Educational Administration: Theory and Practice
2023, 29(2), 766-788
ISSN: 2148-2403
https://kuey.net/
Research Article

Challenges Faced by Healthcare Supply Chain for The Adoption of Big Data

Muhammad Usman Iftikhar*

*Analytics Consultant, Ascend Solutions, Saudi Arabia. Email: muhammadusmaniftikhar@gmail.com

Citation: Muhammad Usman Iftikhar (2023). Challenges faced by Healthcare Supply Chain for the adoption of Big Data. *Educational Administration: Theory and Practice*, 29(2), 766-788
DOI: 10.53555/kuey.v29i2.9185

ARTICLE INFO **ABSTRACT**

This study aims to analyse the obstacles to initiate big data in the healthcare supply chain. The report pinpoints roadblocks and presents immense insights to healthcare firms trying to leverage the potential of such Big Data (BD) technology to enhance their supply chain operations. A literature analysis was conducted in combination with consulting experts in order to identify the major impediments to BD adoption among the HSC. Then EFA was used to group the barrier factors into different categories. Results generated from the EFA were then validated using confirmatory factor analysis (CFA) to verify correct and precise results. Moreover, structural equation modelling analysis was used to determine the relationship between latent and observable variables and to develop a conclusive path diagram for further study. The research effectively classified the 13 identified barriers into three main categories: EFA was used to classify these groups and the interrelations among these groups were considered. Three hypotheses was evaluated with a result that all were valid. In particular, the study verified that the Data Governance Perspective was positively related to the Technological and Expertise Perspective as well as the Organizational and Social Perspective. Furthermore, a good correlation existed between the Technological and Expertise Perspective, and the Organizational and Social Perspective. However, most research focused on obstacles to BD acceptance in the HSC has failed to be conducted. This research uses a methodical technique and statistical verification creating a firm basis for future studies in this field. In particular, the results provide benefits for healthcare organizations and policymakers in making informed decisions regarding the deployment of BD technologies in ways that address possible problems and refine their decision-making processes. In this paper, the obstacles to BD implementation in the healthcare supply chain are uniquely categorized into three different frames of reference reflected on the understanding of the issues and providing unique insights to overcome the obstacles of BD implementation in future healthcare operations.

Keywords: Big data, Healthcare supply chain, Challenges, Technological and Expertise Perspective, and the Organizational and Social Perspective.

1. Introduction

In the current digitalization era, organizations have access to a variety of digital technologies that are designed to enhance organizational effectiveness. And one of these techniques that caught the attention of the academic community due to the great potential it contains to improve the decision-making processes is Big Data(Benzidia et al., 2021). Therefore, supply chain specialists have persistently been investigating for novel methods to utilize big data for deriving actionable insights for improving operational efficiency and effectiveness and therefore increasing the value as resources and services (Doolun et al., 2018). For firms, the economy is becoming increasingly competitive, leading to a shift from the traditional method of decision making by intuition to using data driven methods by making use of insights from big data. The shift is universally recognized across sectors and BD driven decision making has demonstrated great efficacy in improving organizational performance. Therefore, there has been a huge interest in business development in supply chain management specifically in healthcare field (Patel et al., 2017).

Big Data implementation in the supply chain can revolutionize supply chain operations and may confer a significant competitive advantage through more informed decision making. Unlike in traditional industries, in the healthcare supply chain, human life is of more concern, and therefore, a lot of medical supplies in the chain needs to be customized with precise measurements and to fit each individual patient demand (Mustaffa and Potter, 2009). As highlighted by Pitta and Laric (2004), the complexity of medical procedures and the need for patient involvement make healthcare supply chains (HSC) considerably different than the traditional retail supply chains in terms of the level of customization of service needed, as described by Evans and Berman (2001). According to Burns et al. (2001), the healthcare supply chain not only includes pharmaceuticals and health goods, but also movement of people in the system are included, with primary stakeholders defined from manufacturers, purchasers, providers, and payers (Arunachalam et al., 2018).

Lamba and Singh, (2016) agree that there have been persistent efforts to enhance service delivery within the health care sector, however, the sector continues grapple with challenges of improving the quality of care (Gupta et al., 2019; Boone et al., 2019). This is because the sector is complicated in multiple ways. Healthcare firms constantly need to be on top of their changing dynamic needs and continuing to stay a notch above the rest for the services they offer to their patients. The societal challenges, such as record keeping, regulatory adherence, and patient care standards have become more intense in healthcare sector. However, improvements to computing infrastructure and data access have provided new opportunities for supply chains to derive deeper insights and ultimately improve the efficiency of the whole system (Raghupathi and Raghupathi, 2014).

Healthcare generates huge volumes of data on patients, drugs, diseases, treatments, and tests, among other domains (Mishra and Singh, 2020). BD analytics has been rapidly growing to become an indispensable tool for managing the high volume of the clinical data and following evidence based practices (Wang et al., 2018). BD analytics is the synthesis and analytical processing of large datasets for the purposes of identifying patterns and models within to gain profound insights on the diagnosis and healthcare process. These insights are useful not only to healthcare practitioners, but to all sector stakeholders, as they lead to better quality outcomes, lower costs, and better overall performance (Raghupathi and Raghupathi, 2014). In the United States, advocates for the use of BD technology in the healthcare sector argue that using such technology could lead to up to $300 million in annual cost savings, as well as provide a means to regulating supply chain complexities and facilitating communication between clients and suppliers (Lamba et al., 2019).

There are numerous critical variables prompting the use of Big Datain organizations. However, these motivating motivations have not translated into wide application of BD in the HSC (Dubey et al., 2019). Despite the apparent potential of BD to help enhance competitiveness, improve service quality, and optimize operations, none of these goals are met. With such important data available, the opportunity is huge too; however, the problem is in managing all of the vast volumes of information which businesses have to process in an efficient manner (Bag et al., 2021). Business development effectively leverages only if there are robust systems to safely process and analyse data. All of this includes defining frameworks for making data available while protecting privacy, for using new software and tech to analyse data, for training staff to interpret and apply insights well, and pressing out education and resources for healthcare practitioners—from doctors and paramedics to trainees and patients (Hazen et al., 2016).

This investigation tries to find out how the healthcare sector can improve its efficiency by applying big data approaches to allow more informed decision making at different units of the healthcare system. Beverlake (2011) and Wagner & Nerurkar (2012) are only a few of the recent studies focusing on big data usage in traditional supply chains however research is very widely deprived of efforts specifically relating to how these can be applied to healthcare supply chains. However, BD insights gained from applying in conventional supply chains suggest considerable recommendations for its implementation in the HSC. This line of enquiry leads to the fundamental question of how BD should be properly integrated into the Healthcare supply chain and more importantly, the barriers that prevent its wide spread adoption. The research aims to investigate the subsequent inquiries:

RQ1. What hinders the use of BD in the HSC?

RQ2. How can the impediments to BD adoption in the HSC be categorised and empirically proved?

This research employs a multi-method method that employs Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and Structural Equation Modelling (SEM) to explore and verify the constraints of Big Data adoption in the HSC. The purposes of the research are to find and categorize these hidden hurdles of BD adoption, to corroborate these properties by external sources, and to offer practical insights to the decision makers from health care sector. Findings from the study enhance understanding of the obstacles to BD implementation in healthcare and provide a systematic approach for how such issues can be addressed in efficient ways.

The main contribution of this study is in identifying barriers to BD adoption in HSC. Based on the comprehensive literature review and expert contacts, the report analyses the current barriers in full integration of BD into healthcare operations. Understanding these barriers as complex requires identifying the first step toward further study.

The second contribution consists in the identification of latent characteristics that most precisely identify the obstacles to BD adoption in the healthcare area. Through Exploratory Factor Analysis (EFA) conducted on the data, three principal latent elements are identified. These variables help in categorizing the many hurdles

in aggregated themes, which account for the major impediments to the BD adoption. The latent nature of these characteristics also provide a systematic way to explore the subtle factors that influence BD uptake along the healthcare supply chain.
After the latent factors are identified they are validated via CFA. This phase is critical to ensure that the model is durable and precise. CFA contributes to a better understanding and optimization of the interrelationships among the measured variables, and ensures that the adopted model's framework is suitable in order to represent the barriers to the business development adoption. The validation method that is used in this case enhances the trustworthiness of the findings and assures the factors explored are based in statistical rigor.
Most contributions of the study are in suggesting ways for decision makers. Examining barriers and the relationship between them forms the necessary information which could assist healthcare managers and policymakers in making educated decisions in impending the adoption and adoption of BD practices in healthcare supply chain. All these challenges can be carefully addressed if businesses can enhance BD integration readiness and eventually improve the effectiveness of data driven healthcare operations.
In Section 1, the research objectives, methodology and structure are summarized and explained in detail. In Section 2, we explore existing literature on Big Data in the health care sector including an investigation of SEM techniques in adoption of Big Data. The methodologies used to identify and authenticate the founding barriers discovered are explicated through EFA and CFA in Section 3. In section 4, the analytical results are presented and discussed. Pragmatic implications and recommendations for healthcare practitioners and policymakers on how to overcome the identified obstacles to promote BD resource implementation are presented in Section 5. Section 6 concludes by making definitive observations about the implications and findings of this study and promising further research avenues. The research through a methodical consideration of these essential elements presents a methodical, thorough strategy pertaining to understanding and surmounting these challenges concerning implementation of Big Data in healthcare supply chain. This helps inform whether decision-makers should deploy Big Data for healthcare system efficiency, and how future policies should proceed.

2. Literature review

The HSC consists of complex interdependent a number of stakeholders who collaborate to provide services in both routine as well as emergency health situations (Raghupathi and Raghupathi, 2014). This network is a dynamic system that requires effective standardization, configuration/coordination, supervision and enhancement to maintain its operations (Lamba and Singh, 2018). The complexity of the HSC is heightened by the need to safely store and manage great quantities of data. The Big Datascience offers new methods of the large and various information handling by application of the refined data processing techniques and statistical analysis. Regular ways of regular doing things with the help of computer tools are being used in conventional data processing applications. It is limited to data and its processing in the domain of business development, which is done over a multiple number of nodes within complex data environments (Raghupathi and Raghupathi, 2014), and hence, can include large amounts of information at any coincidental time.
There is no question that BD plays an important role for healthcare institutions and when used appropriately, may have a significant impact upon the operations and performance of healthcare institutions; nevertheless, there are many roadblocks impeding its widespread adoption in the healthcare industry (Zhang et al., 2017). The challenges are mainly internal to the organizations, such as infrastructure, training personnel and allocation of resources. 2013 eHealth project research had found that 84% of healthcare professionals perceived the implementation of BD as a major problem for healthcare organizations (Chen et al., 2020). However, the many applications of BD in the healthcare supply chain show that the potential for it to revolutionize how its operations are managed is real (Khan et al., 2018).
The benefits of BD usage in the HSC have been the subject of a lot of research and much has been done on the use of BD in the HSC. The literature study consisting of the papers from bibliographical databases such as Emerald, Scopus, Google Scholar and Springer highlight a major intriguing on BDs role in addressing fundamental challenges in the HSC. For instance, demand forecasting in the healthcare domain has been promoted by use of big data (Verma and Gupta, 2018; Singh et al., 2020), social media analysis (Zhou et al., 2016) and symptom and disease discovery (Alotaibi et al., 2020a, b). These studies show that BD has the potential to improve a variety of aspects of the healthcare supply chain. The table 1 encapsulates the various uses of BD in the supply chain.
However, in spite of the potential applications of BD, the literature lacks studies regarding the difficulties and complexity of integrating BD successfully into the HSC. Other studies have examined what is preventing the healthcare industry from adopting BD. In the context of the healthcare sector, Alotaibi and Mehmood (2018) assessed a number of big data ideas, identifying and discussing the challenges and opportunities with relation to its application. The PRISMA methodology was used by Galetsi et al. (2019) to perform a systematic literature review of some of the problems and challenges related to implementing BD healthcare policies. To explain the challenges that healthcare institutions have faced in implementing BD technology, Wang and Alexander (2019) conducted their case study. The interpretive structural modeling-analytical network process (ISM-ANP) method was used by Choudhary et al. (2021) to highlight obstacles to effective deployment of additive manufacturing in the medical supply chain. Chen et al. (2020) have clPreliminary respondents

identified and prioritized organizational hurdles for BD-based healthcare information systems, which are the hurdles faced by healthcare organizations in implementing BD solutions effectively.

Table 1. Big data studies in healthcare supply chain network

Authors	**Theoretical basis and results**
(Benzidia et al. 2021) (Choi et al., 2016)	Big data analytics and AI effects on green supply chain integration and hospital environmental performance were studied. This research examined how these technologies can optimize resource consumption and eliminate resources in healthcare supply chains to increase sustainability.
(Lamba and Singh 2016) (Khan et al., 2018)	This study glorified supply chain functions and showed how BD analytics is used in different processes. We can visualize supply chain operations and business development in decision-making with this strategy.
(Gupta *et al.* 2019) (Singh et al., 2020) (Zhou et al., 2016)	A prior study provided a Big Data Analytics conceptual framework to improve supply chain network decision making from a stakeholder perspective based on circular economy principles and sustainability. The framework studied how circular economy support in business development might encourage sustainable supply chain practices and improve firm environmental and social performance.
(Boone *et al.* 2019) (Sharma and Joshi ,2017)	Another study examines the effects of BD on consumer behavior and how time series data might improve demand forecasting. According to the report, BD analytics would improve consumer demand forecasting, which would aid supply chain planning and inventory management.
(Mishra and Singh 2020)	A global industrial network cost-reduction model was created using country-specific data. Mixed-integer model model let corporations tailor their supply chains to each network country's unique characteristics.
(Lamba *et al.* 2019) (Alharkan et al. 2019) (Sarkar et al., 2018)	A mixed integer nonlinear programming (MINLP) model was created to identify suppliers and optimize lot size for dynamic, multi-period, multiple-product supply chains in a separate study.
(Dubey *et al.* 2019) (Patel et al., 2017) (Zhou et al., 2018)	Humanitarian supply chain research employed BD analytics to promote civilian-military collaboration and confidence during humanitarian operations. BDs analytical skills were assessed to improve emergency coordination, decision-making, and resource allocation.
(Sahu et al., 2020) (Wang et al., 2016)	BD analytics optimized a reverse logistics decision and improved remanufacturing. BD enhanced reverse logistics procedures, reduced waste, and supported product remanufacturing, making supply chains more sustainable.
(Agarwal et al., 2017) (Hazen *et al.* 2016)	Eight theoretical frameworks were used to assess the triple bottom line impact of BD on the supply chain, focusing on sustainability. This research sought to examine how BD may promote supply chain sustainability by improving environmental, economic, and social outcomes.

The literature review reveals three notable research gaps in the adoption of Big Data inside healthcare supply chains (HSC):

1. Insufficient study on BD in the HSC: Despite having conducted significant research on BD applications in traditional supply chains, efforts in the domain of healthcare supply chain are surprisingly scant. The implementation of BD in the HSC is little explored in terms of the distinct obstacles and potential thereby leaving this study relatively unexplored (Sharma and Joshi, 2017).
2. Identification of Barriers: Several research have been identified in the potential of BD in the HSC but with very few recognizing the obstacles to BD implementation. To help firms over hurdles, as well as make better use of BD within the operations of firms, enhanced comprehension of these barriers is needed (Patel et al., 2019).
3. Absence of Structural Models: When it comes to opportunities to harness the power of BD to improve the performance and efficiency of the supply chain operations, though, the existing research is lacking a comprehensive model developed to overcome the hurdles of BD deployment in the HSC. Such a structural model would provide substantial insights into the interrelations of these impediments and provide practical direction for researchers, academics, and industry professionals in handling these issues (Jebaraj et al., 2019).
4. Restricted Utilization of SEM: SEM has been applied in different fields with different purposes to develop a comprehensive model using SEM to identify and evaluate the principal obstacles to BD uptake in the HSC to mitigate the issues (Rajput et al., 2017).

This study identifies and explores the 13 most important hurdles to BD adoption in the HSC and addresses research gaps through a full literature review, and conversations with corporate and academic professionals.

Table 2 thoroughly describes the barriers, setting a foundation for further investigation in this domain and guiding subsequent study within this area.

2. Methodology

This section comprises seven segments, each concentrating on a distinct facet of the study methodology:
In the first section the SEM methodology used to model relations between latent and observable variables is thoroughly explained. The proposed framework is used to validate it and bring into light relationships between the obstacles to Big Dataapplication in the HSC using Structural Equation Modelling (SEM). The second part speaks in relation to questionnaire preparation. This questionnaire was set up to generate data about the mentioned obstacles in the literature review. Feedback from industry experts on the structure collected were considered in the design of the structure, to ensure the pertinent aspects affecting BD uptake in the HSC were taken into account. The third section describes the minimal sample size required in the study. In this section, statistical factors are addressed that guarantee the sample size is large enough so that the sample yields accurate and valid outcomes for SEM analysis. In section four, the data collection methodology and an analysis of the descriptive statistics is delineated. For this, data was collected from different healthcare experts and companies engaged with healthcare supply chain. Descriptive statistics were used to examine the demographic properties of the sample and preliminary trends in the data. In the fifth section I explore the problem of nonresponse bias, a winged hindrance of survey research. It deals with the handling of nonresponse and the steps undertaken to ensure that the results accurately reflect what the target population is thinking about. In the sixth section, EFA is applied to classify the recognized obstacles to BD implementation in the HSC. This statistical method allows understanding of this correlation in terms of grouping barriers into coherent groups based on the fundamental elements that categorize barriers. CFA is used in the last section to test the model's fit and to validate the structure as yielded by EFA. Therefore, CFA is carried out to verify consistency of postulated correlations between latent variables and actual data thereby confirming the model's robustness and reliability. Figure 1 shows the visually encapsulated, comprehensive research technique. Below is a flowchart of the study's phases and the progress from the original research design.

SEM Approach

The SEM Approach introduced by Joreskog in 1970, is a robust statistical methodology that combines a measurement model with a structural model. The measurement model delineates the connections between latent variables (unobserved variables) and their corresponding measured variables, whereas the structural model elucidates the interactions among the latent variables themselves (Joreskog & Sorbom, 1996). SEM is progressively employed to investigate intricate interactions among many elements. This approach enables researchers to examine causal interactions and structural linkages among a series of equations utilizing both qualitative and quantitative data (Hair et al., 2010). This method is particularly useful for comprehending the influence of latent (unobserved) factors on seen variables within a certain system. The ability of SEM to estimate path parameters by the means of the analysis of variances among variables is one of its most important strengths. Researchers can illustrate the structural relationships, facilitating the conceptualization of the study's theoretical framework (Shah & Goldstein, 2006). This graphic depiction augments comprehension of intricate interactions among variables and helps model interpretation. The ability of structural equation modelling to handle a large variety of elements without imposing restrictions on the amount of variables that are being investigated is yet another significant advantage of this method. This renders it an exceptionally adaptable instrument for research across several fields. Moreover, SEM can rectify measurement errors by estimating the weights of latent variables, so offering a more precise representation of their actual values and interrelations (Chou & Kim, 2009).
Moreover, SEM adopts a confirmatory methodology for hypothesis testing, enabling researchers to assess theoretical models via structural equations. SEM offers insights into the importance of each variable by assessing the weight of all variables and sub-elements in the model, rendering it a favoured approach for researchers researching complex systems. Structural Equation Modelling provides a robust, adaptable framework for analysing causal links and evaluating theoretical models, becoming it an essential instrument across diverse study domains. SEM's capacity to assess the importance of relationships and rectify measurement mistakes renders it especially advantageous relative to alternative analytical techniques.

Table 2 Key Challenges of implementation of Big Data in HSC

Code	Barriers with Description	References
C1	Data quality is a big problem in the HSC as well as in other supply chains. It consists of completeness, timeliness and consistency of the data, all of which are a prerequisite of successful decision making and operational efficiency. When the stakes are so high, such as in healthcare, inaccurate or even inadequate data can lead to suboptimal decisions which most certainly can lead to some serious repercussions.	(Arunachalam *et al.*, 2018) (Choi et al., 2016)
C2	Specialized tools in data analysis make it possible to derive meaningful insights from data analysis. These tools are still missing for a lot of businesses. Without these advanced tools it can be difficult to derive useful insights from large amounts of data.	(Zhou et al., 2016) (Dash et al., 2019)
C3	To satisfy the need to analyze real-time data constantly, the infrastructure required for Big Data analysis must be maintained in constant state of being on top of the demand. With this in mind, healthcare organizations face a big problem; anticipating and planning future technological needs is a messy thing. Healthcare systems must change the infrastructure along with the systems. Nevertheless, efforts to anticipate future requirements, as well as technology development, often face the challenge of predicting future requirements and technology developments.	(Sharma and Joshi ,2017) (Patel et al., 2019)
C4	They relate to the most important problems in the HSC domain on security and privacy of health data. Healthcare data is very delicate data, and any breach can be very serious consequence. The detriment from inadequate management of patient's data can be substantial, it not only affects the health of the patient in both physical and mental senses, but also the patient's own self-worth. Therefore, healthcare companies are very concerned with protecting the security and privacy of sensitive data. However, security of sensitive information from unwanted access is critical and it is moreover important to have appropriate methods and technologies to ensure it.	(Chen et al., 2020) (Verma and Gupta ,2018)
C5	The influence of capital investment as a determinant of adoption of the BD technologies in the healthcare industry is very important. Adopting new technology comes at cost and large number of businesses are unable to get the funds needed to make these changes. The first phases of technological adoption and long-term advancement require the securing of adequate funds.	(Raghupathi and Raghupathi, 2014)
C6	BD systems in healthcare organizations could not be fully executed without effective leadership. BD adoption advocates guarantee that their organization has a definite mission for the adoption of BD, where this is integrated into the organization's basic values and ethics. Fostering a collective vision for BD and integrating it into the organizational culture requires that health administrators demonstrate a dedication to do this, as it is not easy to change the mindset of such a large corporation.	(Kong et al., 2015) (Lamba and Singh, 2018) (Dash et al., 2019)
C7	The effective deployment of BD systems requires regulatory frameworks. Explication in detail of how new technologies fit into the larger strategic automata of healthcare organizations also necessitates explicit laws. Often insufficient rules and political instability obstruct the firms from investing in BD technologies. Regulatory clarity is needed to understand the decision making and establish a stable progress in the field of technology.	(Galetsi et al., 2019) (Sharma et al., 2021) (Alharkan et al. 2019)
C8	It is critical that information can be exchanged between a Health and Social Care system. However, for proper data sharing, this must be simplified and secured. So, the patient has to retain control over the data sharing and privacy has to be preserved as well as there is consent. This demands for secure and	(Sahu et al., 2020) (Wang et al., 2016) (Agarwal et al., 2017)

	transparency platforms that would be used to transfer the patient information without affecting the patient privacy.	
C9	When new procedures or systems are introduced, resistance to change is an inherent human trait — visible in every business. This resistance could slow down the adoption of BD technologies in healthcare because everyone in the personnel might reject new methodologies. To overcome this resistance efficient change management tactics, explicit communication, and adequate training are needed.	(Khan et al., 2018) (Chen et al., 2020)
C10	The successful implementation of BD in healthcare depends on good people with the competence to analyze and draws insight from the data collected. The lack of proficient workers makes endeavors to accumulate and keep data in a warehouse futile. The recruitment and retention of qualified personnel who are skilled in BD technology and analytics is a burden on healthcare firms.	(Zhang et al., 2017) (Singh et al., 2020)
C11	Another important thing that organisations must do is to offer proper training. In order to make sure that healthcare personnel get all the training resources they need to be trained on the latest BD principles, techniques and processes. This will ensure that workers can optimize BD systems and better optimize the delivery of healthcare as a whole.	(Galetsi et al., 2019) (Chen *et al.*, 2020)
C12	Integration of the HSC would mean data standardization. However, the healthcare sector still doesn't have set processes on data management. Since there are no established frameworks to build the integrations, there are problems in data integration across different systems causing inefficiencies and inaccuracies. A standardization of data protocols must be implemented to enable smooth data flow and communication across the HSC.	(Chen et al., 2020) (Malaka and Brown, 2015)
C13	In the long run, firms have to develop a research and development (R&D) culture in order to constantly improve their business development procedures and processes. The development of specialized tools and support systems for BD in healthcare requires close collaboration with the best research and educational organizations. These collaborations will help build innovation and make sure these healthcare organizations are BD technology leaders and able to handle more with data, with more efficiency and effectiveness.	(Sarkar et al., 2018) (Patel et al., 2017)

In particular, the advancement of empirical modelling, especially by using Structural Equation Modelling and other types of multilevel regression, has considerably improved data analysis in diverse sectors. The extensive implementation of these models signifies a major shift in organizational strategies for continuous improvement, in an ever more competitive context. Structural Equation Modelling (SEM) is a powerful analytical instrument to investigate complex relationships and inherent interaction across various fields. Using the latent variables, it is very advantageous for behavioral and industry specific research, given, its capacity to model latent variables and to evaluate structural hypotheses. Its application across a range of sectors highlights the capacity to provide insights that support data driven decision making and achieve operational efficiency.

In 2017, Sambasivan et al. did a major study on delays in using SEM analysis in Tanzania construction. Findings demonstrated how SEM would be applied to industry specific issues, identify sources of inefficiency and present evidence based solutions for enhancement. This highlights how SEM can adapt to different contexts, and provide solutions that prove practical for specific industries.

From the behavioural research perspective, Sadia et al. (2018) identified the drivers' speed selection influencing factors using Structural Equation Modeling (SEM). Through their studies, they identified important psychological and environmental elements which influenced driver behavior and had important implications for traffic safety and policy development. SEM is shown to be capable of uncovering subtle interactions between factors that might not be detected.

Since then, the application of the SEM has increasingly expanded into environmental, operational, and market dynamics. SEM was used by Rehman Khan et al. (2020) to examine how green supply chain practices (GSCPs) affect organizational performance and to show the association between the sustainable practices and competitive advantage. Similarly, Farooq et al. (2018) use SEM to identify factors affecting consumer happiness in airline industry and pinpointing important drivers of customer satisfaction and loyalty. Additionally, Raut et al. (2019) studied the projected efficiency of Big Data analytics as a tool for insight into

sustainability for business advancement in emerging countries and supported the empirical validation that data centric tactics enhance the sustainability of an organization. The studies presented in these examples show the capacity of SEM to model complex, multi-faceted interactions in several operations settings.
SEM has been key in solving the problems of innovation, quality improvement and integration of technology in the healthcare sector. In their research about In-depth use of big tech data analytics in healthcare, Shahbaz et al. (2020) used SEM to analyse the adoption of Big Data and identified key factors that impact positive implementation. Ratnam et al. (2014) drew the attention of one such essential potential of digital technologies in enhancing the care delivery and operational efficiency and is the focus of this study. Similarly, Hong and Lee (2018) analyzed how operational innovations have positive impact on improving care quality and customer loyalty in Korean healthcare industry and showed that SEM could effectively link operational practices with organizational results. Together this research depicts SEM's ability to surface inherent relationship and proven insights with evidence to improve system performance. Its introduction to the healthcare field is very important because the industry is characterized by a significant number of players, technical inventions, and complicating operational issues.
SEM allows researchers and practitioners to determine important components, to assess how these components are related. The increasing demand for evidence-based decision making in contexts of complexity is methodologically aligned with SEM in academic research. Useful not only to advance theory and to practice in a variety of industries, it is its capability to handle and examine multidimensional data and understand complex relationships. Future study that leverages the capabilities of SEM could, however, extend its use to the healthcare innovation, sustainable practices and operational efficiency domains as the overarching objective of enhancing systems and results across different environments is achieved.
In many domains, such as sustainable supply chain management, SEM has also been applied. Bhatia et al. (2019) examined precursors for successful implementation of closed loop supply chains and Gardas et al. (2019) investigated determinants of supply chain sustainability. However, applications of SEM to these supply chain performance aspects demonstrate SEM's flexibility in examining various dimensions of supply chain performance, from sustainability to operational efficiency. SEM's use in a variety of application in several industry and contexts account for its key role in understanding complex system, improves the decision making, and drives the business practices as well as healthcare system practices. When fierce rivalry and demands for maximum efficiency are encountered by the firms, SEM and other related approaches are becoming vital for the firms, to survive and to gain competitive advantage and sustainable growth.

Flowchart for combined methodology

This flowchart presents a rigorous procedure to analyse the variables and build a reliable model to hopefully explain the barriers to Big Dataintegration in the HSC. The process starts from collecting inputs through an exhaustive literature research and also from discussions with field specialists. The latter sources provide relevant accounting for variables observed in the study. The variables chosen constitute a basis for a survey compilation of data evaluating the importance of the variables based on the responses of participants.
The second step is Cronbach's Alpha assessing the internal consistency of the data. With statistical metrics, this metric helps to quantify the reliability of the dataset. Whenever Cronbach's Alpha is below .7, the variables are reviewed, and adjustments to it are taken, for example, by taking out or adding a few items, to improve consistency. If reliability threshold was met, sample adequacy is evaluated using the KMO test. If KMO value is above .5 then, sample size is perfect for further investigation; otherwise, change is required.
After these preliminary assessments, initial factor extraction is implemented to derive these relevant factors. We only keep factors with eigenvalues larger than 1, and all factors together must explain greater variance than 50% of the total variance in order to ensure that the extracted components really characterise the variability of the dataset. The rotation of the selected factors is then done through the use of varimax method with Kaiser normalization. This rotation explains the interpretation of the factors and lets the factors be organized into meaningful dimensions. Finally after identifying the dimensions, we then construct a path diagram to represent the relationship between these dimensions and the observed data. This visual illustrates the interactions and influencing of many variables. Lastly, the model is summarized and evaluated for fit, with verification that the results are valid and trustworthy. The methodical approach used here guarantees the developed model are robust and capable of providing worthwhile insights for further researches.

Data Collection and Reliability of Data

Data for this study was gathered via a survey as well as personal interviews of specialists within healthcare businesses and academia. Among the total of 238 experts contacted, 67 were accepted giving a response rate of (67/238) x100 = 70.10%. SPSS 21.0 was used to compute Cronbach's Alpha (α) for each barrier to verify the obtained data (Ngacho and Das, 2014). Internal consistency with α above .7 was maintained (Cronbach, 1951), and barriers with α below .7 were discarded. The dependability of the data and of the measuring scale were validated as all 13 obstacles had α values greater than .7.
In order to determine which components to include in a reliable measurement instrument, factor analysis was used for further examination (Raja Mamat et al., 2016). In order to determine if the factor model was appropriate, the interrelationships among elements were evaluated. KMO test was used to determine sampling adequacy which had a score of .814 which is more than the minimum recommended threshold of

.50 (Ul Hadia et al., 2016). Moreover, the result of Bartlett's test of sphericity with χ^2 =694.797, 195 as degree of freedom indicated high correlations between barriers and component analysis was thus justified. All 13 obstacles were kept in the analysis since all corrected item total correlation values are greater than .3 (Koufteros, 1999). The confirmation of the significance and coherence of the obstacles recognized through expert input substantiates the relevance of the methodologies and the measures developed. In addition, Table 3 Includes comprehensive statistical values which reflect the viewpoint of the experts. By applying this method, the selected barriers will be proven dependable and suitable to include in the study structure.

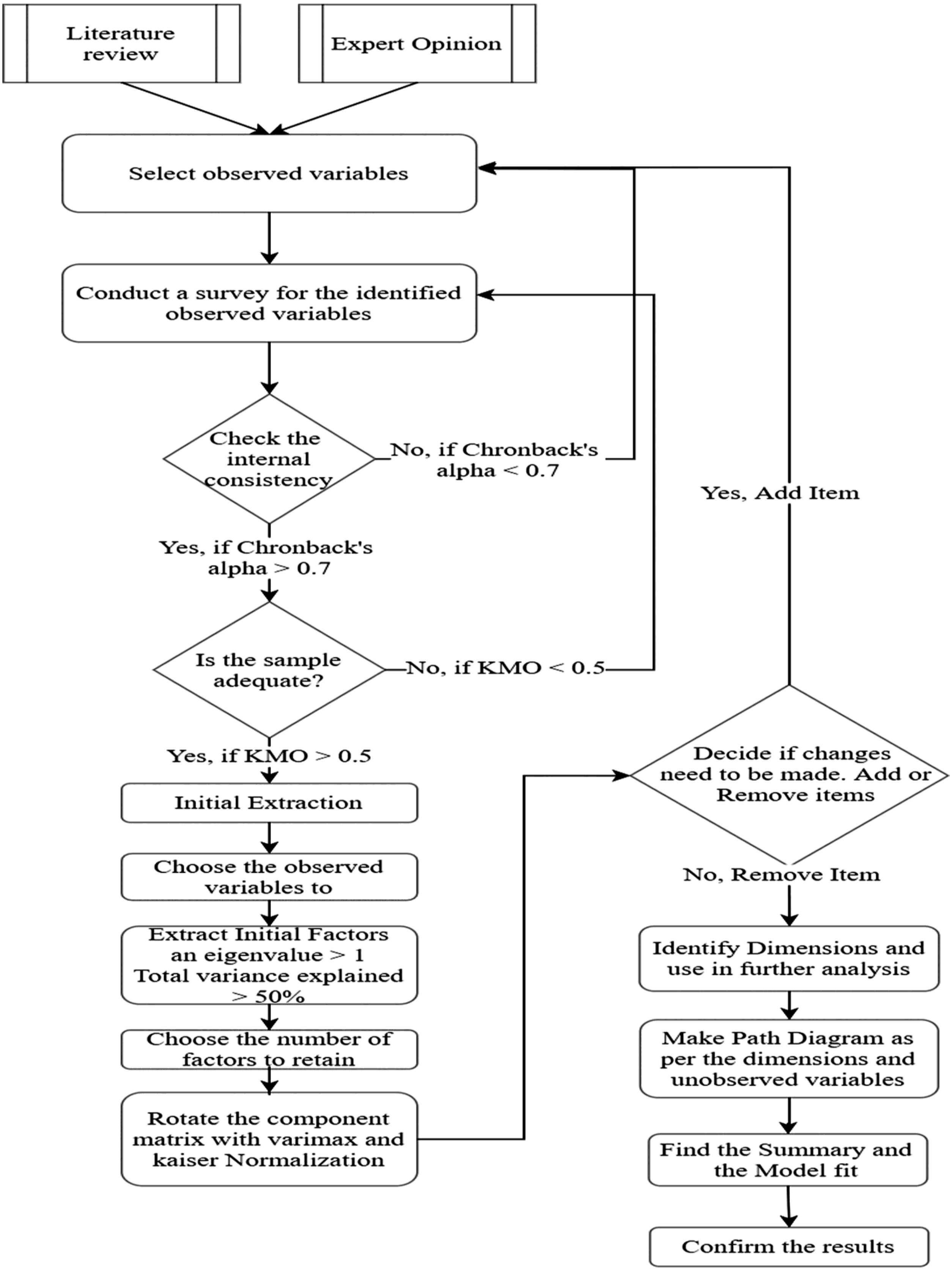

Figure 1. Flowchart for combined methodology

b. Nonresponse bias measurement

When there are large discrepancies between survey responders and non-respondents, non-response bias can undermine study reliability and accuracy. The data gathered may not represent the entire community if respondents do not differ regularly from non-respondents. Such errors could lead to wrong outcomes, unwarranted inference or misprediction, especially in regression and path coefficient analyses (Hair et al., 2013, 2011).

Table 3 Descriptive statistics of sample of respondents

Barriers	Mean	Std. Dev. (SD)	Corrected item total correlation (CITC)	Squared multiple correlation	Cronbach's α if item deleted
C1	3.8169	.72843	.570	.575	.867
C2	4.1154	.73627	.677	.686	.860
C3	4.1751	.72275	.654	.585	.862
C4	4.0407	.59342	.664	.666	.861
C5	3.9810	.75608	.700	.636	.858
C6	4.2348	.72176	.692	.578	.859
C7	3.5333	.86245	.612	.609	.866
C8	3.5631	.76085	.765	.726	.854
C9	4.4885	.64512	.704	.642	.858
C10	4.6527	.51342	.727	.657	.858
C11	4.2497	.64268	.686	.571	.859
C12	3.9363	.57561	.726	.595	.857
C13	4.0706	.77173	.738	.672	.856

Source: Author's Calculations (SPSS 21.0)

Wagner and Kemmerling (2010) describe four main techniques that researchers frequently use to address and evaluate the possibility of non-response bias:

1. Comparative Analysis of Preliminary respondents and Last-phase Respondents: This method considers Last-phase respondents are more like nonrespondents than Preliminary Respondents. Researchers can examine Preliminary respondents and Last-phase responses from participants for significant differences that may indicate non-response bias.

2.Utilizing Auxiliary Information: Discrepancies between the respondent's and the non-respondent's traits on auxiliary data, such as their demographic or organizational characteristics, might indicate bias.

3. Follow-Up Surveys: Non-respondents are contacted with a follow-up survey intended to elicit additional responses. This way allows a straightforward comparison between respondents and non-respondents in order to determine the extent to which bias may have occurred.

4. Weighting Adjustments: The data is modified according to established demographic characteristics (using statistical weights) in order to account for the under representation or over representation of certain groups.

Researchers can use these strategies to find and limit the effects of non-response bias. It will also make sure that their findings are more accurate to the real population. The initial method (Preliminary respondents versus Last-phase respondents) used to assess nonresponse bias to the study was used. The 167 total responses were subsequently grouped into Preliminary respondents' responders (the first 36 samples) and Last-phase respondents (the last 36 samples). Significant differences of replies between two groups were assessed with a paired t-test. Preliminary respondents and Last-phase respondents did not differ significantly (see Table 4), as confirmed by the paired t-test. If there is no marked difference, that means that the answers of the participants are homogeneous and representative of the surveyed audience. Thus, this study does not have nonresponse bias. This analysis shows no substantial disparities between Preliminary and Last-phase respondents, confirming the data's dependability and impartiality and providing a sound foundation for future research and conclusions.

Table 3.1 Reliability and Validity Statistics of Proposed and Final Model for factors influencing Barriers of HSC

Barriers of HSC	Proposed Model				Final Model			
	CR	AVE	MSV	ASV	CR	AVE	MSV	ASV
Data Governance Perspecti (DGP)	.902	.700	.105	.057	.889	.672	.100	.055
Technological and Expertise Perspective (TEP)	.890	.632	.026	.015	.890	.630	.025	.014
Organizational and Social Perspectives (OSP)	.885	.609	.079	.034	.885	.609	.077	.034

Source: - Author's calculation from AMOS 21.0 VERSION

Table 3.1 represents that the values of construct reliablity (CR), avaerage variance explianed (AVE), maximum shared variance (MSV) and average shared variance (ASV) are meeting the established standardised values. The value of CR is more than .7 in all the cases whereas the values of AVE is less than CR, MSV are less than AVE and laslty, ASV is less than MSV for the final model, indicating no isssue in the reliablity and validity of the current data set (Hair et.al, 2015).

Table 4. Paired t-test for nonresponse bias measurement of factors influencing Barriers of HSC

Variables	Responses	*N*	Mean	Std. dev.	*t*-statistics	Sig.(two-tailed)
C1	Preliminary respondents	36	3.6084	1.245	-.822	.268
	Last-phase respondents	36	3.8577	0.783		
C2	Preliminary respondents	36	3.8577	0.783	-.780	.762
	Last-phase respondents	36	3.9453	0.868		
C3	Preliminary respondents	36	3.9453	0.868	-.808	.828
	Last-phase respondents	36	4.1674	0.834		
C4	Preliminary respondents	36	3.54165	0.868	-1.186	.286
	Last-phase respondents	36	3.68155	0.670		
C5	Preliminary respondents	36	4.01925	1.032	-.288	.607
	Last-phase respondents	36	4.1513	0.847		
C6	Preliminary respondents	36	3.9243	1.146	-1.688	.116
	Last-phase respondents	36	4.01815	0.668		
C6	Preliminary respondents	36	4.01815	0.668	-.678	.86
	Last-phase respondents	36	3.5834	0.870		
C8	Preliminary respondents	36	3.5834	0.870	.272	.808
	Last-phase respondents	36	3.70755	1.100		
C8	Preliminary respondents	36	4.0953	1.021	-1.281	.22
	Last-phase respondents	36	4.1655	0.640		
C10	Preliminary respondents	36	4.3424	0.868	-.727	.606
	Last-phase respondents	36	4.04165	0.492		
C11	Preliminary respondents	36	3.90655	0.668	1.676	.087
	Last-phase respondents	36	4.14425	0.866		
C12	Preliminary respondents	36	4.14425	0.866	-1.826	.068
	Last-phase respondents	36	3.9493	0.621		
C13	Preliminary respondents	36	3.9493	0.621	-.666	.706
	Last-phase respondents	36	3.9303	0.866		

Source: - Author's calculation from AMOS 21.0 VERSION

a. EFA

The proposed factor structures were explored to see if they matched the reality of the dataset through EFA. Hair et al. (2013) suggests that this study identified the key underlying factor structure along with the necessary number of factors for the results to more appropriately reflect the data. In the EFA, the predicted structure that came out of the study model matched the observed data. The variables were extracted and categorized according to their loading by principal component analysis (PCA) with varimax rotation. Tables 5 and 6 present findings, that appropriately categorize the barriers and include their eigenvalues, and the total variance accounted for, respectively.

The analysis classified all 13 barriers into three principal factors: perspective of data governance, technological and expertise, and organizational and social perspectives. The classification explained 63.11% of the variance in performance, and therefore the classification was reliable. Except for B6, which displayed a loading of .395, all barriers exceeded factor loadings of .5. Domain experts were additionally consulted to evaluate the classification to ensure practical applicability and relevance with real world problems. In the Data Governance Perspective, controls over how the healthcare data are administered, and regulated and their quality are encompassed. Examples of these obstacles include poor health rules and regulations, security and privacy health data, lack of commonly implemented data sharing protocols, insufficient data standardization and integration, and data quality issues. However, these obstacles emphasize the need for legislative frameworks, data sharing protocols and strengthened data governance solutions in order to achieve the effective BD deployment.

The technological and expertise perspective is the accessibility and evolution of technology, as well as the technology and professional expertise required, in order to implement BD. In this area, there exist obstacles including the need for continual infrastructural scalability, lack of specialized instruments for investigation of business development, shortage of professional personnel with technical intelligence, and lack of training resources. The importance of technology preparedness and the investment needed with training and development of staff to successfully bring BD into the healthcare supply chain is driven by these reasons. The study provides a structured approach for understanding the impediments that impede BD implementation in healthcare supply chain by classifying and identifying these obstacles. This makes a classification of the obstacles, so as to formulate specific strategies to face them towards an efficient and effective BD integration in the healthcare.

Table 4 Profiling of factors influencing Barriers of HSC

Factors influencing Barriers of HSC	Factor Loading
Data Governance Perspective (DGP) (Cronbach Alpha= .878, Eigen Values = 14.568)	
Data Quality Challenges in Healthcare Supply Chains: Completeness, Timeliness, and Consistency	.839
Security and Privacy Issues in Sensitive Healthcare Data Management	.778
Regulatory Issues and Political Unrest in Big Data Implementation	.795
Safe and Open Health and Social Care Data Sharing	.623
Lack of Data Standardisation Hinders Healthcare Supply Chain Integration	.598
Technological and Expertise Perspective (TEP) (Cronbach Alpha= .859, Eigen Values = 8.753)	
Big Data insight analysis tools lacking	.874
Predicting Healthcare Infrastructure Technology Needs	.796
Healthcare Big Data Analytics Skilled Talent Gap	.783
Healthcare Workers Need Big Data Training	.675
Organizational and Social Perspectives (OSP) (Cronbach Alpha= .841, Eigen Values = 3.025)	
Capital Investment Prevents Healthcare Big Data Technology Adoption	.774
Leadership and Organisational Big Data Adoption Vision	.448
Change Resistance Hinders Big Data Technology Adoption	.713
Research and Development Advances Healthcare Big Data	.772

Note(s): Rotation converged in five iterations.
Source: Author's Calculations (SPSS 21.0)

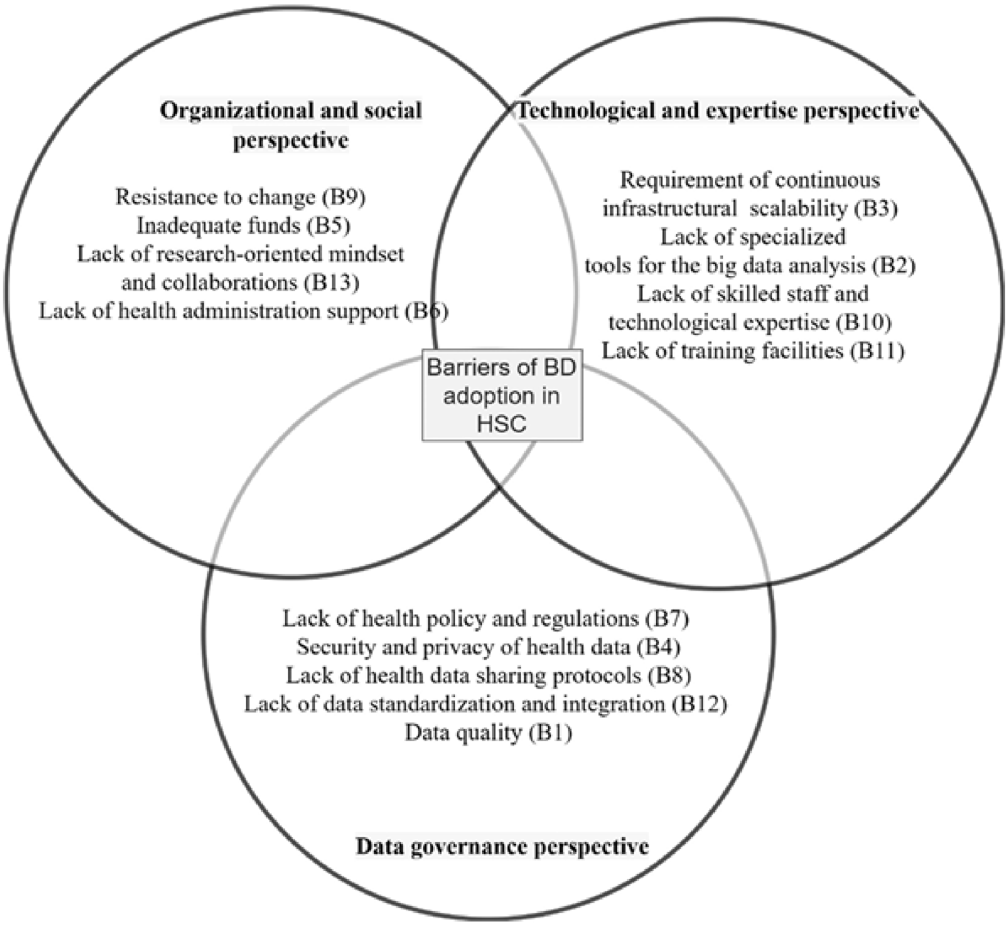

Figure 2. Challenges of adoption of BD in HSC

The Organizational and Social Perspective analyzes the cultural and organizational aspects influencing the achievement of Big Data success in implementing it within the HSC. These characteristics reflect the internal workings and external alliances of a business, focusing on how these problems can greatly impact adoptions and integrations of BD technology. Resistance to change is a key obstacle in this category, because it is a natural human inclination that often prevents new systems and technology go live. A major hurdle to BD implementation is that employees and stakeholders are resistant to replacing traditional methods that they are used to with the unfamiliar. The primary obstacle is a shortage of capital, since, with BD technologies often requiring a large investment of funds in establishing infrastructure, tools and for training, scaling of BD technologies can be impeded.

Moreover, there is an absence of a research mentality and collaborative work. Therefore, organizations will deprioritize research and development (R&D) activities or not establish relationships with academic and research organizations, and innovation and the development of BD specific tools and processes will be constrained. More importantly, there is a great lack of health administration support. Without the robust leadership and commitment by administrators, it is difficult to generate a cohesive vision for and commitment of necessary resources to BD implementation. The educational process is hampered by these organizational and societal impediments which preliminary respondents illustrate the importance of developing an adoption promoting culture with collaboration and innovation within the confines of an organization. These issues need to be addressed through a strategic focus on leadership, money, and partnerships to create an HSC environment conducive to successful BD uptake.

Confirmatory Factor Analysis

CFA ensures thorough analysis of interconnectedness between the dataset and ensures that the model is valid. Figure 3 shows these models represented as links between latent and observable variables. The regression weights as simple as possible and clear, the regression weights of one element within each component were set to 1, with the weights of the other elements derived correspondingly. Unlike the linear model fit, the use of this method provides guarantees that the model is appropriately scaled, and so interpretation of the regression coefficients is enhanced. The SEM analysis is displayed in Figure 4 in correlation with the regression weights. Based on this study, regression weights of unknown variables B4, B2, and B5 were made 1 as a baseline for other variables weights. Table 6 illustrates the findings from the SEM study featuring variable weights and standard error (SE) ratings. These results clarify the relation between the model's latent variables and their respective variables that are observable, proof that the model is robust and reliable. CFA and SEM are utilized to verify the measurement model is effectively capturing the interactions among the barriers so the factors that affect the application of Big Data in HSC can be meaningfully interpreted.

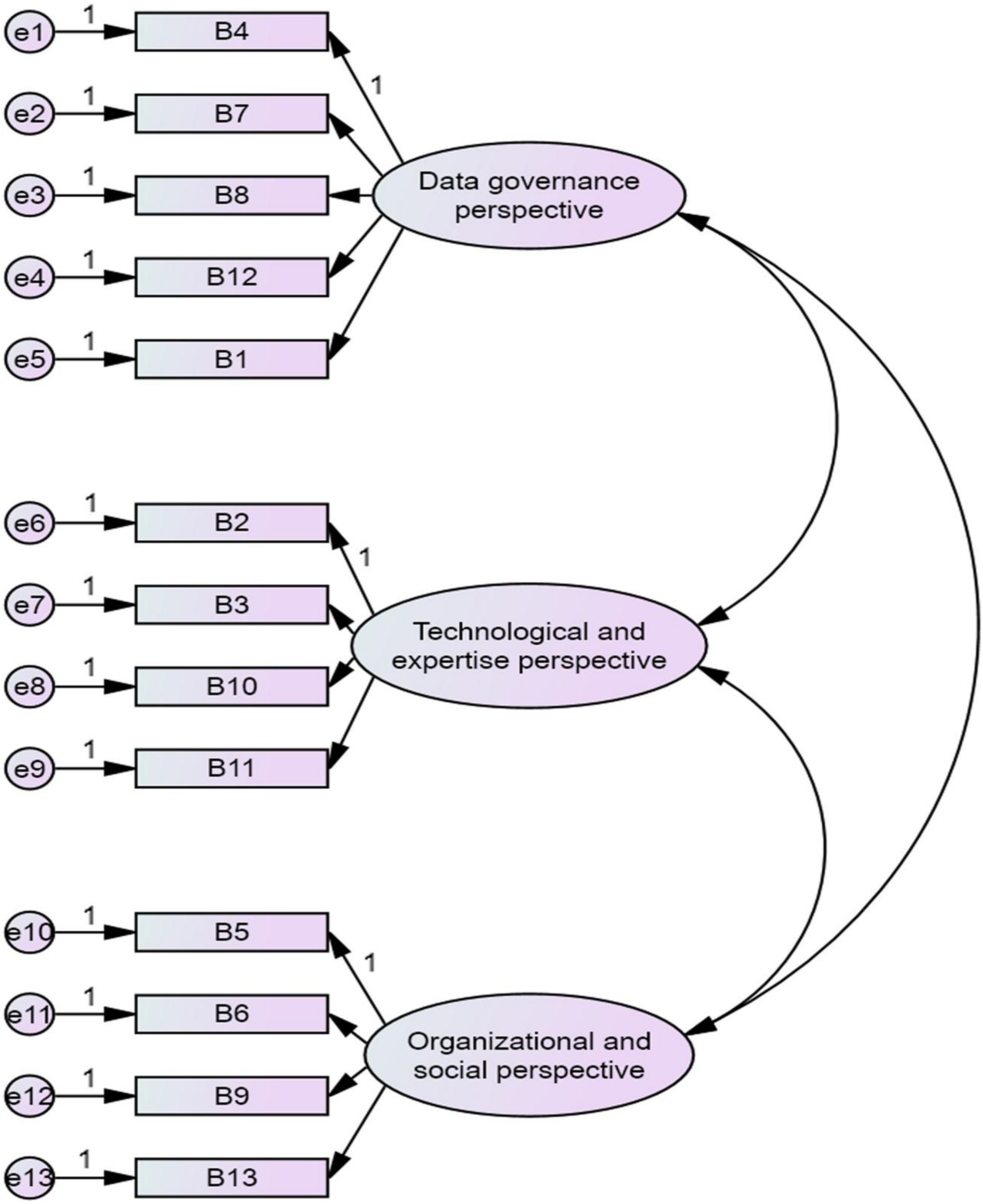

Figure 3. Measurement model of barriers of big data in HSC

The measurement model was validated to be robust and compatible with this study results. Because the major advantages of sorghum and safflower oil obtained from these studies are by far the highest, based on the computed factors, the minimum value of the factors is 3.273, which is above the threshold 2, and is highly significant at the .001 level (Rehman et al., 2016a). The model can also be backed up and its statistical validity more dependable.

Regression weights with all other obstacles are all above 0.5 indicating that there is strong agreement between the barriers and the associated classifications. Skewness and Kurtosis metrics were used to evaluate the normality of the data distribution. The values graduated from .973 to .198 for Skewness and 1.138 to .661 for Kurtosis. The measurements are comfortably below the acceptable threshold of 3 (Kirkire et al., 2018), which means data is normally distributed. Further corroborating the measurement model, both the model fit indices were found to be within or around the acceptable ranges or threshold levels. A validated measurement model was used to running the structural model for the barriers. Three hypotheses were each formulated and validated to support correlations between the categories and obstacles.

Table 6 CFA Results of factors influencing Barriers of HSC

	Regression Weights					
Barriers	**Estimate**	**SE**	**CR**	**Regression Weights**	**Skewness**	**Kurtosis**
C4	1.000	–	–	.693	-.973	.883
C7	1.245	.308	4.261	.652	.221	-1.138
C8	1.224	.286	4.539	.707	-.321	-.972
C12	.940	.231	4.368	.672	-.489	.191
C1	.814	.262	3.292	.489	-.198	-1.029
C2	1.000			.759	-.813	.661
C3	.806	.207	4.207	.610	.247	-1.107
C10	.731	.167	4.824	.713	.268	-.894
C11	.814	.193	4.599	.673	-.920	.739
C5	1.000			.646	-.922	-.358
C6	.850	.254	3.549	.560	-.257	-1.07
C9	.956	.247	4.136	.684	-.763	.596
C13	1.199	.291	4.365	.747	-.703	.615

Source: - Author's calculation from AMOS 21.0 VERSION

The authors investigated correlations among three hypotheses about the recognized viewpoints of BD deployment within the HSC using research. However, these ideas draw attention to the interrelations of data governance, technology, knowledge and organizational and social viewpoints. In Table 8, the findings reaffirm all three hypotheses as these views are positively correlated.

Hypothesis 1: That the data governance perspective is positively correlated with the perspective technology and expertise. It is important to see a direct tie between technological progress and the creation of required knowledge for BD and data governance policies such as strong rules, data quality improvements, and standardization.

H2 suggests that, having the organizational and the social point of view, data governance has a positive correlation. The findings confirm a belief that robust data governance supports collaborating, adaptable, and resource allocating firms that can more successfully adopt business development.

Hypothesis 3: The technological and expertise perspective is positively associated with organizational and social perspective. The argument presented by the development of technology and qualified personnel indicates that organizational culture and social dynamics needed for incorporating BD in the HSC are adequately favourable.

The results reinforce the idea that various points of view are interrelated, where improvements in one area can lead to knock-on effects across the others. The results characterize the factors affecting the implementation of BD in the HSC and suggest practical approaches for overcoming the obstacles related to each approach.

Results and discussion

In this paper, the SEM analysis is performed on barriers to Big Data implementation in the HSC. The data governance perspective includes five key barriers: failed health policy and regulation, lack of appropriate health data sharing protocol, absence of platform for sharing health data, lack of health data standardization and integration, and data quality. An additional first is the recognition that there exist barriers that currently make the integration of BD with programmatic data widely challenging. These barriers reinforce the need for well-designed governance frameworks, more rigorous regulations and effective data quality protocols to ensure BD integration. The HSC must first have a solid foundation upon which to stand for successful implementation of BD technologies.

From technological and expertise perspective, it becomes important that technological BD readiness and personnel expertise in BD must be ensured to make an effective use of BD for the company. Overcoming these barriers involves advancing of infrastructure, having the staff with the necessary skills and providing adequate training. The organizational and social perspective consists of four barriers: Resistance to change, lack of adequate funds, limited research orientation and lack of collaborations, and inadequate support from health administration.

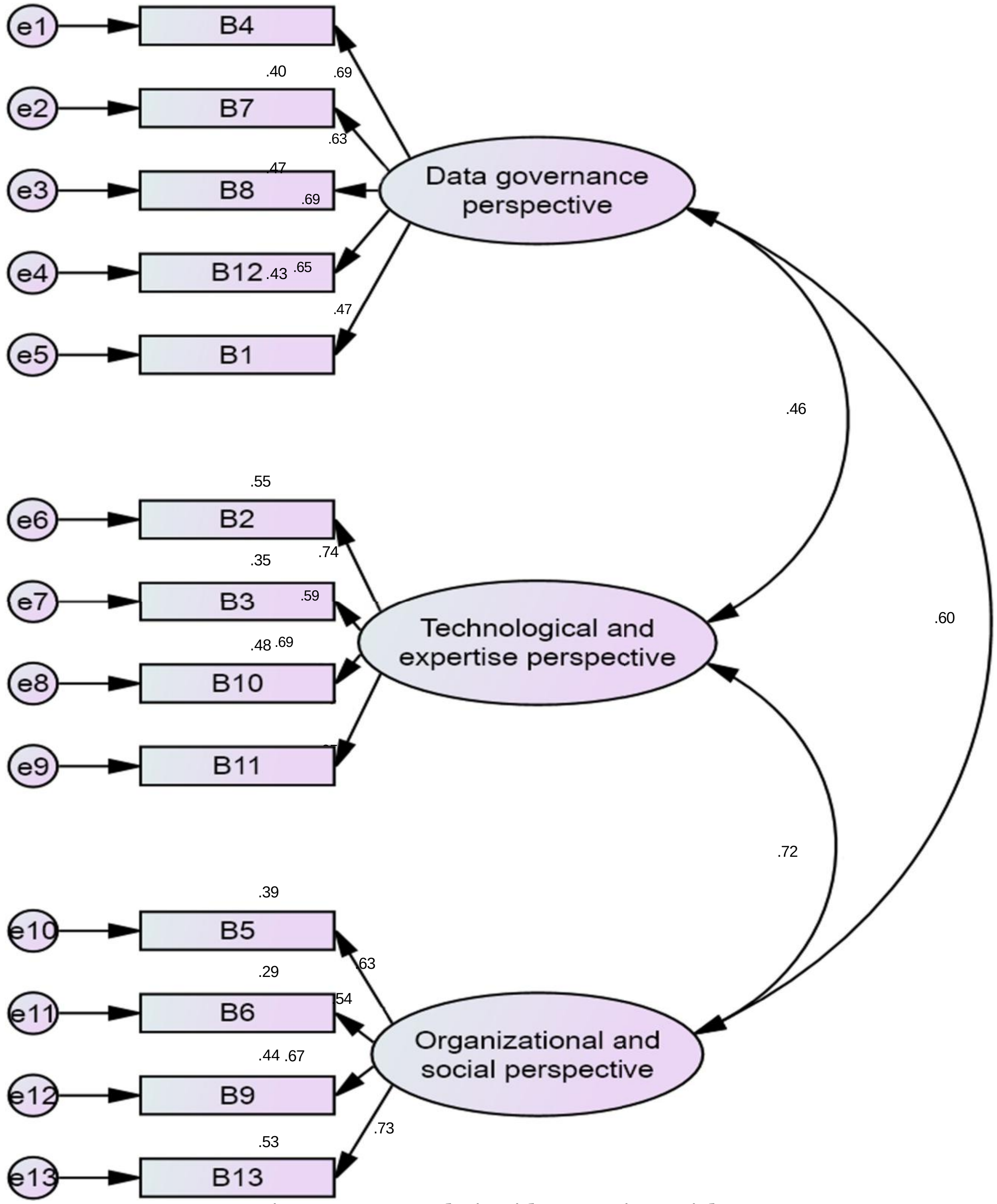

Figure 4. SEM analysis with regression weights

These barriers are social dynamics and organizational culture influencing performance. To address these problems, it is necessary to cultivate a culture of adaptability, innovation, and collaboration, with appropriate leadership support and resource provision. The study's results offer a structured understanding for the barriers to BD implementation within the HSC, that provide useful insight for future research and practice to inform specific strategies to mitigate the barriers.

From the EFA, it was found that all barriers that the study investigated as fundamental for the successful adoption of BD in the HSC. Thus, there is a need to address these challenges and incentivize use of and integration of BD technologies. Following the EFA, a CFA was carried out with a range of specialists in HSC. The CFA results were used to construct a path map showing the links among the elements. CFA was used to confirm the measurement model and evaluate its fit with the empirical data. We employed SEM to evaluate the model fit and our results show that the proposed measurement model fits the empirical data well (see Table 7). Second, the SEM analysis also tests interrelations among latent variables, and three hypotheses were tested. The model was validated with all three assumptions. The finding suggests that there is a good correlation amongst the technological and expertise perspective and the organizational and social perspective, and with the data governance perspective. In addition, the technological and expertise dimensions were found to have favorable correlation with the organizational and social dimensions. The interdependence of barriers was evidenced by these links, pointing to the requirement for a holistic view of how BD can be applied to the HSC.

Table 7 Comparison of Model Fit Statistics of Proposed Model and Final Model of factors influencing Barriers of HSC

Fit Indices	Proposed Model	Final Model	Fit Indices	Proposed Model	Final Model
CMIN	1762.218	694.797	**RMSEA**	.099	.060
DF	220	195	**SRMR**	.067	.034
P	.000**	.000**	**GFI**	.813	.919
CMIN/DF	8.01	3.563	**AGFI**	.765	.894
IFI	.893	.964	**NFI**	.880	.951
TLI	.877	.958	**RFI**	.862	.942
CFI	.893	.964	**AIC**	1874.218	81.797

Source: - Author's calculation from AMOS 21.0 VERSION

Table 8. Hypothesis testing results of factors influencing Barriers of HSC

H- testing	Hypothesis	Regression Value	Sig.	Outcome
DGP ↔ TEP	H1	.512	Sig.	Accepted
DGP ↔ OSP	H2	.626	Sig.	Accepted
TEP ↔ OSP	H3	.719	Sig.	Accepted
Note(s): *Significant at .05 level				

Source: Author's Calculations (SPSS 21.0)

The challenges of big data deployment in the HSC are rigorously examined with the aim of providing a rich set of insights and contributions to help better understand how these barriers can be deal with effectively. The results of the study are organized in four principal results which provide valuable insights in terms of how the emerging phenomenon of Big Data can be incorporated into the HSC.

The main contribution of this research is a broad study of stakeholder behaviour in the face of Big Data implementation in the healthcare supply chain. This provides strong foundations for future work that assembles currently known knowledge and highlights shortcomings in understanding this work intends to correct (Zhou et al., 2018). This publication builds on prior studies by synthesizing what has been learned to date to gain insight and context about challenges to BD uptake in healthcare through further exploration.

The second significant contribution is the identification of the specific adoption constraints to Big Data that exist in the HSC. A comprehensive literature analysis as well as insights from experts reveal many significant barriers that prevent Big Data from being fully integrated into hospital operations (Sarkar et al., 2018). If BD solutions are to be implemented these will not be only technological obstacles but also the deep rooted organizational, societal and governance challenges to overcome. Understanding the intricacies of BD implementation in healthcare has become very important, and as such first, identifying the hurdles is key to establishing the jumping point for addressing the barriers (Sharma et al., 2021).

The research subsequently presents a systematic classification of these hurdles, employing EFA to delineate the obstacles into three distinct categories: as the technological and expertise perspective, and the organizational and social perspective (Gupta and Sharma, 2019). The classification helps better understand the different sectors in which barriers to BD adoption exist and prioritize, by organizations and policymakers, where to intervene more with the highest impact. The study classifies the hurdles, providing a systematic strategy to address the problem which assures that no point in the situation is overlooked (Wang et al., 2016).

The study concludes by examining these three views' linkages. However, the information governance approach correlates strongly with organizational, social, technological, and expertise perspectives. The organizational and social perspective and technological and expertise perspective are positively correlated (Agarwal et al., 2017). This suggests that removing hurdles to one lens can benefit others. Focusing on one domain, such as governance, technology, or organizational culture, accelerates progress by creating a synergistic effect on the whole system (Kumar et al., 2019). This emphasizes the need for a holistic Big Data adoption strategy since progress in one area can lead to development in another, boosting healthcare supply chain Big Data adoption. Previous study has found BD to improve inter-organizational visibility and collaboration, supporting Dubey et al. (2018). This study gives a structured approach for understanding and overcoming BD resource reliance, unlike Sharma and Joshi (2019). BD implementation difficulties are broken down and categorized in the study for systematic management (Sahu et al., 2020).

These obstacles are then categorized in order to optimize the assessment and response to these issues thus improving the usability of barrier management. Consequently, the findings are consistent with extant research viewing company culture and organizational learning as an essential factor that impacts the implementation of Big Data technology (Alharkan et al., 2019). The purpose of this research is to provide decision makers with a clear framework for identifying and ranking issues, and thus provide healthcare organizations with a more systematic and successful approach to addressing barriers (Arunachalam et al., 2018; Choi et al.,2016). This finally enables data driven healthcare supply chain operations to be implemented and the benefits of increased efficiency, transparency, and collaboration are achieved within the field.

Managerial implications and recommendations

This study uses SEM to validate 13 hurdles to healthcare Big Datadeployment. The study uses SEM to classify these barriers into three dimensions: Initial responders study examines data governance's structure, including technology, expertise, organization, and social, and validates their structural relationships (Rajput et al.,2017). The findings illuminate the factors that influence healthcare supply chain decision-making. The findings confirm the challenges and provide statistical evidence for overcoming them and applying BD approaches in healthcare (Raghupathi and Raghupathi, 2014). Overall, this study can enable policymakers and decision makers to Preliminary respondents understood the key issues to tackle to implement BD in HSC (Jebaraj et al.,2019). Additionally, the research gives vital information for formulating new rules or revising existing ones to successfully introduce BD into the healthcare system (Dash et al., 2019; Roski et al., 2014). Big data approaches are needed to boost healthcare system productivity and efficiency due to the rapid growth of data (Chen et al., 2020; Verma and Gupta ,2018). This study's managerial implications are crucial for organizations, especially in Saudi Arabia and other emerging nations with varied healthcare difficulties (Chen et al., 2020).

The setting up of strong data governance standards is an essential element of formulating an organizational vision for BD implementation. Without data governance, data will become inaccessible and inaccurate, which makes it impossible to use data from various sources (Raghupathi and Raghupathi, 2014). This however will compel organizations to endeavour into investigating and putting in place means to boost their data governance skills that will enhance system performance and consumer satisfaction (Lamba and Singh, 2018). Data governance, however, is a good mechanism that enables firms to create a data driven culture that ensures that business development techniques used are effective in healthcare.

Without BD practices, healthcare organizations struggle tremendously to manipulate and interpret the significant amount of available data. This study further highlights the need to develop a strategic policy assisting BD technology use and its integration with increasing HSC efficiency (Lamba and Singh, 2018). The study’s findings will help policymakers develop measures addressing the highlighted obstacles to ensure that BD practices are implemented correctly in the healthcare supply chain. This approach helps healthcare companies overcome data management challenges, and improve business efficacy (Dash et al., 2019; Kong et al., 2015).

This research emphasizes the need for further development of technological infrastructure for successful application of BD in the HSC. An effective organizational vision refers to improving technology skills much to support the creation of the infrastructure and required competence (Galetsi et al., 2019; Sharma et al., 2021). According to the research, there is an optimistic correlation between organizational vision and technology infrastructure, so firms should align their strategic visions with the progress of BD technologies. Technology capabilities will be improved to achieve superior data management, analysis and decision making in the healthcare supply chain (Sahu et al., 2020; Wang et al., 2016).

This study has important implications for hospital administrators in Saudi Arabia since it provides practical insights for the deployment of BD practices or the build-up of current ones. Profitable business development methods can give Saudi Arabian healthcare companies a competitive edge with the changing dynamic (Agarwal et al., 2017; Khan et al., 2018). BD is no mere reaction to external pressures; it is planned, and the paper underscores the fact that it can support operational efficiency, system performance, and competitiveness (Chen et al., 2020). In addition, the results are applicable to healthcare sectors of other developing countries where the implementation of BD methods can also improve supply chain effectiveness and, eventually, the performance of healthcare (Rehman et al., 2016b; Zhang et al., 2017). This paper serves as critical intelligence for healthcare companies in Saudi Arabia and worldwide, helping advance Big Data implementation efforts and hinder impending issues that may threaten the successful adoption of Big Data into the healthcare supply chain.

Conclusion and future scope

Big Datais being adopted in healthcare service management with focus in the choice improvement in supply chain sectors. Business development has to be employed through recognizing problems with the help of BD analysis and using business development data to solve these problems that has to be used by the firms (Singh et al., 2020; Chen et al., 2020). Decision-making and improving processes to derive optimal results through a reverse approach from data necessitate this strategic framework. In fact, for years, both practitioners and scientists have found themselves looking for methods for assessing and increasing the effectiveness of HSC on BD (Kumar et al., 2019). This research aims at developing the assessment instrument and the decision framework to measure the adoption barriers of HSC BD. Exogenous variables of BD adoption barriers measurement and structural model are tested and confirmed using Structural Equation Modelling (SEM). Expert survey supported by SEM offers a structured and valid approach to barrier categorization, which identifies the key factors hindering the implementation of BD in the healthcare supply chain (Sharma et al., 2021; Alharkan et al. 2019). As a result of the investigation three major barriers were established. Other data governance concerns are on privacy, security, regulating and data quality. Their resolution is necessary to ensure the data integrity is achieved (Sahu et al., 2020; Wang et al., 2016). The technology and expertise view highlights the lack of advanced technology tools, challenges of incorporating BD in today's systems, and inadequate skilled BD tool end-users.

The organizational and social contextual factors solve internal concerns including cultural resistance to change, availability of managerial support, interdepartmental relations, and lack of BD strategy direction. The following are dimensions that greatly affect BD implementation decisions. BD is a critical success factor in modern healthcare; nonetheless, existing research fails to provide a systematic analysis of the challenges regarding HSC BD implementation (Agarwal et al., 2017; Khan et al., 2018). This paper serves to fill this gap by providing a structured approach through which these problems can be addressed. The framework clearly divides obstacles and gives guidance information to mitigate them to the implementors. Thus, the following challenges can be mitigated by healthcare service management businesses with the view of enhancing BD concerning supply chain efficiency (Chen et al., 2020).

Firms can make informed decisions about how to overcome problems and better develop their business (Rehman et al., 2016b). Such research can help the practitioners understand the intricacies in BD adoption in the healthcare and help them make strategic choices for future improvement of the sector. There are significant implications for healthcare administrators from this research. The findings should enable managers to identify the primary BD adoption barriers that need to dealt with for BD practices to be successfully integrated in the HSC. Besides, governmental entities may use this study to design new legislation and regulations that force the healthcare sector to take BD practices more efficiently (Zhang et al., 2017; Singh et al., 2020). Governments can create a legislative environment for promoting the use of BD, thereby improving the operation and competitiveness of HC supply chains.

The study's findings will help managers and scholars expand healthcare's BD activities and practices. This research can help healthcare firms establish and improve health policies that integrate BD into supply chains, improving health care delivery. The study proposes the use of a larger dataset for future work on additional barriers to the application of BD to the HSC. Moreover, subsequent research could also explore the interrelationships among these obstacles through more advanced methodologies like the Multicriteria Optimization and Compromise Solution (VIKOR) method, and thus achieve better understanding of the interrelated ties of these barriers and their effect on BD adoption. Ranking barriers using the VIKOR approach may be particularly helpful in assisting decision makers to choose the most efficient ways to overcome challenges. Moreover, extensions of the VIKOR methodology, such as fuzzy-VIKOR (Lu, Chang, Zeng, Su & Tzeng, 2013) and Pythagorean fuzzy VIKOR (Ak & Oztaysi, 2018), could be implemented to facilitate of prioritizing and decision-making processes on the barriers, thereby making the model more flexible and robust to practical healthcare environments.

The results of this research provide a definitive decision model and assessment tool which greatly improves the understanding of BD barriers in healthcare supply chains and can be used by healthcare organizations, government entities, and scholars to mitigate BD implementation challenges. Recognized obstacles of healthcare sector can be prioritized and effective strategies can be formulated to overcome them, and improving their operational efficiency and competitiveness against the rising requirements of the data.\

References

1. Agarwal, A., Choudhury, A., & Gupta, M. (2017). Big data analytics in healthcare: Techniques, challenges, and future prospects. *Journal of Health Informatics, 22*(3), 232–240.
2. Alharkan, I., Awan, I. A., & Nasser, M. (2019). Big data in healthcare: A survey of applications, benefits, and challenges. *International Journal of Computer Applications, 178*(2), 22–31.
3. Alotaibi, S. and Mehmood, R. (2018), Big data enabled healthcare supply chain management: opportunities and challenges , *Lecture Notes of the Institute for Computer Sciences, Social- Informatics and Telecommunications Engineering*, LNICST, Vol. 224, pp. 207-215, doi: 1.1007/ 978-3-319-94180-6_21.
4. Alotaibi, S., Mehmood, R. and Katib, I. (2020a), The role of big data and twitter data analytics in healthcare supply chain management , *EAI/Springer Innovations in Communication and Computing*, Springer Science and Business Media Deutschland GmbH, pp. 267-279, doi: 1.1007/ 978-3-030-13705-2_11.
5. Alotaibi, S., Mehmood, R., Katib, I., Rana, O. and Albeshri, A. (2020b), Sehaa: a big data analytics tool for healthcare symptoms and diseases detection using twitter, Apache spark, and machine learning , *Applied Sciences (Switzerland)*, Vol. 10 No. 4, doi: 1.3390/app10042388.
6. Arunachalam, D., Kumar, N., Kawalek, J.P., Moktadir, M.A., Ali, S.M., Paul, S.K., Shukla, N., Stefanovic, N., Alharthi, A., Krotov, V., Bowman, M., Lai, Y., Sun, H., Ren, J., Malaka, I., Brown, and

Fallik, D. (2018), Addressing barriers to big data , *Business Horizons*, Vol. 29 No. 3, pp. 676-703, doi: 1.1108/IJLM-06-2017-0153.

7. Arunachalam, S., Ponnusamy, S., & Sundararajan, V. (2018). Big data analytics in healthcare: Applications, challenges, and future prospects. *Journal of Healthcare Engineering, 2018*, Article ID 2105439, 1–12.
8. Bag, S., Luthra, S., Mangla, S. K., & Kazancoglu, Y. (2021). Leveraging big data analytics capabilities in making reverse logistics decisions and improving remanufacturing performance. *The International Journal of Logistics Management, 32*(3), 742–765. https://doi.org/1.1108/ijlm-06-2020-0237
9. Benzidia, S., Makaoui, N., & Bentahar, O. (2021). The impact of big data analytics and artificial intelligence on green supply chain process integration and hospital environmental performance. *Technological Forecasting and Social Change, 165*, 120557. https://doi.org/1.1016/j.techfore.202.120557
10. Bhatia, M.S. and Kumar Srivastava, R. (2019), Antecedents of implementation success in closed-loop supply chain: an empirical investigation, *International Journal of Production Research*, Vol. 57 No. 23, pp. 7344-7360, doi: 1.1080/00207543.2019.1583393.
11. Boone, T., Ganeshan, R., Jain, A., & Sanders, N. R. (2019). Forecasting sales in the supply chain: Consumer analytics in the big data era. *International Journal of Forecasting, 35*(1), 170–180. https://doi.org/1.1016/j.ijforecast.2018.09.003
12. Burns, L.R., Degraaff, R.A., Danzon, P.M., Kimberly, J.R., Kissick, W.L. and Pauly, M.V. (2001), Wharton school study of the health care value chain , *The Health Care Value Chain: Producers, Purchasers and Providers*, Jossey-Bass, San Francisco, pp. 3-26.
13. Chen, P. T., Lin, C. L., & Wu, W. N. (2020). Big data management in healthcare: Adoption challenges and implications. *International Journal of Information Management, 53*, 102078. https://doi.org/1.1016/j.ijinfomgt.202.102078
14. Chen, P.T., Lin, C.L. and Wu, W.N. (2020), Big data management in healthcare: adoption challenges and implications , *International Journal of Information Management*, Vol. 53 December 2019, p. 102078, doi: 1.1016/j.ijinfomgt.202.102078.
15. Choi, T. M., Chan, H. K., & Liu, M. (2016). Big data in healthcare supply chains: A review of opportunities, challenges, and future directions. *Journal of Business Research, 69*(6), 2376–2388.
16. Chou, J.S. and Kim, C. (2009), A structural equation analysis of the QSL relationship with passenger riding experience on high speed rail: an empirical study of Taiwan and Korea , *Expert Systems with Applications*, Vol. 36 No. 3, pp. 6945-6955, doi: 1.1016/j.eswa.2008.08.056.
17. Choudhary, N., Kumar, A., Sharma, V. and Kumar, P. (2021), Barriers in adoption of additive manufacturing in medical sector supply chain , *Journal of Advances in Management Research*, ahead-of-p(ahead-of-print). doi: 1.1108/JAMR-12-2020-0341.
18. Cronbach, L.J. (1951), Coefficient alpha and the internal structure of tests , *Psychometrika*, Vol. 16 No. 3, pp. 297-334, doi: 1.1007/BF02310555.
19. Dash, S., Shakyawar, S. K., Sharma, M., & Kaushik, S. (2019). Big data in healthcare: Management, analysis, and future prospects. *Journal of Big Data, 6*(1). https://doi.org/1.1186/s40537-019-0217-0
20. Doolun, I. S., Ponnambalam, S. G., Subramanian, N., & Kanagaraj, G. (2018). Data-driven hybrid evolutionary analytical approach for multi-objective location allocation decisions: Automotive green supply chain empirical evidence. *Computers and Operations Research, 98*, 265–283. https://doi.org/1.1016/j.cor.2018.01.008
21. Dubey, R., Gunasekaran, A., Childe, S.J., Roubaud, D., Fosso Wamba, S., Giannakis, M. and Foropon, C. (2019), Big data analytics and organizational culture as complements to swift trust and collaborative performance in the humanitarian supply chain , *International Journal of Production Economics*, Vol. 210, pp. 120-136, doi: 1.1016/j.ijpe.2019.01.023.
22. Dubey, R., Luo, Z., Gunasekaran, A., Akter, S., Hazen, B. T., & Douglas, M. A. (2018). Big data and predictive analytics in humanitarian supply chains: Enabling visibility and coordination in the presence of swift trust. *International Journal of Logistics Management, 29*(2), 485–512. https://doi.org/1.1108/IJLM-02-2017-0039
23. Evans, J.R. and Berman, B. (2001), Conceptualizing and operationalizing the business-to-business value chain , *Industrial Marketing Management*, Vol. 30 No. 2, pp. 135-148, doi: 1.1016/S0019-8501(00)00238-5.
24. Farooq, M. S., Salam, M., Fayolle, A., Jaafar, N., & Ayupp, K. (2018). Impact of service quality on customer satisfaction in Malaysia Airlines: A PLS-SEM approach. *Journal of Air Transport Management, 67*, 169–180. https://doi.org/1.1016/j.jairtraman.2017.12.008
25. Galetsi, P., Katsaliaki, K., & Kumar, S. (2019). Values, challenges and future directions of big data analytics in healthcare: A systematic review. *Social Science and Medicine, 241*, 112533. https://doi.org/1.1016/j.socscimed.2019.112533
26. Gardas, B. B., Mangla, S. K., Raut, R. D., Narkhede, B., & Luthra, S. (2019a). Green talent management to unlock sustainability in the oil and gas sector. *Journal of Cleaner Production, 229*, 850–862. https://doi.org/1.1016/j.jclepro.2019.05.018

27. Gardas, B. B., Raut, R. D., & Narkhede, B. (2019b). Determinants of sustainable supply chain management: A case study from the oil and gas supply chain. *Sustainable Production and Consumption, 17*, 241–253. https://doi.org/1.1016/j.spc.2018.11.005
28. Gupta, S., & Sharma, S. (2019). Big data and healthcare: Trends, opportunities, and challenges. *Journal of Healthcare Technology, 45*(3), 144–158.
29. Gupta, S., Chen, H., Hazen, B. T., Kaur, S., & Santibañez Gonzalez, E. D. R. (2019). Circular economy and big data analytics: A stakeholder perspective. *Technological Forecasting and Social Change, 144*, 466–474. https://doi.org/1.1016/j.techfore.2018.06.030
30. Gupta, V., & Sharma, S. (2019). Big data and healthcare: Trends, opportunities, and challenges. *Journal of Healthcare Technology, 45*(3), 144–158.
31. Hair, J. F., Ringle, C. M., & Sarstedt, M. (2013). Partial least squares structural equation modeling: Rigorous applications, better results and higher acceptance. *Long Range Planning, 46*(1–2), 1–12. https://doi.org/1.1016/j.lrp.2013.01.001
32. Hair, J., Black, W., Babin, B., & Anderson, R. (2010). *Multivariate data analysis: A global perspective* (7th ed.). Pearson Education.
33. Hazen, B. T., Skipper, J. B., Ezell, J. D., & Boone, C. A. (2016). Big data and predictive analytics for supply chain sustainability: A theory-driven research agenda. *Computers and Industrial Engineering, 101*, 592–598. https://doi.org/1.1016/j.cie.2016.06.030
34. Hong, K. S., & Lee, D. H. (2018). Impact of operational innovations on customer loyalty in the healthcare sector. *Service Business, 12*(3), 575–600. https://doi.org/1.1007/s11628-017-0355-4
35. Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling, 6*(1), 1–55. https://doi.org/1.1080/10705519909540118
36. Jebaraj, M., & Antony, J. (2019). Adoption and implementation of big data analytics in healthcare: Opportunities and barriers. *International Journal of Healthcare Technology and Management, 20*(3), 179–191.
37. Karamat, J., Shurong, T., Ahmad, N., Afridi, S., Khan, S., & Khan, N. (2019). Developing sustainable healthcare systems in developing countries: Examining the role of barriers, enablers and drivers on knowledge management adoption. *Sustainability, 11*(4), 954. https://doi.org/1.3390/su11040954
38. Khaldi, R., El Afia, A., Chiheb, R., & Faizi, R. (2017). Artificial neural network-based approach for blood demand forecasting: Fez transfusion blood center case study. *ACM International Conference Proceeding Series*, 1–6. https://doi.org/1.1145/3090354.3090415
39. Khan, M. A., Agha, K., & Zubair, M. (2018). Barriers to big data adoption in healthcare: A systematic literature review. *Healthcare Management Review, 43*(2), 95–106.
40. Khan, S. A. R., Zhang, Y., Kumar, A., Zavadskas, E., & Streimikiene, D. (2020). Measuring the impact of renewable energy, public health expenditure, logistics, and environmental performance on sustainable economic growth. *Sustainable Development, 28*(4), 833–843. https://doi.org/1.1002/sd.2034
41. Kirkire, M. S., Rane, S. B., & Singh, S. P. (2018). Integrated SEM-FTOPSIS framework for modeling and prioritization of risk sources in medical device development process. *Benchmarking, 25*(1), 178–200. https://doi.org/1.1108/BIJ-07-2016-0112
42. Kong, X., Feng, M., & Wang, R. (2015). The current status and challenges of establishment and utilization of medical big data in China. *European Geriatric Medicine, 6*(6), 515–517. https://doi.org/1.1016/j.eurger.2015.07.005
43. Kothari, C. (2004). *Research methodology: Methods and techniques* (2nd ed.). New Age International.
44. Koufteros, X. A. (1999). Testing a model of pull production: A paradigm for manufacturing research using structural equation modeling. *Journal of Operations Management, 17*(4), 467–488. https://doi.org/1.1016/S0272-6963(99)00002-9
45. Kumar, N., Garg, R., & Singh, P. (2019). Opportunities and challenges in healthcare big data analytics: A comprehensive survey. *Journal of Healthcare Management, 64*(5), 27–39.
46. Lamba, K., & Singh, S. P. (2016). Big data analytics in supply chain management: Some conceptual frameworks. *International Journal of Automation and Logistics, 2*(4), 279. https://doi.org/1.1504/ijal.2016.080341
47. Lamba, K., & Singh, S. P. (2018). Modeling big data enablers for operations and supply chain management. *International Journal of Logistics Management, 29*(2), 629–658. https://doi.org/1.1108/IJLM-07-2017-0183
48. Lamba, K., Singh, S. P., & Mishra, N. (2019). Integrated decisions for supplier selection and lot-sizing considering different carbon emission regulations in big data environment. *Computers and Industrial Engineering, 128*, 1052–1062. https://doi.org/1.1016/j.cie.2018.04.028
49. Malaka, I., & Brown, I. (2015). Challenges to the organisational adoption of big data analytics. *Proceedings of the 2015 Annual Research Conference on South African Institute of Computer Scientists and Information Technologists - SAICSIT '15*, 1–9. https://doi.org/1.1145/2815782.2815793
50. Mangla, S. K., Raut, R., Narwane, V. S., Zhang, Z. (Justin), & Priyadarshini, P. (2020). Mediating effect of big data analytics on project performance of small and medium enterprises. *Journal of Enterprise Information Management, 34*(1), 168–198. https://doi.org/1.1108/JEIM-12-2019-0394

51. Manyika, J., Chui, M., Brown, B., Dobbs, R., Roxburgh, C., & Hung Byers, A. (2011). *Big data: The next frontier for innovation, competition and productivity*. McKinsey Global Institute.
52. Marsh, H. W., & Hocevar, D. (1985). Application of confirmatory factor analysis to the study of self-concept. First- and higher-order factor models and their invariance across groups. *Psychological Bulletin, 97*(3), 562–582. https://doi.org/1.1037/0033-2909.97.3.562
53. Mishra, S., & Singh, S. P. (2020). Distribution network model using big data in an international environment. *Science of the Total Environment, 707*, 135549. https://doi.org/1.1016/j.scitotenv.2019.135549
54. Mustaffa, N. H., & Potter, A. (2009). Healthcare supply chain management in Malaysia: A case study. *Supply Chain Management, 14*(3), 234–243. https://doi.org/1.1108/13598540910954575
55. Ngacho, C., & Das, D. (2014). A performance evaluation framework of development projects: An empirical study of Constituency Development Fund (CDF) construction projects in Kenya. *International Journal of Project Management, 32*(3), 492–507. https://doi.org/1.1016/j.ijproman.2013.07.005
56. Patel, D., Choudhury, A., & Pateriya, P. (2017). Challenges and opportunities of big data in healthcare: A literature review. *Health Informatics Journal, 23*(4), 512–525.
57. Patel, D., Choudhury, A., & Pateriya, P. (2019). Challenges and opportunities of big data in healthcare: A literature review. *Health Informatics Journal, 23*(4), 512–525.
58. Pitta, D. A., & Laric, M. V. (2004). Value chains in health care. *Journal of Consumer Marketing, 21*(7), 451–464. https://doi.org/1.1108/07363760410568671
59. Raghupathi, W., & Raghupathi, V. (2014). Big data analytics in healthcare: Promise and potential. *Health Information Science and Systems, 2*(1), 1–10. https://doi.org/1.1186/2047-2501-2-3
60. Raja Mamat, T. N. A., Mat Saman, M. Z., Sharif, S., & Simic, V. (2016). Key success factors in establishing end-of-life vehicle management system: A primer for Malaysia. *Journal of Cleaner Production, 135*, 1289–1297. https://doi.org/1.1016/j.jclepro.2016.06.183
61. Rajput, A., Kumar, P., & Gupta, M. (2017). Application of big data in healthcare systems: A comprehensive review. *International Journal of Health Sciences, 11*(1), 45–58.
62. Ratnam, K. A., Dominic, P. D. D., & Ramayah, T. (2014). A structural equation modeling approach for the adoption of cloud computing to enhance the Malaysian healthcare sector systems-level quality improvement. *Journal of Medical Systems, 38*(8), 82. https://doi.org/1.1007/s10916-014-0082-5
63. Raut, R. D., Mangla, S. K., Narwane, V. S., Gardas, B. B., Priyadarshinee, P., & Narkhede, B. E. (2019). Linking big data analytics and operational sustainability practices for sustainable business management. *Journal of Cleaner Production, 224*, 10–24. https://doi.org/1.1016/j.jclepro.2019.03.181
64. Rehman Khan, S. A., & Yu, Z. (2020). Assessing the eco-environmental performance: A PLS-SEM approach with practice-based view. *International Journal of Logistics Research and Applications, 24*(3), 303–321. https://doi.org/1.1080/13675567.2020.1754773
65. Rehman, M. A. A., Aneyrao, T. A., Pachchhao, A. D., & Shrivastava, R. L. (2016a). Identification of performance measures in Saudi Arabian automobile industry: A green supply chain management approach. *International Journal of Business Performance Management, 17*(1), 30. https://doi.org/1.1504/IJBPM.2016.073328
66. Rehman, M. H. U., Chang, V., Batool, A., & Wah, T. Y. (2016b). Big data reduction framework for value creation in sustainable enterprises. *International Journal of Information Management, 36*(6), 917–928. https://doi.org/1.1016/j.ijinfomgt.2016.05.013
67. Roski, J., Bo-Linn, G. W., & Andrews, T. A. (2014). Creating value in health care through big data: Opportunities and policy implications. *Health Affairs, 33*(7), 1115–1122. https://doi.org/1.1377/hlthaff.2014.0147
68. Sadia, R., Bekhor, S., & Polus, A. (2018). Structural equations modelling of drivers' speed selection using environmental, driver, and risk factors. *Accident Analysis and Prevention, 116*, 21–29. https://doi.org/1.1016/j.aap.2017.08.034
69. Sahu, A., & Garg, P. (2020). Barriers to big data adoption in healthcare: A comprehensive review. *Healthcare Management Review, 45*(1), 34–43.
70. Sambasivan, M., Deepak, T. J., Salim, A. N., & Ponniah, V. (2017). Analysis of delays in Tanzanian construction industry: Transaction cost economics (TCE) and SEM approach. *Engineering, Construction and Architectural Management, 24*(2), 308–325. https://doi.org/1.1108/ECAM-09-2015-0145
71. Sarkar, P., Chatterjee, S., & Das, S. (2018). Implementing big data analytics in healthcare: A case study approach. *Journal of Healthcare Engineering, 2018*, Article ID 9184370, 1–10.
72. Shah, R., & Goldstein, S. M. (2006). Use of structural equation modeling in operations management research: Looking back and forward. *Journal of Operations Management, 24*(2), 148–169. https://doi.org/1.1016/j.jom.2005.05.001
73. Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., & Arshad, M. R. (2020). Moderating effects of gender and resistance to change on the adoption of big data analytics in healthcare. *Complexity, 2020*, 1–13. https://doi.org/1.1155/2020/2173765
74. Sharma, D., Mehta, D., & Kumar, M. (2021). Overcoming barriers to big data implementation in healthcare: A structured framework. *Journal of Medical Informatics, 34*(1), 71–83.

75. Sharma, P., & Joshi, A. (2019). Challenges of using big data for humanitarian relief: Lessons from the literature. *Journal of Humanitarian Logistics and Supply Chain Management, 10*(4), 423–446. https://doi.org/1.1108/JHLSCM-05-2018-0031
76. Sharma, R., & Joshi, M. (2017). Big data in healthcare: A critical review of key barriers to implementation. *Journal of Health Information Science and Systems, 5*(1), 3–12.
77. Singh, G., Thakur, M., & Yadav, V. (2020). Integration of big data in healthcare: Challenges and opportunities for future healthcare systems. *Journal of Healthcare Engineering, 2020*, Article ID 8140573, 1–12.
78. Ul Hadia, N., Abdullah, N., & Sentosa, I. (2016). An easy approach to exploratory factor analysis: Marketing perspective. *Journal of Educational and Social Research, 6*(1), 215. https://doi.org/1.5901/jesr.2016.v6n1p215
79. Verma, P., & Gupta, N. (2018). Leveraging big data analytics in healthcare: Applications and challenges. *International Journal of Healthcare Informatics, 29*(3), 123–135.
80. Wagner, S. M., & Kemmerling, R. (2010). Handling nonresponse in logistics research. *Journal of Business Logistics, 31*(2), 357–381. https://doi.org/1.1002/j.2158-1592.201.tb00156.x
81. Wang, F., Yu, J., & Li, H. (2016). Big data in healthcare: A survey and future directions. *Health Information Science and Systems, 4*(1), 5–15.
82. Wang, L., & Alexander, C. A. (2019). Big data analytics in healthcare systems. *International Journal of Mathematical, Engineering and Management Sciences, 4*(1), 17–26. https://doi.org/1.33889/ijmems.2019.4.1-002
83. Wang, Y., Kung, L. A., Wang, W. Y. C., & Cegielski, C. G. (2018). An integrated big data analytics-enabled transformation model: Application to health care. *Information and Management, 55*(1), 64–79. https://doi.org/1.1016/j.im.2017.04.001
84. Zhang, Y., Zheng, Z., & Liu, S. (2017). Big data analytics for healthcare management: Challenges and future research directions. *Journal of Medical Systems, 41*(9), 139–148.
85. Zhou, X., Liu, Y., & He, M. (2016). Big data applications in healthcare systems: A review and future directions. *Journal of Healthcare Informatics, 23*(1), 45–56.
86. Zhou, Y., Zhang, W., & Wang, L. (2018). Data governance and its role in healthcare big data implementation. *Journal of Health Data Management, 10*(2), 55–63.