Utilizing Health Analytics in Improving the Performance of Hospitals and Healthcare Services: Promises and Challenges

Mohamed Khalifa and Mowafa Househ

Abstract Health informatics is heading towards utilizing big data analytics, business intelligence, and artificial intelligence in exploring current and potential healthcare challenges and recommending evidence-based solutions to enhance strategic effectiveness and improve operational efficiency. We need to explore various advantages and potential gains of utilizing health analytics in addition to discussing different types of challenges and methods of overcoming these challenges in implementing and utilizing such resources. We conducted a focused review of literature to classify the advantages of implementing and utilizing health analytics. Health analytics challenges and critical success factors were also examined and categorised based on qualitative thematic analysis. Through examining sixty eligible studies, our focused review of literature identified three ways to classify advantages and potential gains of utilizing health analytics; based on healthcare levels, aspects, and dimensions. We also identified three main categories of challenges of health analytics: human, technological, and organisational. Using health analytics, several healthcare aspects can be improved, such as patient safety, healthcare effectiveness, efficiency, and timeliness. Health analytics implementation is faced with various technology, human, and organization related challenges. The non-technological challenges are more difficult and need more time to be resolved, including the development of a clear vision to guide implementation projects.

Keywords Health analytics · Big data · Business intelligence · Artificial intelligence · Healthcare performance improvement · Hospitals

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1 Introduction

The world has experienced more than four decades of progress in digitizing health information; aggregating years of medical practice, research and development data in electronic databases. Healthcare stakeholders are now able to see new opportunities for utilizing big data, which is so called not only for its huge volume but also for its complexity, diversity, and timeliness. Health analytics supports better insights and control for making evidence-based decisions, which should help to improve quality of care and reduce costs (Groves et al. 2016). Health analytics identifies hidden values within big data. Researchers can analyse the data to explore what treatments are most effective for specific conditions or certain populations, identify patterns related to drug side effects, hospital readmissions, or emergency department waiting time (Jee and Kim 2013). Through predictive analytics, Bates et al. (2014) identified and managed common six healthcare cases, to achieve value and reduce costs. These are high-cost patients, readmissions, triage, deterioration, adverse events, and treatment optimization for diseases affecting multiple organ systems. It is reported that almost 30% of hospital readmissions in the United States are identified as avoidable, which represents a great opportunity to improve the delivered healthcare (Bates et al. 2014). A few published studies have focused on reviewing the challenges of health analytics or its benefits and opportunities (Islam et al. 2018; Kruse 2016; Mehta and Pandit 2018). However, none of these reviews discussed, in a structured and detailed approach, the different categories of challenges and the suggested approaches to overcome each category of them. In addition, these published reviews did not discuss the benefits and opportunities of health analytics applications in different healthcare services. Our study aims at exploring and reporting the advantages and potential gains of utilizing health informatics and healthcare big data analytics in addition to discussing different categories and types of challenges and the methods of overcoming these challenges in implementing and utilizing such resources.

1.1 Background

In this section, we are going to present what is health analytics, what is it about, and how is it generally used to improve healthcare and clinical outcomes. In the next two sections, we are going to present some information about the functions and types of health analytics. Health analytics can be defined as a business-driven concept that includes various business intelligence approaches and big data analytics. This concept depends largely on the available and accessible data and information that are collected via well integrating and interoperable systems such as hospital information systems, electronic medical records, clinical decision support systems, and other specialized medical systems (Madsen 2012). Advanced technology applications are collecting more information than ever done. At the same time, senior leaders of healthcare organizations are eager to know whether they are getting the full value from the massive amounts of data and information they have. To know what has happened and the reason why it happened is not enough. Organizations nowadays want to know what is currently happening, what is going to happen in the future and what decisions should be made to achieve the desired outcomes (LaValle 2011). There is a logical relationship between health analytics, healthcare big data, and artificial intelligence. Big data represents the foundation on which health analytics, with its wide spectrum of technologies and methods, can work. At the same time, health analytics provides the technical and methodological framework through which artificial intelligence can be used to extract value or discover new clinical correlations out of massive health data sets (Miller and Brown 2018; Wong et al. 2019).

The Healthcare Information and Management Systems Society in the United States developed a definition for the health analytics, which includes the systematic utilization of clinical, medical, and health related data and information through implementing different analytics approaches and methodologies, such as quantitative and qualitative statistical analysis, contextual analysis, and predicting outcomes to develop decisions and actions and guide better information based strategic and operational healthcare (Cortada et al. 2012). Recently, healthcare data warehouses collect different data types from different systems and sources to create operational healthcare dashboards, strategic scorecards and data stores, since the availability of timely and accurate data is vital to make informed medical and managerial decisions (Nugawela 2013). One of the applications of big data analytics includes newly introduced approaches of employing different sources of data to predict incidents of asthma-related emergency department (ED) visits. To achieve this objective, Twitter data, Google search data, and environment data are gathered. The invented model should support predicting asthma-related ED visits using these real-time data with almost 70% accuracy. These results can be helpful for public health surveillance, ED preparedness, and targeted patient interventions (Ram 2015). Hospital based big data can also be used to design reliable predictive models and tools, which in turn can provide clinicians and decision makers with more robust and evidence-based methods for managing specific patient populations, such as cardiovascular patients (Rumsfeld et al. 2016). Recent post implementation impact studies proved that some evidence-based predictive tools, designed using big data, such as the modified early warning score, have achieved a significant reduction in the incidence of in-hospital cardiac arrests, the proportion of patients admitted to intensive care and their in-hospital mortality (Moon 2011).

1.2 What Does Health Analytics do?

Health analytics can help healthcare professionals and administrators to measure the performance of the various services in hospitals and healthcare organizations through establishing benchmarks to determine what is good and what is bad (Hunt 1998). There are three types of performance measures; key result indicators which should tell you how you have done, performance indicators (PIs), which should tell you what

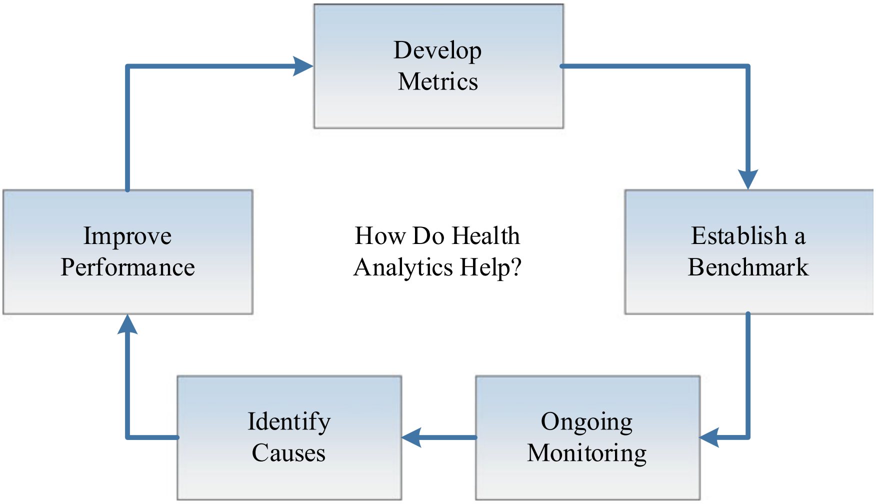

Fig. 1 How do health analytics help improve performance?

to do and key performance indicators (KPIs), which should tell you what to do exactly to increase performance dramatically. Many performance measures used by healthcare organizations actually are an inappropriate mix of these three types (Parmenter 2015). Proper health analytics then help healthcare professionals and organizations to monitor these metrics on an ongoing and regular basis and help to troubleshoot bad performance and to identify root causes of problems. Health analytics also support users in designing, developing, implementing and evaluating diverse key performance indicators which could monitor performance, identify why performance deviation occur, and ultimately improve performance (Fisher and Analytics 2013). Figure 1 shows a simple model of how health analytics work in improving healthcare performance. Recently, many researchers are using big data analytics in developing new KPIs to reflect the actual performance of hospitals and identify methods of enhancing their healthcare efficiency. One study in Denmark used the data of over 2 million patients to develop a cost-bloom model and core KPIs related to measuring the efficiency of healthcare services provided, where a "cost bloom", is defined by the authors as "a surge in healthcare costs that propels patients from a lower to an upper decile of population-level healthcare expenditures between consecutive years" (Tamang 2017).

1.3 *Types of Health Analytics*

The domain of health analytics is currently shifting from the lower level of operational analytics into the highest level of strategic analytics. It is also shifting

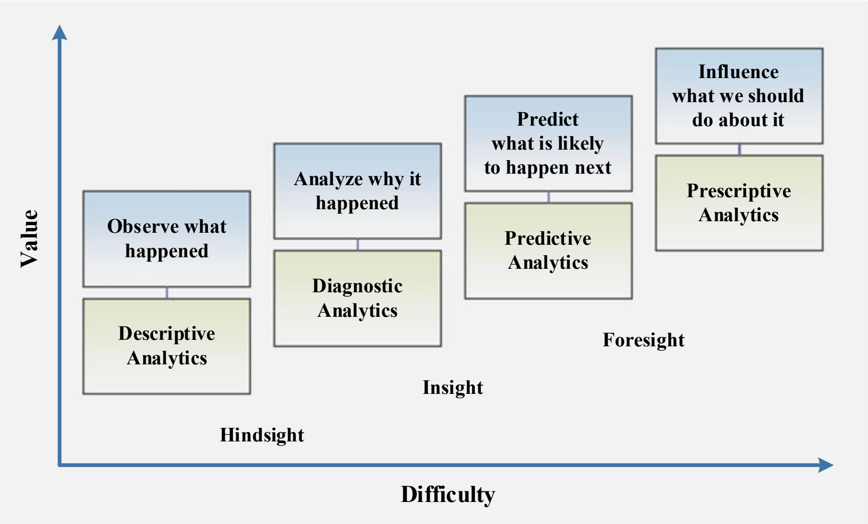

Fig. 2 Types of health analytics

from the simplest descriptive analytics into the most complex diagnostic, predictive, and prescriptive analytics. Very soon, healthcare organizations which used descriptive and diagnostic analytics in monitoring the performance of various healthcare services, will use the most advanced types of predictive and prescriptive health analytics to choose among different feasible alternatives (Russom 2011). Figure 2 shows the four main types of health analytics discussed by most healthcare professionals and researchers and suggested by Gartner (Wang 2016).

2 Methods

We conducted a focused review of literature to collect and examine the reported advantages and potential gains of implementing and utilizing health analytics in improving the performance of hospitals and healthcare services. Challenges of health analytics, including reported barriers and critical success factors were also examined and categorised using qualitative thematic analysis. A comprehensive search for published evidence on “Health Analytics”, “Healthcare Big Data” and “Healthcare Business Intelligence” was conducted using MEDLINE, EMBASE, CINAHL and Google Scholar for publications in available over the last ten years; from 2010 to 2020, published in English language. Table 1 shows the main keywords used in the search and their description. Figure 3 shows PRISMA flow diagram of studies selection and inclusion.

Table 1 Search keywords and their description

Search keywords	Description
Health analytics	Covers all types of health data analytics
Healthcare big data	Managing, analyzing, or extracting health information from health data sets that are too large or complex to be dealt with by traditional methods
Healthcare business intelligence	Strategies and technologies used by healthcare organizations for the data analysis of healthcare business information
Benefits or promises or advantages	All positive outcomes of using health analytics
Challenges or barriers or limitations	All factors that prevent, decrease, or slow down the adoption or implementation of health analytics
Critical success factors or successful adoption or successful implementation	All factors that support, enhance, or facilitate successful adoption or implementation of health analytics

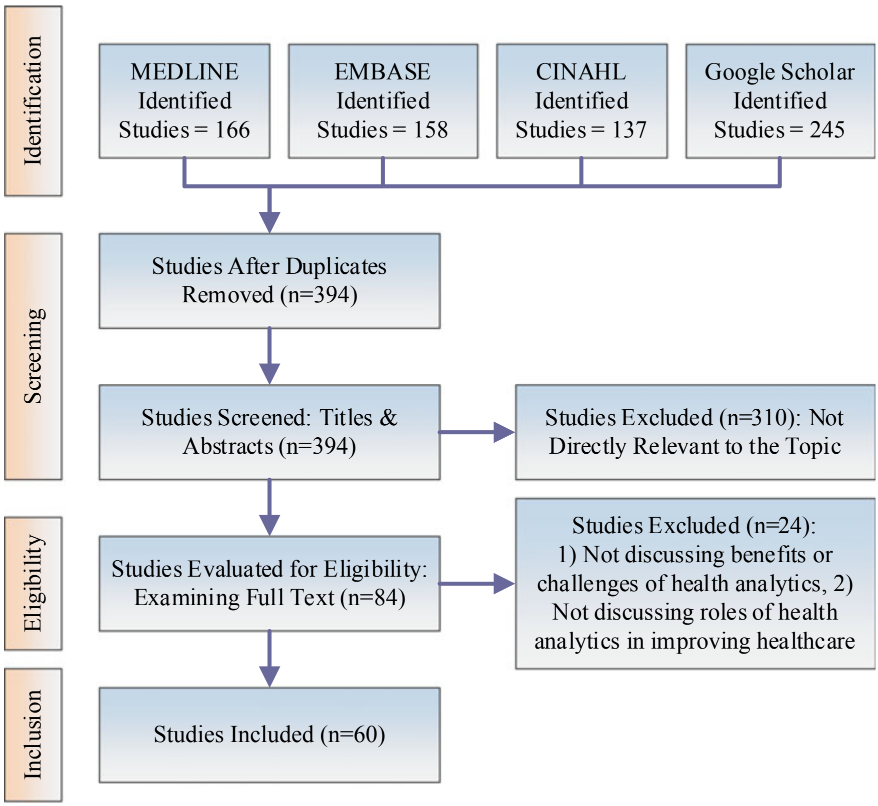

Fig. 3 PRISMA flow diagram of studies selection

3 Results

Through examining sixty eligible studies, our focused review of literature identified three ways to classify advantages and potential gains of health analytics; based on dimensions, aspects, and levels of healthcare. We also identified three main categories of challenges of health analytics: human, technology, and organization.

3.1 Improving Healthcare Performance

Improving the performance of any system depends mainly on having a shared goal that unites the interests and activities of different stakeholders. The proper goal for any healthcare delivery system is to improve the performance of services and increase the value delivered to patients (Kaplan and Porter 2011). If healthcare systems and services performance improve; patients, providers and payers will all benefit with some trade-offs in certain situations, such as the balance between increasing quality and reducing costs. Performance per se includes many of the other goals already addressed in healthcare, such as effectiveness, efficiency, quality and patient safety. It is also fundamental to achieving other important goals such as improving equity and expanding access to healthcare services at reasonable cost (Porter 2010). Healthcare stakeholders often have many goals that are naturally conflicting, such as access to services, profitability, high quality, cost containment, safety, convenience, and patient satisfaction. The Institute of Medicine's own definition of goals for the healthcare delivery system includes no less than six disparate elements: safety, effectiveness, efficiency, timeliness, patient centeredness and equity (Porter 2010). Over the years, healthcare researchers and professionals realized that many, if not all, performance dimensions are still below what is really needed or at least still have a gap that can be improved, including all the six elements defined by the Institute of Medicine. Healthcare organizations need to adopt well researched or tested procedures and technologies, well developed guidelines and standards of care, validated care protocols and multidisciplinary clinical pathways, preventing or removing unnecessary, therefore expensive, unsafe and harmful routines and procedures and reduce undesirable variations in the healthcare provision (Grol et al. 2013).

Healthcare performance improvement is facing challenges, many of them remain to be addressed, such as balancing perspectives, defining accountability, establishing criteria, identifying reporting requirements, minimizing conflict between financial and quality goals, and developing information systems (McGlynn 1997). There is a need, for example, to balance healthcare effectiveness and efficiency to gain the highest net benefit to individuals and society (Donabedian 1988). Efficiency and quality should not be mutually exclusive; the challenge is to merge economic and clinical incentives (Brook et al. 1996). The real challenge is to focus on all the important aspects of performance, using the most valid methodology possible and data evidence available, whilst trying to minimize conflicts among these competing performance aspects (Campbell et al. 2000). According to the three levels of healthcare management and performance, we can classify performance measurements and their related tools, applications, and methods into operational, tactical and strategic levels. Each category has its own objectives, methods of measurement and expected outcomes (Eckerson 2009; Grigoroudis et al. 2012; Hans et al. 2012). Moreover, according to the Donabedian conceptual model, which provides a framework for evaluating healthcare services and quality of care, performance dimensions can be classified differently by being related to the three main elements of the healthcare system: structures, processes, and outcomes. Structure dimension and indicators can be used to measure and report the context through which healthcare services are delivered, including machines, buildings, people, and finance, while process dimension and indicators include measuring and reporting encounters that occur between patients and healthcare professionals during the delivery of healthcare services, and outcome dimension and indicators refer to the effects of healthcare on the health status of patients and populations (Donabedian 1988; Gilbert 2015).

Using both performance levels and performance dimensions, measurable performance aspects can be classified into the main six elements defined; safety, effectiveness, efficiency, timeliness, patient centeredness and equity (Porter 2010; Bauer and Paradox 2014). Safety KPIs are designed to measure and report the extent at which healthcare interventions or procedures are safe and not harmful to patients or professionals. Effectiveness KPIs are designed to measure and report the extent at which healthcare service can produce the desired outcomes and fulfil the planned objectives. Efficiency KPIs are designed to measure and report the extent at which resources of healthcare organizations such as effort, time, and money are well utilized for the planned tasks and objectives. Timeliness KPIs are designed to measure and report the extent at which healthcare is delivered to patients at the most necessary or beneficial time or according to patients' understanding of need. Patient centeredness KPIs are designed to measure and report the extent at which patients are satisfied with the delivered healthcare services and the level of systems' success or failure to meet and satisfy patients' needs, including respecting patients, providing correct and accurate information, relieving patients from avoidable pain or stress. Equity KPIs are designed to measure and report the extent at which healthcare provision ensures eliminating differences between patient groups to achieve the objective of treating all patients equally and delivering best quality healthcare regardless of personal characteristics, such as age, gender, race, ethnicity, education, disability, sexual orientation, income, or location of residence (Brilli et al. 2014; Khalifa and Khalid 2015).

3.2 Challenges of Utilizing Health Analytics

It is now well-recognized that health analytics has the capacity to critically improve healthcare provision. However, the implementation of such technology is still facing different challenges. It is important to identify and define challenges to overcome and success factors to benefit from. The development and implementation of health analytics is a very complex undertaking requiring considerable resources. Yet there is a limited informative set of identified challenges and critical success factors (Yeoh and Koronios 2010). To date, little research has been done on challenges of adopting big data analytics in healthcare (Wang et al. 2015). Health analytics implementation is faced with various technology, human, and organization related challenges; examples are summarized and illustrated in Fig. 4, adapted from Khalifa, 2019 (Khalifa 2019). The non-technological challenges are more difficult and need more time to be resolved, including the development of a clear vision to guide implementation projects and achieve objectives. Successful implementation of such technology is based largely on the type of project funding, the delivered value and the alignments between project objectives and strategic organizational goals. Health analytics should be built with the end users in mind (Adamala and Cidrin 2011; Farrokhi and Pokoradi 2013). A few other studies categorized the challenges that face developing and implementing health analytics and other information systems into six main types, these include human, profession, technology, organization, funding, and regulation or legislation challenges (Khalifa 2013). Figure 5 shows the six main categories of challenges.

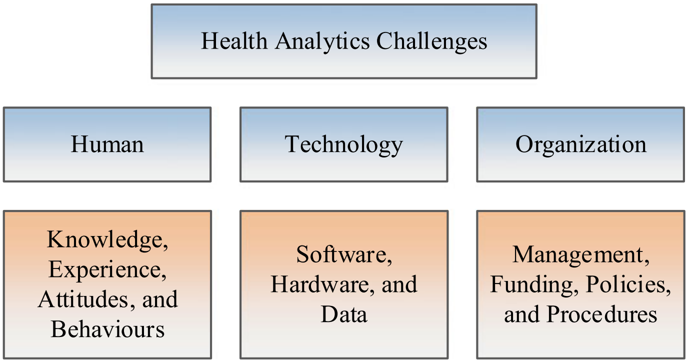

Fig. 4 The three main categories of health analytics challenges

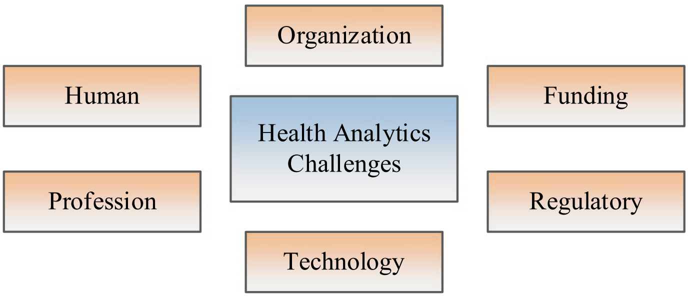

Fig. 5 A model of six suggested categories of health analytics challenges

A few studies worked on explaining delayed or unsuccessfully implemented projects or the underutilization of health analytics technologies by linking this failure to negatively accepting or resisting these technologies by healthcare professionals. The impact of being knowledgeable, skilled, and experienced in computer systems or information technology and the attitude of healthcare professionals towards using such systems and technology in the healthcare context account for the major challenge to successfully implementing and utilizing such systems (Khalifa 2014). Other studies reported that more time and effort were needed to learn new technologies which usually resulted in longer workdays especially during the initial phase of implementing analytical or reporting systems. This might add more work, decrease productivity, or slow down performance, which can also be considered important challenges. Even highly regarded, industry-leading analytics and reporting systems can be challenging to use because of the multiplicity of functions, options and navigational tools (Khalifa 2014; Miller and Sim 2004). At the same time, health information systems research often focuses on the design and implementation challenges, but not enough focus is given to how end users react to such systems. The success of health analytics systems lies beyond the level of good design or the selection of a good system. The degree of fitting the intended use by any system leads users to accept or reject such system (Holden and Karsh 2010). The continuous need for technical and consultation support from different software, hardware, networks and other support service vendors is another challenge which makes larger hospitals more able to implement such systems because of their superior and vast resources (Lorenzi 2009).

In the area of technology which includes the development and implementation of health analytics, we might be able to identify many challenges in relation to the huge expansion of data, in terms of the volume, the velocity of data creation, which might be even more important than the volume, especially for the real-time analysis, and the variety of big data, in the form of text, voice, images and videos, which is another challenge for acquisition, processing and provision of useful information (McAfee et al. 2012). Moreover, one of the technical challenges is the trade-off between generalisability and customisation of health analytics solutions. Some of these solutions are developed using local data. For example, some predictive models were developed using life quality, expectancy scores, or national rates of diseases from certain populations in specific countries. This affects the willingness of patients, clinicians, and other healthcare professionals to rely on such solutions in decision making. It is also essential sometimes to make major adjustments to the health analytics solutions and re-evaluation of their feasibility, validity, accuracy, and reliability before using them in other populations (Khalifa et al. 2019). In addition to the technical aspects of data management we still have a completely different challenge in relation to the ethical dimension of using and sharing patient data. How clinicians and other healthcare professionals use and share patient data should always include protecting patients' privacy and data confidentiality. The increased use of big data analytics and artificial intelligence methods requires reassessment of these basic principles and available legislations, regulations, policies, and procedures, while managing the emerging concerns of patients privacy, data confidentiality, data ownership, and informed patients' consent on using and sharing their data. Accordingly, different stakeholders must have conversations about the appropriate approaches to manage these issues and support the development of such capability in the most just, ethical manner possible (Balthazar 2018).

Yet, developing and implementing health analytics is not only about introducing new technology, this is more about equipping healthcare organizations by tools that enable them to achieve their healthcare objectives and providing users with technical capabilities that make new things possible and by engaging people into changing their behaviours to effectively use the new capabilities to achieve the target outcomes. Top level management commitment and developing policies and procedures governing the implementation and utilization of applications is another crucial organizational challenge (McCarthy and Eastman 2013). Some studies discussed managerial challenges facing the utilization of big data and analytics. Healthcare senior management that assigns smart objectives, develops standards of success, and looks for the right answers is even more important than developing only bigger data; the necessity of a human understanding and insights cannot be simply replaced by powerful analytics. Talent management is another challenge, since data content become cheaper, human input becomes more valuable. The challenge of selecting the right tools to manage big data is another managerial issue. The successful effective evidence-based decision making is another challenge for the management in addition to changing the organization culture from "what we think" to "what we know" (McAfee et al. 2012); identifying organizational top level management information needs (Trkman 2010). Moreover, the increased initial costs, operational and maintenance costs, and uncertain financial benefits of health information systems are frequently cited barriers to the acquisition and implementation of such systems. In addition, some concerns might be raised in the form of ethical and legal questions about the proper acquisition and utilization of systems. Health information confidentiality is one of these factors (Kellermann and Jones 2013).

All these challenges can be classified into three major classes: technological, human, and organizational. They can also be interrelated and interdependent since the development and implementation of information systems is a process of mutual transformation. The organization, the technology and the human behaviours could transform each other during these processes; one way would be to look at behavioural influences on health analytics outcomes in the context of institutional constraints. When this is expected, the process of acquiring and implementing a new system can be planned strategically to help accomplishing the transformation of the healthcare organization. This major change project can succeed only when positively and effectively supported by both top level management and future users (Berg 2001). Published research discusses that technology related factors, such as hardware, software, and data content, is more influential on the descriptive function of analytics rather than on the prescriptive function. On the other hand, human related factors, such as knowledge, experience and skills can be more influential on the prescriptive analytics rather than on the descriptive. The domain of analytics and big data is faced mainly by two challenges: (1) the engineering and technology challenge; this includes the efficient management of large data sets, and (2) the semantics of human knowledge and experience challenge; this includes the ability to find and meaningfully combine information that is relevant to our concern (Bizer 2012). Data volume, velocity, streaming, aggregation, and data variety represent a major challenge facing data processing and visualization for proper descriptive and predictive analytics (Keim 2008). Many hardware and software design challenges might largely influence descriptive and predictive functions of analytics. The design of systems and components that work effectively for health analytics to generate accurate data descriptions and informative predictive models requires an understanding of both the needs of users and the technologies used. Developers must design good interfaces, easy to understand graphics, and easy to use icons to improve the organization of applications and their related functionalities. Other technology related challenges might include data quality versus quantity, data growth and expansion, system speed and system scale, unstructured data, data compliance, security and distributed processing (Kaisler, et al. 2013). As health analytics is one of the most recently introduced technologies, it requires the contribution and innovation of professionals with the highest levels of training, knowledge, and experience, in addition to many other essential skills. These skills must include the ability to conduct research, critical analysis, and creativity, in order to enhance using prescriptive analytics and advising organizations on possible outcomes and answer the question of what should we do next (Evans and Lindner 2012; Katal et al. 2013). Organizational leadership, managerial styles and some other administrative and legal related factors, such as financial issues, policies and procedures play an important role as mediating factors for other technology and human factors (LaValle 2011; Chen et al. 2012).

If the organizations are not ready yet for this kind of change, in relation to the culture and responsiveness, then diverse technology and human investments would not be sufficient to support this kind of transformation (Watson and Wixom 2007). Some studies associate different types of challenges to different levels of analytics. Data quality and readiness is an important determinant of successful operational analytics. IT infrastructure, hardware and software help a lot in building valid and accurate operational models and providing daily support for operational managers (Taylor 2010). On the other hand, tactical and more importantly strategic analytics need higher user skills and experience in extracting meaning and value from data after visualization and description. The input of human knowledge and experience into strategic analytics is more challenging, important and influential than into operational analytics, which can be more data driven than knowledge or experience driven, where strategic organizational intelligence results from, but more important than, individual transformation (Davenport 2009; Liebowitz 2006).

4 Discussion

Health analytics can be used on variable levels, mainly on the individual level of clinicians and healthcare professionals, on the level of hospitals and healthcare provider organizations as well as on the level of healthcare government organizations.

4.1 Clinicians and Healthcare Professionals

Clinicians should have the access to utilise health analytics on the levels of individual patients as well as on the public health level. On the patient level, health analytics can help CDS, evidence-based medicine and personalised medicine. Predictive analytics tools developed and validated using millions of patient records are now used more routinely by clinicians in predicting deterioration of patients in the intensive care, the need for special resources in the ER, readmission or mortality risk (Charlson 1987; Schonfeld et al. 2014; Walraven 2010). On the public health, clinicians are also be interested to use health analytics to predict resource utilisation of their services and how to improve clinical effectiveness and patient safety during their specialised care provision (Rumsfeld et al. 2016).

4.2 Hospitals, Insurance, Pharmaceutical and Other Companies

Hospitals, health insurance in addition to other pharmaceutical and healthcare companies are perfect candidates for using health analytics in improving their businesses. Hospitals can use predictive analytics to better prepare for the changing or increasing demand of their services after an outbreak, a seasonal variation pattern or a natural disaster (Raghupathi and Raghupathi 2014). Some newly introduced tools developed by professionals and scientists, for the analysis of healthcare insurance claims, shows how big data can support detecting fraud, abuse, and errors. Claim anomalies detected using these applications help private health insurers identify hidden cost overruns that transaction processing systems can't detect (Srinivasan and Arunasalam 2013). Pharmaceutical companies can also benefit from health analytics. By tracking which physicians prescribe which drugs and for what purposes, companies can decide whom to target, show what is the least expensive or most effective treatment plan for a disease, help identify physicians whose practices are suited to specific clinical trials (treating a large number of a specific group of patients), and map the course of an epidemic to support pharmaceutical salespersons, physicians, and patients (Koh and Tan 2011). Other healthcare services and biomedical product companies can benefit as well from the applications of big data health analytics through better understanding of the markets, patients' needs and critical success factors of biomedical devices and other products, so that they can inform their research and refine their strategies (Bollier et al. 2010).

4.3 Healthcare Government Organizations

The ministry of health and other government agencies are more interested in providing better health to the people while cost-effectively utilizing available resources. The government can utilise distinct types of health analytics to enhance the value of healthcare provided to people through analyzing the needs for services, geographical distribution of such needs and demands on levels of services (Heitmueller 2014; Parikh et al. 2016; Wang et al. 2016). Improving healthcare accessibility, cost-effectiveness, and equity are among the top priorities of the Australian government (Carter 2008). Governments of many leading countries, including Australia, United States, United Kingdom and Japan, started implementing big data analytics, mainly predictive health analytics, to enhance the control and responsiveness of the government healthcare system to the changing population needs (Kim et al. 2014).

5 Conclusions

Today we are shifting from the lower level of operational analytics into the higher level of strategic analytics and from simple descriptive analytics toward more sophisticated diagnostic, predictive and prescriptive health analytics. Using big data and health analytics, several healthcare performance aspects can be improved, such as patient safety, healthcare effectiveness, efficiency, and timeliness. Health analytics implementation is faced with various technology, human, and organization related challenges. The non-technological challenges are more difficult and need more time to be resolved, including the development of a clear vision to guide implementation projects and achieve objectives. Some studies associate different types of challenges to different levels of analytics. Technical factors, including software, hardware and data quality are important determinants of successful operational analytics. On the other hand, tactical and more importantly strategic analytics might need higher user skills and experience in extracting meaning and value from data after visualization and description. Health analytics can be used on variable levels, mainly on the individual level of clinicians and healthcare professionals, on the level of hospitals and healthcare provider organizations as well as on the level of healthcare government organizations.

Among the main future research directions is addressing some important research gaps in the areas of developing, implementing, and utilizing health analytics in supporting and improving the provision of healthcare services. More research is needed to suggest detailed and specific plans to overcome different types of barriers and challenges of developing, implementing, and utilizing health analytics. The suggested research should investigate methods of overcoming technological, human, and organisational challenges. It should also discuss approaches to identify and prioritise such challenges, so that each healthcare organisation can work on their own priorities and target their most resistant challenges.

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