Mining Minds: an innovative framework for personalized health and wellness support

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***Abstract*—The world is witnessing a spectacular shift in the delivery of health and wellness care. The key ingredient of this transformation consists in the use of revolutionary digital technologies to empower people in their self-management as well as to enhance traditional care procedures. While substantial domain-specific contributions have been provided to that end in the recent years, there is a clear lack of platforms that may orchestrate, and intelligently leverage, all the data, information and knowledge generated through these technologies. This work presents Mining Minds, an innovative framework that builds on the core ideas of the digital health and wellness paradigms to enable the provision of personalized healthcare and wellness support. Mining Minds embraces some of the currently most prominent digital technologies, ranging from Big Data and Cloud Computing to Wearables and Internet of Things, and state-of-the-art concepts and methods, such as Context-Awareness, Knowledge Bases or Analytics, among others. This paper aims at thoroughly describing the efficient and rational combination and interoperation of these modern technologies and methods through Mining Minds, while meeting the essential requirements posed by a framework for personalized health and wellness support.**

Keywords*—*digital health; human behavior; quantified-self; big data; cloud computing; context-awareness; knowledge bases; user experience

I. Introduction

The provision of healthcare and wellness services is expected to drastically change in the upcoming years. This change has particularly been accelerated by the global socio-economic situation, which adds urgency to the need of finding new healthcare solutions. Although the efficient delivery of healthcare and assistance is found of key importance, it is equally or more crucial to reduce as much as possible the need of care. In fact, it is well-known that most prevalent diseases are partly caused by lifestyle choices that people make during their daily living. For example, epidemic illnesses such as obesity are essentially due to unwholesome diets and lack of physical activity. Accordingly, a strong interest has lately been shown by healthcare stakeholders in people's lifestyle management and personal self-care. Bringing these lifestyle diseases under control may have a great impact on healthcare and assistance spending, and certainly on health itself.

To support this new healthcare and wellness era a new concept has recently emerged. Commonly known as "Digital Health", it refers to a renovated and updated view of what was already cataloged in the early 2000s as Digital Health Care [1], which embraces an enormous variety of social, scientific and technological disciplines to empower people to better track, manage, and improve their health and well-being. Likewise, Digital Health joins medical and social knowledge with cutting-edge technologies to reduce inefficiencies in healthcare delivery, improve access, reduce costs, increase quality, and make medicine more personalized and precise. Key concepts supporting this digital health revolution include, but are not limited to, Mobile Health, Connected Health, Wearable Computing, Ubiquitous Computing, Big Data, Cloud Computing and Gamification, among others. One of the most important challenges posed by the Digital Health refers to the use of these technologies in a rational and comprehensive manner, as well as their integration with current and future personalized health services and business.

In this work we describe Mining Minds [2], an innovative framework that builds on the core concepts of the digital health and wellness paradigm to enable the provision of personalized healthcare and wellness support. Mining Minds is further devised to intelligently exploit digital health and wellness data to generate new businesses and services, which are unquestionably called upon to change the actual healthcare and wellness panorama. The remainder of the paper is organized as follows. Section II introduces some of the most prominent applications, frameworks and ongoing projects in the digital health and wellness domain. In Section III, the essential requirements devised for a framework supporting personalized healthcare and wellness services are shown. Section IV provides a detailed description of the proposed Mining Minds Framework, while also introducing the interaction among the components identified for each layer of the framework. In Section V, an implementation of the proposed framework is presented. Section VI shows an exemplary application that showcases the potential of Mining Minds. Finally, main conclusions and future directions are summarized in Section VII.

II. Related Work

The number of applications and systems for personalized healthcare and wellness management has rapidly grown during the recent years. In fact, motivated by the boom of wearable and mobile technology, many commercial solutions are readily available at the reach of most consumers [3]. These solutions, essentially oriented to the fitness domain, are used for detecting very primitive user routines and behaviors, as well as for providing track of progresses and simple motivational instructions. Fitbit Flex [4], Jawbone Up [5] and Misfit Shine [6] are some examples of instrumented bracelets and wristbands accompanied by mobile apps capable of providing some basic recommendations based on the measured taken steps and slept hours. More prominent health and wellness systems have been provided at the research level, yet they are fundamentally prototypes. Examples of these systems are [7] for detecting cardiovascular illnesses, [8] for alerting on physical conditions or [9] for tracking changes in physiological responses of patients with chronic diseases. Some of these systems also provide educational modules and personal coaching for promoting healthier lifestyles and managing health conditions [10], [11]. Broadly speaking, main drawbacks of most of these solutions refer to misperformance, limited application scope and lack of interoperability with other similar systems.

Despite the take-up on the development of healthcare and wellness applications, there exist only a few attempts to build general frameworks for tackling more complex and realistic scenarios. In [12], the authors present a mobile phone platform to collect users' psychological, physiological and activity information for mental health research. Distributed signal processing algorithms for the analysis and classification of sensor data are provided as part of a framework for rapid prototyping of body sensor networks in [13]. A middleware framework integrating multiple interfaces and multiparameter monitoring of physiological measurement is proposed in [14]. Tools to analyze the provenance of mobile health data have also been suggested in [15]. Recently, a novel open framework to facilitate the rapid and easy development of biomedical apps has been presented in [16]. The framework is devised to leverage the potential of mobile and wearable health devices, and provides advanced functionalities for resource and communication abstraction, biomedical data acquisition, health knowledge extraction or adaptive visualization, among others. In the mobile health domain, inspirational open projects such as [17] have also been initiated to help developers produce more clinically useful data and more easily integrate their solutions with other data sources. In the commercial arena, first valuable signs of interest in the development of digital health and wellness frameworks have been shown by key multinational corporations. That is the case of HealthKit ([18], Apple Inc.) and SAMI ([19], Samsung), highly funded initiatives that look forward to paving the path to novel ecosystems for the new health and wellness era.

III. Requirements of a Person-Centered Digital Health and Wellness Framework

The health and wellness status of individuals is normally defined through their physiological, psychological and social states. Diverse types of data are normally required to thoroughly describe these states, ranging from physical -sensory- and logical -personal profile and interests-, to social -human cyber relations- and clinical -medical- data. This poses an important challenge with respect to the intelligent and comprehensive collection, processing and organization of data of that diverse nature. For data collection, an overwhelming number of technologies are nowadays increasingly available, such as wearable self-quantifiers, ambient sensors, SNS or advanced clinical systems, among others. Thus, an important requirement of a personal digital health and wellness framework is to provide a certain level of abstraction from heterogeneous resources to make their utilization transparent to the user, with the aim of being as technologically agnostic as possible. Moreover, it is well-known that health and wellness data goes beyond standardized structured formats such as "traditional" electronic health records, while including other multimedia and unstructured data. Therefore, another primal requirement of these frameworks is to be capable of dealing with this dimension of heterogeneous data, as well as the underlying implications of the management of structured, semi-structured and unstructured data. Not only data variety constitutes a key factor to be considered, but also data volume. Massive amounts of data are generated over time on and around the subject with the advent of new medical and non-medical technologies -Genomic Sequences, 3D Imaging, Internet of Things, Media-Sharing Social Networks-. Accumulating and digesting these amounts of data are not trivial tasks, and need to involve sophisticated processing and storage mechanisms to enable the persistence and availability of the data. Similarly, the rapid pace of data generation makes necessary to also take into account data velocity as a reference factor. This proves to be especially challenging when referred to data that represents real-time regular monitoring, such as continuous electrocardiogram measurements or body motion data. Another important concept that applies to health and wellness data is veracity. Different data types may represent similar concepts or contradict each other, or even be of little interest. Therefore, personal digital health and wellness frameworks may count on governance mechanisms to determine the consistency of the data, ensuring it is certain, meaningful, clean and precise.

The complexity of health and wellness management systems is highly related to the amount of potential users and data collection mechanisms. Determining a precise number of users of these systems is difficult, as it is estimating the complete set of resources that may be used to collect people's health and wellness data during their life. In fact, a significant bunch of data may be generated in the course of a hospitalization or during the measurement of a fitness workout, but little or none data may be generated in the absence of any type of monitoring system. Thus, mechanisms for load balance and scalability are utterly required. Moreover, given the uncertain sort of scenarios and situations that a person may face during their daily living, execution in distributed systems is especially recommended, utilizing the paradigm of parallel computing and "divide and process".

Extracting the determinants of health and wellness is a very challenging task that requires more than simply collecting and persisting personal data. Personal digital health and wellness frameworks must include automatic intelligent mechanisms to process person-centered data and extract interpretable information for ensuring a personalized health and wellness support. Moreover, insights should be gained not only from individual users but from the collectivity. Thus, another important requirement consists of the application of advanced techniques to process information in "de-identified" form to enable population management and deeper insights into cause and effect. These insights can be particularly leveraged by health and wellness care systems to extend, adapt and evolve the knowledge provided by human domain experts.

Health and wellness information and knowledge are principally devoted to support advanced care services. Mechanisms such as alerts, recommendations or guidelines, generally known as service enablers, are particularly used to catalyze both information and knowledge to be delivered in a human-understandable way to users and stakeholders in general. However, most digital health and wellness frameworks only support general service enablers that do not differentiate among people particular needs or interests. Therefore, an important requirement of personal digital health and wellness frameworks is to provide service enablers that operate on a person-centric manner. To do so, expert systems are required, for example, to precisely map user needs to the best possible recommendations, personalize the explanation of the recommendations or customize the mechanisms for the delivery of these recommendations.

All the potential that can be developed by a personal digital health and wellness framework may be wasted if its outputs are not adequately presented to end-users. Users of these systems may be of a diverse nature and play a different role. For example, busy patients may require to get a quick glimpse of their health conditions, fitness enthusiastic customers may wish to observe a detailed description of their vitals and clinical experts may be interested in an "in-depth" description of both health and wellness outcomes of multiple people. Accordingly, user interfaces need to be customized to the needs of each particular subject. Not only the user interface constitutes a key element in a framework of these characteristics, but also the user experience and interaction with the systems. Users perceptions of system aspects such as utility, ease of use and efficiency need to be fed back into the framework in order to provide the most personalized possible experience. In fact, the user experience is dynamic as it is constantly modified over time due to changing usage circumstances and changes to individual systems; therefore, it is mandatory to seamlessly track the user responses and behavior to support a sufficient level of personalization. Apart from usability and flexibility, user adoption and engagement should be also procured through diverse mechanisms such as persuasive rewards, self-monitoring information or social comparisons.

Finally, as it may be obvious, but unfortunately not generally considered, all the aforementioned requirements need to be neatly accommodated to user security and privacy principles. Security and privacy are considered mandatory for systems that build over sensitive information. Necessity of privacy and security is further augmented when a significant variety of services develop on personalized data need to be shared with multiple entities in a distributed way. Data ownership, malicious data usage, as well as regulatory and legal policies are important hindrances in the widespread use and acceptance of health and wellness care systems by users. In fact, it is well-known that many previous attempts in the use of health and wellness systems failed to succeed because of security and privacy issues. Therefore, it is of utmost importance to neatly adequate privacy, security, protection and risk management measures to all the processes concerned in a personal digital health and wellness framework.

IV. Mining Minds Platform

Taking into consideration the requirements presented in the previous section, a novel personal digital health and wellness framework is proposed here. Hereafter referred to as "Mining Minds", this framework consists of a collection of innovative services, tools, and techniques, working collaboratively to investigate on human's daily life data, generated from heterogeneous resources, for personalized health and wellness support. Mining Minds philosophy revolves around the concepts of data, information and service curation, which refer to the adequation, adaptation and evolution of both contents and mechanisms used for the provision of high quality health and wellness services. Motivated by these concepts, a multilayer architecture is particularly devised for Mining Minds. The architecture, depicted in Figure 1, is composed by three main layers, respectively, Data Curation Layer (DCL), Information Curation Layer (ICL) and Service Curation Layer (SCL). An additional one, namely, Supporting Layer (SL), is considered to ensure the suitable operation of the former ones.

In a nutshell, the DCL is in charge of processing and persisting the data obtained from the Multimodal Data Source, which abstractly defines the possible sources of user health and wellness data. This includes, but is not limited to, data from SNS, questionnaires, wearable biomedical devices or ambient intelligence systems, among others. The data processed by the DCL is primarily used by the ICL, which builds on it to infer low-level and high-level person-centric information. This information is principally generated to describe the user context and behavior, and, to some extent, their physical-psychic-social state. The information extracted by the ICL is leveraged by the SCL in order to nurture and evolve the experts health and wellness knowledge. Moreover, information and knowledge are employed to create intelligent health and wellness services, mainly developed through smart recommendations and guidelines. Data, information and services are made available to third party applications through the SL, which provides mechanisms for visualization of outcomes as well as analysis of the user experience, and also ensures security and privacy in all the components and functionalities of the architecture. In the following, the Mining Minds architecture layers are detailedly described.

A. Data Curation Layer

Data Curation Layer, DCL, constitutes the data collection, conformance, and persistence aspects of Mining Minds. This layer is composed of Data Curation, Data Representation and Mapping, and Big Data Persistence components. Data Curation is responsible for the acquisition, labeling and analysis of the data obtained from the diverse sources, in both real-time and offline manners, as generic streams. The format of the acquired streams is based on the source devices, thus their specifications are hosted by device registry of the Data Curation component. To classify the data streams by device and usage, the Data Curation component provides real-time data labeling, which converts the unstructured data into semi-structured format. As the volume of the data collected is large and type of this data is heterogeneous, the possibility of data noise and redundancy is high; therefore, the labeled data stream is forwarded for analysis where several data analysis filters are executed to ensure the reliability of data, keeping its comprehensiveness preserved. Apart from analysis of real-time data, the Data Curation also ensures the reliability of already preserved data with its provenance features. These features are executed as filters over offline data batch processes.

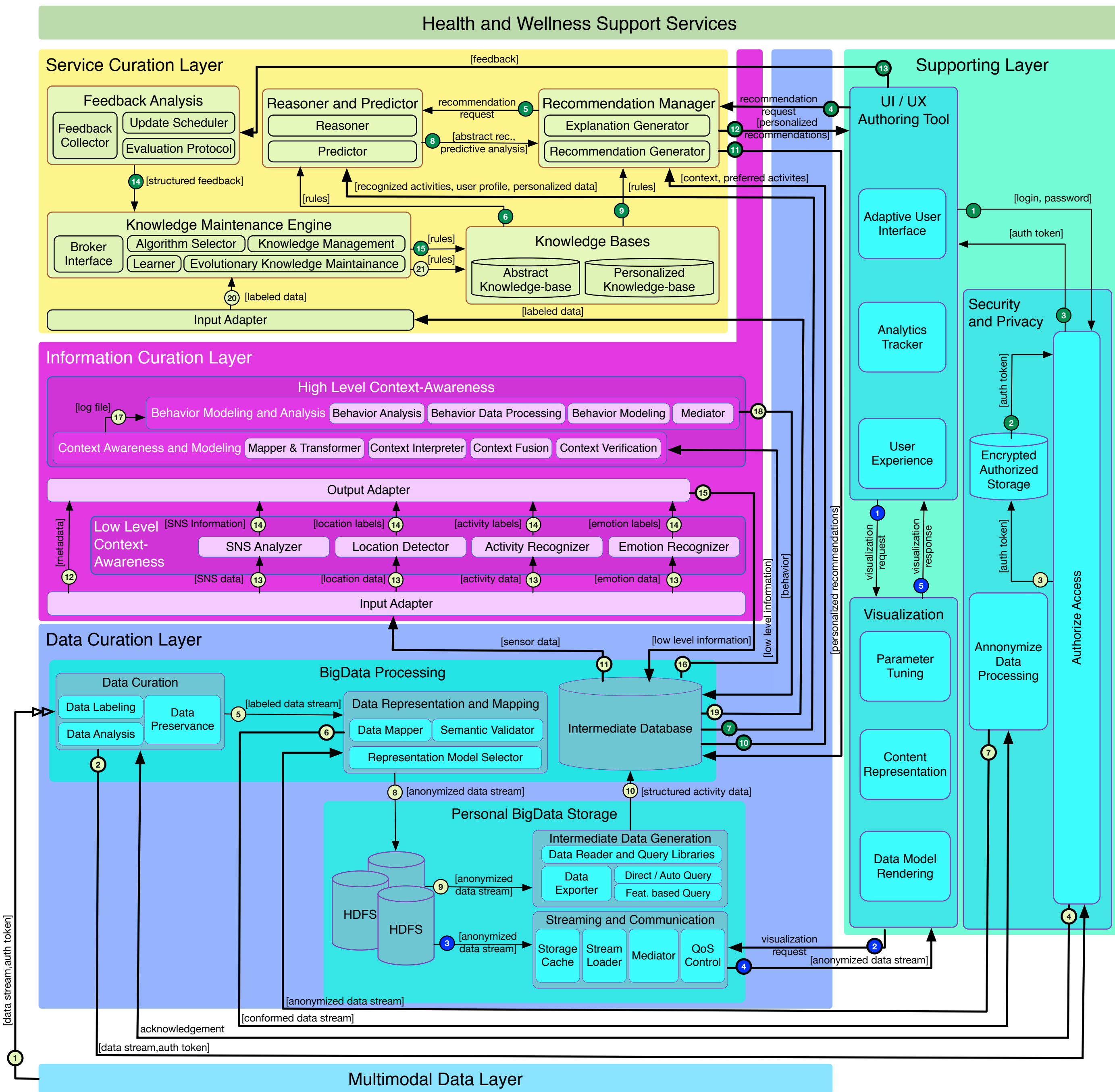


Fig. 1. Mining Minds Framework Architecture and Operational diagram.

After analysis, data streams are forwarded to the Data Representation and Mapping component. The role of Data Representation and Mapping is to conform data according to a standard definition; such that, it is understandable and shareable among layers of Mining Minds and also with third party components and applications. The conformance definition is based upon an ontology, where data from the labeled and analyzed stream is mapped to ontological resources, representing the data as resources with hierarchies. This conformed data model is forwarded to Big Data persistence for storage. The persisted data is made available to other Mining Minds layers through the so-called Intermediate Database. The Intermediate Database consists of a fast processing storage unit that temporarily hosts the data from the Big Data storage to be served in a rapid manner.

The interaction among DCL components is invoked based on three execution scenarios. The first one, as discussed earlier, is purely devised for the curation of the data, where generic streams of real-time data are gathered, conformed and persisted. During this interaction, DCL involves the security and privacy components from SL to request authentication and data stream encryption before persistence in the Big Data storage. For the second interaction, data is requested by SL for visualization. This is a request and response communication where requests for data read are submitted with user identity. Based on the requested time frame and user identity, data is collected from the Big Data storage and returned as a data model to the data visualization component. The third scenario refers to the read of generic data from Big Data storage by ICL and SCL. ICL reads the data model, for example, sensory data, for performing low and high level context analysis, and persists the data model with the inferred information back in the Big Data storage. SCL reads the data model with personal data and context information for the generation of personalized health and wellness recommendations. These recommendations are also persisted back in the Big Data storage of DCL. By persisting all this meaningful data, information and knowledge, Mining Minds ensures their potential utilization by third party applications or components, as well as for analytics.

B. *Information Curation Layer*

Information Curation Layer, ICL, represents the Mining Minds core for the inference and modeling of the user context and behavior. It is composed by two sublayers, namely, Low Level Context Awareness (LLCA) and High Level Context Awareness (HLCA). The LLCA is in charge of converting the wide-spectrum of data obtained from the user interaction with the real and cyber-world, into abstract concepts or categories, such as physical activities, emotional states, locations and social patterns. These categories are intelligently combined and processed at the HLCA in order to determine and track the normal behavior of the user.

The LLCA is composed by four key components, respectively, Social Network or SNS Analyzer, Activity Recognizer, Emotion Recognizer and Location Detector. The SNS Analyzer is in charge of processing the information generated by the user during their interactions in regular social networks such as Facebook or Twitter. This comprises from posts or tweets generated by the user themselves, user mentions, user traces and even global social trends, in the form of both text and multimedia data. From here, personal and general people interests, needs, conducts and states may be determined. The identification of the user physical actions is performed through the Activity Recognizer. This component may build on several sensing modalities as they happen to be available to the user. Examples of these modalities are wearable inertial sensors, video and audio. The output of this component corresponds to elementary activity categories such as 'standing', 'walking' or 'jogging'. Similarly, the Emotion Recognizer is defined to infer user emotional states, such as 'happiness' or 'anxiety', by using sensor data similar to the previous ones, as well as more sophisticated sources exploring human physiological variations and responses. In order to determine the user situation, it is of extreme importance to track the user ambulation. This is the role of the Location Detector, which essentially builds on the data collected through indoor and outdoor positioning sensors, such as video and GPS, to specify the exact location or direction of the user. The selection of all the necessary data for each of these four components is performed by the Input Adapter component. This component gleans the curated data from the DCL based on the particular requirements of each LLCA component (e.g., video data for recognizing the user emotion or GPS data for determining their location). The information generated on top of the LLCA is unified and delivered to the DCL through the Output Adapter component, in order to make it accessible to not only the HLCA but other Mining Minds components and applications.

The diverse categories identified through the LLCA are used by the HLCA to define a more comprehensive representation of the user context and behavior. Two main components are considered to that end. The first component, Context Aware Modeler, enables the modeling and interpretation of the user context. The modeling of the context is performed through ontologies, which have been adopted in the past as a unified conceptual backbone for modeling, representing and inferring context, while its interpretation is done through a rule-based reasoning process. Thus for example, based on the actual time (e.g., midday), location (e.g., restaurant) and inferred activities (e.g., sitting), this component can determine the precise user context (e.g., lunch). A key ingredient of the Context Aware Modeler is the LifeLog Repository. This repository is used to store the contexts determined for the person during the use of the Mining Minds system. This information can be served to other Mining Minds components and applications, although it is primarily devised as input to the second essential HLCA component, so-called Behavior Modeler. The role of this component is to identify the user behavior patterns and routines. For example, if it has been identified that the user normally goes for lunch during a specific time span during work days, it can be determined as a personal behavior pattern or routine of this particular user.

C. *Service Curation Layer*

Service Curation Layer, SCL, provides the means to transform the data and information generated by DCL and ICL into actual services. To do so, SCL supports automatic and expert-based knowledge creation and maintenance, personalized recommendations and predictions, and users feedback analysis. The knowledge creation capability is activated either by the domain expert or knowledge engineer, by using data-driven, knowledge-driven or hybrid approaches. The created knowledge, which is persisted in the Knowledge Bases of SCL, has various levels of granularity, which range from abstract or general to personalized or user-specific knowledge. The knowledge managed by SCL is used to generate personalized health and wellness recommendations. First, the Reasoner component uses the abstract level knowledge for generating general recommendations, that are further personalized by the Recommendation Manager. Then, the Recommendation Manager makes use of the personalized knowledge, which encodes user preferences and contextual information. Once the personalized recommendations are delivered to the user, feedback can be obtained from their acceptance - i.e., recommendation is followed - or rejection - i.e., recommendation is not followed -. The sources of feedback may be of a diverse nature, ranging from explicit feedback provided by the user through questionnaires to implicit feedback obtained from the user behavioral responses. This feedback is analyzed through the Feedback Analysis component, which converts it into information interpretable by the Knowledge Maintenance Engine component. This valuable information is then used by the Knowledge Maintenance Engine to update and evolve the user-based knowledge, in order to ensure a more personalized and adequate health and wellness support.

D. Supporting Layer

The role of the Supporting Layer, SL, is to enrich the overall Mining Minds functionalities through advanced visualization, interactive and personalized UI/UX and adequate procedures to ensure privacy and security in all aspects. The main role of the Visualization component is to adjust the style of the information delivered to the users based on their expertise and role. On the one hand, for example, average users may receive certain recommendations related to their daily life activities in the form of comprehensive textual or audiovisual instructions. More complex analytics may be displayed to human experts in relation to users health and wellness data, information and knowledge.

UI/UX is a major supportive component aimed to engage the end-user with the Mining Minds system in an intuitive fashion. Considering user preferences, habits, attitude and mood, the UI/UX component enables the end-user applications interface to adapt accordingly. This adaptation is required to fine tune the human-computer interaction experience with respect to font size, color, theme, or audio levels, among other characteristics.

Considering the sensitivity and associated concerns of the collected personalized information, the Mining Minds system need to assure and exhibit adequate privacy and security, not only at the storage level, but also during processing and delivery of services. Mining Minds employs state of the art existing cryptographic primitives along with indigenous protocols to exhibit more control over possible states of data. For secure storage, AES standard is particularly considered, whereas for oblivious processing, homomorphic encryption and private matching is used. Taking into account the intensive data flow between end-user applications and systems and Mining Minds, data randomization techniques are considered. These procedures ensure a high entropy for minimal leakage of information. For sharing personalized information and recommendations with the users, an authorized model ensures the legitimate disclosure. Slow processing of information is an effect caused by the encryption; however, to assist partial swiftness to Mining Minds, sensitive and non-sensitive information is decoupled where required.

V. Mining Minds Implementation

An initial implementation of the proposed framework, particularly devised to enable personalized healthy lifestyle and weight management support, is described in the following. Mining Minds is a distributed framework where the cloud environment plays a key role for supporting both persistence and limitless computational power. This implementation has been deployed over Microsoft Azure public cloud environment [20], with every layer as a separate virtual instance. DCL, ICL, and SCL are hosted on standard A4, A2, and A3 MS Azure Instances with Microsoft Windows Server 2012 R2 as guest OS [21], while SL functionalities partake of the others. The cloud-based deployment of layers allows the encapsulation of their responsibilities as well as the re-usability of their features through an inter-layer communication. This communication is implemented by establishing service contracts among the layers, which communicate by means of web services. Most important service contracts are supported by DCL web services, which mostly serve a data model depicting the structure of the Intermediate Database, here hosted by Microsoft SQL Server [22]. This data model is shared among the layers as an object model of service contract. Required data and information is populated by the DCL and provided as responses to information and service curation layers.

To support healthy lifestyle services, in this particular version ICL only implements the Activity Recognizer. The Activity Recognizer consists of a set of steps that mainly combine signal processing and machine learning techniques to define a specific human activity recognition model, here capable of distinguishing among various commonplace activities [23]. The main input of this model corresponds to body motion data, namely, acceleration, which can be broadly obtained from smartphones and wearable sensors. A non-overlapping sliding window of three seconds is used for the data segmentation given the observed good trade-off between speed and accuracy for the activities of interest [24]. Time and frequency features are extracted for their discrimination potential and easy interpretation in the acceleration domain [25]. For the classification process, Gaussian Mixture Models are employed, which have been shown to perform well in combination with similar features and activities [26].

SCL processes the information generated by DCL, ICL and SL for the generation of personalized activity recommendations. Knowledge Bases, Reasoner and Recommendation Manager have been specifically considered in this implementation. The knowledge is created based on different expert clinical guidelines, from which rules are extracted for defining weight management [27] and activity promotion [28] plans. The reasoning process encompasses various tasks, such as real-time query processing, interpretation of knowledge rules for user goal discovery, e.g., ideal weight and calories to be burned per day, and inference of generalized recommendations. In the real-time query processing, user health and wellness information from DCL is collected and transformed into proper input query to be processed by the Reasoner for the creation of the generalized recommendation. During the reasoning, the interpreter analyzes each rule in the knowledge base and fires the appropriate rules using a forward chaining procedure [29]. Generalized recommendations are generated by using the rule-based reasoning [30] and forwarded to the Recommendation Manager for personalization. Recommendation Manager uses content-based filtration techniques [31] to personalize the generalized recommendations with the use of context information including user personal activity level and preferred physical activities.

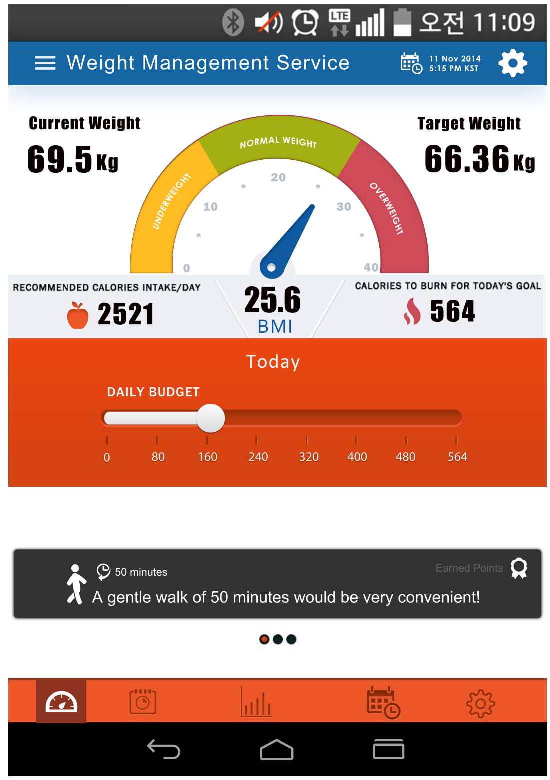
Supporting layer is distributed by components among the data, information, and service curation layers. Primary goals of this layer in this version are security and privacy. The compulsion of encryption while storing sensitive data, such as user age, gender, name, or physical status, is to withstand any compromise on data storage facility or its unauthorized acquisition. Other than secure storage of sensitive data, its processing and evaluation demand modern techniques to make them HIPPA compliant when health-related. Moreover, when deployed on public clouds these systems should be capable of processing direct encryption without losing accuracy. Considering three possible states of data as defined by Microsoft, i.e., data at rest, data in use and data in flight, this implementation uses existing cryptographic primitives along with indigenous protocol to exhibit more control over defined states of data. Concretely, AES [32], Private Matching [33] and Anonymization [34] have been chosen to support that. Besides existing standards, the indigenously proposed system of oblivious term matching [35] is considered to work over direct encryption. To generate high entropy a value matching protocol, Reflection [36], is used to further reinforce the privacy level.

VI. Exemplary Application

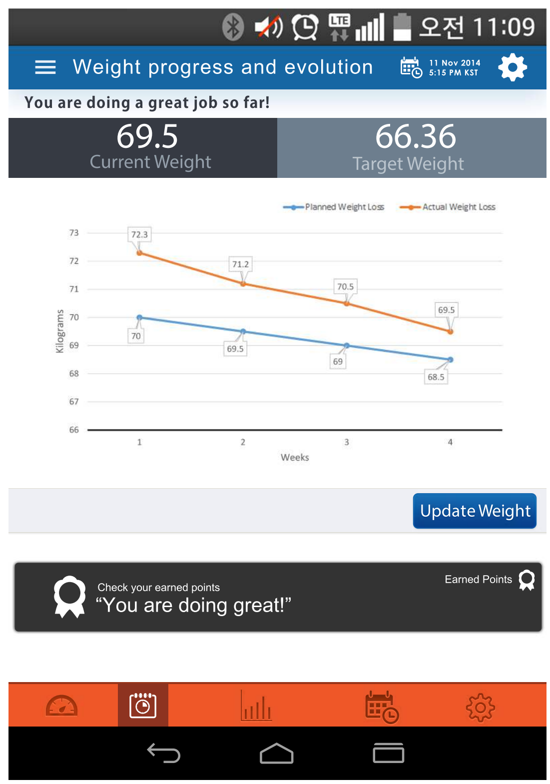
In order to showcase part of the potential of the Mining Minds platform, an intuitive exemplary application has been developed. The application is particularly devised for personalized weight management support, which is here intended through the seamless analysis of the user physical behavior and the promotion of a healthy active lifestyle. Conversely to most health and wellness applications, this app has been designed as an end-user interface to the data, information and services curated by the Mining Minds platform, which processing core develops on the cloud. This presents important advantages for the end-user such as an effective reduction of the smartphone resources consumption, mainly in terms of storage, computation and battery, no need of regular updates of the client application and a more dynamic and interactive experience. The principal features of this application are succinctly described in the following.

In the main screen of this application - Figure 2.a - the user can check prominent information regarding their physical state - under, normal or overweight -, current weight and ideal weight, as well as the estimated amount of calories to be burned every day to achieve the target healthy weight. All these figures are calculated through Mining Minds by utilizing part of the user profile information introduced during the sign up process, like, age, gender, weight and height, in combination with clinical expert knowledge obtained from medical guidelines and reference manuals. Similarly, the amount of calories burned by the user for this particular day is shown in this screen, which is estimated by the Mining Minds platform through analyzing their physical activity. To that end, Mining Minds analyzes the acceleration and GPS sensory data measured by the user smartphone, which is timely streamed to the platform. To promote the user activity to achieve the estimated daily goal, exercise recommendations are given to them in an easy-to-understand manner, with precise indications of the duration of the activity and its execution style, as well as motivational statements for the sake of encouragement. These recommendations are personalized to each particular individual, so only those activities of interest to the user are suggested. Also, based on the user activity profile, the intensity and duration of the activities is specifically customized.

On the second tab of this app - Figure 2.b - the user can check the main progresses in terms of weight loss. To keep track of the user weight, they are requested to timely enter this information, which is then automatically updated into the Mining Minds platform. Mining Minds continuously analyzes the user weight trend and dynamically updates the provided recommendations and instructions to fit in well with the overall weight loss goal. Motivational statements and rewards are also provided by the system based on the user achievements to ensure their engagement. The rest of the tabs, not shown in this paper, are devoted to present other information of interest such as historical records in terms of burned calories, performed activities and given recommendations for the user understanding and knowledge.



(a)



(b)

Fig. 2. Weight Management app snapshots.

VII. Conclusions

This work has presented Mining Minds, an innovative digital health framework for personalized healthcare and wellness support. The framework has neatly been designed taking into account crucial requirements of technologies and applications of the digital health and wellness paradigm. This work has also described the architecture defined to provide the necessary functionality to enable personalized health and wellness care services. An initial realization of the key architectural components, as well as an exemplary application that showcases some of the benefits provided by Mining Minds, have been also presented. The work is ongoing to enhance the existing components, complete the implementation of the devised architecture with new additional components and evaluate the presented architecture and its services on a large scale testbed, which is currently under development.

Acknowledgment

This research was partially funded by the Korean Ministry of Science, ICT & Future Planning (MSIP) as part of the ICT R&D Program 2013. This work was also supported by the Industrial Core Technology Development Program, funded by the Korean Ministry of Trade, Industry and Energy (MOTIE), under grant number #10049079.

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