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Development of an intelligent e-Healthcare system for the domestic care industry

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Abstract

Purpose - In view of the elderly caregiving service being in high demand nowadays, the purpose of this paper is to develop an intelligent e-Healthcare system for the domestic care industry by using Internet of Things (IoTs) and fuzzy association rule mining (FARM) approach.
Design/methodology/approach – The Internet of Things (IoTs) connected with the e-Healthcare system collect real-time vital sign monitoring data for the e-Healthcare system. The FARM approach helps to identify the hidden relationships between the data records in the e-Healthcare system to support the elderly care management tasks.
Findings - To evaluate the proposed system and approach, a case study was carried out to identify the association between the specific collected demographic data, behavior data and the health measurements data in the e-Healthcare system. It is found that the discovered rules are useful for the care management tasks in the elderly.
Originality/value - Knowledge discovery in databases (KDD) uses various data mining techniques and rule based artificial intelligence algorithms. This paper demonstrates complete processes on how an e-Healthcare system connected with IoTs can support the elderly care services via a data collection phase, data analysis phase and data reporting phase by using FARM to evaluate the fuzzy sets of the data attributes. The caregivers can use the discovered rules for proactive decision support of healthcare services and to improve the overall service quality by enhancing the elderly healthcare service responsiveness.
Keywords - e-Healthcare system, elderly care service, Fuzzy Association Rule Mining, Internet of Things
Paper type - Research paper

1. Introduction

Population ageing is a common phenomenon around the world. Taking Hong Kong as an example, the proportion of the population aged 65 and over is projected to rise markedly from 15% in 2014 to 33% in 2064 (Financial Secretary's Office HKSAR, 2013). As a result, due to the increasing needs and to cope with the associated challenges, e-Healthcare systems for supporting elderly healthcare such as real time non-invasively biomedical monitoring without affecting the normal life of a person have been introduced. Although there are large amounts of information about individual health records in the e-Healthcare system, effective analysis tools are lacking for discovering the hidden relationships in the available data. In addition, it is found that in recent years, much research work has been done to support disease prediction or diagnosis, disease correlation, disease risk analysis and drug reaction detection, but rarely in the elderly healthcare service.

While the World Health Organization (WHO) continues to perform studies and surveys for gap analysis of ageing and health in different countries (Paul et al., 2012), research has emphasized that artificial intelligence is useful to discover hidden relationships and trends in healthcare system (Abin et al., 2015). Among them, Association Rule Mining (ARM) is one of the commonest methods that is used to find interesting relationships in the large databases in the healthcare system. Deriving association rules in the healthcare sector has become even more common recently (Jan et al., 2014) due to its simplicity and effectiveness in reflecting human interpretation of the defined categories. In order to handle linguistic representation of the healthcare data more effectively, Fuzzy Association Rule Mining (FARM) was deployed in the e-Healthcare system for elderly care services developed in this research in order to have a more realistic and practical classification of the data attributes in their relationships. By converting the crisp values of the healthcare data with membership functions into different data clusters, depending on their closeness to the predefined member categories, it addressed the problem of dealing with data uncertainties that fall into sharp value boundaries (Bilal et al., 2013). Therefore, it is more efficient and effective to extract potentially interesting rules which are useful in providing health status predications and to drawing special attention to the targeted elderly people under the healthcare monitoring. The collected data are expressed in linguistic terms which makes them more natural and understandable.

Owing to the need for quick responses in managing healthcare tasks, this paper describes different data processing phases of the e-Healthcare system from data collection, analysis and reporting processes. Apart from the potentially useful knowledge discovered in the data analysis phase for supporting proactive healthcare service, the e-Healthcare system provides standard user interfaces and pre-defined procedures to safeguard the operations of the stakeholders, who may have different level of expertise in the caregiving service provision. This ensures the operation procedures are following the formalized work flows. The development not only can help save the lives of the elderly but can deliver a more reliable healthcare service and lead to higher customer satisfaction.

To analyze the available data in the e-Healthcare system, different categories of attributes are examined and selected. Referring to the previous studies related to disease diagnosis and the finding of relationships between the demographic factors and health-related behavior (Kuwahara et al., 2004) “Age” and “Education” characteristics are chosen for the evaluation. Similarly, from the studies on the behavior risk factors to adverse health outcomes (Azari, 2006), “Smoking” and “Drinking” behavior factors are chosen for the analysis. In addition, since health condition monitoring for the elderly (Ayman, Mohammad and Bilal, 2014) commonly uses the “Body and Mass Index – (BMI)”, “Norton scale – Norton” (Marta et al., 2012)and “Modified Early Warning Signal – MEWS” (Cei, Bartolomei and Mumoli, 2009) as the measurement parameters, they are also the target data attributes in the data analysis for determining their association relationships.

The remainder of this paper is organized as follows. The selection of the health datasets, fuzzy theory and association rule mining techniques’ related studies are reviewed in section 2. Section 3 introduces the proposed FARM approach and section 4 demonstrates the approach with an example. Section 5 discusses an experiment for extracting the rules in sample health data. Section 6 gives the conclusions and recommendations for future work.

2. Related studies

Today, the demand for elderly healthcare service is intense. The healthcare industry has evolved to deploy intelligent e-Healthcare systems to support the service delivery as well as to enhance customer satisfaction. Recent research has explored the possibilities of integrating the Internet of Things (IoTs) in the e-Healthcare system to monitor the patient's health status (P. Swiatek, A. Rucinski, 2013). Through the remote sensors of the IoTs infrastructure (Vishakha and Sanjeev , 2015), the health monitoring status can be collected in real time by a wired or wireless transmission network to the central application server (Yang et al., 2014). Certainly, artificial intelligence is widely adopted in the healthcare industry in order to provide health and diseases analysis, prediction or detection. Among the artificial intelligence methodologies that are used in the data mining processes in the medical area, fuzzy association rule mining is one of the popular techniques being utilized (Sunita and O.P., 2010). While Association Rule Mining (ARM) is used to identify the relationships of the crisp data values, Fuzzy Association Rule Mining (FARM) (Hong, Lin and Wang, 2003) has been proposed to solve the real-life problems, with some of the collected data attributes being fuzzy in nature in the actual environment. Although the general workflow of the data mining process of ARM (Chaves et al., 2011) and FARM is to find the frequent itemsets of the transaction records and to derive interesting rules based on the predefined support confidence framework, FARM is found to be more capable to mine potential useful knowledge where the itemsets are categorized and converted to fuzzy terms from the original quantitative values described. This is because FARM prevents the frequent itemsets, with the occurrence greater than or equal to the predefined value called the minimum support, from being ignored due to their values falling into the sharp value boundaries of the data clusters. In fact, many of the recent research studies have adopted the FARM approach in solving problems in different areas including the manufacturing industry (Lee et al., 2015), the education industry (Olufunke, Olanrewaju and Aborisade, 2012), the financial industry (Ho et al., 2012), the healthcare industry (Mahmoodian et al., 2011), etc.

The expert system applications in supporting healthcare services are intended to discover useful knowledge in order to assist caregivers in health diagnosis or prediction (Ilayaraja M.,Meyyappan T., 2015). However, the applications in supporting the elderly healthcare service have not yet been fully explored. In particular, integrating the FARM in e-Healthcare systems in order to provide knowledge support in decision making of elderly healthcare services is lacking. Since the fast responsiveness of healthcare services is important and provides early treatment to the patient at the soonest possible time in emergency cases, the study will also use healthcare sensors – IoTs for the vital sign measurements to expedite the health data collection process. In choosing the data attributes for health data analysis, this paper uses attributes from demographic, behavior and health status data sources which are related to the health condition monitoring. In selecting the demographic data attributes and behavior attributes for the data mining process, it was found that the commonly used evaluation attributes are "Age", "Education" (Kuwahara et al., 2004), "Smoking" and "Drinking" (Azari, 2006) in recent healthcare service research. In addition, since the health data attributes of "Body and Mass Index – (BMI)", "Norton scale – Norton" and "Modified Early Warning Signal – MEWS" are vital assessment references for the health status monitoring of the elderly (Cei, Bartolomei and Mumoli, 2009), they are also chosen for the analysis.

To further define the data value categories or clustering of the selected attributes, for the demographic data, the definition of the fuzzy category of "Age" is derived from reference to the social welfare old age eligibility classifications (Social Welfare Department, 2014), and the fuzzy categories of the "Education" level refers to the government Census and Statistics Department's classification of the schooling level

(Census and Statistics Department, 2016). For the behavior attributes, the fuzzy categories of “Smoking” are according to the definition of the daily cigarette consumption (Census and Statistics Department, 2015) quoted by the Census and Statistics Department and the fuzzy categories of “Drinking” refers to the alcohol consumption definition (Centre for Health Protection , 2014) in the Centre for Health Protection (CHP) of the Department of Health Hong Kong. For the health data attributes, the fuzzy categories of “BMI” are according to the defined Body Mass Index distribution (Centre for Health Protection, 2010) listed in the Centre for Health Protection (CHP) of the Department of Health Hong Kong, and the fuzzy categories of the “Norton” scale (Department of Health & Human Services, n.d.) and “MEWS” (Thorpe et al., 2006) are based on the existing scoring classifications.

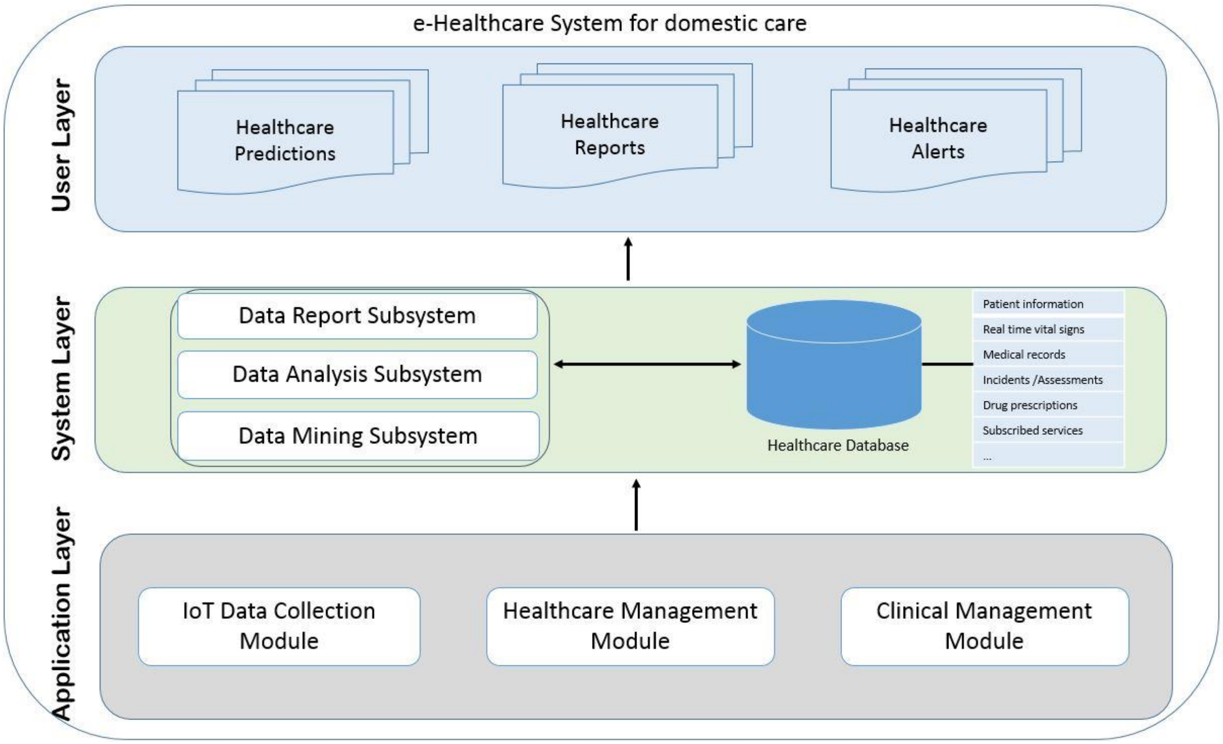
In this work, since FARM is rarely used in discovering the relationships between the demographic data, behavior data and health monitoring data that are commonly found in e-Healthcare systems providing elderly healthcare service, the FARM approach is deployed to find useful information to support the healthcare services, especially to improve the quality and enhance the efficiency in the elderly healthcare service provisions. In particular, by deploying the FARM approach in the selected data attributes, it is expected to extract the association relationships of the common elderly health monitoring attributes (i.e. “Norton” and “MEWS”) among the health information datasets in e-Healthcare systems. The objective of the research work is to provide accurate and fast healthcare service delivery by integrating IoTs and the knowledge discovery module into the proposed e-Healthcare system. In providing improved elderly healthcare services, the fast response time can decrease morbidity and improve the survival rate for different kinds of illnesses of the elders affecting the elderly.

3. Development of e-Healthcare system for domestic care

3.1 System architectural design

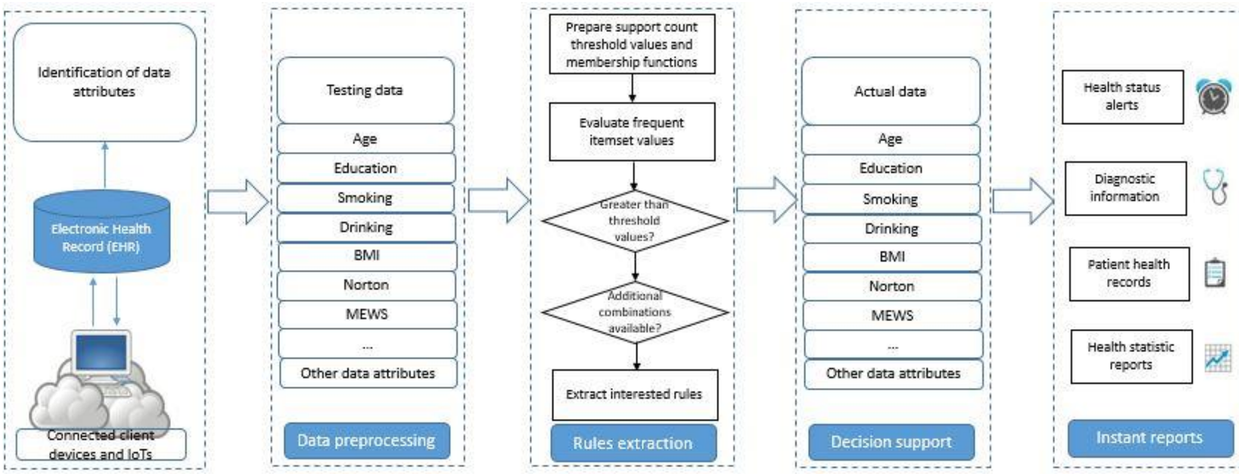
The e-Healthcare system is a web application system. While the system, including the web application server and the database server, reside on the cloud virtualization platform, it provides interfaces to accept data input from various client services. The client services can be different IoTs sensors, healthcare management web interfaces and the integration of other clinical management application systems. The system architecture of the e-Healthcare system is shown in Figure 1.

Figure 1 – System architecture of the proposed e-Healthcare system



The major steps involved in discovering useful and understandable knowledge by integrating the FARM into the system is depicted in Figure 2, while the detailed FARM process is illustrated in Figure 4 - Flow chart of FARM health records. The advantage of the FARM deployment in this system provides not only efficient and effective data classification of the health records but also prevents important rules from being neglected, as in conventional data mining algorithms.

Figure 2 – Overview of the proposed e-Healthcare system deployment method



3.2 System module design

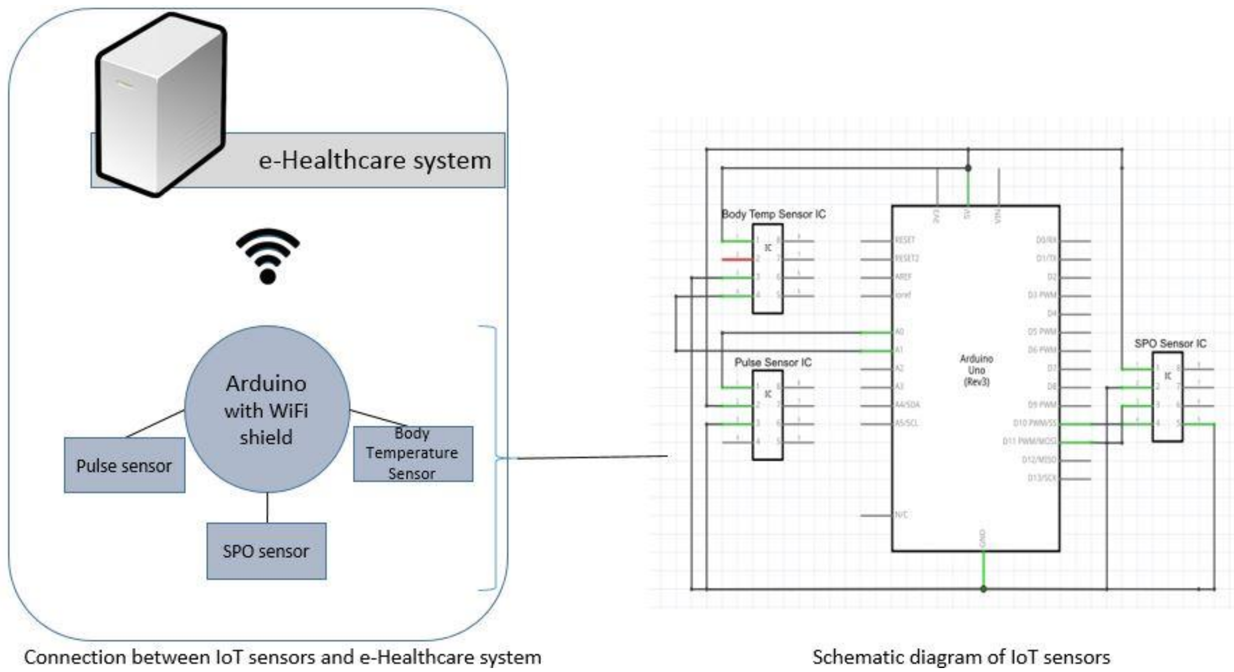
The proposed e-Healthcare system for supporting the domestic care service contains three software modules. The modules supports the functions of the data processing in the data collection phase, data analysis phase and data reporting phase. The details of the important software modules of the system are described below.

i. Data Collection Module

The Data Collection Module has a core function in accepting the data input from different Electronic Health record (EHR) data resources. A data collection portal consists of different interfaces to communicate with various types of import data. For example, there are interfaces to read the data collected from IoTs (Yang et al., 2014) through Hypertext Transfer Protocol (HTTP) and WiFi connections, Web Graphical User Interface (GUI) to accept caregivers' data input and customized interfaces to extract the predefined formats of the EHR from other clinical systems. The centralized database serves as the source of origin of the data attributes for the system analysis module. In this paper, some of the typical vital sign measurements listed in Table 1 were collected by IoTs in an Arduino circuit board, as shown in Figure 3. The Arduino with WiFi shield is capable of capturing and transmitting the vital sign measurement data through the WiFi communication channel to the e-Healthcare system.

Table 1 – Common vital sign measurements collected by IoTs in this paper

Figure 3 –Schematic diagram of the IoT sensors using Arduino Uno and the connection between the IoT sensors and e-Healthcare system



The data attributes used by the Rule Mining Module in the later phase, allow indirect derivation of the vital sign measurement results for analysis. The types of data samples used for the FARM process are sourced from demographic, behavior and health status areas. These data samples include “Age” and “Education” in the demographic category, “Smoking” and “Drinking” in the behaviour category and “Body and Mass Index (BMI)”, “Norton Scale (Norton)” and “Modified Early Warning Signal (MEWS)” in the health status category respectively. There are important factors which are considered to affect the mortality and morbidity of the elderly. While the demographic and behaviour categories of the data parameters are supposed to have been registered into the e-Healthcare system database, the “Norton” and “MEWS” data parameters can be derived from the continuous monitoring of the health status criteria of the patients. The “MEWS” score and Norton scale used in medical condition assessment are shown in Table 2 and Table 3 respectively.

Table 2 – Scoring of Modified Early Warning Score (MEWS)

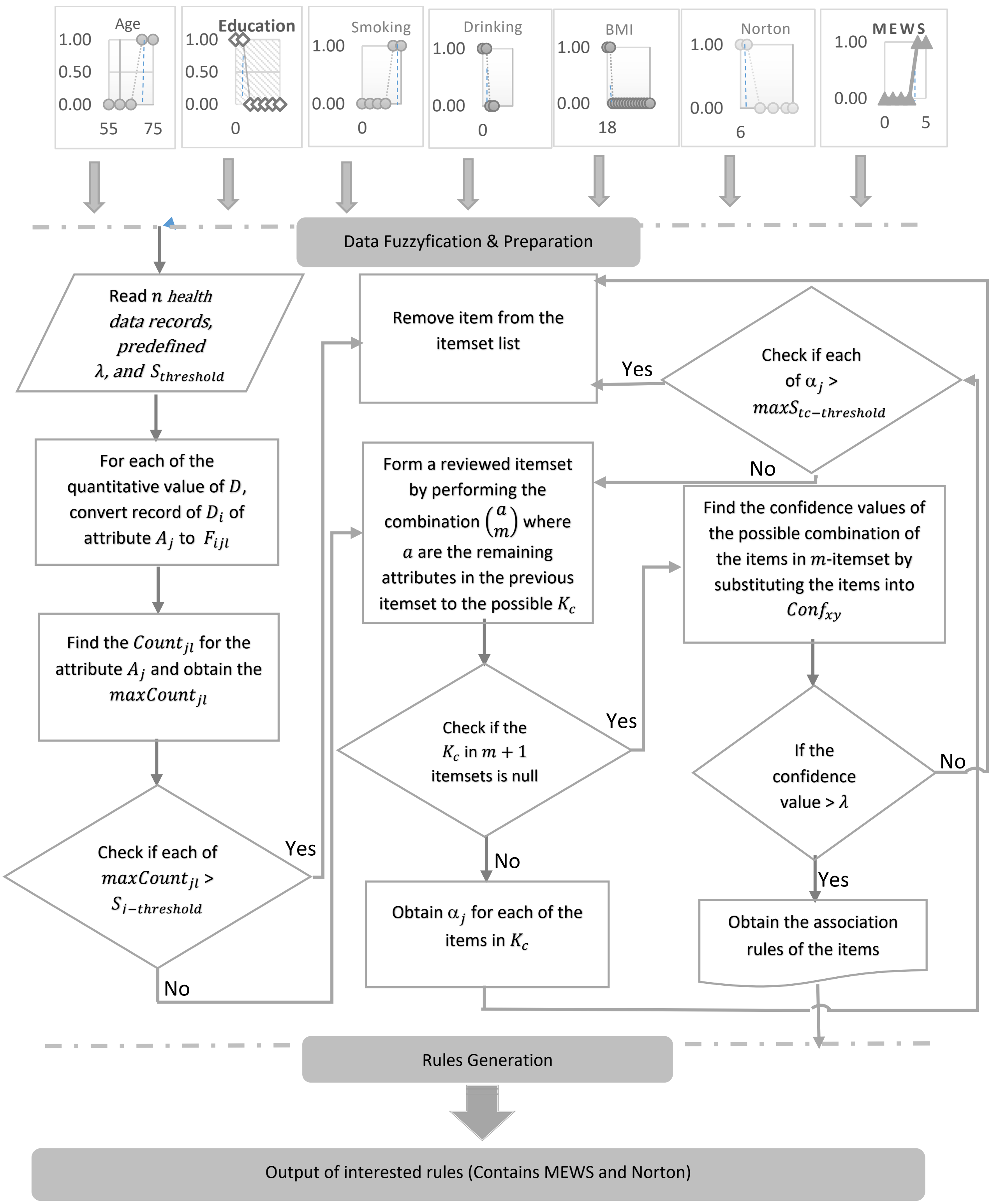
Table 3 – Norton scale (Norton)

ii. Rule Mining Module

The Rule Mining Module provides an intelligent evaluation function to find the association of the selected data attributes in order to support the healthcare decisions and services during the data analysis phase. The module applies the FARM approach from the healthcare data analysis. The symbols and notations are shown in Table 4 and a system flow chart is shown in Figure 4 to illustrate the procedures of the implementation. After the data evaluation processes of the Rule Mining Module, the discovered knowledge or rules can be archived to the database for later use in the Alerting and Reporting Module.

Table 4 - Notations used in the proposed FARM in healthcare system

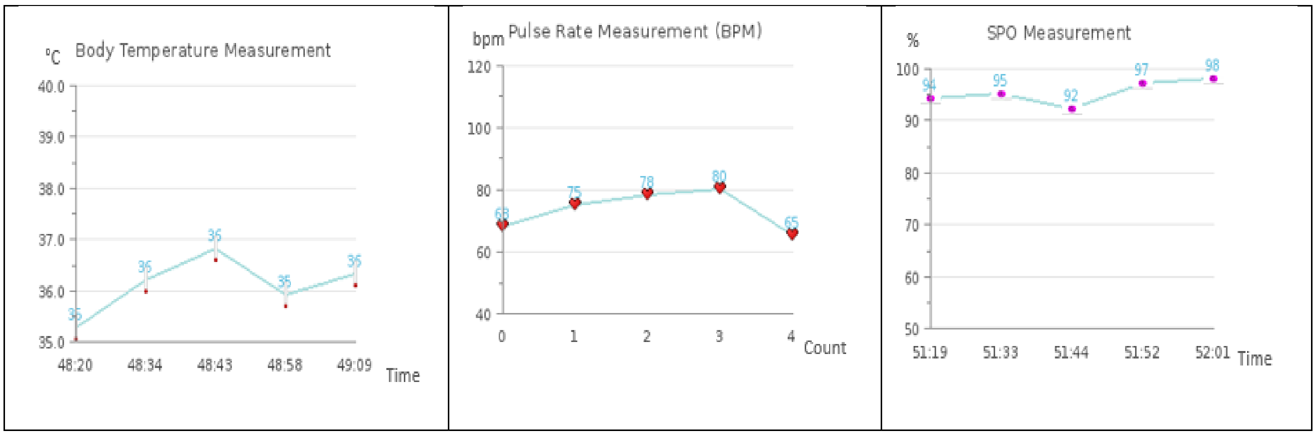
Figure 4 - Flow chart of FARM health records



iii. Alerting and Reporting Module

The Alerting and Reporting Module is for presenting the analytical reports as well as to send alerts or reminders to the caregivers whenever any of the thresholds of the predefined rules in the domestic system are reached or exceeded during the data reporting phase. Figure 5 displays real-time pulse rate measurements of a patient through IoTs which will trigger alerts if there are any detected abnormal monitoring health data. The module is not only capable of assisting in maintaining a quick responsiveness of the healthcare services but the reports can also serve as the baseline for the improvement process of the healthcare service.

Figure 5 – Real-time vital sign monitoring display reports



4. Case scenario

In this section, a test case was established to demonstrate the validity of the proposed FARM approach in mining the relationships of the health data attributes. The FARM steps below against the datasets with the predefined support counts and threshold values, enable extraction of the important rules for the demographic data, behavior data and health data.

Step 1: Identify the intended health data attributes to be analyzed from the health care system, define the corresponding support count of the attributes, as shown in Table 5. The data attributes to be analyzed are listed in Table 6.

Step 2: Import the health data records in Table 5 and convert each of the record attributes to get the membership value according to the particular attribute's membership function and equation. For example, in reading the "Age" attribute "66" from the records, the membership values is "0", "0.8" and "0.2" of the "Age.Low", "Age.Medium" and "Age.High" fuzzy categories respectively. The membership functions and equations of the data attributes are listed in Table 7.

Table 5 - The health data attributes and its support count

Table 6 - The samples of health data records of the targeted attributes

Table 7 - The health data attributes membership functions and equations

Step 3: Sum up the membership values of each of the fuzzy categories of the data attributes. For example, the membership value of "Age.Medium" in the Table 8 is (0.8+0.4+1+0+0+0+0+0+0.2+0) = 2.4 Similarly, the membership values of "Age.Low" and "Age.High" are 0 and 7.6 respectively.

Step 4: Choose the maximum count of the membership values of the fuzzy categories of each of the attributes as for an example, "Age.Low" $\cup$ "Age.Medium" $\cup$ "Age.High" = $0\cup 2.4\cup 7.6=7.6$

Step 5: Compile the maximum counts from Step 4 to get the "1-itemset". Eliminate the items in the "itemset-1" for those membership values lower than the corresponding support count. For example, "Age.High" $\cup$"Predefined Support Count of Age" = 7.6 The result is summarized in Table 8 after the elimination.

Table 8 - Summation of the membership values of the data attributes by fuzzy categories

Step6: Combine the items in Table 8 to generate a "2-itemset", re-evaluate the fuzzy count values by choosing the minimum values of the items. For example, for the item "Age.High Education.VeryLow" appeared in the "2-itemset", the fuzzy count of the item is the summation of the minimum count of the constituent members (i.e. "Age.High" and "Education.VeryLow") in the combination. In this case, the fuzzy count of "Age.High Education.VeryLow) is updated as "$0.2\cap 0 + 0.6\cap 0.33 + 0\cap 0 + 1\cap 1 + 1\cap 1 + 1\cap 0.33+ 1\cap 1 + 1\cap 0.33 + 0.8\cap 1 + 1\cap 0$) = 4.79 and its maximum support count is calculated as "Support Count of Age" $\cup$ "Support Count of Education" = $1.5\cup 1.3$ = 1.5 The list of items in "2-itemset" and their corresponding support counts are summarized in Table 9.

Table 9 - 2-itemset list

Step 7: For each item in the itemset table, remove the items with a membership value lower than the support count. The list of the reviewed itemset is given in Table 10.

Table 10 -List of the reviewed 2-itemset by removing those with membership values lower than the maximum support count

Step 8: Combine the items left in the itemset and re-evaluate their membership values as listed in Table 9. By repeating steps 7 and 8, the higher levels of the itemsets can be found unless there are no additional combinations of the remaining items in the itemset table. The reviewed 4-itemset table is listed in Table 11.

Table 11 - The combination of the items from previous itemset and its membership values

Table 12 - The reviewed 4-itemset after removing the membership values lower than the maximum support count

Step 9: Based on the evaluation of the confidence($x \rightarrow y$) = P(y | x) = $\frac{Support\ count(x \cup y)}{Support\ count(x)}$, a set of association rules are generated. By removing confidence values smaller than the predefined minimum threshold value “95%”, the association rules are listed in Table 13.

Table 13 - List of the association rules from the targeted health data attributes

5. Experimental results and discussion

Based on the test case demonstration of the previous section, experiments were carried out to simulate the data mining process of the healthcare system by using the proposed approach and sample data records. The computer programs were developed in C programming language on a Linux virtual machine with 4 virtual CPUs and 2GB memory. The sample data were generated by the MySQL database with five thousands records, with each of the records consisting of data attributes such as “Age”, “Education”, “Smoking”, “Drinking”, “BMI”, “Norton” and “MEWS”, as illustrated in Figure 6. The membership functions and the support counts of each of the data attributes were pre-defined in a configurable parameter file and read by the C main program. The subsequent itemsets and the final association rules were generated after the computation of the membership values and items combination and evaluation of the support counts of the items. In this experiment, the maximum number of the data attributes left in the itemset after iteration of the combinations and evaluations was 4, and the number of the mined rules was 88. By setting the confidence count to 73, the obtained association rules became 13, as shown in Figure 7. Since the rules of interest concern the relationship between the health data measurement attributes of “Norton” and “MEWS” with other data attributes, therefore only the rules related to “Norton” and “MEWS” were extracted, and are summarized in Table 14.

The results of the case study imply that the applicability of the data mining technique, from a theoretical perspective, through the use of fuzzy association rule mining, is able to fulfill practical needs in the domestic care industry. Since the nature of the health data measurements cannot be simply partitioned as binary, the above experimental result of the rules generation has taken account of the fuzziness of the health data measurements and prevented some of the important measurements to be filtered out by the traditional association rule mining. The process ensures the capturing of all the health data measurement records and avoids some important health indicators which might be possibly ignored by using traditional association algorithms. In addition, the use of the FARM allowed smoother transformation of the health data values into categories and the mined rules are more understandable as they are expressed in linguistic terms. In fact, the mined rules are extremely useful in the healthcare services because they can be used to provide the caregivers with instant alerts or predictions that support fast clinical decisions. Together with the deployment of the IoTs for the vital signs monitoring in the data collection process, the instantaneous alerts based on the mined rules not only can enhance the healthcare service level by reducing the responding time for those patients who required intensive care but also can improve the communication of the caregivers by providing real-time patient diagnosis predictions.

The major benefits of the development of the intelligent e-Healthcare system for domestic care industry by adopting the IoTs and FARM approach are discussed as follows.

i. Improved treatment escalation decision of elderly. The knowledge discovered by the FARM approach serves as intelligence for the e-Healthcare system to support decision making for the elderly in the domestic care industry. The e-Healthcare system can rely on the useful rules to trigger alerts to the caregivers whenever the health status of the elderly required immediate attention. Based on the severity of the alert and the immediately diagnosis of the professional staff, the patients can receive the necessary treatment rapidly to avoid worse from injuries or sickness. The caregivers can further determine if the acute escalation of the patient requires transfer to the hospital intensive care unit, depending on the patient’s health conditions.

ii. Enhanced customer satisfaction. The FARM approach in the e-Healthcare system evaluates all the health data inputs and prevents some of the vital health indicators from being ignored due to being near the boundaries of the classified intervals. Thus, the generated rules for system use are considered to be more comprehensive and valuable. Besides, the alerts based on the extracted knowledge provide a good reference for the caregivers and ensure the elderly have a better quality of healthcare service. The overall efficiency improvement of the e-Healthcare system implementation by integrating the IoTs sensors and the FARM approach reduce the waiting time of the patients who are receiving care services.

iii. Improved quality of elderly care service. Apart from the fast intervention of the caregivers to support the services in responding to the instant alerts triggered by the e-Healthcare system in this study, the development of the data collection through IoTs can replace part of the regular work of the caregivers in vital sign measurements. The development of the e-Healthcare system therefore is a strategic direction to address the overcapacity and overworked service needs as the manpower effort in the domestic care industry has always been stretched.

Figure 6 – Sample generated data records with the selected data attributes

```
|   91 |          1 |       25 |        7 |   22 |      17 |  3.5 |
|   66 |         16 |        5 |        7 | 18.5 |      15 |  3.5 |
|   76 |          3 |       19 |      3.5 |   24 |      11 |    1 |
|   72 |         14 |       23 |        5 | 22.5 |      12 |  4.5 |
|   58 |          9 |       23 |        7 | 22.5 |      20 |    4 |
|   61 |         11 |       11 |        3 | 21.5 |      17 |    1 |
|   81 |          3 |       24 |        0 |   21 |      17 |  2.5 |
|   64 |         18 |       19 |      4.5 | 23.5 |      17 |    1 |
|   71 |          0 |        1 |      3.5 |   22 |      22 |  1.5 |
|   62 |         16 |        1 |      2.5 | 21.5 |      14 |  3.5 |
|   97 |          2 |       24 |        4 | 20.5 |      20 |  2.5 |
|   88 |         10 |        0 |      7.5 |   22 |      19 |  2.5 |
|   68 |          8 |       18 |      5.5 | 21.5 |      19 |    0 |
|   57 |         14 |       10 |      1.5 |   23 |      13 |  2.5 |
|   59 |         17 |        6 |        0 |   18 |       8 |  2.5 |
|   72 |          0 |        0 |        1 | 22.5 |       6 |    0 |
|   60 |         15 |       14 |        3 |   20 |      10 |    0 |
|   89 |          1 |        3 |      6.5 | 24.5 |      15 |    0 |
|   78 |         18 |       15 |        5 | 24.5 |      19 |    3 |
|   97 |         18 |        2 |      2.5 |   18 |       8 |    2 |
+------+------------+----------+----------+------+---------+------+
5000 rows in set (0.01 sec)

MariaDB [hcms]>
```

Figure 7 – Result of the generated association rules of the experiment

```
[benniew@isssms health]$ more reviewed-rules
if (education.verylow) then (age.high) Confidence = 942.340088 / 1279.000732 Confidence (%) = 73.677841
if (smoking.medium) then (age.high) Confidence = 1355.800903 / 1850.998291 Confidence (%) = 73.247009
if (norton.veryhigh) then (age.high) Confidence = 972.600098 / 1330.000000 Confidence (%) = 73.127823
if (education.verylow smoking.medium) then (age.high) Confidence = 358.600037 / 485.050110 Confidence (%) = 73.930511
if (education.verylow drinking.high) then (age.high) Confidence = 339.109833 / 456.009766 Confidence (%) = 74.364594
if (education.verylow bmi.medium) then (age.high) Confidence = 458.209961 / 624.309937 Confidence (%) = 73.394623
if (education.verylow norton.veryhigh) then (age.high) Confidence = 246.490021 / 335.230011 Confidence (%) = 73.528625
if (smoking.medium drinking.high) then (age.high) Confidence = 490.800049 / 669.100647 Confidence (%) = 73.352203
if (smoking.medium bmi.medium) then (age.high) Confidence = 681.200073 / 924.200745 Confidence (%) = 73.706940
if (smoking.medium norton.veryhigh) then (age.high) Confidence = 373.649902 / 507.100342 Confidence (%) = 73.683624
if (drinking.high norton.veryhigh) then (age.high) Confidence = 344.800049 / 468.250000 Confidence (%) = 73.635887
if (norton.veryhigh mews.medium) then (age.high) Confidence = 378.850037 / 518.250000 Confidence (%) = 73.101791
if (smoking.medium drinking.high bmi.medium) then (age.high) Confidence = 252.199936 / 339.000000 Confidence (%) = 74.395264
```

Table 14 – List of association rules of interest

6. Conclusions and future work

Recent research has demonstrated the utilization of association relationships between demographic data attributes and health data attributes in managing the medical condition of elderly patients. For example, some studies have used the relationship of the Norton scale, Age and BMI for predicting prognosis in elderly patients undergoing medical treatment (Rabinovitz et al., 2016) while other studies used the relationship of MEWS, gender, medications and age for predicting the mortality and morbidity of elderly patients. None of these studies considered finding the association relationships between the combinations of the demographic factors, health factors and the behavioral factors.

This paper demonstrates the Proof of Concept (POC) in integrating a non-invasive technique based on the wireless IoTs healthcare sensors to monitor and collect the health data attributes of the patient with an e-Healthcare system. The e-Healthcare system provides further analysis of the association relationship between the collected demographic data attributes, health data attributes and behavior attributes by using the FARM approach. With the mined rules discovered by using FARM, all categories of the data attributes are captured into the rules generation process. The invaluable knowledge is not only easy to interpret but also can serve to provide intelligence for the subsequent healthcare prediction service. By setting up an e-Healthcare system and IoTs prototype and going through the data collection phase, data analysis phase and data reporting phase, the empirical study has shown that by using the FARM approach it is possible to discover useful knowledge between the selected data attributes, especially association rules of the commonly used health data attributes in elderly healthcare, such as “Norton” and “MEWS” with other patient information datasets. The discovered knowledge can be useful in preventing delays due to healthcare service escalation or transfer of the critically ill. In fact, fast capture of the vital sign measurements and the rules generated in the above experiment can be easily integrated into e-Healthcare systems to provide prediction of the health status and alerting functions of the healthcare service provision. The study reveals that the overall quality of the elderly healthcare and rehabilitation services can be improved by the deployment of the e-Healthcare system setup. Eventually, it can also enhance patient satisfaction in the domestic healthcare industry.

It is recommended to extend the current analysis of health monitoring attributes to select other useful data attributes such as the patient’s income, addictive behavior, historical medical records and vital clinical observations through further surveys in future research. From another aspect, with the emerging IoTs applications, it is found that there is more and more IoTs health monitoring system deployment in hospitals and clinics. It is believed by leveraging the IoTs technology and the application of e-Healthcare systems, it can not only provide important vital signs measurements instantly but also more health data varieties to support future health or disease association analysis. As long as the association knowledge is discovered, preventive medical services can be applied in time which could save many lives. Last but not the least, as the data in e-Healthcare systems are growing very fast nowadays, further study of Big Data technologies to handle the huge amount of the collected health data records also needs to be considered.

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