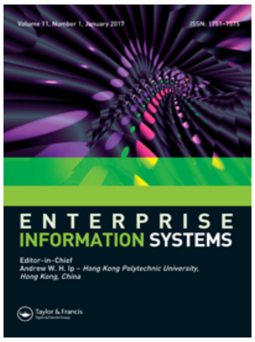

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The design of an m-Health monitoring system based on a cloud computing platform

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Compared to traditional medical services provided within hospitals, m-Health monitoring systems (MHMSs) face more challenges in personalised health data processing. To achieve personalised and high-quality health monitoring by means of new technologies, such as mobile network and cloud computing, in this paper, a framework of an m-Health monitoring system based on a cloud computing platform (Cloud-MHMS) is designed to implement pervasive health monitoring. Furthermore, the modules of the framework, which are *Cloud Storage and Multiple Tenants Access Control Layer, Healthcare Data Annotation Layer*, and *Healthcare Data Analysis Layer*, are discussed. In the data storage layer, a multiple tenant access method is designed to protect patient privacy. In the data annotation layer, linked open data are adopted to augment health data interoperability semantically. In the data analysis layer, the process mining algorithm and similarity calculating method are implemented to support personalised treatment plan selection. These three modules cooperate to implement the core functions in the process of health monitoring, which are data storage, data processing, and data analysis. Finally, we study the application of our architecture in the monitoring of antimicrobial drug usage to demonstrate the usability of our method in personal healthcare analysis.

Keywords: cloud computing; hospital information system; m-Health monitoring system; interoperability; linked data; clinical decision support

1. Introduction

The wide usages of emerging mobile Internet and Internet of Things (IoT) in industries have changed the way that information is acquired, stored, accessed, and delivered (He and Xu 2015; Xu, He, and Li 2014; Perera et al. 2014). This leads to the rise of mobile health (m-Health) systems, which aim to not only enhance the ability of doctors to examine and treat complex diseases at a distance timely but also reduce the infrastructure cost on the hospital's side and the expense on the patient's side effectively. m-Health systems could support various medical services, such as remote health monitoring for at-home senior residents and health data sharing in emergent rescue, which might have been difficult to carry out in the past (Agoulmine, Ray, and Wu 2012; Varshney 2014).

To access timely information and to improve the ability to diagnose and track diseases anytime and anywhere, the adoption of mobile technologies is becoming ideal for the existing

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e-Healthcare systems (Fan et al. 2014). However, the lack of integration and interoperability of the traditional healthcare information systems has hindered the rapidly growing applications of m-Health systems (Kim 2014; Xu, Liang, and Gao 2008). For example, in Shanghai, China, Hospital Information Systems (HISs) have been broadly used in most of the hospitals. The health data collected by medical devices, such as sphygmomanometers, blood-glucose meters, and mobile sensors at home and community hospitals, which reflect people's daily health conditions, can hardly be accessed when patients are transferred to Class-A comprehensive hospitals because there are no platforms for healthcare agencies to share information with each other. Thus, in many cases, patients have to undergo duplicate examinations in one hospital even if they have already undergone examinations in another hospital, thereby increasing costs for patients and delaying therapies.

Cloud computing has the potential to realise data integration and interoperation to achieve pervasive health monitoring because of platform flexibility, operational compatibility, and on-demand service delivery (Choudhary and Vithayathil 2013). Cloud databases have been proposed to provide transparent and secure access for users to heterogeneous databases and various platforms. A four-layer cloud storage architecture is proposed in Huo et al. (2011) to implement a data-intensive application. In Infrastructure as a Service (IaaS) cloud platforms, users are allowed to program the core of their platforms to achieve flexible resource management (Wickboldt et al. 2014). Meanwhile, because software could be consumed in a mode of on-demand pay-per-use on cloud computing platforms, tenant-based resource allocation methods are used to provide remote software consumption in affordable ways to end-users (Espadas et al. 2013). From the above analysis, we could perceive that cloud computing platforms are suitable for m-Health systems to improve system interoperability in affordable ways.

In this paper, a framework of an m-Health monitoring system (MHMS) based on a cloud computing platform (Cloud-MHMS) is proposed to support remote health monitoring, addressing health data integration and interoperation among various medical agencies (e.g. community hospitals and Class-A comprehensive hospitals). The multiple tenant data storage and access method is designed to protect health data security and privacy. We also adopt a linked data model to represent personal health data and their relations. To reduce data heterogeneity and to augment data interoperability, open linked data sources are connected to personal health data to explain the meaning of the data semantically. Process mining and instance similarity calculating methods are implemented to support treatment selection. The prototype of Cloud-MHMS is developed for antimicrobial drug usage monitoring to demonstrate the usability of the proposed method.

The next section discusses related work in health data interoperation and healthcare systems development. Section 3 describes a multilayer Cloud-MHMS framework and explains how cloud computing is more flexible for constructing MHMSs. Section 4 analyses the design and implementation of Cloud-MHMS in detail. Section 5 describes a prototype and its application to demonstrate the usability of the proposed approach in health monitoring. Finally, Section 6 presents the conclusions and future research work.

2. Related work

2.1. m-Health systems and applications

m-Health systems are developed as a synergy of emerging mobile medical services, mobile communication devices, and mobile Internet technologies. Several studies have addressed the construction of ubiquitous information systems (UISs) to support m-Health services in recent years (Touati and Tabish 2013; Varshney 2007). Some works focus on the challenges in the development of MHMSs, especially in interoperation and integration with the HISs.

The IoT-based technologies, together with smart devices and their applications, have been growing steadily in many areas, including in medical services (Xiao et al. 2014). One study (Wamba, Anand, and Carter 2013) provided an overview of RFID technology-based healthcare applications and presented a discussion of current states and future studies in this area. A pilot study on creating a feasible environmental health information infrastructure was presented in Li et al. (2008). A Web-based platform for an environmental health information system that integrates databases, decision-making tools, and geographic information systems for supporting public health services and policymaking was discussed. The paper by Yin, Fan, and Xu (2012) developed a real-time human–machine interface between patients with lower limb paralysis and an extended physiological proprioception (EPP) feedback system to help patients control the exoskeleton. A continuous biomedical signal acquisition system was developed to wirelessly transmit the measurements of signals of body sensor networks to improve the prevention and early diagnosis treatment of chronic diseases. The research showed that m-Health systems were efficient for long-term monitoring (Li, Xu, and Wang 2013). Another study (Maass and Varshney 2012) proposed a conceptual-level method to guide the construction of UISs, thereby enhancing the communications between patients and healthcare professionals to reduce adverse drug events. The proposed method was empirically evaluated, leaving some issues open for further exploration. The article by Al-Bashayreh, Hashim, and Khorma (2013) analysed the context-aware technology in a mobile patient monitoring system. Research in Al-Bashayreh, Hashim, and Khorma (2013) systematically reviewed a context-aware method and its application in the biomedical informatics domain. Context-aware mobile patient monitoring was proven to have potential in m-Healthcare areas, but more detailed works need to be performed due to the immaturity of context-aware technology in practice.

Coexistence and interoperability are important non-functional performances measuring the compatibility of practical enterprise information systems (Niu et al. 2014; He and Xu 2014; Xu 2015). However, ensuring effective m-Health system interoperability with other e-healthcare applications is a significant challenge. Although a number of information systems have been developed to improve the efficiency of medical services and to support making better clinical decisions (Xu and Li 2000; Rahulamathavan et al. 2014; Mattila et al. 2012), interoperation across various enterprise systems is still difficult owing to the complexity of enterprise information systems development in practices including healthcare industries (Hoyland et al. 2014; Xu 2011; Wang and Xu 2008). Research in Yang et al. (2014) designed and implemented an intelligent home-based platform, named iHome Health-IoT, which seamlessly integrated IoT devices (e.g. wearable sensors and intelligent medicine packages) with in-home healthcare services to improve user experience and service efficiency. In Alinejad, Philip, and Istepanian (2012), to improve the compatibility of broadband networks, a cross-layer approach for real-time ultrasound video streaming interoperation over mobile Worldwide Interoperability for Microwave Access (WiMAX) and High-Speed Uplink Packet Access (HSUPA) networks was proposed for m-Health systems. An overview of an m-Health application in Brazil showed that the lack of compliance of health data handling with general regulations was the primary reason for the insufficiency of security that furthermore hindered the deployment of m-Health systems (Iwaya et al. 2013).

2.2. Current research in cloud-based m-Health systems

In several applications, cloud computing is regarded as an effective platform for end-users to achieve pervasive data access (He, Yan, and Xu 2014; Tao, Zuo, et al. 2014). In the manufacturing industry, cloud computing was adopted to realise on-demand use and efficient sharing of available resources (Tao, Cheng, et al. 2014). Cloud computing combined with robotic systems was explored to conduct intensive information fusion in avionics fields (Liu et al. 2014). The combination of cloud computing and IoT was considered as an efficient solution for the integration of different enterprise systems (Cai et al. 2014; Wang, Bi, and Xu 2014; Chi et al. 2014; Wang et al. 2014). The case study in logistic management (Chen, Chen, and Hsu 2014) showed that the efficiency of the logistic systems could be improved through using virtual Web servers together with IoT devices offered by cloud service providers.

Because more services are developed and released to consumers in the cloud platform, researchers not only focus on the development of cloud-based information systems for IoT-oriented applications but also emphasise the evaluation of the quality of services and the negotiation mechanism of services operating within the cloud computing environment (Zheng et al. 2014a; 2014b).

In the medical industry, cloud computing can potentially control costs for patients acquiring healthcare services (Sultan 2014). A private cloud platform was implemented to support ubiquitous healthcare services. Message queues under the publish/subscribe mechanism were adopted to share semi-structured or unstructured medical data among patients and doctors. The testing results showed that the cloud platform is robust, stable, and efficient for ubiquitous healthcare services (He, Fan, and Li 2013). Bahga and Madisetti (2015) reasoned that the integration and analysis of massive Electronic Health Record (EHR) data contribute significantly to improving prediction accuracy and decision-making efficiency. A cloud-based information integration and informatics (III) framework was designed to show that cloud computing platforms allow easier access and efficient analysis of distributed healthcare data.

In the practical applications of healthcare systems based on cloud computing and IoT, data security is one of the most concerned issues, especially for m-Health monitoring. A biometrics approach was explored to use the human body's intrinsic characteristics to ensure the security of the wireless networks used in m-Health systems (Poon, Zhang, and Bao 2006). Industry and government security best practices regarding privacy and security issues arising in m-Health systems were discussed. The security engineering process was designed to develop security architectures for organisations in compliance with the privacy and security legislation of governments (Harvey and Harvey 2014).

All of the above-mentioned works show that m-Health systems have grown fast in recent years. Cloud computing and IoT enable the development and deployment of flexible, portable, and affordable m-Health systems to improve the quality of healthcare services. Much research still remains to be performed regarding the integration and interoperability of different healthcare systems and heterogeneous health data.

3. Cloud-computing-based software architecture of MHMS

The proposed architecture of the cloud-computing-based m-Health Monitoring System (Cloud-MHMS) is divided into three layers, namely the *Cloud Storage and Multiple Tenants Access Control Layer, Healthcare Data Annotation Layer*, and *Healthcare Data Analysis Layer*, as shown in Figure 1.

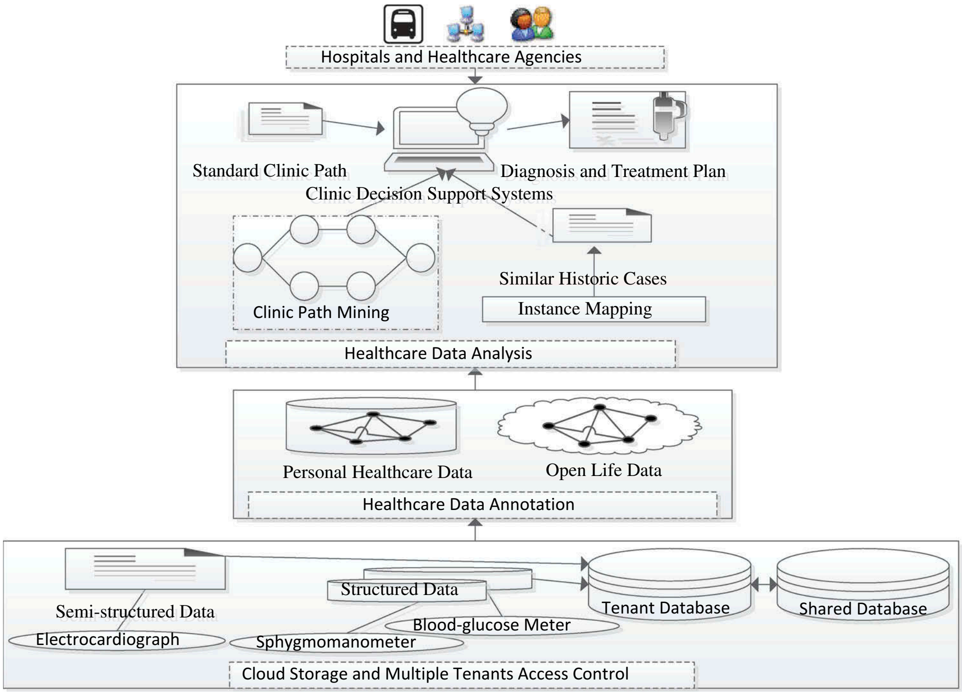

Figure 1. Architecture of Cloud-MHMS.

The *Cloud Storage and Multiple Tenants Access Control Layer* stores healthcare data measured by smart devices such as sphygmomanometers, blood-glucose meters, etc. in patients' daily activities. To ubiquitously access these data for remote healthcare monitoring, the cloud framework is adopted in our research to collect and organise patients' related data. Healthcare data could be transferred to the cloud side through the Internet. To guarantee security and protect the privacy of patients' data, multiple tenant access control is designed to realise data isolation and sharing.

The *Healthcare Data Annotation Layer* solves the problem of data heterogeneity encountered in healthcare data processing. Because medical services are carried out by various hospitals, data generated by HISs are often heterogeneous. This leads to the difficulty of automatic healthcare data understanding among different medical agencies. For instance, the lab reports of patients in one hospital usually cannot be understood by information systems of other hospitals. If healthcare data cannot be interoperated between different HISs, reduplicated medical examinations will reduce the efficiency and increase the cost of medical service delivery. Therefore, semantic healthcare data fusion is crucial for data analysis. In this research, open Linked Life Data (LLD) sets are used to annotate personal healthcare data to integrate dispersed data in a patient-centric pattern for further cloud application.

The *Healthcare Data Analysis Layer* analyses healthcare data stored in the cloud to support personal clinical decisions. In clinical decision support, similar historic cases are useful experiences for treatment plan selection. In Figure 1, process mining algorithms are used to induce clinic paths from personal healthcare data. The similarity calculation formula is designed to compare patients' healthcare data to choose similar patients from historic cases. Medical services are encapsulated and dynamically assigned to carry out medical services if emergency situations are monitored. If abnormal data are detected, patients could be informed to take the right actions, and medical service resources, such as ambulances, would be sent to take rapid responses to the health monitoring systems.

The proposed framework can be implemented to meet different healthcare demands based on service-oriented architecture (SOA) and cloud computing platforms on which medical resources could be encapsulated as configurable Web application services.

4. Design and implementation of cloud-MHMS

The healthcare monitoring system based on the proposed architecture can help doctors monitor and assess patients' health situations by delivering healthcare data from patients to doctors through Web services on the cloud computing platform. According to the proposed framework, four function modules, depicted in Figure 2, that facilitate healthcare data management and application are designed in the Cloud-MHMS system: multi-tenant data storage, data annotation, data analysis, and clinical decision support. The process of m-Health monitoring in Cloud-MHMS includes the following steps:

(1) Multi-tenant Data Storage. With the application of wearable and smart medical devices, measurements, such as blood pressure, glycaemic index, and electrocardiogram, could be monitored out of hospitals by mobile devices. These data are transferred to the cloud side for data remote access and stored in the tenant database, isolated from each other to protect patients' privacy.

(2) Data Annotation. Owing to the heterogeneity of data formats used by various medical devices, health data lack interoperability among distributed healthcare agencies that provide medical services. To share the healthcare data among different medical organisations, it is better to annotate them semantically. Ontology is an often-used method to eliminate data heterogeneity in enterprise information systems (Panetto, Dassisti, and Tursi 2012), but it is difficult to construct a large-scale ontology system to meet the need of large healthcare data. Hence, in this research, the link data model, proven effective in semantic net searching, is adopted to explain the meaning of the data stored in the databases.

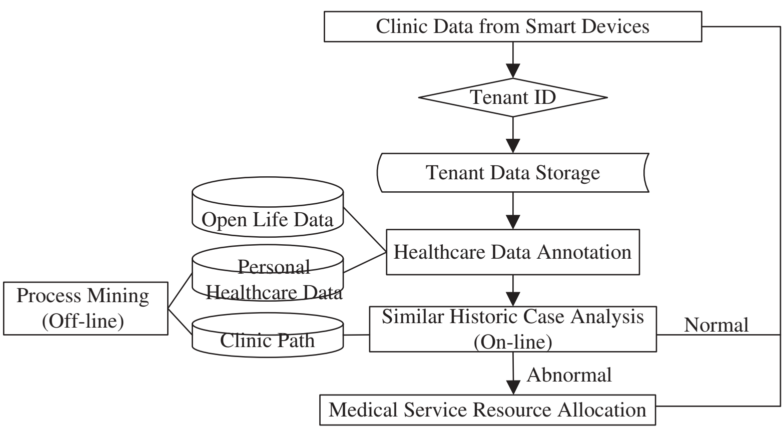

Figure 2. Process of m-Health monitoring in Cloud-MHMS.

(3) Data Analysis. Data analysis includes offline and online analysis. The objective of the offline analysis module is to discover domain knowledge hidden in historic diagnoses and treatment cases. Process mining algorithms are used to analyse the clinic paths for later reference of disease treatment and medicine usage. The goal of online analysis is to assess the health condition of the monitored patients. Although health conditions could be automatically assessed according to the medical rules stored in knowledge bases, owing to the difficulty in transferring human experiences into medical rules (Xu and Li 1993; Kong et al. 2012), case-based reasoning is more useful than rule-based method in clinical decision support. Therefore, the case-searching algorithm is designed in Cloud-MHMS to find similar patients and to compare the current treatments with the clinic paths of similar patients. If differences are found, alarms will be sent to the agencies for adjustment.

(4) Medical Service Resource Allocation. Medical resources are insufficient to meet the needs of high-quality medical services. Therefore, dynamic on-demand medical service resource allocation is crucial to improve the efficiency of medical service delivery. In the proposed Cloud-MHMS, if the monitored individuals are detected being in abnormal health conditions, on-hand medical resources, such as ambulances, drivers, and nurses, will be displayed to decision-makers in emergent medical situations.

In this part, the design of the methods of *Multi-tenant Data Storage, Data Annotation*, and *Data Analysis* will be discussed in detail.

4.1. Design of multi-tenant data storage

To protect patients' privacy while achieving ubiquitous data access in the cloud platform, multi-tenant data storage is designed to store patients' clinical data. The goal of the use of multiple tenants is to protect patients' data privacy while providing virtual storage spaces for healthcare agencies, such as elderly homes, because most elderly homes are not professional in maintaining large amounts of daily health data generated during the activities of healthcare, especially for those who are in poor health conditions.

In multi-tenant data storage, isolation is one main strategy to gain data security. Isolation could be implemented in three ways: isolated database, shared database with isolated data table, and shared data table with isolated data access. Isolated database has the highest level of data security, but it has a relatively high space complexity in data storage and access. Shared data table has the lowest data security, but it is efficient in data storage and access. Isolated data table is a compromise solution to data security and data access.

In our architecture of Cloud-MHMS, shown in Figure 3, considering the efficiency and security of data access, two-level tenants are defined. Tenants in the first level are assigned to healthcare agencies. In this level, isolated databases are adopted to isolate data generated by one healthcare agency from those generated by other agencies. Using isolated databases, the security of data access will be ensured by the authorised healthcare agencies. In the second level, tenant IDs are assigned to individual patients. Shared tables are used to store data generated by the same healthcare agencies. Only authorised users could access the clinical data of particular patients related to tenants. Owing to the huge amounts of patients needing healthcare services, shared tables in this level would allow accessing data more quickly compared with isolated databases or isolated tables.

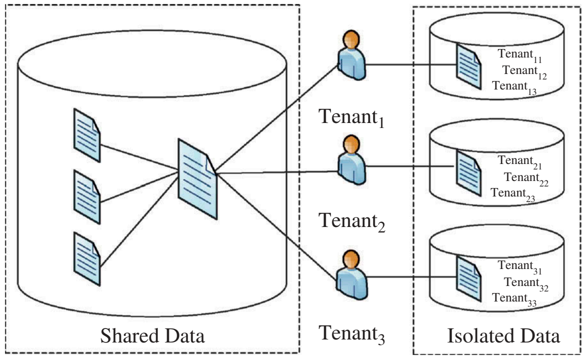

Figure 3. Isolated and shared data in multi-tenant storage.

To store common domain knowledge, including vocabulary, available medical service resources, standard clinic paths for disease treatment, and user authorities for the healthcare agencies, shared documents are established in Cloud-MHMS.

4.2. Data model and data annotation

The health conditions of patients are usually monitored based on physiological indices, such as blood pressure, temperature, and heart rate. Health conditions could be assessed by overall consideration of these measurements. However, due to the insufficiency of medical service resources, doctors hardly have enough time to analyse these measurements carefully for daily healthcare monitoring, sometimes causing the delay of diagnosis and treatment. In this research, we try to describe relations between physiological indices and the diseases using the directed graph *Physiological Indices and Diseases relationship Graph* (*PI–D*) based on the linked data model and annotate the physiological indices through open life data sources to enhance the interoperability of healthcare data.

A *PI–D* is a directed graph $\{V,E\}$, as shown in Figure 4. Vertices in V represent the values of physiological indices or names of diseases. Each acre in *PI–D* means that a disease is related to a measurement associated with a certain physiological index.

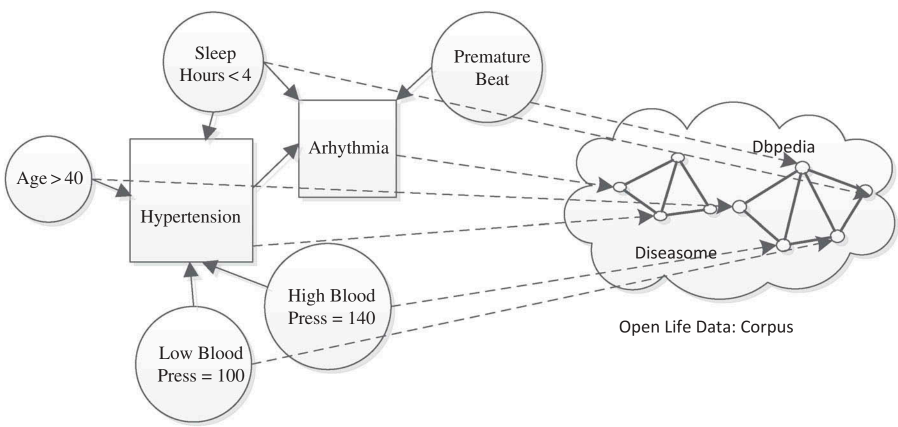

Figure 4. A PI–D graph and health data annotation.

In Figure 4, relations between physiological indices and diseases are described. Figure 4 shows that *Hypertension* and *Arhythmia* are related, such that if one person has *Hypertension*, then physiological indices related to *Arhythmia* need to be monitored more carefully.

In the *PI–D* graph, although physiological data and disease names are related to each other, they can hardly be understood automatically in relation to each other because of data heterogeneity and lack of semantic data descriptions. Corpuses are often considered as common vocabulary references to different format documents. Because personal health data are dispersed in a completely open cloud environment, it will be inefficient and difficult to construct and maintain a centric corpus for health data annotation. Thus, in Cloud-MHMS, we explore using the linked data model and open life data sets to annotate personal healthcare data semantically. As depicted in Figure 4, the open linked data sets *Diseasome* and *Dbpedia* are referred to explain the meaning of the symptoms and diseases for healthcare data interoperation.

4.3. Health data analysis

The data analysis module includes two major parts: clinic process mining and similar patient searching.

Clinic process mining obtains disease treatment paths from historic cases using the α algorithm (Van Der Aalst, Weijters, and Maruster 2004).

In disease treatment, physiological indices are important criteria for doctors to assess patients' conditions to choose appropriate treatment actions. The process of disease treatment is often a time series of treatment actions and physiological indices.

We define the composition of treatment actions and physiological indices as events of disease treatment. For instance (drug, temperature) could be defined as an event in the disease treatment. Then, the time series of actions and physiological indices constitute the event sequences of clinic paths.

We denote a as an action in treatment processes, b as a physiological index value of the patient, then $c_i(a_i, b_i)$ stands for the ith event in the disease treatment. A clinic path C is defined as follows.

$C = \{c_i(a_i, b_i)|a_i \in A, b_i \in B,$ A is the action set, B is the physiological index set, $i = 1, 2,\ldots,n\}$

In the process mining method, clinic path C could be represented by a Petri Net $\{P,T, C,D,U\}$. P represents the place set in the treatment, which are the values of the physiological indices. T is defined as a transition set, which are the events in the treatment. C is the set of directed edges from places to transitions, which means the transition from events of medical services to the health conditions of patients. D represents the length of time of the transitions, which refers to the duration of the events. U is the resource set involved in the medical processes.

Similar patient searching is essential for case-based decision support. Generally, it depends on the calculation of patients' similarities.

Patient similarity is defined as semantic distances between concepts used to describe the symptoms and diseases in patients' health data. If two persons have high symptom and disease similarities, then their treatment plans may be valuable for referring to each other.

In this research, we use formula (1) to calculate the similarity between two patients (Jeh and Widom 2002).

$$\mathrm{Sim}(c_1, c_2) = \begin{cases} 1, \mathrm{if\,dis}(c_1, c_2) = 0 \\ \frac{e^{\mathrm{dis(root,LCA)}}}{e^{\mathrm{dis(root,LCA)}}+1}\left(-\log_{2\mathrm{H}}\frac{\mathrm{dis}(c_1,c_2)}{2\mathrm{H}}\right), \mathrm{otherwise} \end{cases} \quad (1)$$

where $0 \leq \mathrm{dis}(c_1, c_2) \leq 1$, $\mathrm{dis}(c_i, c_i) = 1$.

In formula (1), LCA denotes the least common ancestor node of concepts c_1 and c_2. $\mathrm{Dis}(c_1, c_2)$ is the semantic distance of the concepts of c_1 and c_2 that appeared in the health data of the compared patients, respectively. H is the height of the classification tree.

4.4. Implementation of Cloud-MHMS

The class diagram of the whole system is shown in Figure 5. Class *TreatmentRecommender* provides a treatment recommendation function to end-users to support medical decision-making.

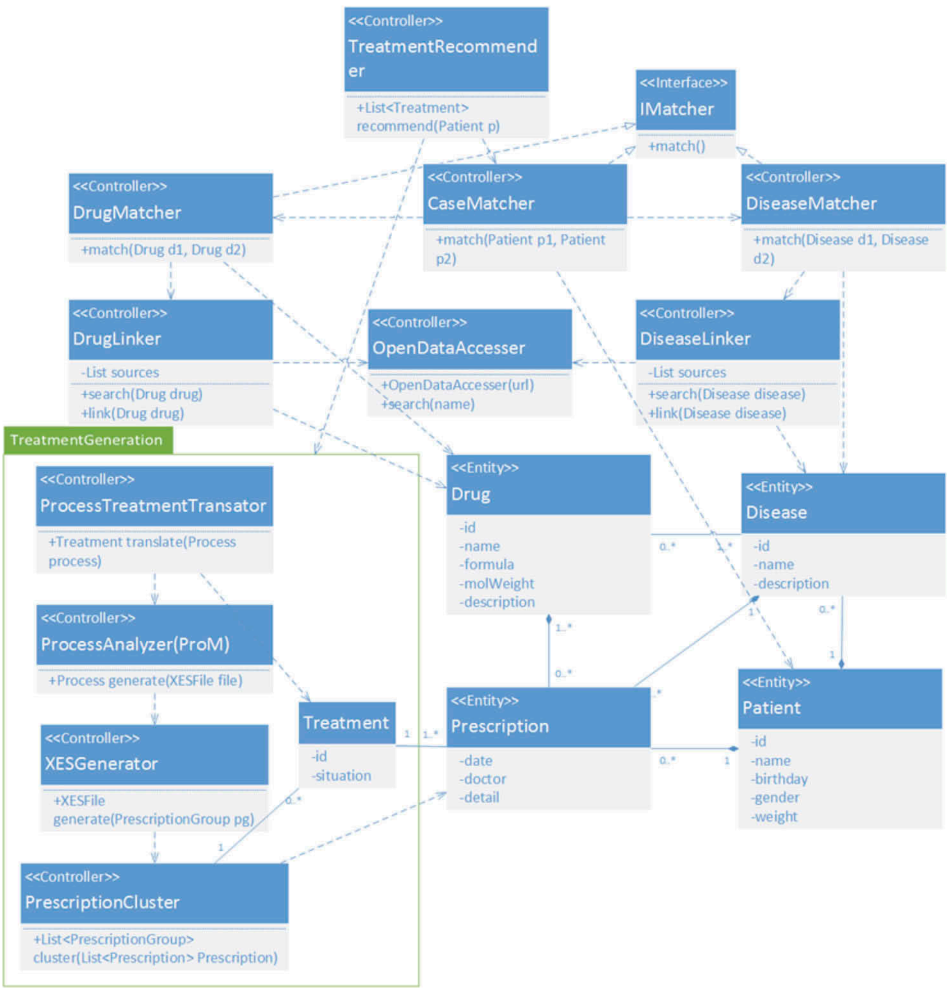

Figure 5. The class diagram of Cloud-MHMS.

As shown in Figure 5, the treatment advices are created by the *TreatmentGeneration* module, which consists of three classes: *PrescriptionCluster, XESGenerator*, and *ProcessTreatmentTranslator*.

PrescriptionCluster groups the *Prescription* records from the databases into *PrescriptionGroups*.

XESGenerator translates the records in a *PrescriptionGroup* into the form of an *XES* file.

ProcessTreatmentTranslator translates the process generated by *ProM* into medical treatments.

Through the *treatment generation* module, clinic paths for different diseases are mined from raw prescription records. Patients with specific diseases are related to clinic paths through prescriptions of the patients.

The *IMatcher* interface, which is implemented by three classes – *DrugMatcher, CaseMatcher*, and *DiseaseMatcher* – is designed to compare two different instances (i.e. records of two different patients) by calculating their similarity. *CaseMatcher* helps *TreatmentRecommender* to determine which historic medical record is most similar to the current patient so that the same clinic path could be referred to in clinical decision-making. The classes of *DrugMatcher* and *DiseaseMatcher* are used to assess the similarity of two patients from the viewpoints of drugs and diseases, respectively.

Medical domain knowledge is needed to match different drugs or diseases. As mentioned in Section 4.3, open life data sets are conjoined to provide medical domain background knowledge to those data recorded in the Cloud-MHMS system. This is displayed through the *IOpenDataLinker* interface and jointly implemented by *DrugLinker* and *DiseaseLinker*, which, respectively, link to drug descriptions and disease definitions in open life data sources, such as *DrugBank* and *Diseasome*, accessed by the *OpenDataAccesser* class.

For each patient, the system will record his/her name, birthday, gender, etc. as basic information. The diagnosis, symptoms in prescriptions, and lab tests could be recorded by doctors in community hospitals. Some related health data can also be collected through IoT-connected medical devices. These data can be viewed by the doctors in the comprehensive hospitals using the Cloud-MHMS to realise cooperative healthcare monitoring.

5. Case study and discussion

The Cloud-MHMS platform is an m-Healthcare prototype composed of a couple of software services that address the most common m-Healthcare application requirements, such as remote data access, health data security, data interoperability, and clinical decision-making support. The Cloud-MHMS platform is an effective e-Health SaaS solution that provides the tools to facilitate the collection, storage, and analysis of personal healthcare data. Using the Cloud-MHMS platform, General Practitioners (GPs) can access not only inside-hospital patients' data but also outside-hospital and in-other-hospital patients' data if they have the requisite permission.

5.1. Scenario analysis of multi-level health monitoring

With the limitation of medical service resources, in Shanghai, China, more routine health monitoring activities are assigned to doctors in community hospitals guided by those in Class-A comprehensive hospitals, which deliver advanced clinical care, scientific research, and medical education, to achieve multi-level health monitoring. The

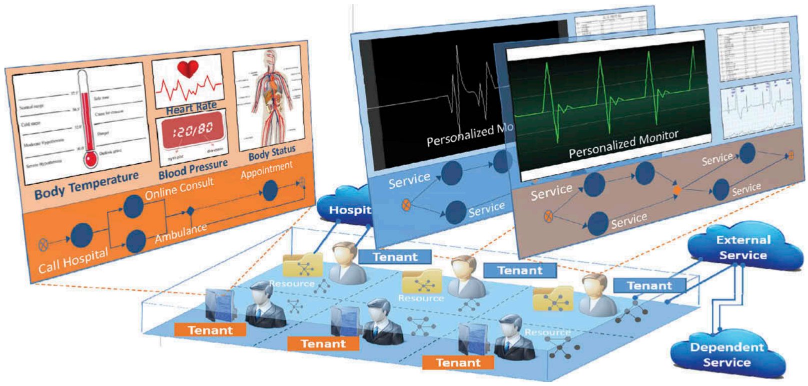

Figure 6. Application mode for health monitoring based on Cloud-MHMS.

scenario of this type of application, supported by the Cloud-MHMS platform, is illustrated in Figure 6.

The application model depicted in Figure 6 is also called *Cloud Hospital*, which has attracted much attention from researchers and participants in the areas of medical services in recent years. Cloud hospitals and cloud-based m-Health monitors take advantage of cloud computing to meet the rapidly growing requirements for m-Health monitoring of residences and health data sharing between community hospitals and Class-A comprehensive hospitals. Cloud-based m-Health monitors are especially helpful for users who are unavailable or find it unnecessary to visit doctors in Class-A comprehensive hospitals.

As shown in Figure 6, physiological indices measured by devices such as blood-glucose meters are transferred to the server side of the Cloud-MHMS platform. The Cloud-MHMS platform compares the personal data to the similar historic cases to assess the monitored individuals' health conditions out of hospitals. If abnormal symptoms are detected, the medical service resources available will be allocated from allied hospitals to provide the required services.

In the multi-level diagnosis and treatment shown in Figure 6, three types of roles are involved in cloud-based healthcare monitoring. They are individual patients, community hospitals, and Class-A hospitals. In this case study, we take antimicrobial drugs usage monitoring as an example to demonstrate the usability of our method in personal healthcare analysis.

Community hospitals help hospitals to provide health monitoring to people who need frequent healthcare services. For example, seniors in Shanghai are encouraged to request medical services from community hospitals, especially for chronic diseases.

Individuals will be guided by the Cloud-MHMS to take daily healthcare services from community hospitals. The Class-A comprehensive hospitals only respond to the patients transferred from community hospitals or transferred by the Cloud-MHMS in emergent situations.

With Cloud-MHMS, patients could choose to store their health monitoring data affordably in scalable data spaces. It is possible for medical administration institutions to dynamically deploy the public medical resources in an area to provide, as much as possible, higher-quality healthcare services to residences.

5.2. Case study of antimicrobial drug usages monitoring using Cloud-MHMS

Antimicrobial resistance has become a global and grave problem partly caused by the abuse or misuse of antimicrobial drugs by doctors who are not experienced in personal treatment plan making for certain diseases. If data related to antimicrobial drug usage could be shared across different hospitals, it could be helpful for doctors and patients to reduce antimicrobial resistance to a certain extent.

In this section, the application of Cloud-MHMS in antimicrobial drug usage monitoring is demonstrated from the health data annotation phase to the health data analysis phase, including process mining and similar patient searching for clinical decision support.

Figure 7 illustrates the annotation of personal health data using the open data sources *Drugbank* and *Depedia*.

In Figure 7, the health data of *patient:10081* is organised and displayed in linked data format. Figure 7 illustrates that *patient:10081* has caught disease *bronchopneumonia*. The meaning of the disease *bronchopneumonia* could be annotated by the concept *depedia: bronchopneumonia* in open linked data *Depedia*. Using this annotation, *patient:10081* could be semantically connected by SPARQL (Buil-Aranda et al. 2013) to other patients who are also related to the vocabulary entry of *depedia:bronchopneumonia* in *Depedia*.

Figure 8 uses the plug-in α algorithm of ProM to discover clinic paths for certain disease treatments.

In Figure 8, the practical clinic path of using an antimicrobial drug to treat the disease *bronchopneumonia* is mined from historic treatment plans. Note that several antimicrobial drugs are combined in the therapy. The treatment process is composed of several sequences of medical service activities so that process mining methods are suitable for healthcare monitoring data analysis.

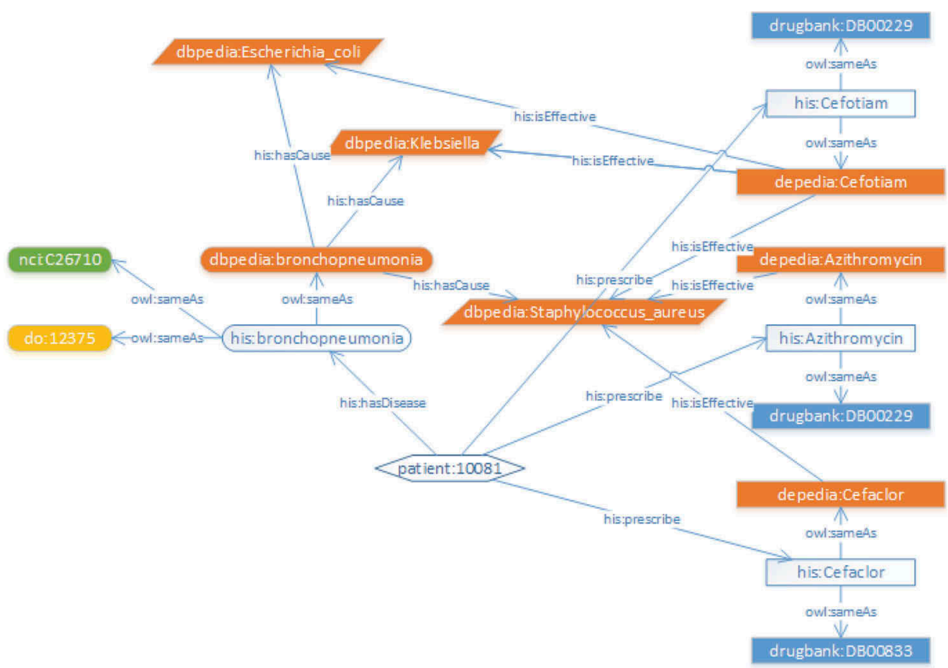

Figure 7. Health data annotation.

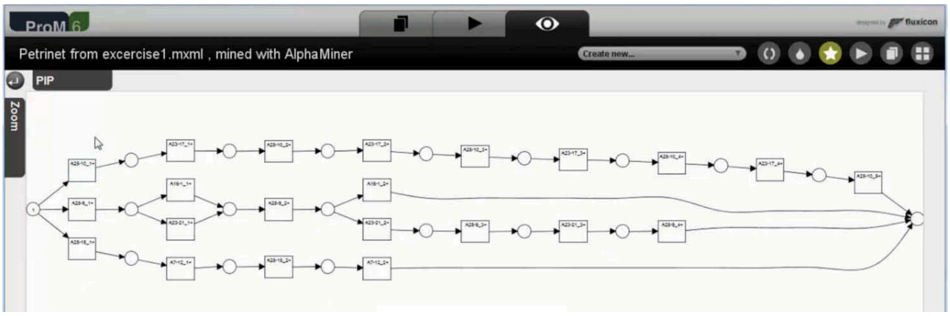

Figure 8. Clinic path mining.

Figure 9. Decision support based on similar historic cases and medical service resources allocation.

Figure 9 demonstrates how to support clinical decisions by referring to similar historic medical cases and dynamically allocating medical resources.

In Figure 9, the basic information of patients, such as gender, date of birth, etc., are displayed. The symptoms and diagnosis are also accessed through the Internet so that the doctors in community and Class-A comprehensive hospitals can monitor and assess the health conditions of the patients. In Figure 9, the diagnosis is *J18.0 bronchopneumonia*, and the symptoms in this case include *fever* and *cough*. This information, including lab test results, could be shared through the cloud computing platform when patients are transferred from one hospital to another.

In Cloud-MHMS, the algorithm is designed to calculate patient similarity for clinical decision support. In Figure 9, the patient *ID 1237* is selected as a similar instance with a similarity value of *0.73*. The treatment process and the status *cured* are displayed for doctor reference. To make full use of limited medical resources, the available quantity and position of the apparatuses and ambulances for emergent medical services are listed in the interface of *Personal Health Data Analysis* in Figure 9.

5.3. Discussion

The topics regarding mobile technology, IoT, and big data analysis based on cloud computing have attracted much attention from researchers and practitioners in the healthcare industry. Various m-Healthcare systems have been proposed and developed to support daily health monitoring or emergent medical rescuing. We discuss the performances of scalability, security, mobility, interoperability, flexibility, clinical decision support, and users oriented in m-Healthcare systems by comparing our method, Cloud-MHMS, with several other m-Healthcare platforms. The comparisons are shown in Table 1.

It could be found in Table 1 that the mobility of delivering healthcare services has been improved by adopting smart devices such as RFDI, smart phone, etc. together with wireless networks, transforming data from the patient's side to the hospital's side. Meanwhile, the complexity of the health data environment has been increased greatly because smart devices have generated huge amounts of diverse data related to varied physiological indices. Therefore, the performances concerned with huge data storage and analysis, such as scalability and interoperability, have gained increasing attention from designers in the development of m-Healthcare systems.

In m-Healthcare systems, the decision support functions are crucial to end-users. Numerous methods have been explored to augment the clinical decision support ability of m-Healthcare systems. Knowledge-based technologies, such as rule-based reasoning in Chen et al. (2012) and ontology-based context analysis in Lee and Kwon (2013), have been considered effective to some extent to support decision-making using explicit domain knowledge.

Table 1. Comparison with other methods.

	Cloud-MHMS	Knowledge-based System (Chen et al. 2012)	Ontology Model-based System (Lee and Kwon 2013)
Scalability	High, Cloud Computing	Medium, Component-based Framework	Low, Embedded System
Security	Medium, Tenant Isolation	Not Discussed	Not Discussed
Mobility	High, Cloud Computing	High, Mobile Devices and Wireless Network	High, RFID
Interoperability	High, Open Linked Data	Low, Component-based Framework	Low, Embedded System
Flexibility	High, Service Oriented Architecture	Medium, Component-based Framework	Low, Embedded Devices
Clinical Decision Support	Medium, Process Mining and Case-based Reasoning	Medium, Rule-based Reasoning	Medium, Ontology and Context Management
Users Oriented	Allied Healthcare Agencies	Special Hospitals Using Smart Medical Devices	Smart Home-based Healthcare Agencies

However, with the application of IoT technology and smart devices in medical services, rapid data accumulation has brought challenges to as well as opportunities for improving clinical decision support by big data processing methods. Notably, for senior people or patients who have chronic diseases, numerous data generated by routine health monitoring are more significant to clinical decision support. In contrast to the explicit knowledge-based technologies used in Chen et al. (2012) and Lee and Kwon (2013), our method, Cloud-MHMS, tries to mine and share implicit expertise experiences hidden in historic medical cases, which are more intuitive for decision-makers.

6. Conclusion and future work

Providing high-quality medical services to citizens has always been the essential responsibility of many governments. However, the booming requirements of healthcare monitoring, aggravated by the problem of an ageing population, such as in China, are hardly satisfied due to the limitation of public medical resources. Decentralised and general diagnosis is one of the approaches to relieving the contradiction between the growing medical service requirements and limited medical resources by appropriately assigning patients between community hospitals and Class-A comprehensive hospitals. To fulfil diagnosis decentralisation and generalisation, health data sharing and interoperation are key technical points to be addressed.

This research proposes a cloud-computing-based architecture to realise MHMSs for decentralised diagnosis, emphasising personal health data storage and utility. The contributions of this research include the following aspects.

A multiple-level architecture of an MHMS is designed based on cloud computing. The proposed architecture consists of layers of multiple tenant storage, health data annotation, and health data analysis. Health data are collected from smart devices and transferred to the cloud side. The cloud storage provides affordable data space to tenants on-demand through decreasing the cost of maintaining data for both hospitals and patients. A multiple tenant mechanism insulates personal health data from each other to protect individuals' security and privacy.

The data annotation method is proposed to solve the problem of health data heterogeneity and improve the interoperability of personal healthcare data. We use the linked data model to represent health data and connect them to open life data to supply background knowledge semantically in order to improve data interoperability.

For health data analysis, we introduce process mining and similar patient searching algorithms to support personalised treatment plan selection. The plug-in α algorithm of ProM is adopted to discover clinic paths for certain diseases. A similarity calculation formula is designed to choose similar historic treatment plans, and then the similar plans are recommended to doctors for references in clinical decision-making.

To carry out medical services in emergencies or to rapidly respond to the transferring of patients from one hospital to another whenever abnormal medical situations are detected, available medical resources are displayed in the proposed Cloud-MHMS system to guide medical agencies to dynamically allocate medical resources.

The case study of antimicrobial drug usages monitoring of the proposed system demonstrates that it offers significant flexibility to meet the requirements of on-demand, out-hospital healthcare monitoring. It also provides an approach to support clinical decision-making under a big data environment caused by the applications of IoT and mobile Internet technologies.

Future research work will focus on the design of cloud HISs associated with m-Healthcare systems and the novel method of health data analysis using the linked data model.

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