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Emerging information technologies for enhanced healthcare

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ABSTRACT

The appropriate collection and consumption of electronic health information about an individual patient or population is the bedrock of modern healthcare, where electronic medical records (EMR) serve as the main carrier. This paper first introduces the main goal of this special issue and gives a brief guideline. Then, the present situation of the adoption of EMRs is reviewed. After that, the emerging information technologies are presented which have a great impact on the healthcare provision. These include health sensing for medical data collection, medical data analysis and utilization for accurate detection and prediction. Next, cloud computing is discussed, as it may provide scalable and cost-effective delivery of healthcare services. Accordingly, the current state of academic research is documented on emerging information technologies for new paradigms of healthcare service. At last, conclusions are made.

1. Introduction

Healthcare covers complex processes of the diagnosis, treatment, and prevention of disease, injury, and other physical and mental impairments in humans. The patients' consumption of products and services provided by hospitals and other institutions forms the healthcare industry. The healthcare industry is especially fastest-growing part of the economy of many countries in modern society, not only the more economically developed countries like those in Western Europe and North America, but also in areas of high growth, such as China and India.

The proper collection, management and utilization of health information play a critical role in detecting medical problems [5] and identifying innovative solutions and allocating resources [1] to treat patients. Information technologies are widely employed to improve the quality of healthcare services [4]. In the evolution of those improvements emerging technologies are not only used anymore for the general management of health systems, such as those in used in hospitals and clinics, but they are also focused on development and implementation of other solutions, such as those for rehabilitation purposes and for prevention, e.g. using serious gaming. Moreover, technologies are not solely used anymore for therapeutic purposes, but analysis using big data and cloud computing can reveal trends and can be used predictive medicine. Additionally, the enormous increase of the number and capabilities of sensors and smart sensor systems vastly increases the possibilities of generation and usage of data. Existing methodologies for the detection and analysis of medical conditions can and will have to be revised and extended. In healthcare times are truly changing due to emerging information technologies.

The enhancements that emerging information technologies offer are not only really necessary, but could not have come at a better time also. The cost relating to the demographic changes of an ageing population in industrialized nations is expected to place a significant burden on healthcare systems and economies [99,100]. In the near future the number of retired people (with an increased life expectancy [103]) will approach the number of working people worldwide [104] and the shrinking workforce will probably not be able to sustain the current level of support to elderly.

This paper first surveys the emerging state-of-the-art information technologies for enhanced healthcare and tries to provide insight on how the developments in IT impact on healthcare

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practices. Finally, authors provide a reflection on this challenging field, in a broader context.

2. Emerging medical information technologies

Technology offers possibilities, but also poses challenges. Science is obliged to support this evolutionary process.

2.1. Trends

There are a number of significant technologies and emerging models that are making a big splash on the healthcare information technologies and applications [4–7]. The following trends can be observed:

- *Health sensing:* There's been a sharp incline in the quantity and variety of consumer devices and medical sensors that capture some aspect of physiological, cognitive and physical human health. The implementation of these technologies empowers the end-users (e.g. chronic patients) by providing means to monitor and record the status continually and, if the need arises, seek remote assistance.
- *Big data analysis in Healthcare:* With the increasing digitization of healthcare, a large amount of healthcare data has been accumulated and the size is increasing in an unprecedented rate. Discovering the deep knowledge and values from the big healthcare data is the key to deliver the best evidence-based, patient-centric, and accountable care.
- *Cloud computing in Healthcare:* With healthcare providers looking at solutions to lower the operating costs, emerging technologies such as cloud computing can provide an ideal platform to achieve highly efficient use of computing resources, simplify management, and improve services in a safe and secure manner. Cloud computing can support the analysis of the big data mentioned above. There is no doubt that the adoption of these innovative technologies in medical fields can create significant opportunities. Nevertheless, many challenges still need to be addressed in order to achieve truly enhanced healthcare services.

It is widely accepted that the high quality healthcare services lie in the effectiveness and efficiency of health problem detection, innovative solution identification, and medical resource allocation, which in turn depend heavily on the proper collection, management and utilization of health information. The aim of this survey is to document state-of-the-art researches and implementations of the emerging information technologies on creating new means to access and use health information and consequently improving the quality, safety, and efficiency of the health care.

Since electronic health records serve as the main carrier of the health information, Section 2.2 gives a brief review on the adoption of EMR (Electronic Medical Record) systems in different countries. The emerging technologies on health sensing, big data analysis, and cloud computing, show tremendous promise on enhanced health information collection, utilization, and management. In Sections 2.3 and 2.4 the current state of academic research and industry implementation on technologies for enhanced healthcare are presented, especially in health sensing and in big data analysis, and Section 2.5 analyses the use of cloud computing as underlying healthcare computing infrastructure. Finally, Section 2.6 summarizes new paradigms of healthcare services enabled by these technologies and makes recommendation for future research.

2.2. Electronic medical record

According to Health Information and Management System Society (HIMSS) Analytics [2] and ISO/TS 18308 standards [3], the medical records of a patient may refer to Electronic Medical Record, Electronic Health Record and Personal Health Record (PHR).

- *Electronic Medical Record* (EMR) is created and controlled by a healthcare institution, e.g. a hospital. It is the legal record of what happened to the patient across inpatient and outpatient environments in the institution.
- *Electronic Health Record* (EHR) is generated and maintained within an institution or community. It is a record in digital format and it is theoretically capable that it is shared across multiple institutions within a community, region, or state. EMR can serve as a data source for the EHR. Once the EMR data are shared with other institution, they become EHR.
- *Personal Health Record* (PHR) is typically a health record that is initiated and maintained by an individual. It provides a complete and accurate summary of the health and medical history of an individual by gathering data from many sources, including EMRs and EHRs.

Since EMRs are the sources of EHRs and EPRs, the adoption of EMRs serves as the foundation for the acceptance of the later two medical data formats. Without loss of generality, this paper mainly focusses on EMRs, the discussion of which can be generalized to EHRs and EPRs.

With the notion that EMRs are the main carrier of electronic health information and the bedrock of modern healthcare, EMR systems are widely deployed for the exchange of medical information among various healthcare related parties [8]. Using United States as the example, the survey in 2009 [9] has shown that only 9.1% of U.S. hospitals had deployed a basic or comprehensive EMR system. While by the end of 2011, according to the National Ambulatory Medical Care Electronic Health Record Survey, the percentage of primary care providers who have practiced EHRs doubled from 20% to 40% between 2009 and 2011. In 2010, the goal was set that by 2014, 80% of physicians should be using EHRs, however recent surveys show that 82% of physicians indicated that they are currently using an EMR system or plan to do so [8]. These numbers are significant because the first step towards widespread adoption of standards-based health IT is simply getting the systems in place and converting the data into an electronic format.

By using EMR as the carrier of medical information, emerging information technologies provide great potential for facilitating research and improving quality in medical practice [6]. This chapter focuses on three most prominent areas, i.e., health data collection, health data analysis and utilization, and healthcare computing infrastructure and subsequently analyses the impact of all of this on healthcare practice.

2.3. Health sensing

The fast development of embedded computing and sensing technologies has opened up new opportunities for pervasive and unobtrusive health data collection [10]. In general, the health sensing technologies [96–98] promise to achieve the real-time monitoring and recording of the patients' health status with high precision, which provide great potential to reduce the cost and inconvenience of patients' visits to the physician. They are considered as a cornerstone technology for the early abnormity detection and intervention and effective management of patients [11].

Based on the provided functionalities, there are mainly two primary types sensors for health data collection [10,96] physiological and motion sensors. The former are used to detect and record the physiological indices or physical states of patients for diagnosis or treatment purpose, e.g., measurement of blood glucose, blood pressure, ECG (electrocardiogram), EEG (electroencephalogram), EMG (electromyography), etc. A variety of unobtrusive wearable devices have been reported, e.g., wireless necklace for ECG measurement [15], the cuff-less and wearable Blood Pressure metres [13], clip-free eyeglasses-based wearable devices for monitoring heart rate and pulse transit time [12], h-shirt-based device for arterial blood pressure estimation [16], wearable photonic textiles for pulse oximetry [17], and a mobile-phone-based device for health monitoring rate and temperature measurement [18]. These embodiments are capable of providing measurements ubiquitously and unobtrusively.

The integration and fusion of multiple biomedical sensors can provide diverse high-level functionalities of health state monitoring. Examples of these are:

- *Heart state sensing:* Heart decease is one of the main causes for sudden death. Sensing and monitoring technologies for heart deceases have attracted great attention from both healthcare industry and information processing societies. Heart signals include heart rate, heart rate variability (HRV), RR, P-QRS duration [19], which can be extracted from the ECG of the patients [20]. An algorithm for accessing the quality of ECGs was proposed in [21], which demonstrated that the quality of captured ECG via mobile phone or wireless sensors is good enough for heart disease diagnosing. Leijdekkers [22] reported a personalized Cardiac Rhythm Management system using a smart phone and a wireless ECG sensor. The system can record and diagnose abnormal cardiac arrhythmias. Cheng [23] reported real-time cardiovascular disease detection on a smartphone, which detected irregular rhythmic beating of the heart to indicate the risks of heart diseases.
- *Sleep sensing:* Sleep is not just a passive process, but also rather a highly dynamic process that is terminated by waking up, which highly reflects the healthy state of people. Researchers have conducted sleep sensing using wearable devices, body sensor networks and mobile phones. Such solutions can be divided into two categories: (1) Sleep sensing by clinical or wearable devices, which needs the user to wear some devices for sleep monitoring [25]; (2) Unobtrusive sleep quality sensing, in which the users do not need to wear any monitoring device [26]. The unobtrusive sleep monitoring is more convenient to users, because a recent site survey [24] showed that most of the people preferred unobtrusive measurement if they are requested to undergo sleep monitoring.

In specific applications and fields complex mathematics in combination with ICT can assist in performing and improving measurements. Examples of these are paper "Fundus image based classification and grading of cataract" and paper "A real time displacement estimation algorithm for ultrasound elastography".

Motion sensors are mainly exploited for people navigation, motion state, or activity estimation. The available sensors for motion can be roughly classified into two categories, i.e., *wearable sensors* and *ambient sensors*. The former achieves motion state estimation without interaction with an external infrastructure, e.g., the accelerator, compass, gyroscope, and inertial measurement unit. The later works with interaction with external infrastructure for measurement of body activity, e.g., Wi-Fi and Bluetooth, infrared, microphone, centre of pressure/gravity, and cameras. Application of motion sensing is presented in at least the following five different areas:

- *Pedestrian location:* An important context for assisting elders living is to be aware of their real-time locations. Implementations for this include existing dead reckoning (DR) methods, using either shoe-mounted IMU [31] or smartphone, and rely on the acceleration signal [32] to locates one's current position according to his/her previous location and motion between two locations.
- *Activity recognition:* Activity recognition plays the key role in posture and activity monitoring of the elderly and the disabled and neurological rehabilitation [33]. The typical algorithms utilizing RGB-D information for action recognition can be categorized into two types, i.e., skeleton-based [33] and depth map-based approaches [34].
- *Falls detection:* Automatic fall detection can reduce the response time between a fall happens and medical treatment, as a result can reduce the probability fatal damage happens due to fall [29]. Existing solutions mainly use accelerometer and gyroscope to get motion information of human, then the thresholding algorithm is designed to distinguish fall according to monitored data [30].
- *Gait analysis:* Gait analysis is to estimate the parameter of feet's motion by wearable sensor, which is very useful for disease diagnosis and mobility evaluation [27]. The parameter of gait includes: (1) step regularity and stride regularity; (2) step symmetry; and (3) cadence. Since gait monitoring requires long-term monitoring and data analysis, body sensor network comprised by wearable motion sensor and smartphone is a feasible choice [28].
- *Balance training:* Balance training plays a fundamental role in rehabilitation for people with poor balance such as the elderly, disabled and those recovering from injury [37]. The typical balance training solutions use visual centre of pressure (COP) feedback measured by a force plates to improve the balance in diverse activities [35–37].

In addition to the existing two main types mentioned above a new type of sensors is emerging: derived sensors. Regular existing sensors measure things like motion and new sensors e.g. measure facial expressions or the sound level of humans in a room. ICT (Information & Communication Technologies) can be used to derive and infer measurements, for example by analysing measures over time or by combining sensory input from different sources ('sensor fusion'). It is also possible to use artificial intelligence in this analysis and with that for example from motion sensor input deduce how long a person has been sitting or even attempt to measure the psychological wellbeing of people ('cognitive sensors').

2.4. Big data analysis in healthcare

Health data describing the phenotypes and treatment of patients covers multiple data sources including medication, laboratory, imaging and narrative data, which are underused and have much greater potential to be unleashed than is currently realized [105].

Actually, it is widely recognized that using diverse data analysis technologies to consume the medical data provides great potential for the healthcare improvement [4,5]. Information Retrieval and Data Mining are two dominant ways for the medical data utilization.

Note that these technologies can be used for two usage categories: first to obtain information for generic use, about groups within the researched population, and secondly to obtain information about specific individuals. The two goals are quite different and implementations of both data storage and of search and query technology differ a lot. An example of the first use is the analysis of large databases to find the cause and spread pattern of the Q fever, with the underlying goal to stop the dispersion of the disease, by using predictive analysis over time and geographical areas. Such an application of technology is necessary given the long incubation period and the seriousness of the disease. An example of the latter is to find 'medical pathways' for individuals in large amounts of apparently unrelated data and use those not only for that individual, but also as input for prevention programmes for other individuals that have very similar pathways. In other fields, such as the retail industry, such usage focused on individual citizens is called 'mass personalisation'.

2.4.1. Medical information retrieval

Information retrieval (IR) is the process of searching within large document collections for the information most relevant to a user's query, which is about finding something or retrieving small subsets of documents that already is part of the available document sets. Note that for IR, the returned information is exactly in the same way it is stored, i.e., there is no value addition to the document sets. The goal of IR is to retrieve the required information as fast as possible and as accurately as possible. The IR in healthcare domain mainly covers medical text retrieval and medical image retrieval.

For medical text search, it is becoming a critical technique for the rapid and effective access of patient information, since the clinical text about diagnosis results, treatment plans and patient summaries is the main body of the EMR. Actually, the medical records track is established in TREC [42]. The medical text retrieval can be seen as a domain-specific text search task, where the big challenge is to deal with the complexity and ambiguity within medical records and queries [41,44]. With the support of standard terminologies or domain ontologies, such as the International Classification of Disease (ICD), Unified Medical Language System (UMLS), and Medical Subject Headings (MeSH), semantic-based text search approaches are widely utilized to tackle the ambiguity problem in medical search. A frequently used mechanism for improving the search quality is query expansion [101] and reformulation [43]. In [38,40], the semantic resources are exploited to represent queries in an expressive and meaningful context, through which to fill the semantic gap among the queries and EMRs and then to improve the medical search quality. Six existing domain-independent semantic similarity measures are adapted to the biomedical domain [39]. By defining the subsumptions as parent–child relationships between concepts, the medical hierarchy is exploited to address the granularity mismatch problem derived from the ambiguous queries [39].

For medical image retrieval, there are mainly two ways to address this task, i.e., text-based and content-based approaches. The former uses the annotated textual information about the medical images for their retrieval. Since the annotated texts describe the content of the associated images, e.g., the present body part, the modality of the image, the disease or abnormity depicted, the available text retrieval approaches can be employed directly to find the relevant images of the given keywords based queries. The typical examples of text-based medical image retrieval systems include *BioText* [45], *Yale Image Finder* [46], *ARRS Goldminer* [47]. Similar to the medical text search, the inherent complexity of medical terminologies make these systems cannot generate expected results. To improve the quality of text-based image retrieval, several researches on using MeSH and UMLS ontologies for query expansion are presented. For example, the authors of [48] demonstrated that the query expansion using MeSH in PubMed can improve the medical image search significantly. By using the MeSH and UMLS ontologies to conduct the query expansion, the study in [49] illustrated the improvement of the text-based image retrieval in the ImageCLEF competition datasets. However, due to the fact that the text-based approach requires manual annotation, which is time consuming and subjective, and they cannot effectively represent the semantic information in medical images. Thus, to support effective image searching, retrieval methods based on the image content were developed.

In the content-based approach, the visual features of the image content are employed for medical image retrieval. For the image indexing, the medical images are represented using automatically generated descriptors, which are usually numerical by nature and are represented as vectors of numbers [50]. For the image search, the user gives a sample medical image, the retrieval is performed by comparing descriptors of the query images to those of all images in the database [52]. Even though colour is one important visual feature for image description, it is not used for medical image retrieval, due to the fact the most medical images are grayscale. Two widely used visual features in medical image search are texture and shape [50,52].

- Texture, is a set of metrics reflecting the spatial organization of pixel values (about colour or intensities) of an image. From the statistical angle, an image texture can be quantified as a measure of the arrangement of intensities in a region. Two widely used approaches are co-occurrence matrices (using spatial relations of similar grey tones to capture numerical features) and edge detection (using the number of edge pixels in a defined region to represent a texture characteristics). Since the semantic details within an image structure is detected for quantifying the perceived features, texture is widely used for medical image search.
- Shape: the shape of a particular region that is being sought out. Shapes will often be determined first applying segmentation or edge detection to an image. After segmentation, the resulting segments can be described by shape features that commonly exist, including those with invariances with respect to shifts, rotations and scaling.

Recently, multimodal image retrieval arises as an active research topic [51]. Multimodal image retrieval is the process of using both text-based and visual-based techniques for retrieval. In multimodal retrieval the user provides textual queries and query images and retrieval should provide an ordered set of images related to that complex query.

This Special Issue contains two examples of the latest developments in this field: paper "Semantic Interoperability of Controlled Vocabularies in Medicine: A Case Study" and paper "Diversity-aware retrieval of medical records".

2.4.2. Medical data mining

Data mining (DM) is the computing task to discover unsuspected patterns from the observational datasets to help users to make better decision [62]. In general, the discovered patterns are novel understandings and represent something hidden in the available dataset that the users did not know before. Different from IR without additional value added to the returning results, the rule of DM is to reveal insight into the data that is not quite obvious. The application of data mining algorithms for medical data analysis and utilization can be classified into two categories, i.e., unsupervised (descriptive) and supervised (predicative) approaches.

The unsupervised methods mainly concern data clustering, i.e., grouping data into clusters by measuring the similarity between objects or EMRs to discover unknown patterns or relationships in the available datasets. The typical unsupervised data mining approaches covers data clustering, association rule mining, and sequence discovery [54].

Based on the NHIRD (National Health Insurance Research Database) dataset from Taiwan National health Insurance, the authors of [56] applied an association rule algorithm and studied the comorbidity of ADHD (Attention Deficit/Hyperactivity Disorder).

The found association rules of psychiatric disorders in ADHD children validate previous research results of the same problem. Since NHIRD dataset contains antacid claim records along with prescription records, all the different use patterns of antacids are analyzed by using association mining to discover the co-prescription patterns [62], the results showed that five most frequently used drug sets with antacids are found. Patient stratification is the division of the patients into multiple groups. The patients in each group have similar characteristics, such as symptoms, prognosis or treatments. The authors of [57] proposed to use a combination of abstracted disease, finding, procedure and medication features to measure inter-case similarity, the experimental results demonstrated that it can potentially help find similar cases from a case base for evidence-based practice. A two-stage analytical approach is proposed in [58] for using EMRs to measure morbidity profile dissimilarity among patient cohorts. The first stage of the approach employed ICD-9 (International Classification of Diseases, version 9) for computing the odds ratios that describe adjusted differences in prevalence between two cohorts, the results of which are combined for the general morbidity dissimilarity index in the second stage. The experiments on nine cohorts of patients illustrated the effectiveness of the proposed approach. Similarly, ICD ontology is used to extract phenotype information from the free-text in EMRs, the structural information contained in the EMRs are extended and utilized for producing fine-grained patient stratification and disease co-occurrence statistics [59].

Supervised data mining usually build models based on prior knowledge gained by training on previously annotated data to predict the outcome of interested new data, i.e., the knowledge of historical data are generalized for the prediction of unpredicted/unclassified data [53]. The typical supervised approaches for medical data mining includes prediction, classification, and regression [54].

The authors of [60] used regression to develop machine learning based models to predict the survival of heart–lung transplant patients. Three variable selection methods, i.e., learning-based, expert-defined, and common sense-based methods, are employed and evaluated by the domain-experts and be considered prior to the organ transplantation. The results indicate that the proposed integrated data mining methodology has better performance than the conventional approaches commonly used in this area. In [61], three popular classifier building approaches, i.e., neural networks, decision trees and logistic regression, are employed to develop a classifier for the prediction of breast cancer survivability. A very large dataset including more than 200,000 cases is used for the comparison study, where 10-fold cross-validation methods is adopted to measure the unbiased estimate of the three prediction models. The final results showed that the decision tree (C5) has the best prediction performance and he logistic regression models came out to be the worst one. The authors of [62] developed the clinical reference information model and physical data model to manage the various information entities and their relationships in traditional Chinese medicine clinical data. Three classification methods, namely support vector machine, decision tree and Bayesian network, are employed to discover the knowledge of syndrome differentiation. Also, the association mining is used to extract the useful acupuncture point and herb combination patterns from the clinical prescriptions.

An example of the use of data mining for predictive usage is paper "Dynamic Risk Model of Coronary Heart Disease for Ubiquitous Healthcare".

When mining for data and retrieving info it is a good practice to store learned info and share this knowledge. An example of an implementation supporting this is paper "OpenClinical.net: a platform for creating and sharing knowledge for decision making and best practice in healthcare".

One of the best practices in healthcare is to use only treatments that are 'evidence based'. This usually implies that the treatment in question has to be tested for quite some time. However, using big data technologies, it is very much possible to deliver a similar level of evidence in a relatively short period of time if the amount of data is big enough. This side-effect of the use of big data can have a profound impact on the way new medicines and interventions are implemented in the health field.

2.5. Cloud computing in healthcare

Health data collection and utilization provides the foundation for evidence-based healthcare with guarantee of the healthcare service improvement [5]. To make the healthcare affordable, many health providers are looking for more innovative solutions for reducing the cost of healthcare delivery [1].

With the emergence of cloud computing technologies, the connectivity allowed by the Internet is exploited to make users have the ability to utilize scalable, distributed computing environments. e-Health cloud has been viewed as an appropriate platform to deploy standard medical information systems for its scalable and cost-effective services delivered by cloud service providers [1,6].

The efforts of building e-health cloud can be grouped into three categories, i.e., (A) health data storage and manipulation, (B) security and privacy protection, and (C) e-health service delivery.

2.5.1. Health data storage and manipulation

Cloud computing presents a great opportunity for healthcare providers to shift the burden of managing and maintaining the complex medical data to the cloud. There have been some research or engineering efforts that exploit the storage and computing potentials provided by cloud to improve the efficiency and effectiveness of the health data storage and management.

The authors of [63] proposed a six-layer cloud platform architecture which utilizes message queue as a cloud engine, and each layer thereby achieves relative independence by this loosely coupled means of communications with publish/subscribe mechanism. The empirical study showed that the implementation of the proposed cloud architecture can support adaptive accessing of massive semi-structure or unstructured medical data, which make it satisfy high concurrent requests from ubiquitous healthcare services. A Cloud-based intelligent hospital file management system is proposed in [64], which aims to improve some of the limitations of traditional hospital management systems, e.g., limited storage capacity of the hardware devices, slow performance of the hardware due to the huge amount of data, and the resource sharing across different platforms. Considering the high volume of medical images is leading to scalability and maintenance issues with existing picture archiving and communication system (PACS) and network, the researches on using Microsoft Windows Azure as the cloud computing platform for the implementation of Medical Image Archive system in the cloud are reported [65]. Similarly, a Medical Image File Accessing System, which is implemented based on Hadoop and HDFS [66], is presented in [67] to solve the exchanging, storing and sharing on medical images across the boundaries between hospitals.

An interesting example of a large multidimensional cohort study and biobank is Lifelines (http://www.LifeLines.net). It is based on a cohort study started in 2006 in the North of the Netherlands and now contains some 165,000 individuals that are followed for 30 years. It covers information on environmental exposures, (epi)genetics, psychological and social factors, as well as data on healthcare use to cover societal impact. Its huge database is very valuable and is available for the international scientific community.

Quite a different approach for obtaining an analysing healthcare data is described in paper "P2Care: A Dynamic Peer-to-Peer Network for Collaboration in Personalized Healthcare Service Delivery".

2.5.2. Security and privacy protection

Security and privacy protection is important for healthcare implementations. Healthcare is about people and they and their treatment require a sufficient level of CIA:

- C = confidentially, the end-user wants to control access to their own health data (this includes the privacy aspect);
- I = integrity, preventing measurements data transfer errors, but also preventing data quality pollution, for example due to commercial activities;
- A = availability, which amongst others includes automatic and secure backups, health data being available to the appropriate health(care) provider on a need-to-know basis (also when the end-user is incapacitated) and resilience upon disruptions. An example of the latest development in the area of availability in healthcare is paper "Impact of Sensor Nodes Scaling and Velocity on Handover Mechanisms for Healthcare Wireless Sensor Networks with Mobility Support".

Security has many aspects, as described in ISO/IEC 27001:2013 [99], but for healthcare the requirements should even be broader: citizens require a sufficient level of Quality of Service (QoS). QoS not only includes the many aspects of security, but also for example 'adaptability', which can be described as the agility towards change. This Special Issue and this survey are a clear sign of that change is perpetual, also in healthcare. To be able to benefit from change it is conditional that the services provided and their implementation are agile enough, e.g. by modular design and the application of international standards, to prevent expensive modifications and maintenance.

Implementing a sufficient level of security and quality of service is not trivial. In the cloud, computing resources including storage is provided by a third party service provider. Since data in the cloud typically resides in a shared environment, users will know neither the exact location of their data nor the other sources of the data collectively stored with theirs. Therefore, in this Internet-based computing paradigm, users are universally required to accept the underlying premise of trust [68]. Thus, even though the use of cloud-based data sharing platforms increased, the privacy related problems have prevented their adoption in the healthcare domain [69].

The diverse security and privacy concerns surrounding medical data have been studied widely over the last few years. Many organizations have published their reports [3,70,71] on the security and privacy issues for the manipulation of medical data in the networked systems. According to [72], the most widely used regulations are the Health Insurance Portability and Accountability Act (HIPAA) and the European Data Protection Directive 95/46/EC. In these regulations, there are two fundamental issues for the privacy of medical data sharing, i.e., privacy protection during transmission and privacy protection of stored data. The former has been studied widely and addressed by the Secure Socket Layer protocol (SSL) [73] and Transport Layer Security (TSL) protocol [74]. The latter is less studied and of greater relevance to storage as a service [69] in the cloud computing paradigm, where the outsourced data is stored on the site of the cloud service provider.

Through the application of the general privacy technologies in the healthcare domain, many researches on privacy protection of healthcare data are reported [72]. For example, the privacy policy is adopted in [76,77,80,81] for the privacy protection in the healthcare system. An optimal method of k-anonymisation is provided in [76,95] for de-identification of personal health data. The combinations of cryptography and data security protocols [75,78,79,82–84,106] are employed to handle the security and privacy issues for the development of secure healthcare systems. In particular, the attribute-based cryptography [78] is used to construct a secure and privacy-preserving EHR system that enables patients to share their data in the cloud. The studies [75,78–80,83] deal with the problem of record-level privacy protection (i.e., addressing the privacy concern in the process of access and utilization of each individual medical record). Their solutions focus on the patient centric control of the medical data access. The medical data exchanging between organizations is addressed in [76,77,81,84,107]. Their resulting solutions concentrate on the dataset-level privacy protection (i.e., addressing the privacy concern in the process of access and utilization of a whole set of medical records).

2.5.3. e-Health service delivery

The vision of cloud computing promotes ubiquitous healthcare becoming a key service delivery model [85], which urgently needs to reflect the view of the Healthcare system as a Service (HaaS). Driven by this vision, there are have been some efforts to study using the available Cloud platform for e-health service delivery.

For example, Accenture Medical Imaging Solution is proposed by Accenture and AT&T as cloud based medical imaging service, which is built for the medical professionals for reviewing the medical images such as X-rays, MRI and CT scans in a remote way. A cloud-based system for clients with mobile devices or web browsers is reported in [87] for hosting ECG data analysis services, where the ECG data can be uploaded to the cloud platform from a mobile phone at a certain frequency, and the algorithms for ECG enhancement, ECG quality evaluation and ECG parameters extraction are triggered in real time using for ECG data analysis. Through the PHRs with multiple external systems for accurate safety alerts, patient monitoring, etc., the authors of [88] presented a cloud emergency medical service system, which covers a variety of activities performed from the time of a call to an ambulance service till the time of patient's discharge from the emergency department. A cloud-based system to automate the process of collecting patients' vital data is reported in [86], where a network of sensors connected to legacy medical devices is adopted to deliver the data to a medical centre's "cloud" for storage, processing, and distribution. It can provide users with 24/7 automatic real-time data collecting.

Services delivered via e-health can have quite an impact in specific situations. An example of this is paper "Impact of Mobile Diabetes Self-Care System on Patients' Knowledge, Behaviour and Efficacy".

2.6. Impacts to healthcare practice

2.6.1. Enabling local empowerment

The expectations on improving the quality of medical services while simultaneously reducing the cost urge the public policy makers to explore the various options of transforming healthcare. One key element of the transformation driven by the information technology is replacing the concept of "patient" by "consumer" [89] and empowering individuals to assume responsibility for their health, i.e., the individuals are driven by the emerging medical information technologies to seek better medical knowledge to make informed decisions regarding their healthcare needs with value aligned quality [4].

On the other hand, emerging technologies and growing integration is evolving into intelligent and partially autonomous local implementations that support end-user self-reliance and self-determination, while at the same time providing supporting tele-services like tele-monitoring and tele-care. Empowering customers can be done by surrounding them with a supporting social and technical collaborative network [90].

2.6.2. Boosting preventive care

In order to reduce the healthcare delivery cost with increased quality, the other key transformation of modern healthcare is a fundamental shift in the emphasis of preventive care [92]. Different from traditional reactive models caring only for sickness or diseases, the preventive care adopts a proactive healthcare model by setting a high value on disease prevention and wellness. By focuses on the prevention of disease rather than treatment, its final goals are to reduce the overall cost of healthcare by lowering the probability of disease onset and improve the medical care quality by early intervention.

The United States Congressional Budget Office has stated that one key focus for healthcare innovation is preventive care [91]. However, the previous study showed that preventive cares are difficult to implement due to the limited healthcare resources [93]. The new solutions on health sensing, health data consumption and health service delivery promise to promote practical preventive care by engaging patients or consumers in taking control of wellness and disease prevention by using interactive, patient-oriented technology that works with data from physicians' electronic health record systems.

2.6.3. Fostering collaborative healthcare

The emerging information technologies facilitates health related information collection, sharing and flowing among a community including patients, health care providers, medical data analysts, and medical regulators, which make the diverse activities about health sensing, utilization and health service delivery can be conducted by multiple distributed entities or organization. It is highly valuable to merge the diverse IT technologies and then multiple healthcare activities to foster sustainable healthcare ecosystems for collaborative healthcare delivery.

In the world of collaborative healthcare, diverse medical data sources and services are readily available to patients, care takers and physicians through a network of information systems in a community of clouds. For example, at the point of care, according to the preference of a physician, relevant health data may be retrieved from multiple sources, enabling intelligent decision making of diagnosis and prognosis by invoking complementary services from the healthcare service network. The collaborative healthcare paradigm has great potential to improve the health-care delivery and potentially lead to new business models and ecosystems [94].

3. Conclusion

In health and care there are challenging times ahead. Emerging medical information technologies offer possibilities, but also pose challenges. Trends in health sensing, big data analysis and cloud computing in healthcare show interesting new developments. They can enhance healthcare abilities, boost preventive care and foster collaborative healthcare. Of course, an integral approach is necessary in practice, abiding important aspects such as security and privacy protection and enabling local empowerment. For instance, using the ''as a service'' concept to implement service oriented architectures with event driven workflows and collaborative networks can be used to create solutions supporting future healthcare, but by the very nature of healthcare such implementations are not trivial and should be end-user centric, really empowering them and taking ethical aspects into account. Obviously, this special issue does not cover all the aspects and applications of the emerging technologies in healthcare. That could be the big chance for the future.

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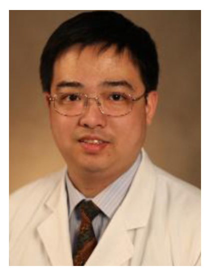

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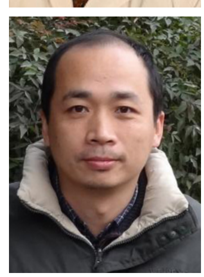

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