The Intelligent Medical Platform: A Novel Dialogue-Based Platform for Health-Care Services

Taqdir Ali, Jamil Hussain, Muhammad Bilal Amin, Musarrat Hussain, Usman Akhtar, Wajahat Ali Khan, Ubaid Ur Rehman, and Sungyoung Lee, Kyung Hee University

Byeong Ho Kang, University of Tasmania

Maqbool Hussain and Muhammad Afzal, Sejong University

Ho-Seong Han, June Young Choi, and Hyeong Won Yu, Seoul National University Bundang Hospital

Arif Jamshed, Shaukat Khanum Memorial Cancer Hospital and Research Centre

The proposed Intelligent Medical Platform is a dialogue-based medical decision-making system that provides medical coaching and recommendation services, based on incremental learning methodology. The prototype demonstrates 90% accuracy for knowledge acquisition, 80% satisfaction level of user interaction with the system, and 95% accuracy for system integration with the legacy system.

Digital Object Identifier 10.1109/MC.2019.2924393
Date of current version: 12 February 2020

Technological advancements in the domain of medical adherence have greatly enhanced the related field of health coaching, which enables more patient -oriented health-status monitoring and provides personalized recommendations.[1] As reflected by the plethora of literature, e-coaching systems facilitate everyday activities, such as physical activities,[2] medical alerts,[3] and social concerns. Consequently, the user is provided with more opportunities to follow a healthier lifestyle in different aspects of well-being and health care.

Beun et al.[4] proposed an automated e-coaching system for insomnia therapy. The system uses a variety of persuasive strategies to improve the therapy experience for insomnia patients. Similarly, a personality coach, named *Peach*,[5] analyzes the personality factors of humans for 10 weeks and recommends personality-trait changes. Additionally, it keeps track of provided suggestions on personality improvement. Similarly, WebDietAID is a web-based interactive system that advises users about their nutrition.[6] It analyzes users' health condition, presents guidance regarding nutrition constraints, and assesses their behavior change. Another interesting e-health counselor system, proposed in Schulman et al.,[7] enhances the user-confidence level using interviews.

However, a key aspect missing from these systems is an interactive dialogue feature, which can significantly improve the effectiveness of them by assisting users in real time. Using a knowledge base, a smart-dialogue manager is able to integrate question-answering sessions, user requests, and natural language with computer vision in computational linguistics.[8] Current e-coaching systems, constrained to single-turn settings, lack the conversational ability of interaction, self-evolvable knowledge representations, and any notion of context while interacting with the user. Similarly, the current solutions lack the ability to add accurate incremental knowledge through machine learning and the contributions of human experts. Moreover, the existing systems have limited semantic interoperability, knowledge representation, reasoning, and capabilities to enable user interaction and to authenticate knowledge evidence.[9]

Our proposed system, the Intelligent Medical Platform (IMP), uses the strengths of dialogue-based technologies and health-care information systems. The proposed innovative incremental learning methodology makes use of user interactions to adapt internal knowledge structures. The knowledge is acquired from diverse sources, including both structured data, such as electronic medical and health records and relational patient data, and unstructured data, such as text and images. Lastly, domain experts verify and validate the extracted knowledge using ripple down rules (RDR) methodology.

The key contributions of the IMP include the following:

- an interactive interface to support users' multimodal interactions (text, voice, and image)
- incremental knowledge-learning mechanisms to create and maintain evolutionary knowledge bases.

DIRECTIONS OF MEDICAL PLATFORM

The rise of personal assistants (such as Siri) have educated users about dialogue-based interactive environments. Therefore, dialogue-based user interaction with the system and user-friendliness are important aspects of a medical platform for enhancing the user-satisfaction level. The dialogue system depends on the knowledge base. Therefore, the system relies on accurate knowledge extracted from diverse data, and the medical platform must be equipped with an intelligent mechanism to extract accurate insights and knowledge. A rich approach for knowledge maintenance (RDR) and a productive standard method for knowledge sharing using a medical logic module (MLM) can provide flexibility in knowledge representation and sharing. Evidence can be a confidence-building measure because this information provides support for the actions taken by stakeholders in medical platforms. The users are usually concerned about the authenticity of the generated recommendation. The white-box approach of recommendation and online authentic evidence can enhance the users' satisfaction level. In summary, our proposed IMP deals with directions of interactive dialoging, knowledge maintenance, and evidence support to increase users' confidence.

SYSTEM METHODOLOGY AND ARCHITECTURE

The proposed system has five important aspects:

1. knowledge extraction and engineering
2. dialogue-based conversation
3. data acquisition
4. user-interface adaptability
5. system interoperability.

In this section, we describe these five aspects with the help of system architecture depicted in Figure 1.

Knowledge extraction and engineering

The key features of knowledge extraction and engineering include knowledge acquisition from multimodal sources and its validation and verification. Knowledge extraction obtains knowledge from structured data, textual data, and images, while knowledge engineering enables physicians to verify and validate the extracted knowledge and create or modify knowledge using heuristics. These aspects are covered by the knowledge extraction module and the knowledge engineering tool (KET) module, respectively, as shown in Figure 1.

The actionable knowledge acquisition component within the knowledge extraction module identifies hidden knowledge in structured data. This component models the knowledge in RDRs. The primary reason for selecting RDRs is the ease of adding and evolving knowledge by a physician with minimum effort using incremental learning methodology.

The descriptive knowledge acquisition component within the knowledge extraction module extracts knowledge from textual medical resources, such as published articles, clinical notes, guidelines, and protocols. The main processes used by this component are preprocessing, information extraction, semantic analysis, and ontology management.

The task of gathering knowledge from medical images, such as X-rays, magnetic resonance images, and computerized tomography scans, is the responsibility of the visual recognition component within the knowledge extraction module. This research comprises four major features: category classification,

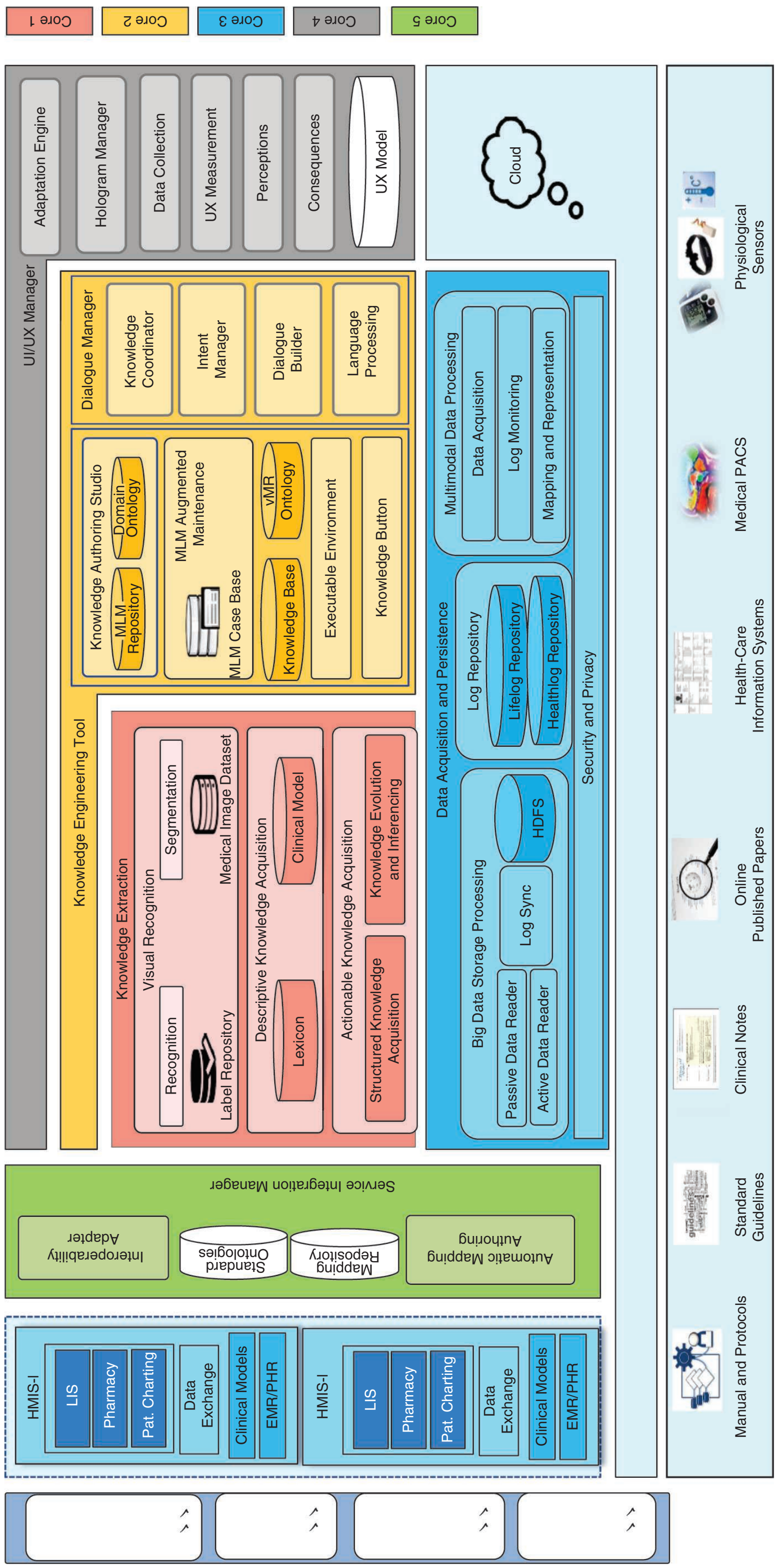

FIGURE 1. The architecture of the IMP. Pat.: patient; HMIS: health-management information system; EMR: electronic medical record; HDFS: Hadoop Distributed File System; vMR: Virtual medical record; UI: user interface; UX: user experience; LIS: laboratory information system; PACS: picture archiving and communication system; PHR: personal health record.

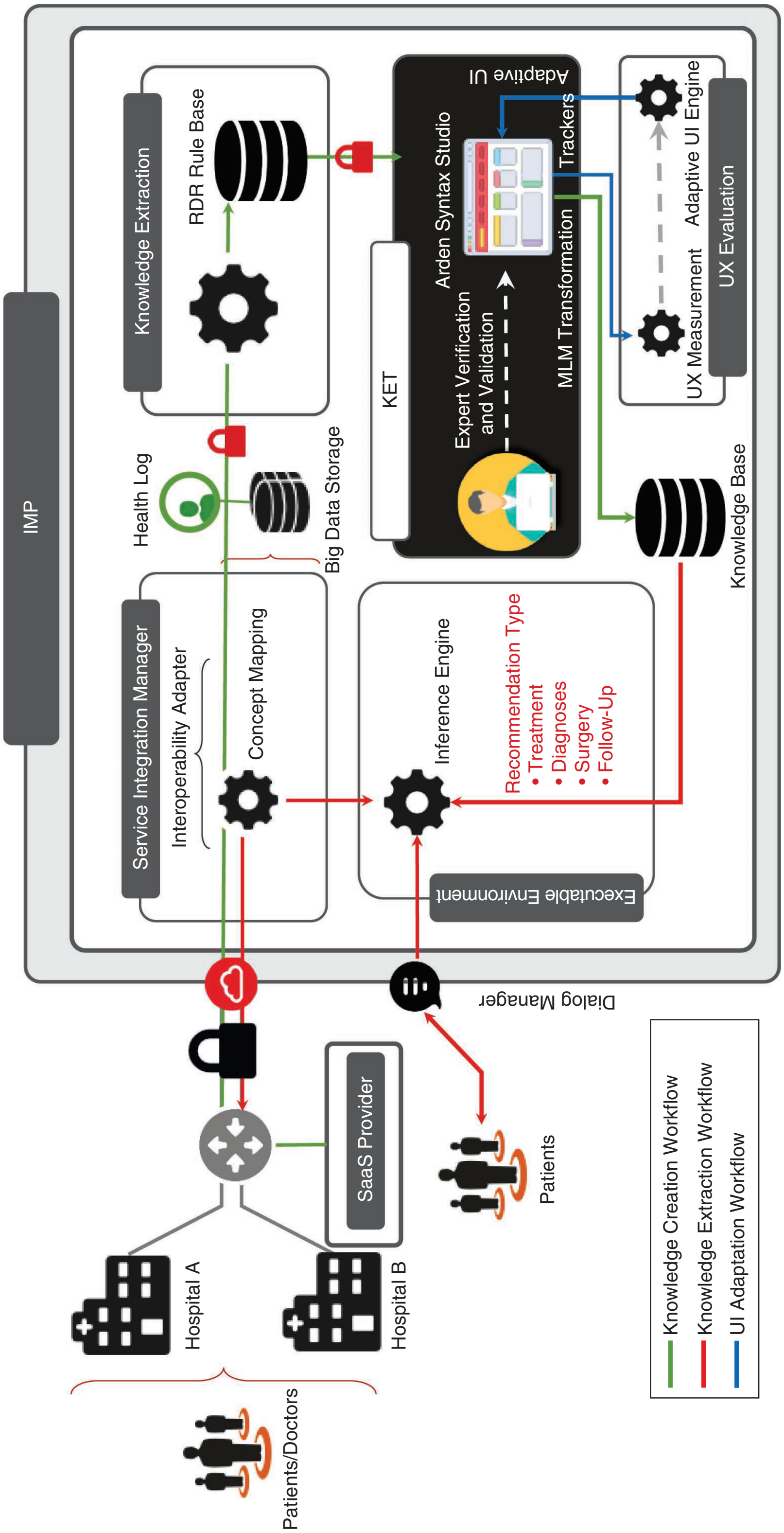

FIGURE 2. An implementation scenario for the IMP. SaaS: software as a service.

segmentation, local feature extraction, and model collation. Category classification deals with automatic recognition of image and organ types by using the deep convolutional neural network model. The aim of segmentation is to partition the image into a meaningful segments, called *regions of interest* (*ROIs*), and identify a specific ROI for processing.

The KET module transforms the plain and RDR rules into shareable and interoperable knowledge. The knowledge shareability is realized by the Health Level 7 standard knowledge representation Arden Syntax MLM. The amalgamation of the standard data model, Virtual Medical Record (vMR), and standard terminology, Systematized Nomenclature of Medicine—Clinical Terms, enhances the interoperability of the knowledge. The Arden Syntax Studio component is designed to create shareable and interoperable MLMs from the plain rules. The system ensures the transformation of plain rules to MLMs. The MLM Validator and MLM Augmented Maintenance confirm completeness, certify precision, and resolve duplications/conflicts.

The knowledge base gives recommendations using the MLM Augmented Case Base reasoner and is invoked by the executable environment component within the KET module. The direction of knowledge authenticity using high-quality online evidence is realized by the knowledge button component.[10]

Dialogue-based conversation

This module facilitates communication in a dynamic dialogue environment by text, voice, and images between the patients and the system. The conversation aspect of the platform is handled by the dialogue manager component in the system's architecture. The five parts of this component are input handler, dialogue builder, intent manager, knowledge coordinator, and output handler. When the user interacts with the system in real time using an interface, the input handler recognizes the user's voice and generates a keyword pair. The sub-dialogue builder takes this keyword pair as an input and maps it to an ontological model in intent manager for identifying the user's intent. The knowledge coordinator identifies the current context based on the extracted keywords and identified user's intent. Depending on the identified context, the response handler will generate a response and forward it to the Output Handler. The Output Handler gives the desired format to the generated response and starts communicating with the user accordingly.

Data acquisition

The main goal of data acquisition is to collect the data from multimodal data sources in structured and unstructured formats and place the data in nonvolatile storage, the Healthlog Repository and Hadoop Distributed File System.[11]

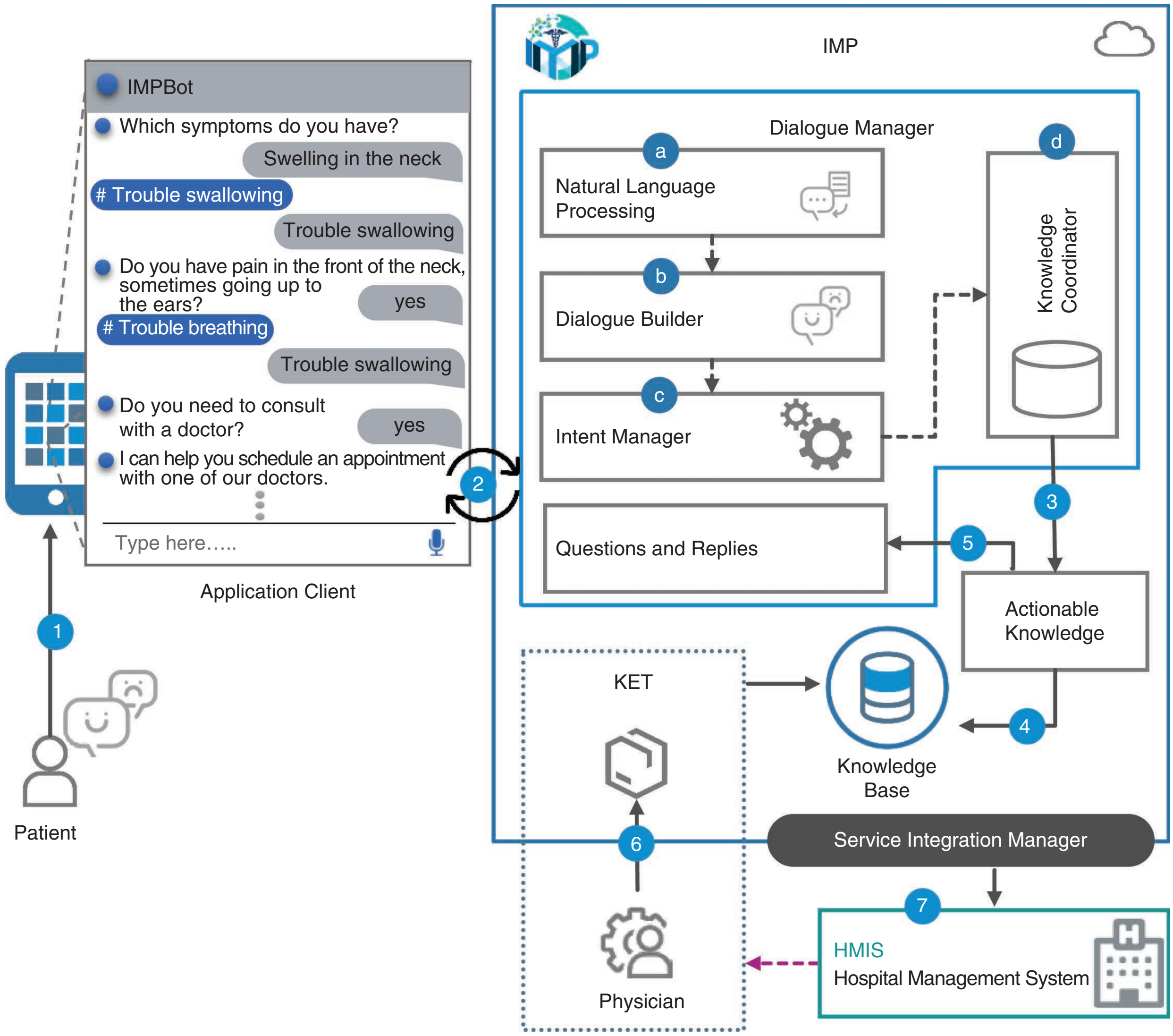

FIGURE 3. A dialogue-based e-coaching scenario (patient centric).

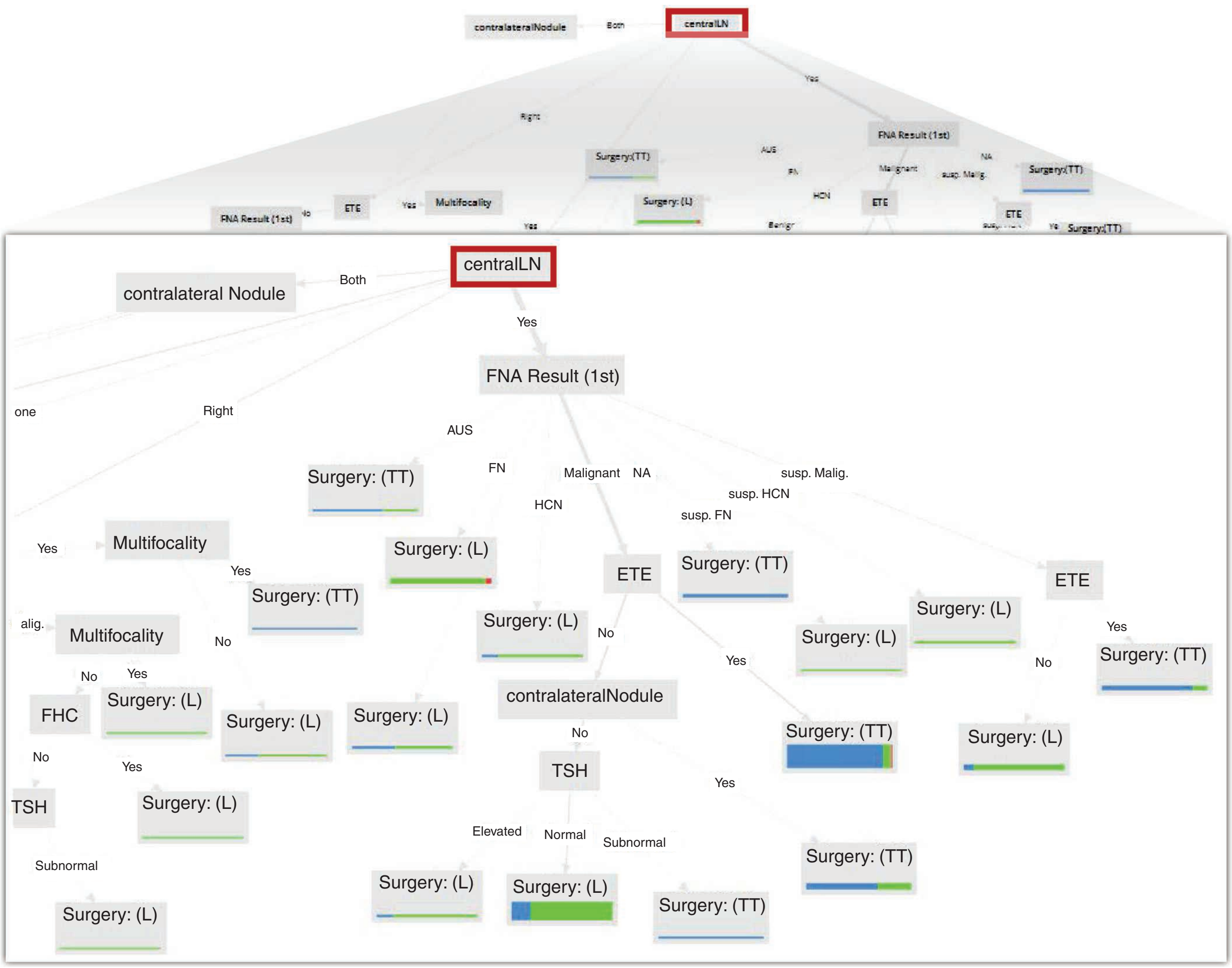

FIGURE 4. The resultant partial tree model. FNA: fine needle aspirations; TT: total thyroidectomy; AUS: atypia of undetermined significance; L: lobectomy; FHC: familial history of cancer; TSH: thyroid-stimulating hormone; ETE: extrathyroid extension; HCN: Hurthle cell neoplasm; FN: follicular neoplasm; NA: not applicable; Susp.: suspicious; Malig.: malignancy.

This functionality is handled by the data acquisition and persistence module in the IMP system's architecture. The multimodal data processing component within the data acquisition and persistence module handles two types of data:

1. observatory data, which are semantically enriched and stored into the Healthlog Repository using its flexible representation and mapping
2. interventional data, which are unstructured and consist of the different biological and physiological sensory data.

These data are stored in the big data storage component. The Healthlogs of patients are continuously monitored to alert patients when some disease reaches critical condition.

User-interface adaptability

The UI/UX manager module handles the research direction of user interactions with the system and provides user-friendly features. It deals with user experience (UX) evaluation during the use of the KET interfaces. It adapts a user interface (UI) based on the evaluated UX. The

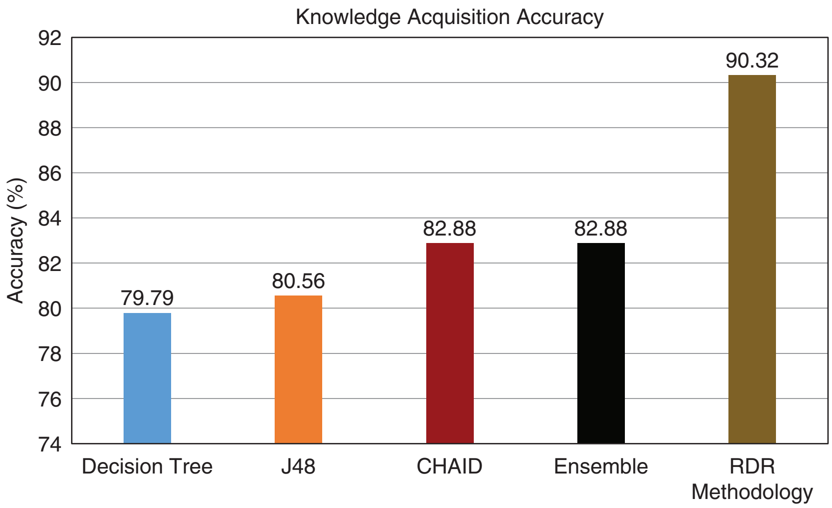

FIGURE 5. Knowledge acquisition accuracy.

UX is assessed by measuring and learning from user behavior and emotional response with both implicit and explicit ways by incorporating the human behavior research. The UX measurement component within the UI/UX manager module provides inferencing and modeling for UX evaluation. It also deals with the adaptive UI based on a model-driven approach that aligns with a UI according to the context of use. The context-of-use triplet consists of a user, platform, and environmental aspects that can support adaptive UI behavior.

Service integration manager

Tasks involving data interoperability and IMP integration with legacy health-management information systems are handled by the service integration manager module. It works in two phases: offline and online. The offline phase, automatic mapping authoring, defines alignments of legacy systems data with the IMP-compatible standard format. The online phase, the interoperability adapter, exposes interfaces working on top of the generated alignments for these legacy systems to use the services of the IMP. Automatic mapping authoring uses SPheRe[12] matching systems for finding the alignments between the models and storing them in the mapping repository in the form of electronic medical record (EMR)–fast healthcare interoperability resources (FHIR) mappings. The interoperability adapter[13] uses the mappings stored in the mapping repository for conversion among legacy and IMP-compatible formats.

CASE STUDY

In this section, we describe two service scenarios:

1. knowledge acquisition (physician centric), an offline process to create the knowledge base for dialoging
2. dialogue-based e-coaching (patient centric), an online process to provide real-time recommendation services to the patients.

We deployed a prototype version of the IMP in our collaborative Seoul National University Bundang Hospital (SNUH) in South Korea. We targeted the diagnosis, treatment, and follow-up recommendation services for thyroid cancer (TC) in SNUH. The detailed implementation scenario is depicted in Figure 2.

The case study comprises two different workflows for knowledge creation and knowledge execution. These scenarios reveal the implemented functionalities of all system modules. The system is integrated with the health-management information systems of SNUH to retrieve patient data for knowledge extraction and execution.

Knowledge-acquisition scenario (physician centric)

SNUH provided us with posttreatment data related to TC from 500 anonymous patients. These data were stored in the FHIR-compliant Healthlog repository. Simultaneously, the knowledge was extracted from the data using decision-tree algorithms [J48, Chi-square automatic interaction detection (CHAID), and decision tree] by the majority-voting, ensemble-learning technique in the form of knowledge rules. The extracted rules using a data-driven approach were verified and validated by physicians using the KET with incremental-learning methodology. The physicians added new rules and updated existing rules using heuristics, and 1,238 production rules were added to the knowledge base for diagnosis and treatment. The system transformed the 1,238 production rules into 63 corresponding MLMs for shareability purposes. UX evaluation was also based on the physicians' interaction with the KET during the creation and validation process. The interface was dynamically updated based on the user's preferences.

Dialogue-based e-coaching scenario (patient centric)

The IMP enables patients to interact with the system using IMPBot, which provides dialogue-based e-coaching services in the form of recommendations, alerts, and follow-ups. Figure 3 depicts a TC diagnosis scenario to give a recommendation to the patient.

TABLE 1. Personal profile information of the volunteers who participated in the evaluation of KET (n = 10).

Attributes	Number of users	% of users	Mean (standard deviation)
Age (years)			38.40 (11.057)
20–30	3	30	
31–40	3	30	
41–55	4	40	
Gender			
Male	7	70	
Female	3	30	
Disabilities			
Vision	4	10	
Limb	1	50	
No	5	40	
Education			
Graduation	5	50	
Postgraduation	5	50	
Experience with tools (like KET)			
Yes	4	40	
No	6	60	
Experience in domain (years)			7.60 (4.37)
1–5 years	4	40	
5–10 years	3		
11–15 years	3		
Upper-limb usage			
Right hand	3	30	
Both	2	20	
Left hand	5	50	

First, the patient registers with the IMP platform to use its services. The patient interacts with IMPBot by providing initial signs and symptoms in the form of voice or text, as shown in Figure 3. The dialogue manager analyzes the patient's response using natural language processing to find out the user's intention. The knowledge coordinator executes the dialogue query through actionable knowledge to find an appropriate answer/question using RDR inferencing on the knowledge base. The executed knowledge gives a response in the form of a recommendation, alert, answer, or even a question. Questions and replies in the system have different templates, which are used to present the system's response.

Based on the patient's response, the system infers other symptoms using an incremental inferencing mechanism and inquiries from the patient. For example, the system gives the suggestion "#Trouble swallowing" or asks another question like, "Do you have pain in the front of the neck, sometimes going up to the ears?" Sometimes, the system is unable to generate an appropriate response due to the lack of knowledge in the knowledge base. Then the system sends an alert to the physician to provide an answer to the query. The physician answers the patient's query and also adds new knowledge to the knowledge base.

RESULTS

The knowledge extraction methodology was evaluated for 500 TC patients from SNUH. We selected decision tree, J48, and CHAID algorithms by using ensemble-learning methodology with 10-fold cross-validation to compare with RDRs. We converted the final tree model into plain rules by applying the tree-to-rule algorithm. The resultant tree model is shown partially in Figure 4. The machine-learning model's accuracy was 79.79% with decision tree, 80.56% with J48, and 82.88% with CHAID, without expert intervention, as depicted in Figure 5.

The plain rules are transformed into an RDR representation scheme by incremental-learning methodology with physician involvement. The physician involvement is mandatory in the RDR validation and verification process. By updating existing rules and adding new ones, the accuracy of RDR methodology increased up to 90.32%, as shown in Figure 5. A sample rule is given as follows.

Rule: If 'Fine Needle Aspirations' = 'Malignant' and 'Gender' = 'male' and 'Extra Thyroid Extension' = No and 'Lymph Node Metastases' = No and 'Distant Metastasis' = No and Multifocality = No and Radiation = No and 'Familial History of Cancer' = No and 'Thyroid Stimulating Hormones' = Yes Then Surgery(Total Thyroidectomy)

We performed a user-based evaluation for adaptive UIs in KET that are automatically generated based on the evaluation of the UX.

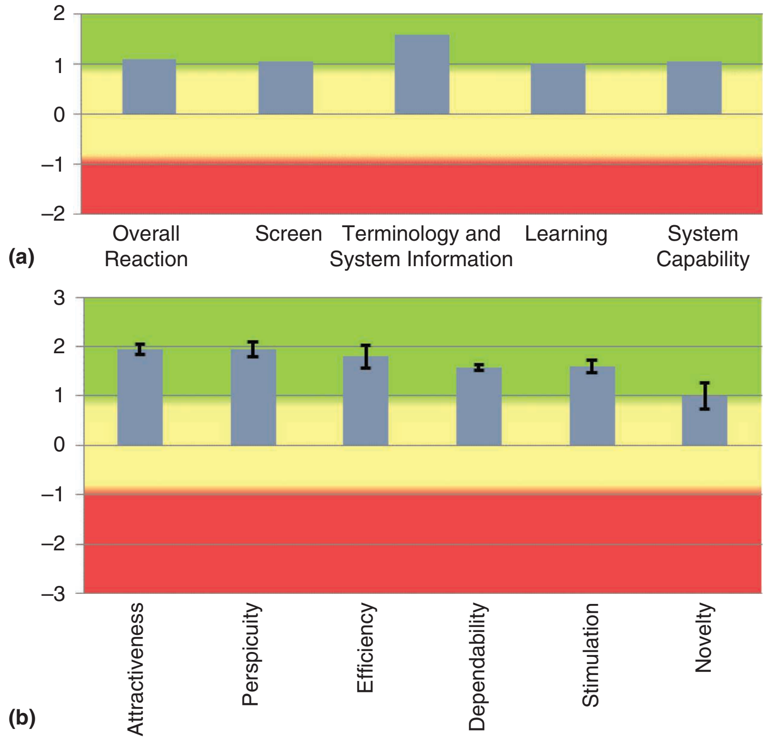

FIGURE 6. (a) QUIS results for five factors and (b) UX results for six factors.

Recruitment criteria

For evaluation, we recruited 10 participants (physicians at SNUH). Each of them was a physician of oncology and had experience diagnosing and treating TC patients. Physicians were asked to provide such information as age, gender, vision impairment, and extent of expertise with authoring tools (Table 1).

Evaluation session

The participants were provided with initial training in using the KET module. They were briefly addressed for half an hour regarding the purpose of the research and then indicated their willingness to be included. During the session, we explained the hypothesis that the adaptive UI improves the overall efficiency and user satisfaction with the system. A web-based interface was provided to each of the participants to use the system for writing the selected five rules. Each user was asked to use the system in a standalone manner and record his/her opinion about the system.

Results collection

To get the system evaluation results, two questionnaires were distributed to the users: the Questionnaire for User Interaction Satisfaction (QUIS)[14] and the User Experience Questionnaire (UEQ).[15] QUIS version 5.0 with a five-point Likert scale was developed for measuring the overall satisfaction with the system by the users. The UEQ assessed the UX along with classical usability aspects by measuring the users' expressed feelings, impressions, and attitudes about using the system. The latter consisted of six-dimension scales for evaluating attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty. The scales of the questionnaire were grouped by quality: pragmatic (perspicuity, efficiency, and dependability) and hedonic (stimulation, originality).

Figure 6(a) shows the results of the QUIS with the mean value for each scale. The alpha-coefficient values are higher than 0.7 for all of the scales except for terminology and system information. This may be due to the user's misinterpretation of the terminology and system information.

Figure 6(b) shows that the results of all of the scales are quite good, including the hedonic and pragmatic aspect of the KET. The value of Cronbach's alpha coefficient of attractiveness is higher than 0.7, which shows that users like the adaptive UI generated by the UI/UX manager. The value of Cronbach's alpha coefficient for novelty is low, meaning that it does not play an important role in the adaptive UI.

The service integration manager currently considers the EMR format compliant with the clinical document architecture (CDA) and IMP format as vMR. The accuracy achieved for conversion is 93% from CDA to vMR and 95% from vMR to CDA. The details about this conversion process and the accuracy are given by Norman et al.[14] In future, we intend to use FHIR as the mediator standard for the IMP.

The next generation of healthcare informatics systems will be defined by their ability to create, process, evolve, and maintain dialogue-driven knowledge bases. The IMP provides a novel solution by integrating dialogue-based interactive decision support systems with knowledge curation activities, leading to more concise and effective applications in the area of e-coaching. IMP demonstrates the feasibility of a natural conversational environment with a mesh of advanced technologies. ■

ACKNOWLEDGMENTS

This research was supported by the Ministry of Science and ICT (MSIT), South Korea, under the Information Technology Research Center support program (IITP-2017-0-01629) supervised by the Institute of Information and Communications Technology Planning and Evaluation and by an IITP grant funded by the MSIT (2017-0-00655).

REFERENCES

1. T. A. Miller and M. R. DiMatteo, "Importance of family/social support and impact on adherence to diabetic therapy," *Diabetes Metab. Syndr. Obes. Targets Ther.*, vol. 6, pp. 421–426, Nov. 2013. doi: 10.2147/DMSO.S36368.
2. J. M. Gabriele, B. D. Carpenter, D. F. Tate, and E. B. Fisher, "Directive and nondirective e-coach support for weight loss in overweight adults," *Ann. Behav. Med.*, vol. 41, no. 2, pp. 252–263, 2010. doi: 10.1007/s12160-010-9240-2.
3. M. Allen, L. I. Iezzoni, A. Huang, L. Huang, and S. G. Leveille, "Improving patient–clinician communication about chronic conditions: Description of an Internet-based nurse E-coach intervention," *Nurs. Res.*, vol. 57, no. 2, pp. 107–112, 2008. doi: 10.1097/01.NNR.0000313478.47379.98.
4. R. J. Beun et al., "Improving adherence in automated e-coaching," in *Proc. Int. Conf. Persuasive Technology*, 2016, pp. 276–287. doi: 10.1007/978-3-319-31510-2_24.
5. M. Stieger, M. Nißen, D. Rüegger, T. Kowatsch, C. Flückiger, and M. Allemand, "PEACH, a smartphone-and conversational agent-based coaching intervention for intentional personality change: Study protocol of a randomized, wait-list controlled trial," *BMC Psychol.*, vol. 6, no. 1, p. 43, 2018. doi: 10.1186/s40359-018-0257-9.
6. A. Riva, C. Smigelski, and R. Friedman, "WebDietAID: An interactive Web-based nutritional counselor," in *Proc. AMIA Symp.*, 2000, pp. 709–713.
7. D. Schulman, T. W. Bickmore, and C. L. Sidner, "An intelligent conversational agent for promoting long-term health behavior change using motivational interviewing," in *Proc. AAAI Spring Symp.: AI and Health Communication*, 2011. [Online]. Available: https://www.aaai.org/ocs/index.php/sss/sss11/paper/download/2401/2854
8. J. Thomason, S. Venugopalan, S. Guadarrama, K. Saenko, and R. Mooney, "Integrating language and vision to generate natural language descriptions of videos in the wild," Univ. of Texas at Austin, 2014. [Online]. Available: https://www.aclweb.org/anthology/C14-1115/
9. M. A. Musen, B. Middleton, and R. A. Greenes, "Clinical decision-support systems," in *Biomedical Informatics: Computer Applications in Health Care and Biomedicine*, E. H. Shortliffe and J. J. Cimino, Eds. Berlin: Springer-Verlag, 2014, pp. 643–674.
10. M. Afzal, M. Hussain, T. Ali, W. A. Khan, S. Lee, and B. H. Kang, "MLM-based automated query generation for CDSS evidence support," in *Proc. Int. Conf. Ubiquitous Computing and Ambient Intelligence*, 2014, pp. 296–299. doi: 10.1007/978-3-319-13102-3_49.
11. O. Banos et al. "The Mining Minds digital health and wellness framework," *Biomed. Eng. Online*, vol. 15, no. 1, p. 76, 2016. doi: 10.1186/s12938-016-0179-9.
12. M. B. Amin, R. Batool, W. A. Khan, S. Lee, and E.-N. Huh, "SPHeRe,"

ABOUT THE AUTHORS

TAQDIR ALI is a postdoctoral researcher in the Ubiquitous Computing Laboratory, Kyung Hee University, South Korea. His research interests include knowledge acquisition and e-health standardization. Contact him at taqdir.ali@oslab.khu.ac.kr.

JAMIL HUSSAIN is a Ph.D. student in the Ubiquitous Computing Laboratory, Kyung Hee University, South Korea. His research interests includes user interface and user experience research and design. Contact him at jamil@oslab.khu.ac.kr.

MUHAMMAD BILAL AMIN is a Korea research fellow at the National Research Foundation Korea and a research professor at Kyung Hee University, South Korea. His research interests include software architecture, cloud computing, and data science. He is a Member of the IEEE. Contact him at bilal@oslab.khu.ac.kr.

MUSARRAT HUSSAIN is a Ph.D. student in the Ubiquitous Computing Laboratory, Kyung Hee University, South Korea. His research interests include knowledge extraction and text processing. Contact him at musarrat.hussain@oslab.khu.ac.kr.

USMAN AKHTAR is a Ph.D. student in the Ubiquitous Computing Laboratory, Kyung Hee University, South Korea. His research interests include big data and scalability problems in linked open data. Contact him at usman@oslab.khu.ac.kr.

WAJAHAT ALI KHAN is an assistant professor at Kyung Hee University, South Korea. His research interests include ontology mappings, health-care standards compatibility, and Semantic Web services. He is a Senior Member of the IEEE. Contact him at wajahat.alikhan@oslab.khu.ac.kr.

UBAID UR REHMAN is a Ph.D. student in the Ubiquitous Computing Laboratory, Kyung Hee University, South Korea. His research interests include dialogue management, security, and privacy. Contact him at ubaid.rehman@oslab.khu.ac.kr.

SUNGYOUNG LEE is a professor at Kyung Hee University, South Korea. His research focuses on ubiquitous computing and applications, context-aware middleware, and activity and emotion recognition. He is a Member of the IEEE. Contact him at sylee@oslab.khu.ac.kr.

BYEONG HO KANG is an associate professor of computing and information systems at the University of Tasmania, Australia. His research interests include expert systems and knowledge-acquisition systems. Contact him at byeong.kang@utas.edu.au.

MAQBOOL HUSSAIN is an assistant professor at Sejong University, South Korea. His research interest includes artificial intelligence, health-care interoperability standards, and clinical decision support systems. Contact him at maqbool.hussain@sejong.ac.kr.

MUHAMMAD AFZAL is an assistant professor at Sejong University, South Korea. His research interests include evidence-based knowledge acquisition, text processing, and information extraction. He is a Member of the IEEE. Contact him at mafzal@sejong.ac.kr.

HO-SEONG HAN is a professor at the Seoul National University Hospital and chair of the Department of Surgery at the Seoul National University Bundang Hospital, South Korea. His research interests include hepatobiliary surgery and laparoscopic surgery. Contact him at hanhs@snubh.org.

JUNE YOUNG CHOI is a professor in the Department of Surgery at the Seoul National University Bundang Hospital, South Korea. His research interests are in the study of thyroid nodules, thyroid cancer, parathyroid disease, and adrenal disease. Contact him at juneychoi@snubh.org.

HYEONG WON YU is a doctor in the Department of Surgery at the Seoul National University Bundang Hospital, South Korea. His research focuses on the treatment of thyroid nodules and thyroid cancer. Contact him at hyeongwonyu@gmail.com.

ARIF JAMSHED is a consultant radiation oncologist at the Shaukat Khanum Memorial Cancer Hospital and Research Center, Pakistan. Contact him at arifj@skm.org.pk.

J. Supercomput., vol. 68, no. 1, pp. 274–301, 2014. doi: 10.1007/s11227-013-1037-1.

13. W. A. Khan et al. “An adaptive semantic based mediation system for data interoperability among health information systems,” *J. Med. Syst.*, vol. 38, no. 8, p. 28, 2014. doi: 10.1007/s10916-014-0028-y.
14. K. L. Norman, B. Shneiderman, B. Harper, and L. Slaughter, *Questionnaire for user interaction satisfaction*, College Park, MD: Univ. Maryland, 1998.
15. B. Laugwitz, T. Held, and M. Schrepp, “Construction and evaluation of a user experience questionnaire,” in *Proc. Symp. Austrian HCI and Usability Engineering Group*, 2008, pp. 63–76. doi: 10.1007/978-3-540-89350-9_6.