length of $\boldsymbol{F}$ = 0, if length of $\boldsymbol{M}$ = 0;

1. **n** = length($\boldsymbol{M}$);
2. add $\boldsymbol{r}_i$ to $\boldsymbol{F}$;
3. ***for* i = 1 to *m* −1**
4. ***nc1*** = conditions_length_of ($\boldsymbol{r}_i$); // *nc1* is the number of conditions of rule $\boldsymbol{r}_i$
5. ***nc2*** = conditions_length_of **(**$\boldsymbol{r}_{i+1}$); // *nc2* the number of conditions of rule $\boldsymbol{r}_{i+1}$
6. ***if nc2 nc1*** then
7. ***goto*** step 3; // increment *i*
8. ***else if nc2*** > ***nc1***
9. *remove* $\boldsymbol{r}_i$ from $\boldsymbol{F}$; // empty F
10. *add* $\boldsymbol{r}_{i+1}$ from $\boldsymbol{F}$; // add the rule with maximum condition to F
11. ***endif***
12. ***endfor***

End

The final output of Algorithm 3 is the specific rule(s) obtained from the list of matched rules. However, in many cases, several rules have the same number of condition attributes, which makes the maximum specificity equal for those rules. Another level of resolution strategy can be introduced to break the tie, but which strategy to use remains debatable because the next level of conflict resolution strategy might eliminate the rule most relevant to a specific user's input. In our proposed case, we allow all such rules to generate recommendations for delivery to the end users. We let the users choose the most relevant recommendation for their own cases.

An alternative to the proposed strategy is a multilevel conflict resolution strategy in which the output (i.e., number of satisfied or matched rules) of one strategy is the input to the next strategy if the preceding one has not resolved it. Each strategy further analyses the matched rules to resolve the conflict and generate a final recommendation. Some possible criteria for conflict resolution used in rule-based expert systems in the literature (Awad & Huntington, 1996; Durkin & Durkin, 1998; Lucas & Van Der Gaag, 1991; Pakiarajah, Crowther, & Hartnett, 2000) include prioritization (the rule with the highest salience score), defined meta-rules (specialized rules for resolving conflicts among matched rules), ordering rules or their conditions in the knowledge base, minimum specificity (rules with minimal conditions), refractoriness (not allowing a rule to fire twice on the same data), recency (depth-first: i.e., take the data that arrived in working memory most recently and find a rule that uses them), breadth-first (rules that have been activated for a long time), LEX (apply recency; if there is still a conflict, apply specificity), and random strategy.

Those strategies can be used in any combination depending on the requirements of the domains. The proposed maximum specificity conflict resolution strategy of the KRF can easily be changed by developers to meet the requirements of their targeted domain application.

4.3.3 | Results generator

Once the conflict resolver algorithm has determined the final correct rules, they are executed and concluded by generating physical activity recommendations and educational facts. These recommendations are appended with other relevant information, such as a service request ID and user ID, and forwarded to the end user's application or written to a file. In the Mining Minds platform, the final output of the proposed framework is prepared as a Java object in a structured format with mandatory and optional parts. If the results are generated from multiple rules, the recommendations are provided as multiple options or alternatives from which the user selects. In the stand-alone Version 1.0 of the KRF, the detailed results are generated in a structured format and stored in a comma-separated file; see Appendix A for further details.

5 | CASE STUDY: DISCOURAGING SEDENTARY BEHAVIOURS AND INDUCING AN ACTIVE LIFESTYLE

In this case study, we focus on sitting, lying down, and standing sedentary behaviours and generate appropriate physical activity recommendations for them. The reason of picking only these activities is that sedentary behaviours are grouped into two categories (Owen et al., 2010). The first category, sitting and lying down, has approximate MET values of 1.0 to 1.5, and the second category, standing, self-care, and slow walking, has MET values of 1.6 to 2.9 (Owen et al., 2010). To generate recommendations, we first studied research and guidelines on sitting, lying down, and standing and then translated that information into a knowledge model. The proposed knowledge model contains appropriate recommendations and educational facts for those sedentary behaviours. We transformed the knowledge model into to a set of 19 rules that we use to generate recommendations.

This simulation of the proposed KRF is merely an example. The framework is generic and can easily be adapted to build knowledge-based recommendation systems for other domains. The only adaptation required is to provide the knowledge rules and necessary data for executing the rules in the specified format.

5.1 | Sedentary behaviours, recommendations, and educational facts

The knowledge rules used for the recommendations are translated from research on sedentary behaviours and available online guidelines. We first identified a list of potential harmful sedentary behaviours and then generated recommendation messages and educational facts about them.

5.1.1 | Translating guidelines for sedentary behaviours

We extensively studied online guidelines and research evidence describing prolonged sitting, standing, and lying down. The guidelines are translated into different behaviours on the basis of sedentary time. A partial list of the most frequent sedentary behaviours is shown in Table 2.

We categorized the extracted behaviours into the categories of prolonged sitting, standing, and lying down, which we further categorized in terms of sedentary time. Each sedentary behaviour is uniquely represented using the sedentary behaviour ID specified in column 3. The criterion column describes the criteria that must be satisfied for a behaviour to be recognized as sedentary.

5.1.2 | Guideline translation into sedentary behaviour recommendations

To avoid sedentary behaviours and induce an active lifestyle, appropriate solutions need to be provided by engineering work sites, homes, and public places to prevent unnecessary sitting and lying down and persuading individuals to move and perform muscular activity or by using a system to recommend appropriate physical activity. This study is focused on the latter solution because the former is expensive and infeasible for individuals to implement. However, individuals also face several challenging issues in implementing the second option, including deciding (a) when to take a break or perform physical activity, (b) what type of activity to perform, (c) how long to be active, and (d) why to bother with activity at all. A physical activity recommendation service can address challenges a–c, and challenge d can be resolved by providing educational facts or cards with the recommendations.

The recommendation service translates appropriate messages from the sedentary behaviour guidelines. Table 3 shows appropriately translated recommendation messages for some of the sedentary behaviours shown in Table 2.

In Table 3, column 4 describes a type and amount of physical activity in the form of a recommendation message. The quality of the recommendation messages is improved by domain experts, so the suggestions are easy and quick to understand and follow. Column 3 represents identifiers for the recommendation messages, and column 2 contains the criteria for when to generate and provide each recommendation.

5.1.3 | Translating guidelines into educational facts

To effectively treat sedentary life patterns, individuals need to be motivated to be more active and discouraged from sedentary behaviour. Providing such motivation and discouragement is why a recommendation system is needed. To motivate users, the system provides information about the benefits of active living; to discourage sedentary behaviours, it provides the risks of sedentary living. This is an implicit education of individuals with

TABLE 2 A partial list of the most frequent sedentary behaviours

Sedentary behaviour	Activation value	Sedentary behaviour ID	Criteria	Reference or evidence
Prolonged sitting	>=(15–20) min	SB1	=15-min sitting in a workplace	(Mercola, 2014a)
		SB2	15–20 (or >15) min continuous sitting	(Santas, 2015; Vernikos, 2011)
		SB3	>20-min sitting for obese and overweight diabetic adults	(Dunstan et al., 2012)
	>=50 min	SB4	50-min continuous sitting	(Mercola, 2014b)
	=1 hr	SB5	1-hr continuous sitting in chair for nonobese adults	(Thosar, Bielko, Mather, Johnston, & Wallace, 2014)
		SB6	1-hr sitting at a desk during work	(Mercola, 2014c)
	>=3 hr	SB7	3-hr or more continuous sitting	(Park, 2012)
	>=4 hr	SB8	4 hr or more per day of sitting	(Levine, 2012)
	=6 hr	SB9	6 hr of uninterrupted sitting	(Kulinski et al., 2014)
	>=7 hr	SB10	7-hr/day sitting for middle-aged women with no physical activity	(Van Uffelen et al., 2013)
	>=8 hr	SB11	8 hr/day of sitting	(Mercola, 2015)
Prolonged standing	=2 hr	SB12	2-hr standing in a workplace	(Gregory & Callaghan, 2008)
	>=4 hr	SB13	4-hr standing/day in a workplace	(Magora, 1972)
		SB14	4-hr standing in workplace	(Tomei, Baccolo, Tomao, Palmi, & Rosati, 1999)
	=1 hr	SB15	1-hr continuous standing for males	Standing on the job (Canadian Women's Health Network, 2006)
	>=6 hr	SB16	6-hr standing/day for pregnant women	(Killham, 2016)
	>=8 hr	SB17	8-hr standing/day for pregnant women	(Eskenazi et al., 1994)
Prolonged lying down	=1 hr	SB18	1-hr lying down	(Convertino, Bloomfield, & Greenleaf, 1997)
	>=1 week	SB19	1 week of prolonged bed rest	(Stuempfle & Drury, 2007)

TABLE 3 A partial list of recommendations for the sedentary behaviours specified in Table 2

Sedentary behaviour	Criterion	Recommendation ID	Recommendation	Reference
Prolonged sitting	15–20-min sitting	R1SB1	Take a break! Get out of your chair or couch every 15 min; merely stand up and then sit back down or stretch for 20–30 s.	(Mercola, 2014a)
		R2SB2	Change your posture every 15–20 min throughout the day or "sit smarter with yoga": incorporate yoga postures while you sit and be aware of your breathing.	(Santas, 2015; Vernikos, 2011)
		R3SB3	Do 2-min bouts of light-intensity activity every 20 min to increase the chance of preventing diabetes.	(Dunstan et al., 2012)
	50-min sitting	R4SB4	You've been sitting too long; take a 10-min walk. Avoid sitting for more than 50 min an hour.	(Mercola, 2014b)
	1-hr sitting in a chair for nonobese adults	R5SB5	Take a 5-min walk for every hour you spend in your chair.	(Thosar et al., 2014)
	1-hr sitting at a desk during work	R6SB6	Stand up! Do at least 10 min of exercises at your desk.	(Mercola, 2014)
Prolonged standing	2-hr standing in workplace	R7SB12	Take a sitting break! Rest for 4–5 min 2–3 times per hour of standing.	(Gregory & Callaghan, 2008)
	4-hr standing in workplace	R8SB13	Change working position frequently! Working in one position brings physical health risks.	(Magora, 1972)
	1-hr standing for males	R9SB15	Perform preventative stretching! Relax your legs every 30 min.	("Preventing work-related injuries: Standing on the job,2006")
	8-hr standing/day for pregnant women	R10SB17	Try to put your feet up at work and rest with your feet higher than your head.	(Eskenazi et al., 1994)
Prolonged lying down	1-hr lying down as bed rest	R11SB18	Bodies are made to move! Please have a walk of 5 min 2–3 times every hour of inactive lying down.	(Convertino et al., 1997)
	1-week prolonged bed rest	R12SB19	Stand up! Move and stretch your body to stimulate your cardiovascular, digestive, and excretion systems.	(Stuempfle & Drury, 2007)

Note. R = recommendations; SB = sedentary behaviour.

sedentary lifestyles and can be considered as a *reward and penalty* theory of active living. We implement this theory by providing data from our proposed reasoning and recommendation framework.

To find the appropriate data for the reward and penalty theory, we studied sedentary behaviour and guidelines and translated them into a list. A partial list of those data is shown in Table 4.

TABLE 4 A partial list of educational facts to motivate active living and discourage sedentary living

Sedentary behaviour	Criterion	Facts ID	Educational facts or cards	Reference
Prolonged sitting	20 min for obese and overweight diabetic adults	F1SB3	Breaking up periods of prolonged sitting with 2-min bouts of light-intensity activity every 20 min results in a 24% reduction in postprandial glucose area under the curve and a 23% reduction in insulin area under the curve in overweight and obese adults, compared with uninterrupted sitting.	(Dunstan et al., 2012)
	1-hr sitting in chair for nonobese adults	F2SB5	Taking a 5-min walk for every hour of sitting can reduce the heart disease risks associated with chronic sitting.	(Thosar et al., 2014)
	3 hr or more of continuous sitting	F3SB7	Sitting for more than 3 hr/day can cut 2 years off of your life expectancy, even if you exercise regularly.	(Park, 2012)
	4 hr/day or more of sitting	F4SB8	A nearly 50% increased risk of death from any cause and about 125% increased risk of events associated with cardiovascular disease, such as chest pain (angina) or heart attack, can result from sitting for more than 4 hr/day.	(Levine, 2012)
	6 hr of uninterrupted sitting	F5SB9	6 hr of uninterrupted sitting effectively counteracts the positive health benefits of a whole hour of exercise.	(Kulinski et al., 2014)
	7 hr/day of sitting for middle-aged women with no physical activity	F6SB10	Women who sit for more than 7 hr a day have a 47% higher risk of depression than women who sit for 4 hr or less per day.	(Van Uffelen et al., 2013)
	8 hr/day of sitting	F7SB11	Even if you exercise, sitting 8 hr/day significantly increases your risk of dying from any cause, and sitting for more than 8 hr/day is associated with a 90% increase in the risk of Type 2 diabetes.	(Mercola, 2015)
Prolonged standing	2 hr of standing in a workplace	F8SB12	Continuous standing for 2 hr results in discomfort in your lower back.	(Gregory & Callaghan, 2008)
	4 hr of standing/day in a workplace	F9SB13	Standing for more than 4 hr/day produces lower back pain.	(Magora, 1972)
	4 hr of standing in workplace	F10SB14	Standing for 4 hr increases the chance of chronic venous insufficiency (leg problem) by 50%.	(Tomei et al., 1999)
	1 hr of continuous standing for males	F11SB15	Regular standing increases the risk for atherosclerosis (hardening of the heart arteries) in men.	("Preventing Work-related Injuries: Standing on the Job, 2006")
	6 hr of standing for pregnant women	F12SB16	Standing more than 6 hr per day is linked with preterm births and low birth weights, as well as high blood pressure for the mother.	(Killham)
	8 hr of standing/day for pregnant women	F13SB17	Pregnant women who stand more than 8 hr in a working day have a high chance of spontaneous abortion.	(Eskenazi et al., 1994)
Prolonged lying down	1 week of prolonged bed rest	F14SB19	Muscle strength decreases by 20–30% after only 1 week of complete bed rest.	(Stuempfle & Drury, 2007)

Note. FID = facts ID; SB = sedentary behaviour.

In Table 4, the translated educational facts are shown in column 4, and their sources are cited in column 5. Column 2 describes the criteria for triggering the facts, and column 3 gives each fact's ID number, such as Fact 1 for Sedentary Behaviour 3. As indicated in Tables 3 and 4, we provide only recommendations for some of the sedentary behaviours, whereas we provide only educational facts for others and both recommendations and educational facts for still others.

5.2 | Creation and transformation of a sedentary behaviour knowledge model

We created a decision-tree-based knowledge model, shown in Figure 5, for the translated sedentary behaviours, their recommendations, and their educational facts (KMSBRF). The leaf nodes in KMSBRF represent knowledge rule IDs for physical activity recommendations and educational facts. This is a partial model that could easily be extended and updated by adding other sedentary behaviours, such as reading, watching television, or playing video games, along with associated rules for recommendations and facts.

In the proposed decision-tree-based knowledge model, the (*) notation represents a *recommendation rule* associated with a sedentary behaviour, and the (**) notation represents a *facts rule* associated with a sedentary behaviour.

To generate recommendations and educational facts, the proposed KMSBRF knowledge model is transformed to produce rules and enable the reasoning and recommendation framework to execute them to generate physical activity recommendations and educational facts. A partial list of the rules is shown in Table 5.

In Table 5, the rule conditions are the criteria that must be satisfied for the system to be notified that a sedentary behaviour has occurred and that a recommendation or fact is required to interrupt it and educate the user. The conclusions of the rules can be only a recommendation (e.g., R4 and R5), a fact (e.g., Rn), or both (e.g., R1, R2, and R3). These rules are represented in JSON format, as specified earlier.

The educational fact or card can be a light negative message (e.g., F8SB12) or a strong negative message (e.g., F3SB7), including threats to discourage the individual from being sedentary. It can also be a motivating message, such as F2SB5, to induce the user to engage in an active lifestyle. Usually, educational facts are provided for prolonged sedentary activity, rather than short sedentary, behaviour.

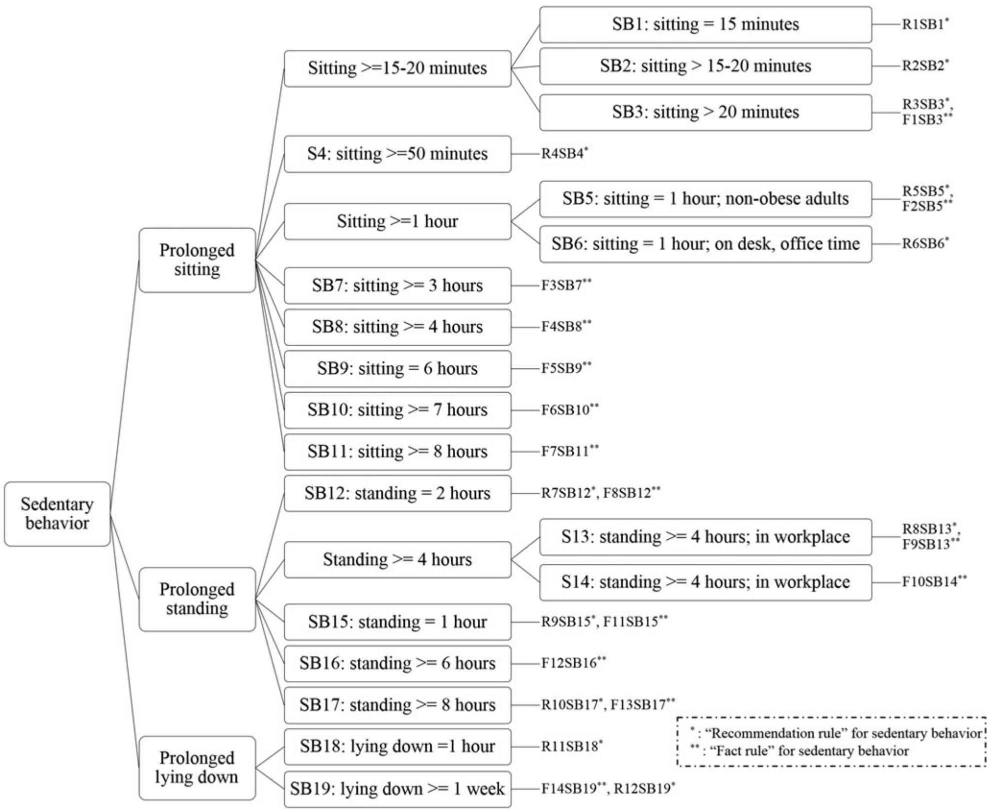

FIGURE 5 Knowledge model of sedentary behaviours (SB), recommendations, and educational facts

TABLE 5 A partial list of the knowledge rules used to generate recommendations and educational facts

Rule ID	Rule conditions	Rule conclusions: Recommendation	Rule conclusions: Fact or card
R1	If (Activity = Sitting, Duration ≥ 1 hr, AgeGroup = Adult, WeightStatus = Non-Obese)	R5SB5	F2SB5
R2	If (Activity = Sitting, Duration ≥ 20 min, AgeGroup = Adult, WeightStatus = Obese, Disease = Diabetes)	R3SB3	F1SB3
R3	If (Gender = Female, Activity = Standing, Duration ≥ 7 hr, AgeGroup = Adult, HealthCondition = Pregnant, HistoryPhyActivity = No)	R10SB17	F13SB17
R4	If (Activity = Sitting, Duration ≥ 1 hr, Location = Office)	R6SB6	–
R5	If (Activity = Lying Down, Duration ≥ 1 hr, Location = Home)	R11SB18	–
Rn	If (Activity = Standing, Duration ≥ 4 hr, Location = Office)	–	F10SB14

Note. R = rule; F = fact; SB = sedentary behaviour; - = Nil.

6 | IMPLEMENTATION, EXPERIMENTS, AND EVALUATION RESULTS

We implemented the proposed reasoning and recommendations framework as part of the Mining Minds platform in a distributed cloud-based environment. The data and knowledge items were made available to the framework, which executed them to generate recommendations and educational facts. This section describes the implementation details of the framework and experiments performed on a stand-alone application using the sedentary behaviour scenario.

6.1 | Implementation of the framework

Originally, we implemented and developed the proposed KRF in the distributed Microsoft Azure Cloud environment under the umbrella of the Mining Minds platform. In the Mining Minds platform environment, the KRF is located on the SCL layer and has dependencies on the DCL, KCL, and SL layers for data, knowledge, and results display. The original communication view of the KRF in the Mining Minds environment is shown in Figure 6. For data and knowledge loading, we used RESTful Web Services.

The stand-alone application of the KRF is implemented in the Java Eclipse IDE with open-source support that can be run under any 32-bit or 64-bit Windows operating system as part of a big system or as a stand-alone application. The open-source application released as part of this study

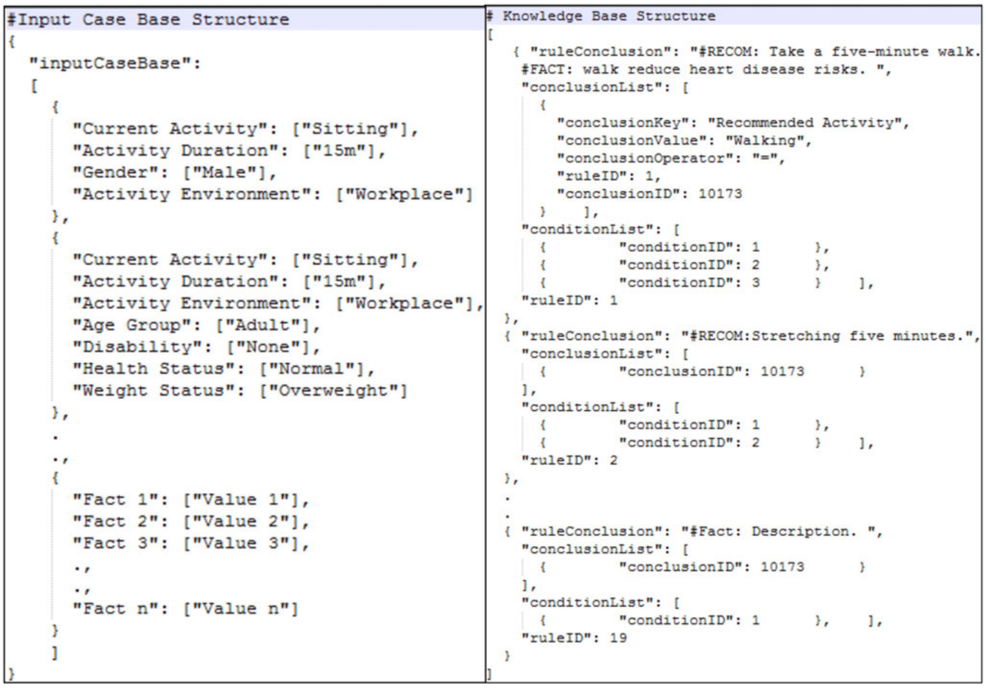

FIGURE 6 Implementation view of the proposed reasoning and recommendation framework on the Mining Minds platform. SL = supporting layer; UI = user interface; UX = user experience

can be used from the GitHub repository (Ali & Sadiq, 2016). To use the framework as part of a big system in a distributed environment, Web services need to be implemented to load knowledge and data from the data schema and the knowledge base.

In the stand-alone implementation of the KRF, the knowledge base and data can be locally provided from a database or file system. In our stand-alone implementation of the application, we released an open-source initial Version 1.0 with the knowledge base and query cases represented in JSON format. The open-source implementation of the framework as a stand-alone application can help the research community; developers can adapt it to their own domains by changing the knowledge base. The research and development community can easily contribute to the framework and enhance its functionality. A brief description of the stand-alone application is provided in Appendix A.

The core modules pattern matcher, conflict resolver, and results generator of the framework are written in Java programming language to minimize their dependency on one another. Each module requires the output of the previous module for its tasks. The modularized implementation of the framework enables developers to use the code from each module in their own decision support systems.

6.2 | Experiments and result analysis

We evaluated the stand-alone version of the KRF. To perform experiments on the stand-alone version and evaluate its performance, we first set up the experimental environment and then evaluated the test case for generating recommendations. Finally, we analysed the results.

6.2.1 | Experimental setup

We set up the stand-alone version of the KRF in a local Windows environment on a PC with an Intel® Core™ i5-4590 CPU at 3.30 GHz and 8-GB memory. For the performance test, we prepared a test case base of 40 input cases, structured as shown in Figure 7a, and generated the results from the KRF using the 19 rules shown in the knowledge base in Figure 7b.

We prepared these input cases by asking 10 volunteers (ages 26–38 years) to use the Mining Minds application for 2 weeks during their normal daily routines. The Mining Minds application recorded the sedentary behaviours of these volunteers and combined them with their personal profile information to form the input cases. In the knowledge base, we used 11 rules for prolonged sitting, six rules for prolonged standing, and two rules for prolonged lying down or bed rest.

6.2.2 | Evaluation criteria

For performance evaluation of the KRF, we considered the average execution or response time and overall accuracy as the evaluation metrics. The average response time was measured by summing the time for the pattern matcher and conflict resolver to reach their conclusions for different rule samples (in the knowledge base) and input cases (in the input case base).

(a). Input case base.

```
#Input Case Base Structure
{
  "inputCaseBase":
  [
    {
      "Current Activity": ["Sitting"],
      "Activity Duration": ["15m"],
      "Gender": ["Male"],
      "Activity Environment": ["Workplace"]
    },
    {
      "Current Activity": ["Sitting"],
      "Activity Duration": ["15m"],
      "Activity Environment": ["Workplace"],
      "Age Group": ["Adult"],
      "Disability": ["None"],
      "Health Status": ["Normal"],
      "Weight Status": ["Overweight"]
    },
    .
    .,
    {
      "Fact 1": ["Value 1"],
      "Fact 2": ["Value 2"],
      "Fact 3": ["Value 3"],
      .,
      .,
      "Fact n": ["Value n"]
    }
    ]
}
```

(b). Knowledge base.

```
# Knowledge Base Structure
[
  { "ruleConclusion": "#RECOM: Take a five-minute walk.
   #FACT: walk reduce heart disease risks. ",
   "conclusionList": [
     {
       "conclusionKey": "Recommended Activity",
       "conclusionValue": "Walking",
       "conclusionOperator": "=",
       "ruleID": 1,
       "conclusionID": 10173
     }   ],
   "conditionList": [
     {        "conditionID": 1      },
     {        "conditionID": 2      },
     {        "conditionID": 3      }    ],
   "ruleID": 1
 },
 { "ruleConclusion": "#RECOM:Stretching five minutes.",
   "conclusionList": [
     {        "conclusionID": 10173      }
   ],
   "conditionList": [
     {        "conditionID": 1      },
     {        "conditionID": 2      }    ],
   "ruleID": 2
 },
 .
 .
 { "ruleConclusion": "#Fact: Description. ",
   "conclusionList": [
     {        "conclusionID": 10173      }
   ],
   "conditionList": [
     {        "conditionID": 1      },    ],
   "ruleID": 19
 }
]
```

FIGURE 7 Structures of the (a) input case base and (b) knowledge base of the knowledge-based reasoning and recommendation framework

6.2.3 | Experiments and result analysis

In our experiments, we evaluated the core module of the KRF, reasoning, and recommendation. For the knowledge and data integration modules, we used the local knowledge base and input case base shown in Figure 7. We performed two experiments from different perspectives, as described below.

Experiments 1 and 2

In the first experiment, we evaluated the performance of the KRF in terms of average execution time to generate final recommendations for the whole input case base while varying the number of rules in the knowledge base: 5, 10, 15, and all rules. In the second experiment, we measured the average execution time for a varying number of input cases, 10, 20, 30, and all cases, while using all rules in the knowledge base. The results of these experiments are shown in Figure 8: We observed an average execution time of 12.75 ms in the first experiment and 15 ms in the second experiment.

In these experiments, we also measured the average execution time for the pattern-matching process, rules conflict resolution process, and overall system operation and found that the implemented framework performed well with varying numbers of rules in the knowledge base and different numbers of input test cases. Figure 8 shows that the time taken by the system was similar in the two cases. Experiments 1 and 2 returned the results shown in Figures 9 and 10, respectively.

Figure 9 shows detailed results of the subexperiments, that is, Experiments 1–4, which were based on subsets of rules from the knowledge base and the whole test case base of 40 cases. These results show that increasing the number of rules increases the time taken to execute the test cases by the same ratio for all samples. The time taken by the conflict resolver converges to closely located points because most of the input cases have no conflicts.

Similar to Experiment 1, Experiment 2 also comprises four subexperiments (Figure 10) but with a varying number of input test cases against a constant number of rules (19) in the knowledge base. The behaviour of the system is similar to that seen in Experiment 1. The time of execution increases in a uniform manner as the number of input cases increases.

The execution or response time of a real-world reasoning and recommendation system is important because of the potential for growth in the knowledge base and due to increases in the number of requests from users. As implemented, the framework will perform consistently. One deduction from this analysis is that categorizing the rules in the knowledge base could result in better execution time. Figures 9 and 10 show that recommendation generation is faster when the numbers of rules and input test cases are smaller.

Experiment 3

In this experiment, we separately measured the accuracies of both the pattern matcher and the conflict resolver and combined those results with an inspection method using test case–based validation. For the inspection method, we first labelled the list of 40 input cases by assigning expected

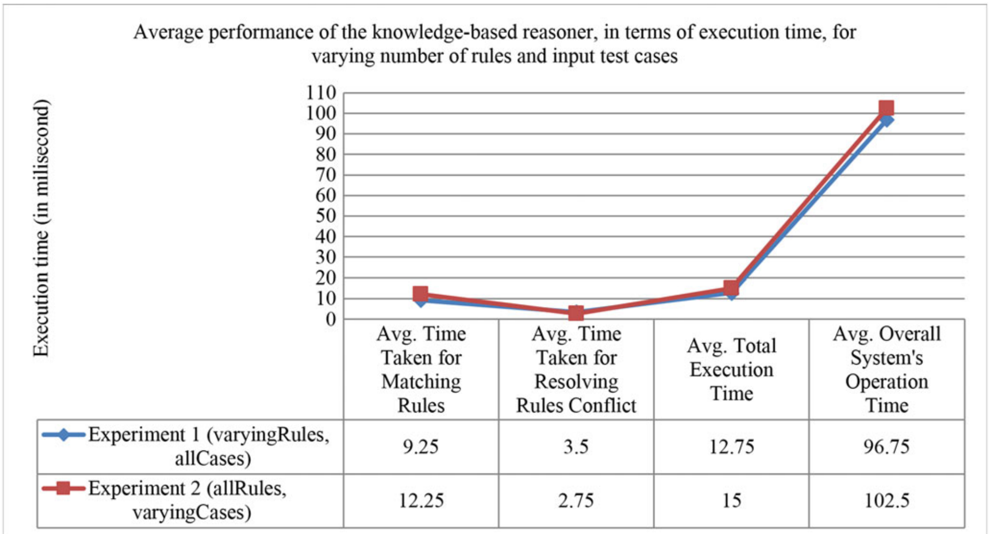

FIGURE 8 Average execution time for the knowledge-based reasoning and recommendation framework

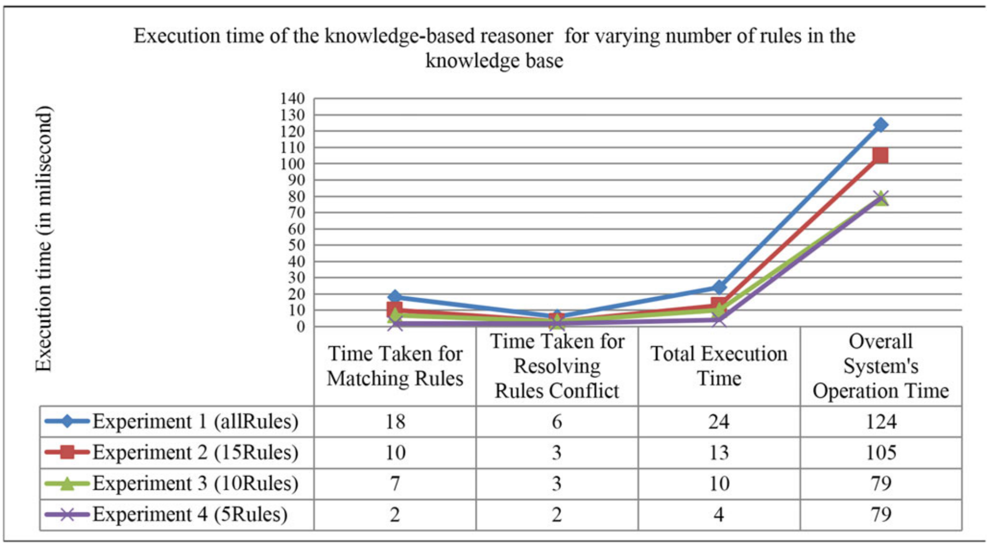

FIGURE 9 Execution time for the knowledge-based reasoning and recommendation framework with varying numbers of rules in the knowledge base

results for the pattern matcher and conflict resolver. With those expected outputs for each input case made, it is easier to evaluate and validate the test results of the KRF.

To accomplish this task, we applied all 40 input cases to the KRF and stored the system-generated recommendations in comma-separated files. The results of the KRF and human-labelled input cases were inspected manually and matched 100% correctly due to the rule-based reasoning methodology that exactly matches facts with the rules. These results validate the working methodology of the implemented KRF. The detailed statistics of these results are shown in Table 6.

Table 6 shows that, out of 40 input cases, 24 (18 + 6) cases were successfully executed by the pattern matcher without conflict, that is, one or zero rule matched, and were used for recommendation generation. For the other 16 input cases, the pattern matcher found multiple conflicting rules and provided them to the conflict resolver. The first eight cases were successfully resolved to a single rule for recommendation generation. The remaining eight cases had two or more rules with the same specificity, and the conflicted resolver provided them all to the result generator.

The last column of Table 6, conflicting rules with no resolution, does not mean that our proposed framework failed to resolve the conflict between multiple-matched rules. It simply states that all three matched rules had equal specificity and were therefore considered equally important for recommendation generation. This aspect of the KRF can be further improved by introducing other levels of conflict resolution mechanism, for example, priority or weight-based mechanisms.

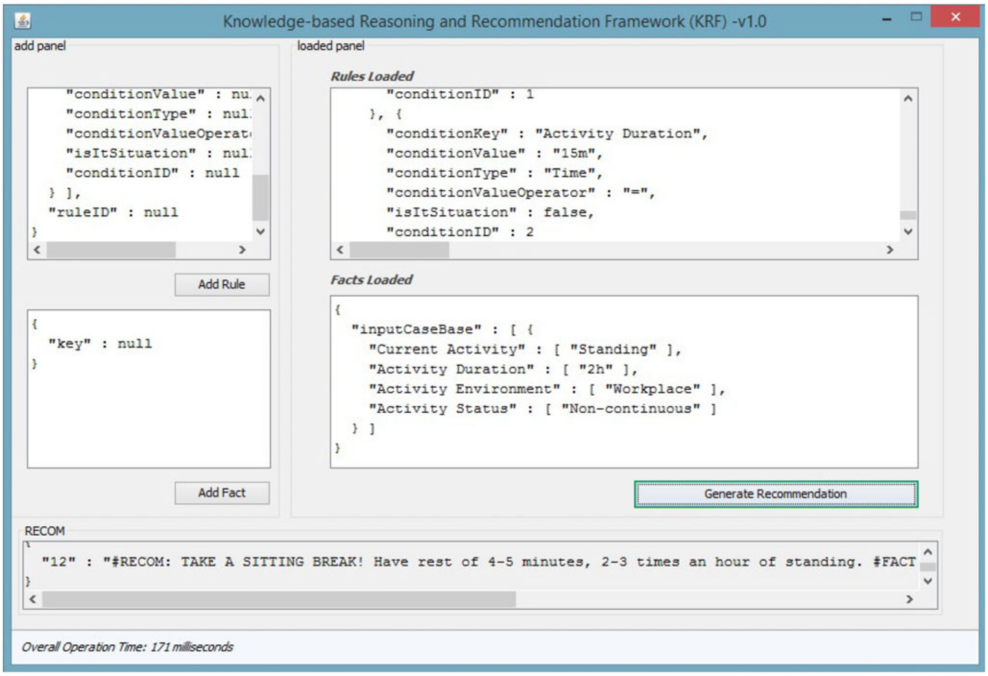

FIGURE 10 Execution time of the knowledge-based reasoning and recommendation framework with a varying number of input cases in the test case base

TABLE 6 Detailed statistics of the results from the KRF pattern matcher and conflict resolver for the input case base

Number of Input cases solved with statistics of matched and resolved rules	Nonconflicting rules		Conflicting rules with resolution			Conflicting rules with no resolution	
# of (M. Rules)* $\xrightarrow{\text{resolved}}$ # of (R.Rules)**	$1 \xrightarrow{\text{Resolved}} 1$	$0 \xrightarrow{\text{Resolved}} 0$	$2 \xrightarrow{\text{Resolved}} 1$	$3 \xrightarrow{\text{Resolved}} 1$	$4 \xrightarrow{\text{Resolved}} 1$	$2 \xrightarrow{\text{Resolved}} 2$	$3 \xrightarrow{\text{Resolved}} 3$
Number of input or test cases	18	6	3	3	2	5	3

(M.Rules)*: Matched Rules

(R.Rules)**: Resolved Rules

7 | DISCUSSION OF SIGNIFICANCE, CHALLENGES, AND LIMITATIONS

Knowledge-based reasoning and recommendation applications are gradually being introduced in the health care and well-being domain for promotion of healthy lifestyles among users. We developed an open-source framework to facilitate such research and allow others to easily develop their own reasoning and recommendation applications. This will save a lot of time because researchers and developers can now build their applications on top of this framework simply by adapting and updating its knowledge base to their domains. We expect that the framework will further improve the quality of knowledge-based reasoning and recommendation systems because it is extendable and applicable to all knowledge-based recommendation areas.

The implementation of KRF is accompanied by several challenges. Some of the difficult challenges we faced were designing structures for the knowledge base and input cases, handling the data types and operators used in the rules during the matching process, and resolving conflicts among the candidate list of rules for possible decision making. For the knowledge representation, we chose a structured JSON format with explicit conditions and conclusions. Each part contains further structured objects for holding condition attributes and facts (queries) in key–value format. The issue in real-world knowledge-based recommendation systems is providing an efficient and intuitive way to explain the recommendations or decisions to the end users. The representation of rules in separate conclusions and conditions in this sophisticated and structured format helped us resolve that problem. The current implementation of the framework supports a limited number of operators and data types and needs further enhancement. The only currently supported data types in the rules conditions are Boolean, Integer, String, and Time. The application has no current support for complex or user-defined data types. Similarly, the only supported operators are EQ("="), NOT_EQ("!="), LT("<"), GT(">"), LT_EQ("<="), and GT_EQ(">="). Logical operators (logical AND, logical OR) are not yet supported; hence, rules containing those operators cannot yet be executed. Another issue faced during our implementation of the KRF was how to intelligently choose a single final rule as the best one for the input case at hand. Approaching a solution to that problem will require attention to the business rules of each organization (whether they need a single solution or a set of candidate solutions). In the current implementation of the KRF, we implemented a maximum specificity conflict resolution algorithm that picks the rule with the maximum number of conditions satisfied during the pattern matching process. However, that solution still produces multiple-candidate solutions, which need one or more other resolution mechanisms, such as a priority-based approach or a meta-rules-based approach. The best resolution mechanisms will vary from domain to domain, and we have therefore left it to future KRF users to build their own solutions.

8 | CONCLUSIONS AND FUTURE DIRECTIONS

This paper presented a knowledge-based reasoning and recommendation framework that effectively integrates real-time user activity and personal profile data with knowledge rules in a semi-automatic way. It uses a rule-based reasoning methodology to generate physical activity recommendations for sedentary users. The adopted rule-based reasoning methodology uses a forward-chaining approach and a maximum specificity conflict resolution strategy to achieve the objective of an accurate and personalized physical activity recommendation matched to users' specific daily routines. Our application of the KRF in a sedentary behaviour scenario demonstrated its efficiency and accuracy; it generated reliable and personalized physical activity recommendations and educational facts. The developed KRF has an average execution time of 12.75 and 15 ms for successful recommendation generation for varying numbers of rules and input cases, respectively. The accuracy of the pattern matcher (correctly matching input cases with rules) and the conflict resolver (resolving conflicting rules) was 100%, which validates the working of the KRF.

Furthermore, we have released the proposed framework as a stand-alone, open-source application (Ali & Sadiq, 2016) that can be easily adapted to other domains by simply changing the knowledge base. This application can be extended by the research community to other applications in a variety of domains.

In the future, we plan to introduce an index-based reasoning and recommendation mechanism that will index the knowledge rules on the basis of certain criteria, such as the type or time of sedentary behaviour. In this way, the request for rules from the knowledge base will be index-based rather than requiring the system to load all rules at once. This will enhance the speed and accuracy of the KRF. We will also enhance the conflict resolver with a rule-weighting mechanism for more accurate and precise selection of the appropriate rule(s) for execution.

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AUTHOR CONTRIBUTIONS

Rahman Ali proposed and formulated the idea; conceived, designed, and performed all experiments; and wrote the paper. Muhammad Sadiq implemented the idea as an open-source application; Maqbool Hussain and Taqdir Ali contributed to the investigation, design, and representation of the knowledge base and verification of the algorithms; Muhammad Afzal assisted in the design and formation of the paper's contents and proofread the grammar; Sungyoung Lee and Asad Masood Khatak provided advisory comments, remarks, and financial support for the research.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

ORCID

Rahman Ali http://orcid.org/0000-0002-9171-8573

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Rahman Ali received a PhD in Computer Engineering from Kyung Hee University, South Korea, in 2016; an MPhil in Artificial Intelligence from the University of Peshawar, Pakistan, in 2009; and a BSc from the Government Jahanzeb College Saidu Sharif, Swat, Pakistan, in 2002. Currently, he is working as an Assistant Professor in the Quaid-e-Azam College of Commerce, University of Peshawar, and has also served at IIT, University of Science and Technology, Bannu, as a lecturer and at the Laboratoire d'Informatique de l'Universit du Maine, France, as a research assistant. His main scientific interests are in the areas of machine learning, data mining, reasoning and inference, recommendation systems, and natural language processing. He has authored more than 40 publications and contributions to conferences. Also, he has participated in international- and national-level conferences and workshops on machine learning, recommender systems, and ubiquitous computing.

Muhammad Afzal received his PhD from Kyung Hee University, South Korea, in 2016 and MS degree from the School of Electrical Engineering and Computer Science, National University of Sciences and Technology, Pakistan, in 2009. He secured his BS degree in Computer Science from Kohat University of Science and Technology. He is now working as an Assistant Professor at Sejong University, Seoul, South Korea. He has been serving as a proctor of HL7 International for conducting HL7 Standard Certification Exams in Pakistan since 2010. He is an author of more

than 50 papers. His current research includes evidence-based knowledge acquisition and systems, precision medicine, applications of machine learning, text processing, and information extraction.

Muhammad Sadiq received his MSc degree from the University of Peshawar Pakistan. He is a research scholar and software engineer for data analytics and visualization. He worked with Xululabs LLC on big data analytics and with Orbit Software solutions as a data science team lead for more than 4 years. Currently he is pursuing his MS degree from Kyung Hee University, South Korea.

Maqbool Hussain received his PhD from Kyung Hee University, South Korea, in 2016, and MS degree from the School of Electrical Engineering and Computer Science, National University of Sciences and Technology, Pakistan, in 2009. He is now working as an Assistant Professor at Sejong University, Seoul, South Korea. His research interest includes artificial intelligence, health care interoperability standards, and clinical decision support systems.

Taqdir Ali is a PhD scholar in Ubiquitous Computing Laboratory, Department of Computer Engineering, Kyung Hee University, South Korea. He received his BS degree in Computer Science from Kohat University of Science and Technology in 2006. His current research interest includes artificial intelligence, knowledge acquisition, knowledge interoperability, clinical decision support system, and e-health standardization.

Sungyoung Lee received his BS degree from Korea University, Seoul, Korea. He got his MS and PhD degrees in Computer Science from Illinois Institute of Technology, Chicago, IL, 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, IL, 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, and activity and emotion recognition. He is a member of ACM and IEEE.

Asad Masood Khattak received his M.S. in Information Technology from National University of Sciences and Technology, Islamabad, Pakistan in 2008. He got his Ph.D. degree in Computer Engineering from Kyung Hee University, South Korea in 2012. He worked as Post-Doctoral Fellow at the Department of Computer Engineering, Kyung Hee University, South Korea for seven months and later joined the same department as Assistant Professor. He is currently working as Associate Professor at Zayed University, UAE. His research focus is User Profiling, Ontology, Knowledge Management, and Context-aware Computing. He is currently leading three research projects and participating in three additional research projects in the same research fields. He has authored/coauthored more than 80 journal and conference articles in highly reputed venues. He is IEEE member.

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APPENDIX A.

The GUI of the stand-alone, Version 1.0 of the KRF is shown in Figure A1, which contains three panels: (a) add panel – for adding rules and facts to the knowledge base and input case base, (b) loaded panel – for showing the rules and facts loaded from the knowledge base and input case base, and (c) RECOM panel – for displaying the final decisions made by the KRF, with a status bar for displaying KRF performance from the perspective of overall operation time. The panels also contain command button controls for adding new rule(s) and test case(s) or facts and generating recommendations.

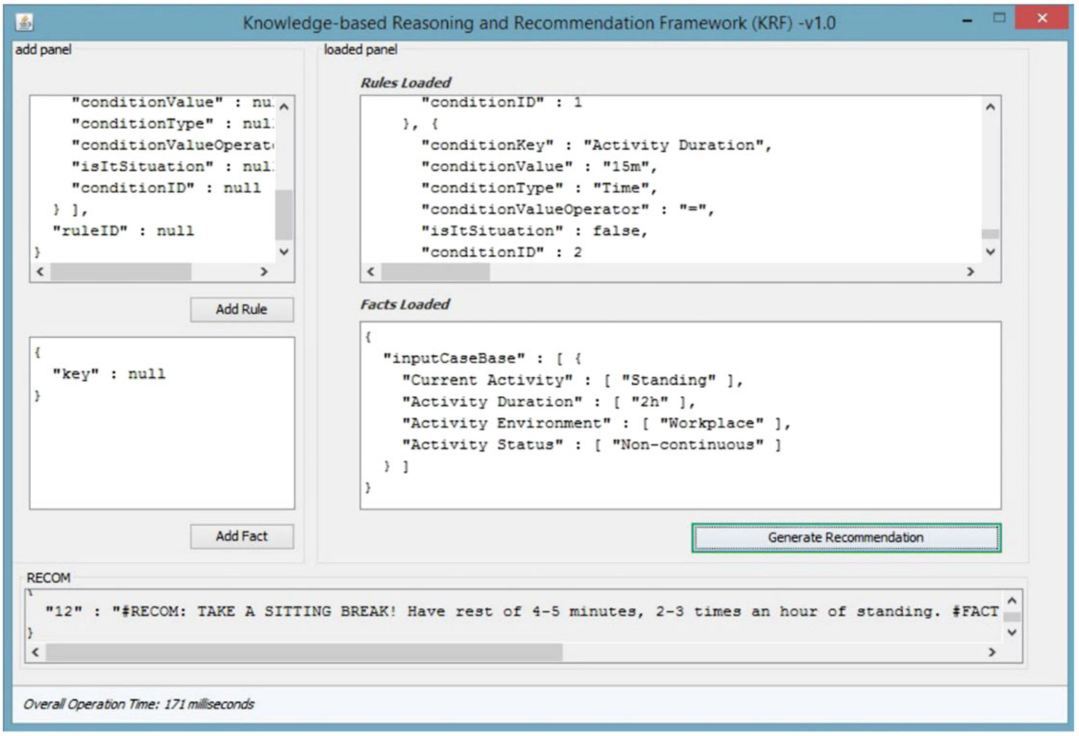

FIGURE A1 Graphical user interface of the stand-alone application of the knowledge-based reasoning and recommendation framework

The application works for both batched input or test cases and single input cases. The input cases and rules are stored and placed in krf_input_cases.json and krf_knowledge_base.json files, respectively, at the root directory of the KRF. When a new rule or input case is added to those files, they are first validated and then appended to the end of the file and loaded to the GUI. To generate recommendations, input cases

TABLE A1 Detailed results of the knowledge-based reasoning and recommendation framework for different input cases

Input case	Matched rules	Time taken for rules matching	Conflict resolved rules	Time taken for conflict resolution	Total time taken	Conclusion
Current Activity = Sitting Activity Duration = 4 hr Activity Status = Non continuous	8–7	0 s/1 ms	8–7	0 s/1 ms	0 s/2 ms	**ruleConclusion:** #FACT: Sitting more than 3 hr/day can cut 2 years off of your life … **ruleConclusion:** #FACT: A nearly 50% increased risk of death …,
Current Activity = Standing Activity Duration = 2 hr Activity Environment = Workplace	12	0 /1 ms	12	0 s/0 ms	0 s/1 ms	**ruleConclusion:** #RECOM: TAKE A SITTING BREAK! …#FACT: Prolonged continuous standing for 2 hr results discomfort in your lower back.,
Current Activity = Sitting Activity Duration = 1 hr Activity Status = Continuous Activity Environment = Workplace Age Group = Adult Weight Status = Non-obese	6-5-4-2	0 s/0 ms	5	0 s/0 ms	0 /0 ms	**ruleConclusion:** #RECOM: Take a five-minute walk … #FACT: Taking a 5-min walk for every hour of sitting can reduce the heart disease risks associated with chronic sitting

are provided in the lower part of the add panel, and the Generate Recommendation command button is used. The results are generated and written into a recommendationResults.csv file in the root directory of the KRF. In a single input case, the results (conclusion) of the final resolved rules are pushed into the RECOM panel on the GUI. The structure of recommendationResults.csv is shown in Table A1.

The conclusion part of the file contains descriptions and the optional part of the recommendations (not shown in these examples) for the input cases in column 1. KRF users can direct this column to the GUI to be displayed to their users. In the description of the conclusions, the keywords #FACT and #RECOM indicate that the description is either an educational statement for the user or an actual recommendation to be followed, respectively. In this table, the first column shows the input test case with the facts provided. The second column shows the results of the pattern matcher algorithm with the numbers for the rules that matched the input case. Column 3 shows the time taken by the pattern matcher to match the rules. Column 4 shows the results of the conflict resolution algorithm, with the final selected rules shown. In the last case, four rules (6-5-4-2) were matched by the pattern matcher, of which only Rule 5 was found appropriate by the conflict resolver and used to generate recommendations and facts (as shown in the last column). The time of the conflict resolver is shown in column 4. Column 5 shows the accumulative time for the pattern matcher and conflict resolver.