Ideation Phase
Literature Survey

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Literature Survey

Healthcare is a booming sector of the economy in many countries [1]. With its growth, come challenges including rising costs, inefficiencies, poor quality, and increasing complexity [2]. U.S. healthcare expenditures increased by 123% between 2010 and 2015—from $2.6 trillion to $3.2 trillion [3]. Inefficient—non-value added tasks (e.g., readmissions, inappropriate use of antibiotics, and fraud)—constitutes 21–47% of this enormous expenditure [4]. Some of these costs were associated with low quality care—researchers found that approximately 251,454 patients in the U.S. die each year due to medical errors [5]. Better decision-making based on available information could mitigate these challenges and facilitate the transition to a value-based healthcare industry [4]. Healthcare institutions are adopting information technology in their management system [6]. A large volume of data is collected through this system on a regular basis. Analytics provides tools and techniques to extract information from this complex and voluminous data [2] and translate it into information to assist decision-making in healthcare.

Analytics is the way of developing insights through the efficient use of data and application of quantitative and qualitative analysis [7]. It can generate fact-based decisions for "planning, management, measurement, and learning" purposes [2]. For instance, the Centers for Medicare and Medicaid Services (CMS) used analytics to reduce hospital readmission rates and avert $115 million in fraudulent payment [8]. Use of analytics—including data mining, text mining, and big data analytics—is assisting healthcare professionals in disease prediction, diagnosis, and treatment, resulting in an improvement in service quality and reduction in cost [9]. According to some estimates, application of data mining can save $450 billion each year from the U.S. healthcare system . In the past ten years, researchers have studied data mining and big data analytics from both applied (e.g., applied to pharmacovigilance or mental health) and theoretical (e.g., reflecting on the methodological or philosophical challenges of data mining) perspectives.

Clinicians, healthcare providers-suppliers, policy makers and patients are experiencing exciting opportunities in light of new information deriving from the analysis of big data sets, a capability that has emerged in the last decades. Due to the rapid increase of publications in the healthcare industry, we have conducted a structured review regarding healthcare big data analytics. With reference to the resource-based view theory we focus on how big data resources are utilized to create organization values/capabilities, and through content analysis of the selected publications we discuss: the classification of big data types related to healthcare, the associate analysis techniques, the created value for stakeholders, the platforms and tools for handling big health data and future aspects in the field. We present a number of pragmatic examples to show how the advances in healthcare were made possible. We believe that the findings of this review are stimulating and provide valuable information to practitioners, policy makers and researchers while presenting them with certain paths for future research[10].

The process of analyzing big data, or big data analytics (BDA) can tackle large volume, high velocity data streams enabling personalized medicine, which provides physicians with a more comprehensive (in-depth) understanding of an individual's health. For instance, BDA can be applied to improve diagnostic treatment decisions amidst unaided human inference [11], [12]. The focus on the potential benefits of BDA has never subsided in research papers, technical blogs, and videos, motivating researchers to design solutions to address the aforementioned issues [13]. However, BDA has presented challenges in multiple business domains in the last decade. There is considerable hesitation to invest in big data technologies due to lack of standardization, a rapidly-evolving technology stack, complicated architecture design, a skill set which is difficult to learn, high resource and cost requirements, and data management, storage, access and analysis challenges. Another issue is the lack of a standard protocol of communication between the BDA team and the business side; the BDA team typically does not have enough background knowledge of business domain to model the analytics as per business requirements and the business side does not have the appropriate analytics knowledge (algorithms, technology stack, etc.) to tune and guide the BDA results according to personal needs. In fact, Gartner estimated that 85% of big data and BDA projects were failing in 2019 due to aforementioned issues [14]. BDA applications in healthcare are also (currently) plagued by these issues.

According to the WHO report, LOS is considered one of the most important monitoring and performance factors in hospitals[15]. Because of its effectiveness and equity, LOS is used to evaluate the efficiency of both the medical and the financial sections [16]. ICU is considered one of the most resource-consuming departments in the medical sections. Most elderly ICU patients are exposed to aggressive medical procedures to keep them alive, and about 33% of them die after a prolonged LOS [17]. Moreover, the time after discharging a prolonged LOS patient is critical as 55% of patients died within six months of being discharged [18]. In addition, the average cost for patients who have a prolonged ICU LOS is seven times the cost of the patients who do not have a prolonged LOS [18]. Therefore, there is a need for an accurate LOS prediction system to estimate patient LOS in the ICU in advance.

Predicting the LOS in ICU is beneficial from different aspects in terms of the patient medical plan and family, the hospital, and the insurance companies. The medical team can take accurate medical decisions and design an appropriate medical plan for the patient if they know his/her LOS in advance. As well, the predicted LOS could also provide the family with the information about the expected date to leave the ICU which is an indicator to the speed of recovery and can help them to arrange and manage their budget. Hospitals could also use the predicted LOS value in reducing costs, improving health care and as a base for early mobilization from the ICU [19]. Moreover, predicting LOS leads to improving the resources utilization, the efficiency of ICU care and reduction in the illness cost [20], [21], [22], [23]. It also reduces the risk factors before getting admitted to the hospital [24] and during the patient's accommodation [25]. Therefore, systems such as Standardized Early Warning Scoring System (SEWS) are used in predicting the in-hospital mortality rate and the LOS [26].

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