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Review

Smart health: Big data enabled health paradigm within smart cities

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ABSTRACT

In the era of "big data", recent developments in the area of information and communication technologies (ICT) are facilitating organizations to innovate and grow. These technological developments and wide adaptation of ubiquitous computing enable numerous opportunities for government and companies to reconsider healthcare prospects. Therefore, big data and smart healthcare systems are independently attracting extensive attention from both academia and industry. The combination of both big data and smart systems can expedite the prospects of the healthcare industry. However, a thorough study of big data and smart systems together in the healthcare context is still absent from the existing literature. The key contributions of this article include an organized evaluation of various big data and smart system technologies and a critical analysis of the state-of-the-art advanced healthcare systems. We describe the three-dimensional structure of a paradigm shift. We also extract three broad technical branches (3T) contributing to the promotion of healthcare systems. More specifically, we propose a big data enabled smart healthcare system framework (BSHSF) that offers theoretical representations of an intra and inter organizational business model in the healthcare context. We also mention some examples reported in the literature, and then we contribute to pinpointing the potential opportunities and challenges of applying BSHSF to healthcare business environments. We also make five recommendations for effectively applying 'BSHSF to the healthcare industry. To the best of our knowledge, this is the first in-depth study about state-of-the-art big data and smart healthcare systems in parallel. The managerial implication of this article is that organizations can use the findings of our critical analysis to reinforce their strategic arrangement of smart systems and big data in the healthcare context, and hence better leverage them for sustainable organizational invention.

1. Introduction

Recently, many municipalities have invested in the development of ICT infrastructure to decorate all their branches with technological setups to support big data applications to provide ambient automation and promote social control and management for the environment. The prospects of smart cities are really very promising, and different smart device manufacturing groups, for instance, IBM and Intel, are launching diverse initiatives to consolidate their guidance in this sector. They have recognized ten important fields that will play key roles in making a smart city: smart health, smart security system, smart building, smart government, smart tourism, smart grid, smart transportation, smart environment, smart home, and smart lifestyle (Caragliu, del Bo, & Nijkamp, 2009). Every component of smart cities is based on large-scale dataset analytics that present public safety, economic development, pollution, traffic conditions and so on. Moreover, the proliferation of smart devices with minimal cost of computing power and storage and the development of electronic communication are allowing the exploration of healthcare data. The volume of these datasets amounted to approximately 500 PB (petabytes, 10^{15} bytes) in 2012, which is comparable to the contents of 10 billion file cabinets, and these data volumes will increase to 25,000 PB by 2020, which is equivalent to the contents of 500 billion file cabinets. Due to this data deluge, the US healthcare data volume alone will soon touch the ZB, zettabyte (10^{21} gigabytes) scale and, not long after, the YB, yottabyte (10^{24} GB) (IHTT, 2013). By definition, big data in healthcare also introduces some complicated issues, such as non-uniform data distribution and parallel processing with a large number of variables, which are inefficiently handled by existing analytical methods. Big healthcare data is devastating not only due to its volume but also the heterogeneous nature of data and speed at which it

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must be managed (Frost, 2015). Therefore, we mainly consider the medical domain for this study.

The inclusion of big data in smart healthcare systems has led to the new innovative era of existing electronic and mobile health (e/m-health) that are paying to diminish costs and increased efficiency (Varshney, 2014). Different organs of healthcare systems such as physicians, hospitals, insurance companies, and pharmacies, are exploring paths to better understand big data application within smart systems so that they can properly classify their prospects to reduce costs, improve services, and streamline processes. In the healthcare context, significant advances have been made by using different smart devices; however, this field is still in its nascent stages, and there are many multidisciplinary problems that remain unaddressed (Solanas et al., 2014). Therefore, in this article we present a vision of smart healthcare systems in the big data era that enables many opportunities to improve the quality and safety of patient care, reduce costs and wastage, conduct healthcare research, and enable better management and service in healthcare industries (Varshney, 2013). Though big data enabled smart healthcare systems lead to anticipated results across various scenarios, they also have some potential challenges in regard to technical complexities, security and privacy concerns, economic constraints, data complexities, and also cultural aspects.

This article provides an advanced overview of big data and smart systems in healthcare. The rest of this article is organized as follows. In Section 2, we review the existing literature regarding three components – smart systems in healthcare, the city context, and big data characteristics in the medical domain. Then we describe paradigm shifting trends in health, city, and data dimensions. We explore different healthcare technologies in the existing literature. Then we propose the architectural framework of Big data enabled SMART healthcare systems (BSHSF). We provide examples of the implication of big data and SMART healthcare systems reported in practice and the existing literature as well. Then we discuss different challenges of developing BSHSF, after which we offer some new research directions. Lastly we conclude our study in Section 9.

2. Principal components

Though smart health and big data both are individually very new concepts, they have received a lot of attention by academia and industry recently. Smart health could be a modern application of big data within the context of smart cities which can present an extraordinary intelligent user centric environment. However, as smart health and big data are both young fields, we have to analyze their current development to extract different opportunities. In the following part of this section, we conduct a brief review of three key items of this study.

2.1. Smart cities

The concrete concept of smart cities has not been precisely defined, and it has been treated as a vague idea till now. However, according to IBM (www.ibm.com/smarterplanet/us/en/smarter_cities/overview/), "smart city" is defined as the intelligent utilization of advanced technology to sense, examine, process and integrate large volumes of useful information of core systems in running cities. Moreover, a smart city can provide intelligent responses to different kinds of daily needs, including citizens' livelihood, security systems, public transportation and environment, public health, and industrial and commercial activities (Pramanik, Zhang, Lau, & Li, 2016a; Qin, Li, & Zhao, 2010). Smart cities represent an imminent need, and are the real form of "smart earth" applied to customized zones to realize the intelligent and integrated management of cities. In smart cities, different datasets are continuously analyzed to present smart planning ideas, smart construction models, smart management, and so data are treated as a fuel of any smart system (Cocchia, 2014). In order to describe the structure of a smart city, there are three important layers – perception layer, network layer and application layer – which are considered in Su, Li, and Fu (2011), where each layer analyzes and processes massive datasets. These three layers can make the future world more and more appreciable and quantifiable, with increasing interconnection, interoperability and intelligence. To offer more efficient and effective city management and regulation, data sources of smart cities are not limited to sensor data only; social media data, GPS data, transactional data, and telephone call data also have a vast contribution to make a city a real-time city (Kitchin, 2014b). For citizens all these data and their analysis offers insights into city lifestyles, supports everyday living and decision-making, and empowers different visions for urban development.

In the healthcare context, a smart city can help hospitals to achieve smart healthcare. A smart city can introduce some intelligent management systems to support the digital collection, processing, storage, transmission, and sharing of internal citizen information such as personnel information, social information, and so on. Moreover, the infrastructure of a smart city can also support the following sections of healthcare systems - the intelligent management and supervision of health data, medical equipment and supplies, communication systems, automated management and supervision of public health, thereby solving many health hazard problems (Su et al., 2011). In essence, smart cities include many automated systems such as smart home, smart transportation, smart healthcare, and smart tourism which enable citizens to use different advanced services, to manage cities, and to create the motion for fruitful and curative actions.

2.2. Smart health

In smart cities we want to know how advanced tools and technologies are being leveraged by the medical sector to improve healthcare services. The infrastructure and technology of smart cities reconstruct the thinking behind existing healthcare systems (e.g. m-health, e-health) and telemedicine to create a new and comfortable ubiquitous concept that is called smart health. Moreover, smart health integrates ideas from ubiquitous computing and ambient intelligence applied to predictive, personalized, preventive and participatory healthcare systems (Röcker, Ziefle, & Holzinger, 2014). Smart health is strongly connected to the concepts of wellness and wellbeing (Suryadevara & Mukhopadhyay, 2014) and includes a large volume of data, collected by large amounts of biomedical sensors, (e.g., temperature, heart rate, blood pressure, breathing rate, volume, etc.), genomic driven big data (genotyping, gene expression, sequencing data), payer–provider big data (electronic health records, insurance records, pharmacy prescription), and social media data (patients' status, feedback, responses) actuators, to observe and predict patients' physical and mental conditions. Smart health is a nascent but promising field of study at the intersection of medical informatics, public health and also business, alluding to intelligent healthcare services or enhanced cognitive capabilities through the IoT (internet of things). In an elaborate sense, smart health defines not only ICT development, but also a state-of-thinking, a way of lifestyle and approach, and a vow for connected entities to improve healthcare facilities in the home, city, country and globe with the aid of a number of intelligent agents (Clancy, 2006). Recently, researchers have started to think about the application of big data in smart healthcare systems. Though there have been many controversial statements about Big Data, in the healthcare context it can be represented more accurately using 5'V' characters which we discuss in the next section.

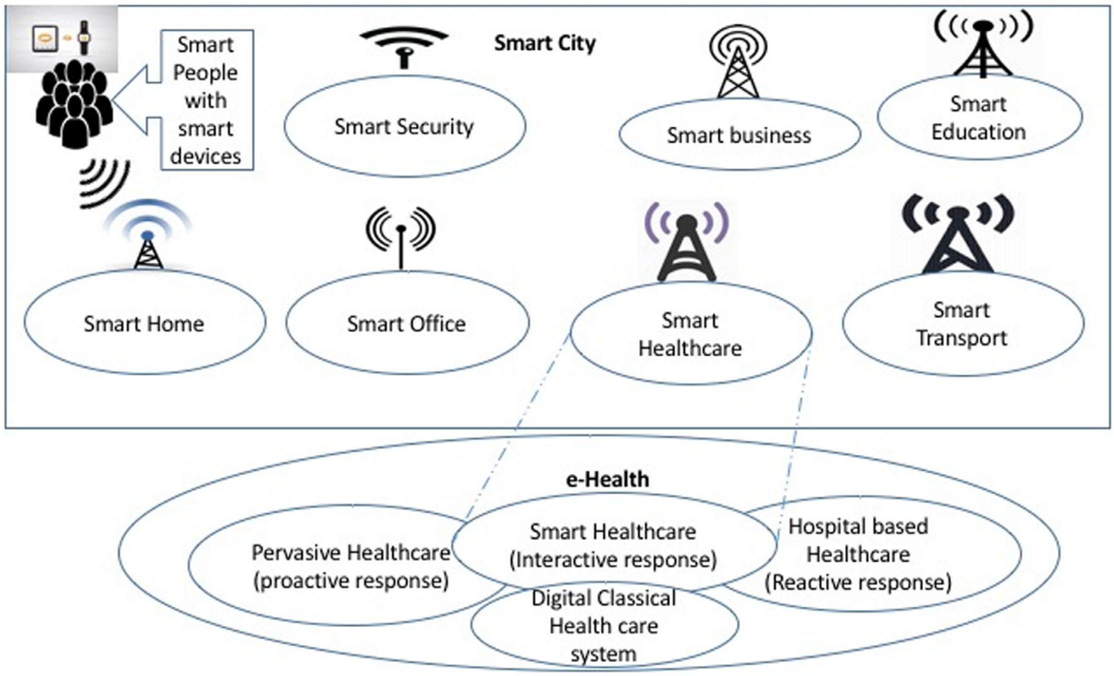

Fig. 1. Major components of a smart city and smart health.

Big data applications in healthcare organizations can provide significant benefits which include detecting diseases at an early stage when they can be prescribed more easily and effectively. The major initiatives of the National Science Foundation (NSF) related to big health data analytics is the NSF Smart Health and Wellbeing (SHB) program (NSF, 2012). The main goal of the SHB program is to address ICT issues in the big data context that support a much-needed revolution in healthcare from being reactive and hospital-centered to proactive and patient-centered, and accentuate well-being rather than disease control (Chen, Chiang, & Storey, 2012). A number of healthcare systems have been introduced in the last two decades such as digital healthcare system, electronic healthcare system, hospital-based healthcare system, pervasive healthcare system, and finally smart healthcare system. Through investigating the relevant literature, we present our concept of smart health in Fig. 1 (lower large oval). We represent smart health as a cohesive system of three different healthcare schemes: pervasive healthcare, digital classical healthcare and hospital-based healthcare where all processes are considered in the electronic healthcare (e-healthcare) environment. This e-healthcare mainly involves the use of electronic health records (EHR) for storing, accessing and processing all medical data (Peng, Dey, & Lahiri, 2014).

Pervasive healthcare is a proactive system where medical facilities are equipped with wireless local area networks (LANs), so physicians, surgeons, doctors, nurses and staff can review and update a patient's medical data from every positional setting using handheld devices (Varshney, 2003, 2007).

Digital Classical healthcare is a reactive system. This is an ordinary healthcare approach where doctors visit patients after receiving a call from them. Unlike the traditional classical healthcare system in Aday (2004), digital healthcare systems involve the use of electronic healthcare records (EHR) and ICT tools as well.

Hospital-based healthcare is a fixed place healthcare service where EHR and modern ICT tools are widely used, and all previous health records are extensively investigated to make decisions on future actions (Jha et al., 2006). Recently, different smart tools and techniques (T&T) have been deployed in hospitals to enable more effective and real-time treatment, though most hospital-based healthcare systems have been reactive till now.

2.3. The 5 "Vs" of big data analytics in healthcare

Three well-known characteristics – volume, velocity, and variety – are treated as the primary characteristics of big data in healthcare because all these properties are seriously considered in theory and practice (Groves, Kayyali, Knott, & Van Kuiken, 2013; Sakr & Gaber, 2014). Recently some practitioners and researchers have introduced two other new characteristics of big data in healthcare – veracity and value (James et al., 2011). Though these two dimensions of big data are less significant in other fields and treated as secondary characteristics, they are being seriously considered in the healthcare context for shifting the medical care paradigm to smart systems (Groves et al., 2013).

From the last decade, health-related data have been exponentially rising due to the application of smart devices and social media in healthcare services (Raghupathi & Raghupathi, 2014). The big data in healthcare mainly includes 3D imaging, medical records, radiology images, genomics and biometric sensor readings. Moreover, these generated raw sequencing health data amount to approximately 4 TB (terabytes) for each person (Chen et al., 2012). Though the health data volume is excessively large, fortunately, advancements in data management and processing techniques, particularly machine learning, and software intelligent agents are enabling innovative platforms to be developed for more effective and efficient management and manipulation.

In smart healthcare systems, data collection and modeling processes are being conducted at high velocity, almost in real time, which means that there is a rising prospect for big data analytics in healthcare to give immediate feedback on a patient's surrounding environment. As data generating and storage processes have changed due to the use of smart devices, and 26 billion IoT devices will be functional by 2020 (Middleton, Kjeldsen, & Tully, 2013), it is necessary to update the retrieving, analyzing, and decision-making processes with respect to the context. To present different healthcare applications, such as clinical text mining, predictive modeling, survival analysis, patient similarity, genetic data analysis, and intelligent services, the requirement of real-time responsiveness should be considered as the highest priority (Sakr & Gaber, 2014; Groves et al., 2013). Though some healthcare data are usually static such as x-ray film and paper files, most data are dynamic and represent regular monitoring, such as multiple regular diabetic glucose measurement, blood pressure readings, and pulse rate on electrocardiograms (ECGs). In many medical situations, real-time data such as heart beat monitoring and trauma monitoring for blood pressure can assist to measure the difference between life and death, and these data also reduce patient morbidity and mortality through detecting infection at an early stage, so that the proper treatment can be applied. The last primary dimension of big data is the variety of data - structured, semi-structured, and unstructured - which is the nature of data that makes healthcare systems not only challenging but also interesting. In ongoing healthcare systems, structured and semi-structured data include instrument readings, EHR, and communication data that are widely analyzed to enable effective healthcare. Though a number of unstructured data such as genetics and genomics data, office medical records, paper prescriptions, radiograph films, MRI, and CT scan data are analyzed in existing healthcare systems, some emerging unstructured datasets such as paper prescriptions, location, patients' status, feedback, responses, insurance records, and pharmacy prescriptions are cascading into the smart healthcare realm (Raghupathi & Raghupathi, 2014). The prospect of big data in the medical context lies in integrating the alignment of regular data with new emerging data. Thus, big data from multiple sources can support effective and efficient intelligent actions in smart services.

Big data can never be 100% accurate, and so must be construed with high attention, to be clinically useful. As unstructured data are extremely dynamic and all too often erroneous, information quality issues of data content are of acute concern in healthcare (Lukoianova & Rubin, 2014). In the healthcare context, the truthfulness (veracity) of data assumes the simultaneous scaling up of granularity. Therefore, in order to improve the synchronization of various services in hospitals, healthcare systems should either ignore erroneous data or filter them with respect to a certain threshold of veracity. Moreover, results from reliable health data analytics support a system to reconstruct healthcare services to reduce health expenditure, while increasing diagnostic accuracy, drug quality and safe treatments. However, high-velocity heterogeneous datasets severely hinder the ability to purify data before use and making the right decisions, thereby magnifying the issue of data "genuineness" (Herland, Khoshgoftaar, & Wald, 2014). Another secondary characteristic of big data in healthcare is value. Big data generates value only when applied to make better and faster decisions (Agarwal & Dhar, 2014; Demirkan & Delen, 2013). According to the McKinsey report (James et al., 2011), US healthcare could capture more than $300 billion in value per year from big data where value mainly comes from the reduction of healthcare expenditure. Recently, Centers for Medicare and Medicaid services (CMS) also settled on a number of big data tools that already generated more than $4 billion in recovered costs in 2011 alone. Cleveland Clinic (2011) has recognized big data as the best contemporary medical innovation in the world.

Finally, it is justified in the literature and in practice that the 5Vs represent an exact starting point for a discussion about big data analytics in smart healthcare. However, some other issues should be considered, such as big data enabled T&T, architectures, and platforms, because without a radical change of these issues it is not possible to achieve significant value from big data (Lau, Zhao, Chen, & Guo, 2016).

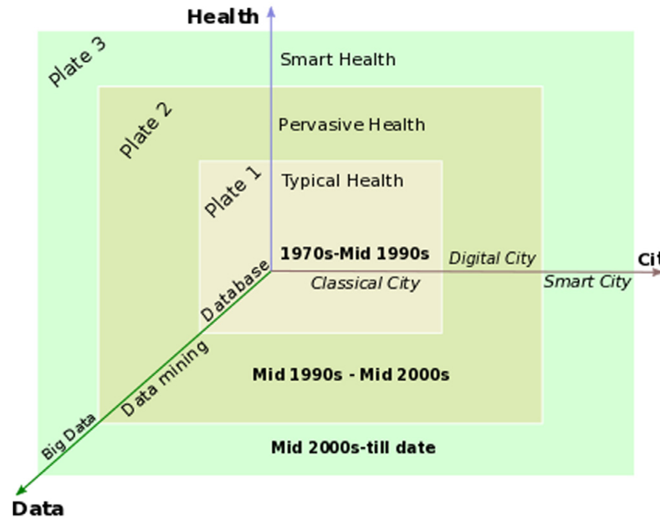

Fig. 2. Paradigm shifts in health, city, and data.

3. Paradigm shifting trends

This study focuses on three important dimensions: health, city, and data. In this section we look back at the development and paradigm shifting trends of these three dimensions over the last four decades and how far they have come. During this time, we have seen a new academic field emerge around the areas of health, city, and data through innovations involving sensor networks, distributed data storage and processing, manipulation and transmission of large volumes of heterogeneous data, the specification of artificial and cognitive-based algorithms to support decision-making, introduction of different social media, and the creation of other systems that link people, healthcare systems, business processes, administration, and governance in a city (Chen et al., 2012). We identify three paradigm shifts in regard to each dimension: (a) from typical health to pervasive-Health, and then to smart-Health in health dimensions (Clancy, 2006), (b) from classical city to digital city, and then to smart city in the city dimension (Cocchia, 2014), and (c) in data dimensions-database has shifted to datamining and then finally to big data (Wu, Zhu, Wu, & Ding, 2014). These paradigms have developed over time to incorporate data science, healthcare technology and different citizens' needs that relate to the information systems and ICT infrastructure of a city. We depict these paradigm shifts in three plates in Fig. 2, which classifies them in terms of involved technologies, analytics and applications.

In plate 1 – database, classical city, and typical health – all three systems are interrelated within a process. In classical cities, healthcare systems typically involved doctors visiting patients with traditional tools, and to preserve and process citizens' data simple database management systems (DBMSs) were used. During the 1970s to mid-1990s, all systems were reactive and the technological innovation was very limited; therefore, the subsequent part of this section just investigates the transition from plate 2 to plate 3.

Digital city, Pervasive health, and Datamining are three components of plate 2 where a digital city uses a number of datamining approaches such as classification, clustering, and regression in order to present better healthcare, administrative services, security and privacy services, better education services, and comfortable living services for citizens (Topol, 2012). Datamining is a revolutionary innovation that was first introduced in 1994, which aims to recognize valid, new, potentially useful, and logical correlations and patterns in data by searching through large datasets to discover patterns that are too complex for database technologies to detect (Koh & Tan, 2011; Herland et al., 2014). Therefore, digital cities and pervasive health both shifted from classical cities and typical health respectively through replacing database T&T with datamining T&T. They both provide proactive services for people. Along with datamining techniques, pervasive healthcare also uses different communication techniques to provide ubiquitous healthcare services. The innovation of different wireless communication models in the mid-1990s and pervasive healthcare approach attracted more attention from both academia and industry (Varshney, 2007). This type of healthcare approach still has some technical and administrative obstacles. The main goals of pervasive healthcare are to remove location, time and other constraints while reducing long-term costs and improving the quality of health services (Varshney, 2003).

Finally, plate 2 shifted to plate 3 where digital cities shifted to smart cities and healthcare systems provide smart services through deploying big data analytics T&T. Plate 3 presents the current state of the world. In the mid-2000s different social media were introduced and different smart devices invented and so the characteristics of generated data became more complex and complicated as well. A smart city must provide smart health and so we can think of a smart city as being an embedded system that includes smart health (Chourabi et al., 2012). Though some researchers and practitioners assume that digital and smart cities are two faces of the same coin, there are a number of technical and conceptual differences, such as in a digital city, sensors are purpose-specific and network systems are centralized, whereas in smart cities, sensors and network systems should be shifted to large-scale instrumentation-pervasive sensors and ubiquitous high-speed distributed networks (Balakrishna, 2012). Moreover, all components of a smart city such as smart health, smart security, and smart transport must be coupled with big data enabled devices, applications and interactions to present cognitive and intelligent services, whereas the city and healthcare system in plate 2 are not ready to adopt internet of things (IoT) and big data T&T. Therefore, Su in Su et al. (2011) stated that a smart city is the product of a digital city integrated with the Internet of Things and big data. In addition to the above, digital and smart cities have differences regarding the complexity of technological challenges, security and privacy challenges, financial constraints, and organizational and cultural aspects (Dameri, & Cocchia, 2013; Pramanik, Lau, and Yue, 2016b; Pramanik, Lau, Yue, Ye, & Li, 2017). In Table 1, we summarize the key characteristics of paradigms (plates 1, 2, and 3) in relation to technologies, analytics and applications.

4. Advanced healthcare technologies

Big data analytics in smart healthcare has emerged as an important and novel area of study both for practitioners and researchers, reflecting the magnitude and impact of health data-related complications to be solved in contemporary health services. Moreover, the opportunities in these two areas have generated a great deal of excitement in both the practice and research community. Whereas healthcare organizations focus on effectiveness and implementations for applications, researchers need to continue to discover and advance the health technologies (Peng et al., 2014). Presently, there are three broad technical (3T) branches – Intelligent Agents, Machine Learning, and Text Mining – all of which are contributing to the promotion of healthcare technologies. The branching of these three technical (3T) areas is projected to highlight the main characteristics of each area; however, some of these areas may leverage analogous fundamental concepts. In each technological area we present some key characteristics, some recent studies, and impacts on practices (see Table 2).

4.1. Intelligent agents

An agent is an autonomous software entity that collects input and interacts with its surroundings, executing some given tasks in order to achieve desired goals (Moreno & Garbay, 2003). In the healthcare domain, intelligent agents are one of the most exciting research paradigms for developing software applications and they must be able to perceive the physical and virtual world using different sensing devices (Wooldridge, 2009). Agent-based computing systems in healthcare have been referred to as ‘the next significant revolution in healthcare service development through software’ (Isern, Sánchez, & Moreno, 2007) and ‘the emerging software innovation to shift health paradigm to smart healthcare system’ (Yuan, Lai, Zhao, Xu, & Zhang, 2005). Moreover, intelligent software agents demonstrate unprecedented potential for delivering highly automated, intelligent health care in the home. In the medical domain intelligent agents have already been deployed for different tasks such as health information retrieval from large-volume data sources (Peng et al., 2014), decision support systems for diagnosis and care (Wimmer, Yoon, & Sugumaran, 2016), patient, doctor, and nurse scheduling, co-operation among different medical components (e.g., diagnosis, medicine) to manage pervasive healthcare (Su et al., 2011), development of education, training, and services, and medical information sharing (Mohan et al., 2009). After investigating the existing literature, we found some major applications of intelligent agents such as health data management, planning, allocation, and decision system, pervasive care service, and integrated system. Moreover, we found software agent systems in other areas such as bioinformatics, simulation, automation, and medical image processing (Chella, Frixione, & Gaglio, 2008; Richard, Dojat, & Garbay, 2004). Table 2 summarizes the brief information about intelligent agent in healthcare domain.

4.2. Machine learning (ML)

In recent years, a good number of research works have appeared in the biomedical engineering and artificial intelligent literature, which describe the application of machine learning (ML) techniques to design classifiers for anomalies (diseases, viruses) detection or medical diagnosis. Moreover, there has been a dramatic increase in the application of machine learning methods, tools, and techniques that can help solve diagnostic and prognostic complications in advanced healthcare systems. Machine learning is being used to increase the performance of clinical parameters and the combinations of the variety of medical prognoses such as the prediction of disease progression, decision support for therapy or surgery, knowledge extraction from emerging research and practice, and overall healthcare system management (Magoulas & Prentza, 2001). The machine learning approach is also being used to analyze heterogeneous health data (e.g. X-ray reports, ECG reports, tomography reports, temperature, pulse, and blood pressure reports). Medical data has some common complex properties such as subjectivity, impression, noise, and incompleteness. In order to address these challenging issues recently, some neural network approaches have already been deployed in machine learning. Although the complex properties of medical data impose constraints on conventional healthcare techniques, neural network based machine learning approach can offer a significant contribution to the healthcare context as they can properly integrate the elusive qualities of human reasoning with the compulsive thoroughness, precise logic, and perfect memory of computers (Maren, Harston, & Pap, 2014). Through investigating existing research and practice we can argue that successful utilization of machine learning methods, tools and techniques can assist healthcare systems to offer wide prospects to facilitate and

Table 1
Summary of paradigm shifts in regard to health, cities, and data.

Period	Components	Key Characteristics	Technologies	Analytics	Applications
Plate-1 (1970s–Mid 1990s)	Database Typical Health Classical City	• Systems are DBMS-based, allowed structured content (Chen et al., 2012) • Reactive Response (Solanas et al., 2014) • Efficiency and autonomy challenges (Menon & Sarkar, 2016)	➢ Organization-Centric Technologies ➢ Statistical learning technologies ➢ DBMS technologies	• Association rule mining • Database segmentation and clustering	❖ Computer-Supported decision support systems ❖ Management information system ❖ Software based system development
Plate-2 (Mid 1990s–Mid 2000s)	Datamining Pervasive Health Digital City	• Systems are Web-based, allowed structured and semi-structured content (Chen et al., 2012) • Proactive response (Solanas et al., 2014) • Accuracy challenge	➢ User-centric Technologies ➢ Machine learning, Artificial intelligence, Neural networking, A/B testing	• Anomaly detection • Graph mining • Semantic analysis	❖ Web 1.0 applications (e.g. static website) ❖ Integrated network Analysis ❖ AI technologies in business settings
Plate-3 (Mid 2000s–Till present)	Big Data Smart Health Smart City	• Systems are Mobile and sensor-based, allowed heterogeneous content (Chen et al., 2012) • Cognitive and Interactive response (Solanas et al., 2014) • Acute security and privacy challenges (Kitchin, 2014a)	➢ Context aware technologies ➢ HDFS(for storing) and MapReduce (for processing) ➢ Advanced Machine learning, Artificial intelligence, Neural networking, and software agent	• Cognitive network and sensor data analytics • Social network analysis • Sentiment analysis • Smart Visualization	❖ Web 2.0 applications (e.g social media) ❖ Advanced AI technologies in business settings ❖ Smart system with cognitive approach

Table 2
Summary of 3T applications in the Healthcare Context.

Technology	Key characters	Tools/Systems	Application	Impact
Intelligent agent	Autonomy Flexibility Intelligent Proactivity	CHIS (Tentori, Favela, & Rodriguez, 2006), CARREL (Cortés et al., 2000), CARREL+ (Tolchinsky, Cortes, Modgil, Caballero, & Lopez-Navidad, 2006), ROCHAS (Chen, Ma, Ullah, Cai, & Song, 2013), SHARE-IT (Walliser, Brantschen, Calisti, & Schinkinger, 2008), MeVisLab (Ritter et al., 2011), Aingeru (Tablado, Illarramendi, Bagüés, Bermúdez, & Goni, 2005), K4Care (Isern et al., 2011), HeCaSe2 (Isern et al., 2007), Bioagent (Webb & White, 2004) GerAmI (Corchado, Bajo, & Abraham, 2008), NeLH (Nealon, 2003)	Planning and resource allocation; Decision Support System; Medical data management; Action synchronization, Pervasive healthcare	Efficient decision making, more effective scheduling, and automatic management.
Machine learning	Learning by itself Learning by memorization of given facts	LCP (Zhou et al., 2008), ESTDD (Keleş & Keleş, 2008), CanPredict (Kaminker, & Zhang, Watanabe, & Zhang, 2007), PredictSNP (Bendl et al., 2014), GPCRpred (Bhasin & Raghava, 2004), The da Vinci robot, ADMET (Hou, Wang, & Li, 2007), AR + NN (Karabatak & Ince, 2009)	Diagnosis, Prognosis, Medical imaging, Signal processing Treatment and recommendation, drug discovery and development, and Surgery	Improve robotic surgery system, Develop prediction and prognosis method, Design advanced diagnosis system Develop medical imaging and signal processing system
Text mining	Information retrieval and representation from unstructured data	MedScan (Novichkova et al., 2003), TXTGate (Glenisson et al., 2004) PubMatrix (Becker et al., 2003), BioRAT (Corney, Buxton, Langdon, & Jones, 2004), MedLEE (Friedman & Hripcsak, 1998), AFDS (Chapman, Dowling, & Wagner, 2004)	Biomedical research, knowledge discovery, and knowledge management	Improve diversity of biomedical research

enhance medical services (e.g. diagnosis, medicine, surgery, nursing) to assure the effectiveness and efficiency of healthcare treatments. We examined the intellectual growth of machine learning in medical applications via several different research studies, and then we identified some major ML application streams in healthcare such as ML in prognosis and diagnosis (Kononenko, 2001), ML in drug discovery (Burbidge, Trotter, Buxton, & Holden, 2001), and ML in surgery (Lanfranco, Castellanos, Desai, & Meyers, 2004). Medical diagnostic reasoning is the most remarkable application area of intelligent systems. Therefore, ML tools and techniques are currently well suited for analyzing medical diagnosis in specialized diagnostic problems (Kononenko, 2001). Medicine discovery is also attracting attention as a relatively straightforward economic value for ML medical application creators (Cheng, Li, Zhou, Wang, & Bryant, 2012). IBM (http://watsonhealth.ibm.com/Watson-Drug-Discovery.html?lnk=mpr_buwh) has introduced its own health ML applications in drug discovery since its early days. Recently, Google also took on the drug discovery challenges and started to represent itself as a host company that raises and creates economic value by working on medicine invention with the help of ML tools and techniques. A number of ML tools, applications and impacts are summarized in Table 2.

4.3. Text mining

Healthcare information systems comprise a large volume of textual and numeric data about patients, treatments, administrative notes, visits, physician notes, etc. The electronic health records (EHR) encapsulate information that could lead to: development of the quality of healthcare, promotion of healthcare research initiatives, reduction in erroneous medical diagnoses and prognoses, and eliminate unnecessary healthcare costs (Koh & Tan, 2011). However, the unstructured textual documents that contain the health information are wide ranging in complexity, length and use of technical terminology, making knowledge discovery more challenging. In the medical domain a number of text mining tools can facilitate a unique opportunity to extract critical knowledge from textual data archives (Chen, Fuller, Friedman, & Hersh, 2005). The applications of text mining in healthcare are twofold: medical research and medical services. Concerning research purposes, a number of text mining approaches are widely employed to scrutinize large numbers of academic articles in published databases and to analyze the diversity of biomedical studies in existing literature (Chen et al., 2005). As it is true that no researchers encounter any new sequences or genes without previous knowledge about them, it is quite likely that some characteristics and relationships among biological objects remain unnoticed in the literature because the relevant information is scattered and no researcher has properly linked them (Cohen & Hersh, 2005). Due to the limited capacity of the human brain, researchers have only specialized in a few sub-domains (e.g. several particular genes), while text mining tools and techniques offer appropriate links among many subdomains for discovering new knowledge or formulating hypotheses (Yandell & Majoros, 2002). In order to address biomedical research and the variety of users, several research groups have developed integrated text-mining frameworks. For instance, the MedScan system is an integrated text mining tool that can extract relationships among different biomedical entities (Novichkova, Egorov, & Daraselia, 2003). TXTGate is one more text mining tool that performs gene-based text profiling and clustering using the data contained in multiple online biological records (Glenisson et al., 2004). Recently, text mining-based predictive models have been used to deliver smart healthcare services where predictive models can automatically code unstructured information with text mining classification and functioning (Raja, Mitchell, Day, & Hardin, 2008). A number of text-mining tools, applications and impacts are summarized in Table 2.

5. Smart healthcare system framework

High-quality services are essential in healthcare systems because some serious consequences can result from simple erroneous diagnoses or treatments. According to Zhan and Miller (2003), each year worldwide patients need to stay 2.4 million additional days in hospital purely because of medication-related errors. These errors also cause 32,000 deaths and $9 billion in costs anually. Moreover, 1.5 million preventable adverse reactions occur each year in healthcare systems. Addressing these problems here we propose a smart healthcare system framework that avoids errors and reduces healthcare costs. Our proposed framework also improves the coordination of care, provides opportunities for healthcare organizations to deploy big data platforms and technology, and presents ubiquitous healthcare solutions with less risks and increased intelligent services. In the proposed system, we try to adopt a smart system with appropriate application of 3T and maximize the potential of big data analytics in healthcare. In smart healthcare systems different smart devices, smart phones, and sensors are used for uninterrupted health monitoring, which can play a significant role in improving healthcare services and assuring real-time responses (Baig & Gholamhosseini, 2013). Fig. 3 shows the conceptual framework of a big data enabled smart healthcare system (BSHSF) which includes data sources, big data analytics, smart service-based architecture and logistic support, and knowledge discovery services.

Healthcare systems use a large amount of heterogeneous datasets to improve their service quality. These datasets are either structured, semi-structured, or unstructured. Big data in healthcare originate from various internal (e.g., electronic health records, diagnosis reports, clinical decision support systems, Computerized physician order entry, etc.) and external sources (e.g., insurance, government sources, etc.). These data sources deliver data in different formats such as flat file, .csv, text, figure, etc. According to (IHTT, 2013) health data type includes-web and social media data (smartphone apps, website, blogs), surveillance data (e.g. sensors, close circuit television (CCTV), communication access television (CATV), geographic information systems (GISs)), transaction data (e.g., billing), biometric data (e.g., finger print, X-ray, pulse and pulse-oximetry reading, blood pressure, retinal scan), and human-generated data (e.g., doctor prescription, e-mail, paper documents).

Moreover, Big data source component is responsible to clean collected data where raw data are transformed into formatted datasets. Using the processes of extract, transforms, and load (ETL), data from various sources is cleansed and organized. Depending on nature of heterogeneity (e.g., structured, unstructured), numerous data formats can be used as input to the big data analytics platforms and tools.

Prepared datasets are analyzed in big data platforms and tools in the second component of the framework. The most important and popular platform for big data analytics is the open-source distributed computing platform Hadoop (Apache environment), which can perform the twin roles of data organizer and analytic tool as well. Distributed computing is a significant character of Hadoop that allows one to process extremely large amounts of data by distributing partitioned datasets to several relevant servers (processors/machines), each of which solve specific chunks of a major phenomenon and then integrate them to present the final result (Raghupathi & Raghupathi, 2014; Agarwal & Dhar, 2014). A number of big data platforms and tools such as MapReduce, PIG, HBase, Cassandra, Oozie, Avro, Mahout, etc. are used to process large volumes of data with various structures or no structure at all. All these platforms and tools support the Hadoop distributed platform (Sakr & Gaber, 2014; Sakr, Liu, & Fayoumi, 2013). In the healthcare domain, all big data platforms and tools can be classified into three broad categories. They are (a) management platforms and tools (Big Data Appliance, Pentaho Data Integration, SAP HANA; Russom, 2013), (b) visualization platforms and tools (Tableau, Infogram, FusionCharts; Russom, 2011), and (c) computational platforms and tools (HDFS, MapReduce; Russom, 2011).

Analytical results from different platforms and tools are used to provide quality healthcare services in the next component, where the system assures data monitoring, privacy, and security agreement between consumers and service providers. Advanced 3T techniques are widely used in healthcare services. In the healthcare domain different 3T algorithms and models can learn from past examples in clinical data and then present intelligent and real-time healthcare services for consumers. Healthcare services are provided by the different components (e.g. medicine department, diagnosis department, surgery department) of healthcare systems where each component presents single or multiple services which complement each other for different purposes. To provide smart healthcare services we have to develop service oriented infrastructure that facilitates the development of automated and intelligent systems by supporting modular design, integration and cooperation of applications, and computer programming recycling. Different models under this infrastructure support collaborative

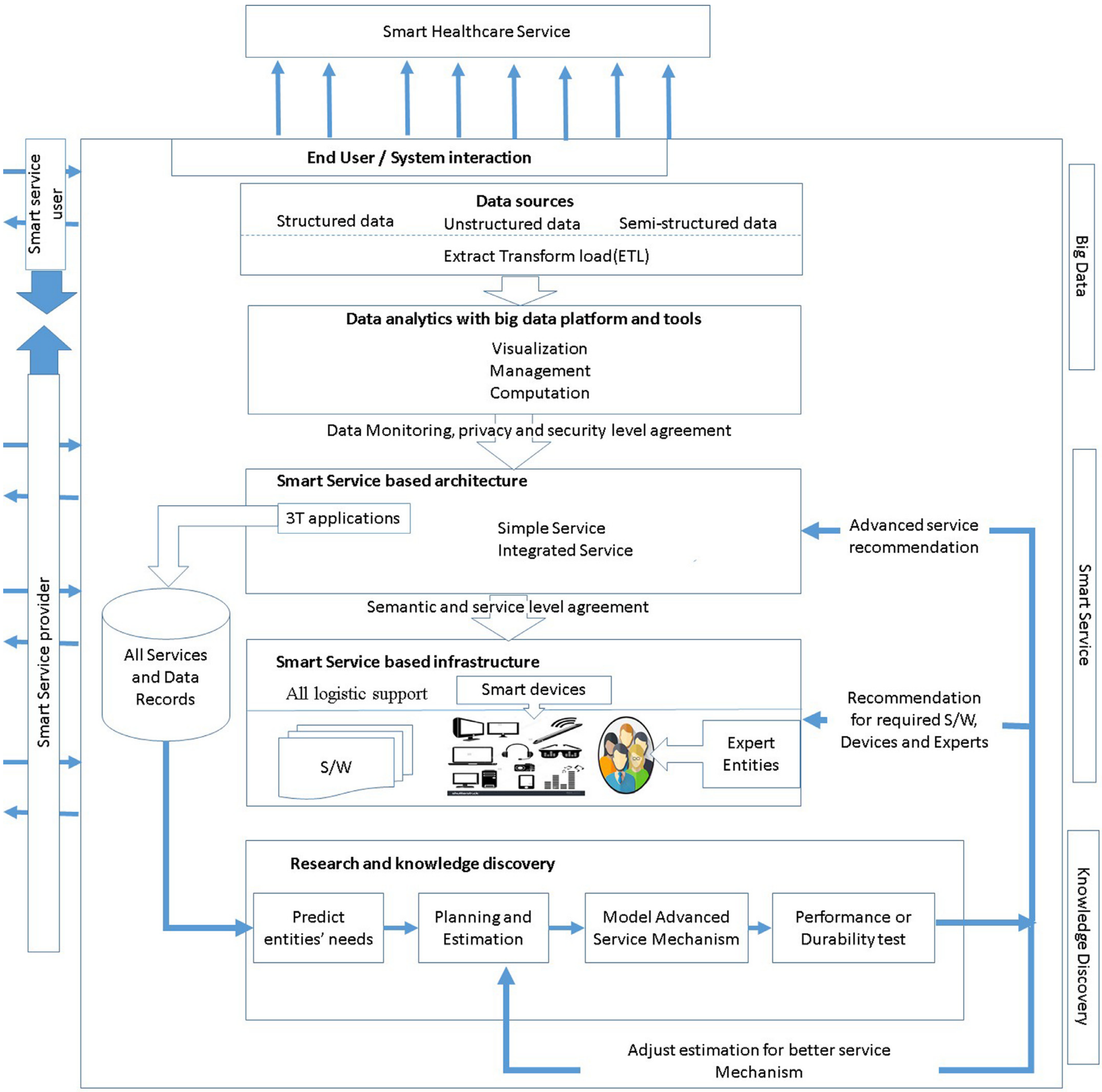

Fig. 3. An applied conceptual framework for a big data enabled healthcare system.

actions between service operations on different platforms and between applications executed in different programming environments with semantic and service-level agreement. Finally, smart healthcare services are presented where healthcare knowledge is triggered into different intelligent actions. These actions are delivered by the integrated support of different intelligent software packages, hardware devices, and human experts.

Research and knowledge discovery in healthcare can provide some recommendations on advanced facilities to meet users' needs based on historical data collected from previous services. These recommendations also assist to update the healthcare services at regular times. Research results also properly notify the service provider for updating infrastructure in order to adopt any novel services. Moreover, in our proposed framework, we try to accommodate many different stakeholders, where patients, doctors, and nurses, must support hospitals, dispensaries, non-conventional providers, medical schools, and insurers. Furthermore, there are device manufacturers; pharmaceutical, biotechnology, and IT firms; consultancy groups; research organizations; and government and public agencies.

With the adoption of our proposed BSHSF, healthcare organizations can present solutions to the following challenges - supply chain management, privacy and security challenges, coordinated care, and coordinated information systems. BSHSF assures high -quality healthcare systems through enabling interdisciplinary teams to work together among stakeholders (see Fig. 4). BSHSF allows automation of business processes that can successfully reduce the costs related to error-ridden manual processes. It can reduce

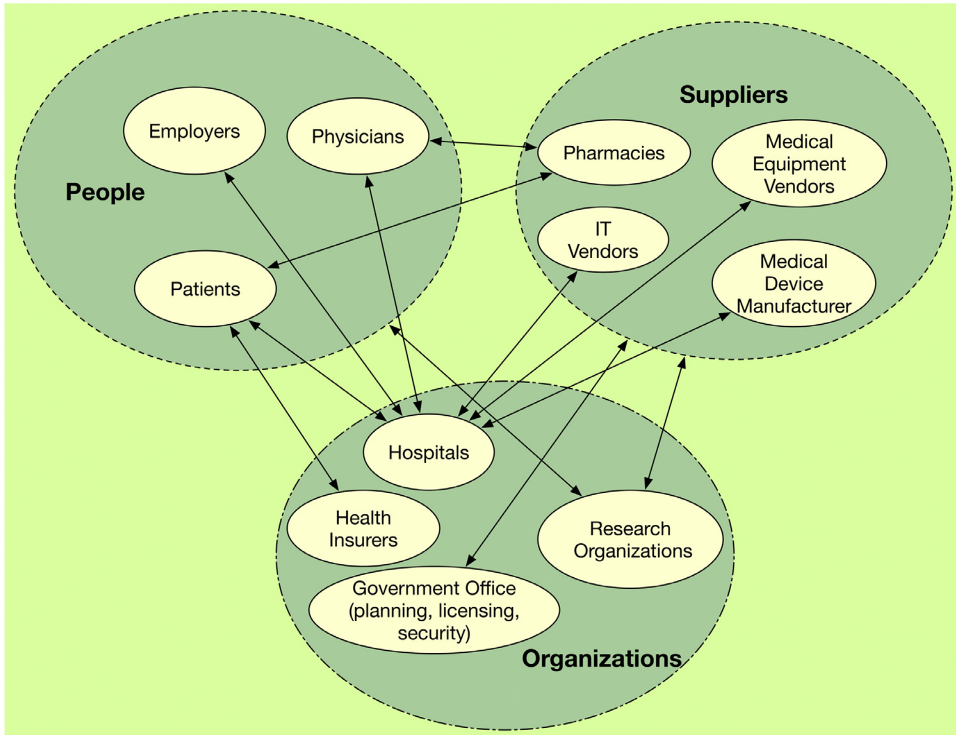

Fig. 4. A simple network among healthcare vendors which are grouped into three categories.

health costs, improve contract management, and achieve service of better quality. Moreover, through adopting BSHSF, any healthcare business organization can enjoy the embedded role of IT where information systems are utilized to produce, capture, store, process, and communicate timely information to all cohorts for efficient synchronization of healthcare.

In BSHSF, different stockholders are linked via digital networks and the cross-plays among these entities generate a large volume of valuable data that facilitate healthcare organizations to innovate and grow. However, the data deluge also creates serious privacy problems that may cause a regulatory backlash and hinder further organizational invention. To address the challenge of information privacy, the BSHSF approach will use different effective and efficient anonymization, and cryptographic models in data collection, manipulation, and released systems. In essence, business focused on BSHSF offers an opportunity to develop a new healthcare approach that can help improve security and privacy, simplify maintenance, reduce costs, and better use information technology in the healthcare industry.

6. Examples of implementations

There is no defined methodology to develop smart healthcare systems and so there is no specific starting point for an organization to adopt these approaches. In this section we review several smart healthcare projects and draw on publicly obtainable information from diverse resources, including purveyor websites. There is a limited number of studies to cite in this newly arriving field. The examples of implementations were collected from reliable but secondary sources. However, they are interpretative of the prospect of smart healthcare services in the big data environment.

In the United States, the National Center for Bio-computation (NCBC) in collaboration with Stanford University School of Medicine and the Department of Surgery has launched a project named smart health monitoring system (SHMS) for developing mobile telemedicine technologies for physiological, experimental, and environmental monitoring to assist NASA's commitment to anthropoid exploration (NCBC,1998). Moreover, from the existing literature, we investigate several smart health monitoring approaches such as in Maki, Ogawa, Matsuoka, Yonezawa, and Caldwell (2011) where a health monitoring system is proposed for caring for senior citizens where a call from a wireless phone to a server computer allows transmission of a graphical chart via the wireless phone, in Hande, Polk, Walker, and Bhatia (2006) another monitoring system was developed to monitor ECG, BP (Blood Pressure), and pulse-oximeters from a remote location, and in Leijdekkers and Gay (2006). Smart phones and wireless (bio) sensors were used to develop a personalized heart monitoring system. In practice, hospitals for sick children (SickKids) in Toronto use a smart approach for preventing life-threatening nosocomial infections. SickKids applies advanced analytics to large amounts of data collected from different monitoring devices for early detection of potential signs of infection (IBM Software, 2015). This advanced method can give an alert one day earlier than the previous method (IHTT, 2013). Above five systems mainly focus on smart-health monitoring systems which are some steps toward promoting patients' autonomy and also, they provide a personalized monitoring approach that gives the patients more confidence and improves their quality of life. Moreover, all these systems' results show that these monitoring systems help to reduce costs and complications through implementing earlier treatment.

In the United Kingdom, two hospitals – NHS Royal Brompton Hospital (RBH) and NHS Harefield Hospital (HH) – jointly run a system to provide interactive collaboration solutions including touch enabled LCD displays and SMART Bridgit Collaboration Servers and software to enable high-quality and secure data collaboration between the two organizations (NHS, 2009). This smart data sharing approach assists to give real-time responses and so they are now looking to enlarge the services to join more hospitals and to provide global collaboration via their collective solutions.

North York General Hospital (NYGH) recently started to use a real-time analytic model to develop a biopsy system for prostate cancer to help prevent infections (NYGH, 2016). Here, different automated surgical systems are deployed that use a big data analytics mechanism to develop decision-making and an overall service system. Smart room technology is another example of smart healthcare systems. This room is designed by the University of Pittsburg Medical Center (UPMC). This smart room system is intelligent enough to disseminate diverse sets of patient data to different provider categories. This room assists in proper decision-making about clinical care and also can exclude 60% to 70% of redundant actions related to documenting routine clinical care (Cerrato, 2011).

For the purpose of identifying diabetes physicians at Harvard Medical School (HMS) and Harvard pilgrim healthcare (HPH) recently introduced a smart diagnosis system that can easily differentiate between Type I and Type II diabetes. This system never uses any bio sample such as blood or urine for diagnosis but utilizes four years' worth of data from multiple sources (IHTT, 2013). Similarly, the Mayo Clinic (2010) uses an advanced image processing algorithm to detect brain aneurysms or to measure the how close to a brain aneurysm a patient is. This algorithm presents 95% accuracy in aneurysm detection and significantly improves patient outcomes. Therefore, the Mayo clinic has been honored as the best neurology and neurosurgery hospital for 2016–2017.

In 2008, Hong Kong started its own SMART healthcare. Under the smart healthcare mission, Hong Kong's legislative council has approved US$90.5 million for implementing the initial phase of an EHR program. This program mainly establishes a central record pool where records are collected from different private hospitals, private clinics, private diagnostic centers, radiological image centers, laboratories, the Department of Health and the Hospital Authority (HIMSS, 2016). To develop a smart integrated bio-diagnostic system, the EC (European Commission) supported a project during 2005 to 2009. This project was coordinated in the UK where the consortium was an influential body including three universities, four companies, nine research institutes, ten SMEs and four clinical groups covering all the related problems. The total cost of this project was US$22.73 million and its main focus was to develop a cancer diagnostics and prognostics system (McNeil & Wenn, 2010). The project's result already shows that diagnosis and prognosis quality increases significantly with earlier, more appropriate, and less costly healthcare services.

In China, Wuzhen Internet Hospital (WIH) was founded by "the We Doctor Group" in 2010. This virtual hospital offers China's largest online medical registration booking system, hospital treatment and healthcare service platform (WIH, 2010). About 0.2 million from more than 19 hundred cooperative key hospitals in 27 states (provincial regions) have quantified 270 million consultants (Hao, 2015). As it is a virtual healthcare platform, patients do not have to waste time traveling and waiting to consult a renowned expert.

After investigating 19 projects on smart-healthcare systems we gained a lot of experience. Based on our experience in Section 8, we have introduced some research guidelines for an organization when it wants to convert its existing system into a smart system.

Table 3 summarizes different smart healthcare and big data enabled healthcare systems or projects with their objectives, opportunities, and challenges.

7. Discussion

Smart systems and big data individually have the potential to produce significant value in medical care outcomes and services. Smart healthcare systems integrate and leverage smart schemes among different entities such as doctors, patients, nurses, and IT staff in hospitals where these integrated systems can help improve service value, assure security and privacy, simplify maintenance, and reduce costs. They also exploit innovative IT, and enhance healthcare knowledge and opportunities for development and testing in various extraordinary circumstances. At the same time, big data analytics echoes a boundless improvement to leverage the benefits of the present complicated environment in healthcare. The use of big data in the medical domain can improve the overall healthcare process in two main dimensions: improvement of the quality of care and increasing of efficiency and productivity (Sakr & Elgammal, 2016). Therefore, when big data tools and techniques are included in any smart system they can have immense potential for revolutionizing healthcare services. In the previous section, though we have seen that only a few projects or systems are considered to encompass both a smart system and big data simultaneously, it is obvious that big data enabled smart healthcare systems (BSHSF) facilitate the advanced processing of high-volume and high-speed heterogeneous health data to allow more accurate and effective real-time actions. In a BSHSF healthcare environment, the complete processed data can help to improve the understanding of diseases and pinpoint new health problems and improve healthcare knowledge to be more efficient than ever before. Therefore, healthcare systems will have to be updated significantly for stakeholders to gain the benefit of BSHSF. Under a BSHSF environment, the whole healthcare system must use some new tools and technologies to offer cognitive care services. So the adoption of the BSHSF paradigm by citizens requires the accomplishment of technological, economical, logistic, physical, and mental requirements; otherwise the deployment of new technologies for IT innovations makes people nervous. In BSHSF, the required devices and the deployed tools and techniques are evaluated with respect to availability, continuity, scalability, privacy and security, complexity, levels of granularity, and functioning quality (Solanas et al., 2014). To provide highly valued healthcare services, there are some common concerns for BSHSF approaches. These are the challenges of optimized care delivery, advance sensor deployment, integration and dynamic interaction with patient records, big data management and cloud, and data security and privacy. These challenges are very multifaceted, as technical, financial, organizational, and social issues become intertwined. Moreover, there are some other challenges of usability and human-computer interactions such as improving reliability and granular understanding of the application of different smart devices. With technological complexities, financial constraints and cultural aspects, adoption of BSHSF approaches is another challenge. Finally, BSHSF approaches are designed for serving humans, not machines, who can behave like moral agents. This signifies that customers are people who can recognize and are close-packed with ethical matters. Accordingly, all moral concerns should be profoundly considered from a user-centered view by giving consideration to the motivations of targeted customers of BSHSF approaches in medical applications.

However, in order to address various technical challenges in the big data-based smart healthcare paradigm, organizations can contract with numerous vendors including AWS, Cloudera, and MapReduce Technologies that offer open source Hadoop platforms (Sakr & Elgammal, 2016). Many proprietary options are also easily accessible. Furthermore, a good number of platforms among these are cloud models, making them widely accessible. In practice, the BSHSF system can bring about significant benefits for health-care organizations ranging from single-physician offices and multi-provider groups to large ubiquitous healthcare networks in different use cases and application setups. Moreover, in BSHSF, intelligent healthcare analytics can be leveraged to several applications such as genomic analytics, patient profile analytics, and remote patient monitoring, with the aim of turning large amounts of data into actionable information that can be exploited to identify needs, provide services, predict problems and prevent crises in an automated way. Though big data -enabled smart healthcare systems offer numerous opportunities for healthcare organizations,

Table 3
Smart and/or big data enabled healthcare systems or projects.

SL.No	Organizations/Platform	Country	Launching year/duration	Main objectives	Key opportunities	Key challenges	Sources
1.	NCBC	USA	1998	Telemedicine Technology	Offers remote diagnosis and treatment of patients	Reliability in deployment phase	NCBC (1998)
2.	NHS-RBH and NHS-HH	UK	2009 (launching smart service project at 2014)	Collaborative healthcare	Medical data sharing (diagnosis report, treatments)	Mutual trust and data security	NHS (2009)
3.	NYGH	Canada	2016 (Smart diagnoses)	Adopt transperineal approach in biopsy	Remove unwanted infection for prostate cancer	Collaboration among different surgeries	NYGH (2016)
4.	UPMC	USA	2010	Medical data distribution	Remove unnecessary actions	Data privacy and security	(Cerrato, 2011)
5	MHCG	Australia	2010–2012	Elder care	Service efficiency and effectivity	Adaptation is major challenge	MHCG (2010)
6	HMS and HPH	USA	2012	Diabetes diagnoses	Identify diabetes from data not use bio sample	Processing heterogeneous and large volume health data	HMS and HPH (2012)
7	Mayo Clinic	USA	2010	Detect brain aneurysm	Develop smart neurosurgery system	Main challenge is in classification	Mayo Clinic (2010)
8	Hong Kong Smart Health	Hong Kong	2008	Data integration	Develop decision making system	Data privacy and security	HIMSS (2016)
9	EC-health project	UK	2005	Cancer diagnostics and prognostics system	Extract more appropriate bio-diagnostic result	Proper data integration is main challenge	(McNeil & Wenn, 2010)
10	SickKids	Canada	2015	Preventing nosocomial infection	Early detection of future infection	Data volume	IBM Software (2015)
11	IOR	Italy	2011	Develop treatment system	Granular understanding of the clinical disparities within families	Handle heterogeneous datasets	IOR (2011)
12	BCBSMA	USA	2011	Patients' outcome	Efficiently identify high risk disease groups	Data complexity (volume and velocity)	BCBSMA (2011)
13	WIH	China (Virtual plat-form)	2010	Ubiquitous virtual healthcare platform	Save time and take real-time response	Data privacy (doctors/ patients)	Hao (2015) and WIH (2010)
14	IHIE	USA	2004	Information exchange network	To support interoperability over connected hospitals	Provide secure communication channel and develop mutual trust	IHIE (2004) and Groves et al. (2013)
15	HDI (Health data initiative)	USA	2010	Healthcare data dissemination and accelerate user sophistication	Harnessing the power of data, support research groups and policy makers	Heterogeneity and Size of data	HDI (2010)
16	OsSc	Italy	2014	Monitoring clinical trails	To support clinical research	Data analytics and integration	OsSc (2014) and Groves et al. (2013)
17	Collaboration of AstraZeneca and Healthcore(CAH)	England and Sweden	2011	Observational studies on chronical illness	Enhance community health Support research and development	Real time decision making	CAH (2011)
18	PatientsLikeMe.com	USA	2004	Developing patients' network, Sharing experience as a patient.	Develop real-time research platform Find effective and efficient healthcare solutions	Privacy and security on sensitive data (e.g. illness)	PatientsLikeMe (2004)
19	Sermo.com	USA	2005	Social network for physician; Develop medical crowdsourcing entity for physician	Present virtual doctor lounge for ubiquitous treatment	Data authenticity	Sermo (2005) and James et al. (2011)

currently they are not widely applied in practice due to the lack of technical support and minimal security (Sakr & Elgammal, 2016). Moreover, in the healthcare industry, different smart tools and big data platforms require a great deal of programming, skills the typical end-user may not possess. Considering the only recent emergence of a smart system and big data analytics in healthcare, governance legal issues including the right of possession, data privacy, individual and organizational security, and standards have yet to be addressed. In the healthcare industry, the above challenges are, certainly, significant drawbacks, and so appropriate trade-offs are required (Raghupathi & Raghupathi, 2014). However, in order to successfully address the challenges, new holistic assessment and design ideas as well as truly multidisciplinary development approaches will become necessary.

8. Future research guidelines

We now discuss several new interdisciplinary research directions that have become possible. Research centered on BSHSF presents a prospect to develop novel theories, methods, and models to define better strategy, and to support proper outline and implementation, and also to allow different scientific automated services in terms of practice and benefaction for healthcare accomplishment. Here, we list the five most important research directions:

a) *Improve the context-aware health paradigm:* Context-aware computing is a research field that often claims healthcare to be a promising area of application. In BSHSF all healthcare applications are able to adapt to dynamic circumstances and respond consistently within the context of practice. For developing context-aware healthcare models, we need to draw on expertize from multiple disciplines including computer science, social science, business, and medical science.
b) *Strengthening the supply chain management system in the healthcare context:* Though appropriate supply chain management can reduce direct or indirect healthcare costs (e.g. inaccurate or incorrect data), till now it has remained fragmented and incomplete in the healthcare context (Ebel, Larsen, & Shah, 2013). In SMART healthcare systems, interorganizational supply chains allow organizations to conduct business through combined distributed systems involving composite, large-scale, transactional decision activities (Sakr & Elgammal, 2016; Sakr & Gaber, 2014). Strengthening healthcare supply chain management could deliver affordable healthcare services for millions of people around the world.
c) *Explore the prospects of the healthcare industry with new data-sensing intelligent systems and social media capabilities:* Health 2.0 allows social media capabilities for care collaboration: the use of social media tools promotes collaboration among different healthcare entities such as patients, their caregivers, medical professionals, and other stakeholders in the healthcare domain (Eytan, 2008). Medicine 2.0 is also another similar concept to health 2.0 but it is more research oriented (Hughes, Joshi, & Wareham, 2008). Therefore, through conducting rigorous research, we have to explore novel prospects for the synergies among social media capabilities and healthcare facilities. We also concentrate on improving data sensing mechanisms (e.g. algorithms, models, methods) for discovering new knowledge from large amounts of collected datasets.
d) *Explore a common healthcare platform through sharing health data and collaborating with partner organizations:* The collective and interoperable medical data exchange platform seamlessly links a variety of disparate, remote applications with electronic health records (EHRs) to allow real-time data analytics and generates a central data pool of health records at a data store, along with enabling controlled access to the data pool (Myers et al., 2007). The information sharing across R&D communities among different healthcare organizations allows expansion of their research foundation. Such common healthcare platform also creates vibrant guidelines for intellectual property and guaranteeing patient-centric attitudes during teamwork. In the business context, such platform also enables organizations to establish a clear view of efficacy and wellbeing of both their own healthcare services and those of other similar organizations.
e) *Conduct complementary research on information privacy and security issues related to BSHSF:* In BSHSF, a huge number of people, devices, and sensors are connected via digital networks and the cross-plays among these entities generate enormous volumes of valuable data and this facilitates organizations to innovate and grow. However, the data deluge also raises serious privacy and security concerns (Menon & Sarkar, 2016) which may cause a regulatory backlash and hinder further organizational innovation in the healthcare context. In BSHSF, technical research team should give special focus on to develop privacy methods, security tools and techniques for all healthcare services. Moreover, in BSHSF service providers also develop privacy strategies to capture data from “smart” and embedded healthcare devices and different customer (patient) engagement networks, such as blogs, patient-attraction websites, hospital stalls, and mobile devices.

9. Conclusion

The widespread application and adoption of smart devices in municipal areas has resulted in the appearance of smart cities. By the same token, the deployment of advanced technologies and smart machineries has the potential to refurbish healthcare systems as they already have gained ground and revolutionized other industries. This paper has investigated the change of technologies and applications in the context of data, city, and healthcare. This transformation is a paradigm shift that allows people to learn different problems with superlative governance and innovative real-world visions. In this study, we also explored different advanced 3T applications which have already gained much more popularity in recent years as a vision of inspiring innovation and economic growth and providing automated and well-organized healthcare management and city development. Moreover, this article has also proposed a big data enabled smart healthcare framework (BSHSF) that offers conceptual models of intra and interorganizational business operation. To that end, the several challenges are highlighted in the discussion section that must be addressed. In the healthcare context, as big data and SMART systems become more important, issues such as ensuring privacy, protecting security, establishing quality and control, and frequently refining the tools and technologies will garner attention. Accordingly, we formulated some guidelines for organizational researchers so that they can better leverage BSHSF opportunities to achieve sustainable competitive advantages and continuous growth. However, BSHSF approaches are in a blossoming phase of development, but rapid growth of advanced 3T applications can hasten their maturing process.

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