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Socio-technical factors influencing big data analytics adoption in healthcare

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ABSTRACT

The purpose of this study is to determine the key socio-technical factors influencing big data analytics adoption in healthcare services. A systematic literature review was conducted using peer-reviewed scholarly publications spanning from 2013 to 2023 to illuminate the influencing factors. Twelve papers focused on the factors influencing big data analytics (BDA) adoption in healthcare services were included for review. The factors were divided into four major groups namely i) person, ii) technology, iii) organization, and iv) environment. Analytical skills define a person, whereas technology is characterized by system quality and information quality. Organization support, organization resources, training, data governance, and evidence-based decision-making are all associated with the organization. Finally, government regulations are allocated to the environment. This review presents evidence of the socio-technical factors that influence big data analytics adoption in healthcare services. The findings from this review recommend future big data analytics adoption in healthcare services to carefully evaluate the factors identified in this study.

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1. INTRODUCTION

The rise of healthcare information management systems is generating vast amounts of healthcare data. Analysis of this huge data offers boundless potential results for discovering knowledge. Big data analytics (BDA) is the method of examining these massive and fast-moving data streams, allowing for personalized medicine. BDA encompasses a range of technologies, practices, methodologies, and applications that analyze vast data to empower companies in comprehending their markets, and businesses, and making informed decisions [1]. In healthcare, BDA applications offer potential benefits like improved patient-centered care, early disease outbreak detection, insights into disease mechanisms, healthcare quality monitoring, and enhanced treatment development. Information technology (IT) experts are consistently developing new applications with big data capabilities to support healthcare stakeholders in creating value [2]. Besides, effectively managing healthcare data can lead to benefits such as developing effective drugs and devices, detecting billing fraud, and delivering rapid services [3]. It also contributes to addressing global health challenges, encompassing disease prevention, public health surveillance, and efficient provision of crucial medical aid during emergencies.

The introduction of new inventions disrupts established workflows, as their acceptance and implementation require time. Regulatory concerns also arise in the context of innovation. Utilizing BDA raises ethical and legal questions, which might explain the healthcare sector's slower adoption compared to industries like banking and marketing. Consequently, it is debatable whether enacting regulations at this stage would stifle technological growth or foster it [4]. Regulatory goals should balance protecting the public interest with promoting technological progress and enhancing the quality and accessibility of healthcare services.

The healthcare sector lags in implementing BDA as compared to other sectors such as retailing and banking industries [5]. Regardless of the potential significance of BDA applications, healthcare organizations continue to struggle to attain the full benefits of BDA due to many challenges. The challenges include the unavailability of appropriate IT infrastructure, enormous investment costs, data privacy, and security issues, as well as data quality and complexity [6]. Evidence indicates that 60% of the surveyed healthcare organizations failed to establish a clear, integrated initiative strategy and vision for analytics implementation [7]. The adoption of BDA may not be accomplished unless managerial challenges are addressed effectively. This implies that healthcare organizations still unclearly understand the reasons that impede BDA adoption. However, most recent studies on BDA concentrate on the development of architectural frameworks and analytical techniques for healthcare systems using BDA [8], [9]. The architectural frameworks are more focused on the technical aspects for performing activities such as data gathering, pre-processing, data analysis, interpretation, and visualization are the primary concerns. Hence, the primary goal of this study is to concentrate on the socio-technical factors that influence the adoption of BDA in healthcare services.

Recent literature has been evolving with discussions concerning the utilization of big BDA in healthcare. For instance, Batko and Ślęzak [10] analyzed the possibilities of using BDA in healthcare. Khanra *et al.* [11] highlighted the applications of BDA, the value delivered by BDA, and a comprehensive framework for the use of BDA in healthcare. Galetsi *et al.* [8] focused on how BDA is utilized in the health sector to create organizational values/capabilities. Moreover, previous reviews frequently endeavors to summarize the technologies employed in BDA [12], the advantages provided by BDA [8], and the obstacles associated with BDA in the healthcare field [13], [14].These review studies are not aimed at providing a thorough examination of BDA adoption factors literature in healthcare. There is a paucity of research aimed at identifying the key factors contributing to the successful adoption of BDA in healthcare. There are healthcare organizations wish to implement BDA to reap its benefits, and it is now in the early adoption stage [15]. Hence, a thorough adoption strategy for BDA is required to close the knowledge gap and assist healthcare organizations in replacing outdated systems that cannot compete with BDA systems. Therefore, the present study aims to address the research gaps in the literature on key socio-technical factors influencing BDA adoption in healthcare services by conducting a systematic literature review (SLR) across various databases over 10 years between 2013 and 2023. Two major contributions of the current study are as follows: i) synthesis of the literature on key socio-technical factors critical for BDA adoption in healthcare services, and ii) provides evidence of how the socio-technical factor influence BDA adoption, particularly in healthcare services. The findings will extend the current understanding of BDA adoption in healthcare services and contribute to BDA literature.

The rest of the paper is organized as follows. The next section presents a brief overview of the evaluation models used to categorize the BDA adoption factors. The third section outlines the methodology followed in this SLR. This is followed by a section on this study's findings. The fifth section discusses the outcomes of this study. The sixth and seventh section describes the limitations of the present study and presents the concluding remarks of this SLR respectively.

2. EVALUATION MODELS

Resource-based view (RBV), technology-organization-environment (TOE) framework, information systems success model (ISSM) was used to categorize the antecedents that influence BDA adoption in the healthcare sector. These frameworks provided a comprehensive lens to examine the factors at play. By drawing on these established frameworks, this study aimed to create a richer understanding of the complex interplay of factors that influence BDA adoption in healthcare.

2.1. Research based-view

RBV is a strategic management framework that emphasizes the importance of internal resources for achieving sustained competitive advantage. Pioneered by works like "the resource-based view of the firm" [16] and "firm resources and sustained competitive advantage" [17], RBV argues that organizations should focus on internal resources rather than solely on external factors. In the context of healthcare and BDA adoption, the RBV framework highlights the significance of a healthcare organization's unique resources and capabilities. These resources can be tangible, such as data infrastructure and healthcare facilities, or intangible, such as skilled personnel with expertise in data analysis and a culture of data-driven decision-making. The RBV model emphasizes two key characteristics of resources: heterogeneity and immobility. Heterogeneity refers to the uneven distribution of resources across organizations, with some possessing more valuable or rare resources than others. Immobility signifies the difficulty or cost associated with replicating or acquiring these resources by competitors. In the context of BDA adoption, a healthcare organization with a strong data science team (intangible resource) or a robust data management system (tangible resource) would be better positioned to leverage BDA for strategic advantage. RBV's focus on internal resources aligns well with the challenges of BDA adoption in healthcare. By understanding their unique resource base, healthcare organizations can identify strengths and weaknesses that may influence their BDA implementation strategies. Figure 1 shows the RBV model.

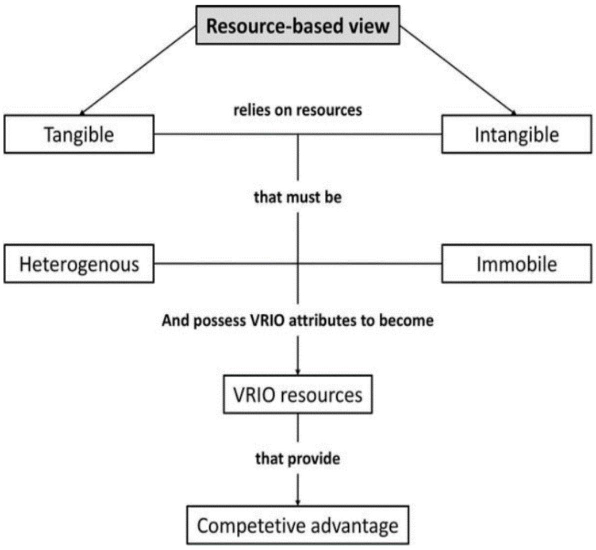

Figure 1. Resource-based view model [18]

2.2. Technology-organization-environment

The technology-organization-environment (TOE) framework, initially introduced by Tornatzky *et al.* [19] primarily examines the organizational aspect as a critical perspective for predicting technology adoption decisions. It encompasses three distinct dimensions: technology, organization, and environment. As depicted in Figure 2, these three dimensions interconnect and collectively impact the decision-making process regarding the adoption of technological innovations. The TOE framework can give a unique viewpoint on IT adoption [20]. One of the most thorough techniques to analyzing creativity is the examination of contingency factors impacting corporate choices [21]. The TOE approach may be used to conduct a systematic analysis of the impact of innovation inside an organization. As the variables in the TOE setup may vary across different contexts, it is necessary to enhance the richness of the analysis.

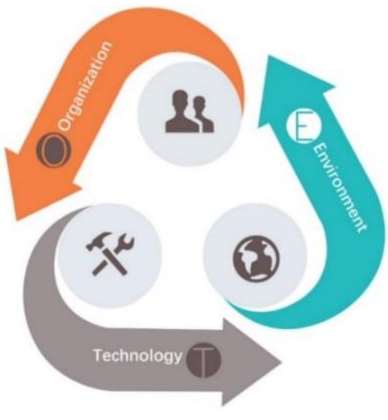

Figure 2. TOE model [19]

2.3. Information systematic success model
The information systems success model (ISSM) (alternatively called the *Delone and McLean IS success model*) is an information systems (IS) theory that seeks to provide a comprehensive understanding of IS success. The model identifies, describes, and explains the relationships among six of the most critical dimensions of IS success. The model was first developed by Delone and McLean [22]. Ten years later, it was further developed by the original authors in response to input from other academics involved in the field [23]. The ISSM is regarded as one of the most prominent ideas in current IS research and has been referenced in hundreds of academic publications. As shown in Figure 3, system quality, information quality, and service quality influence user intention to use, use, and satisfaction, which in turn influence the net benefits. The ISSM has been utilized in earlier research to evaluate the success of an IS, including those employed in the healthcare industry [24]–[26].

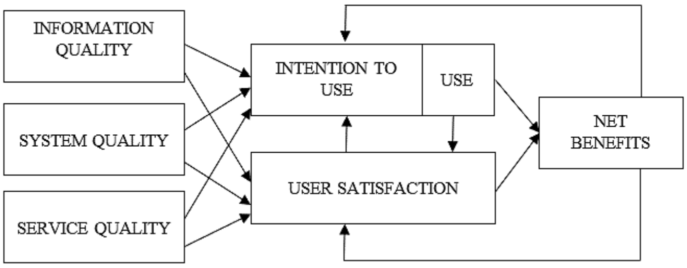

Figure 3. ISSM model [23]

3. METHOD
A SLR was conducted to identify the key socio-technical factors that influence BDA adoption in healthcare services. The SLR question was "What are the factors that influence BDA adoption in healthcare services?". The review adhered to preferred reporting items for systematic reviews (PRISMA) [27]. This methodological approach ensured a rigorous and transparent search process. By following PRISMA guidelines, the review comprehensively identified relevant studies, minimized bias in selection, and established a foundation for drawing reliable conclusions about the factors influencing BDA adoption in healthcare.

3.1. Research strategy
Articles were searched across six academic databases: ScienceDirect, PubMed, Emerald Insight, ProQuest, and IEEE Xplore. These databases encompass a broad range of healthcare, information technology, and business management literature, ensuring a rich and diverse pool of potential studies for analysis. Exploration of electronic databases for publications using keywords "big data" or "big data analytics" along with "healthcare", "medicine", or "biomedicine". Articles published within a 10-year timeframe of 2013 to 2023 were searched from the selected databases.

3.2. Study selection
Duplicate articles were removed before further review. Titles and abstracts of potential articles were assessed against three inclusion criteria: i) being written in English, ii) being full-text articles, and iii) focusing on BDA in healthcare. Peer-reviewed articles were selected to ensure scientific rigor and external evaluation by reviewers. The remaining full-text articles were examined to determine their eligibility for extracting factors related to adopting BDA in healthcare services. Only articles reporting empirical findings on BDA adoption factors in healthcare services were included for further analysis and synthesis.

3.3. Data extraction and analyses
Data from the included articles were extracted and recorded into a table by the main reviewer and then cross-checked independently by a second reviewer. The table included details such as authors, publication year, country of study, study design, and findings regarding factors influencing BDA adoption in healthcare. Each article underwent a repeated process of interpretation and coding using the evaluation models by the main reviewer, with the second reviewer independently verifying the extracted data during each cycle. Subsequently, a thematic analysis was conducted to merge similar findings from the articles based on the evaluation models. Any discrepancies were discussed among the team to achieve consensus on the description and interpretation of each category.

4. RESULTS AND DISCUSSION

4.1. Studies selection

Figure 4 illustrates the progression of information in the SLR. The initial keyword search yielded 6,676 articles published between 2013 and September 2023. From these, 1,778 articles were included based on titles, while 4,851 were excluded. Further evaluation of abstracts and keywords led to 27 relevant articles being retained for examination, while 1,751 were excluded. 12 articles were included in the review to extract key influencing factors.

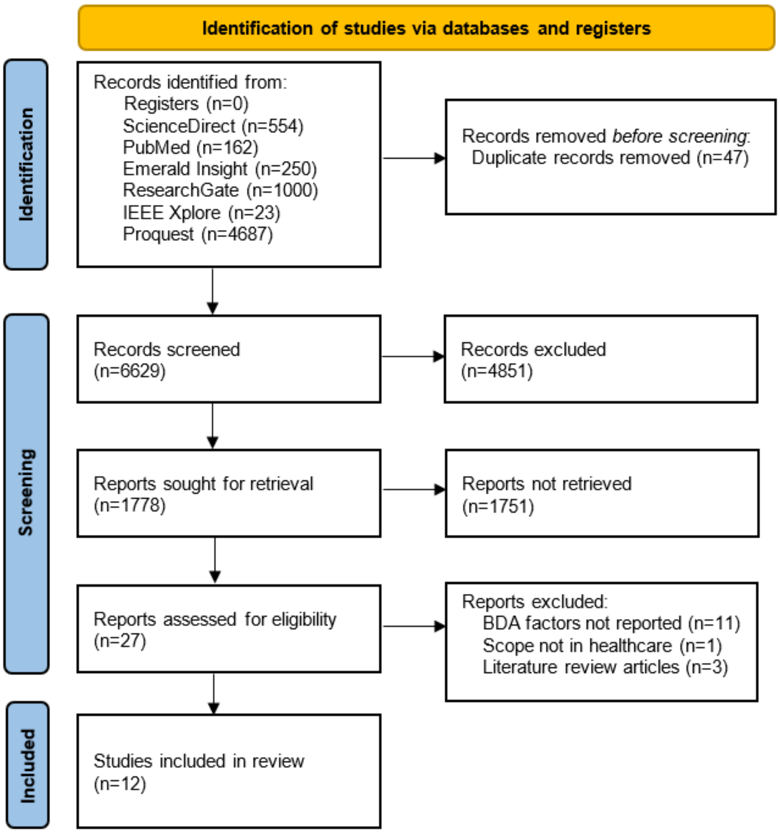

Figure 4. SLR information flow diagram

4.2. Characteristics of included studies

The SLR analysis identified 12 articles for further consideration. Figure 5 depicts a temporal trend showing a steady increase in the number of articles related to BDA adoption in healthcare services from 2013 to 2023. The line graph suggests variations in the annual publication of articles related to factors influencing BDA in healthcare. Notably, there are peaks in 2014, 2019, 2021, and 2023. The trend line shows that the number of published articles is expected to continue to increase in the future. This suggests that there is a growing interest in the BDA adoption in healthcare services and that more research is being conducted in this area.

Table 1 presents the characteristics of studies included in the review. The studies cover a diverse range of countries, including the United States of America (USA), Europe, and Asia. The USA contributes the most significant number of articles, accounting for 41.67%. The remaining countries have a considerably lower representation, with only 1 study each from Germany, Korea, and Taiwan, and 2 studies from both India and Malaysia. Survey and mixed methods are the popular research methods adopted in the studies, both accounted for 33%, followed by interview and content analysis share the same percentage number of studies which is 17%. The participants involved in the interviews and surveys vary widely including patients, clinicians, hospital operators, pharmaceutical companies, researchers, IT professionals, healthcare employees, academicians, specialists, data scientists, and BDA experts. For the content analysis, the studies utilized diverse sources for data collection, such as publicly available reports, vendor sites, and big data project material.

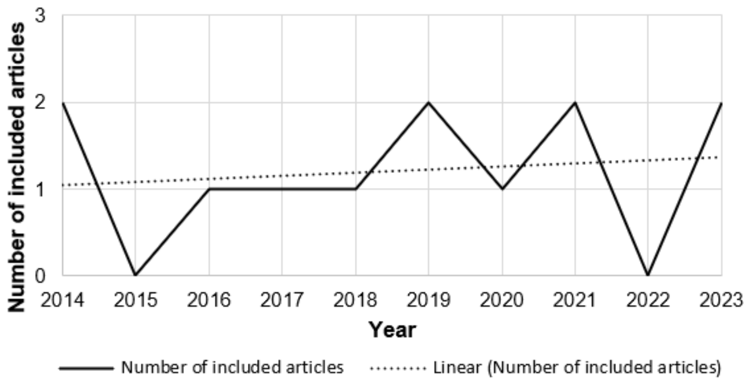

Figure 5. BDA adoption in healthcare services included articles

Table 1. Characteristic of studies included in the review

Studies	Countries	Methods	Participants/Materials
[3]	USA and United Kingdom (UK)	Content analysis	Publicly available material from numerous sources, including vendor sites.
[28]	Germany	Interview	Patients, clinicians, hospital operators, pharmaceutical companies, research and development (R&D), payors, and medical product providers.
[29]	USA	Survey	Chief information officer, chief technology officer, vice president of technology, director of IT, managers of analytics, and chief data officer.
[30]	Korea	Interview and survey	Researchers, professors, or experts who had research experience in big data and health IT areas, completing projects or publishing papers related to big data in healthcare.
[31]	USA	Content analysis	Big data projects material from multiple sources such as practical journals, print publications, case collections, and reports from companies, vendors, consultants, or analysts.
[32]	USA	Content analysis and interview	Review of literature, industry reports, and expert opinion.
[33]	USA	Survey and content analysis	Senior IT executives in US hospitals, databases maintained by the centers for Medicare and Medicaid Services
[34]	Taiwan, Canada	Interview	Physicians, medical staff, scholars, big data specialists, and researchers.
[35]	India	Interview and survey	Expert healthcare-related industries and in academics.
[36]	Malaysia	Survey	Healthcare employees.
[37]	Malaysia	Survey	Academicians, specialists, data scientists, BDA experts, industry experts, and IT directors involved in healthcare.
[38]	India	Survey	Front-end executive, back-end executive, and IT staff executive.

4.3. Classification of BDA adoption in healthcare antecedents

BDA adoption in healthcare services is categorized into four categories: person, technology, organization, and environment. This category acknowledges that successful BDA implementation goes beyond just the technology itself. It requires factors related to the individuals using it (person), the capabilities of the technology (technology), the healthcare organization's structure and culture (organization), and the broader healthcare landscape (environment). By considering all these aspects, healthcare institutions can create a more holistic approach to BDA adoption, fostering successful integration and maximizing the potential benefits for patients, providers, and the overall healthcare system. Figure 6 illustrates the percentage of BDA factors extracted from the included studies. The figure shows that the most common BDA factors are organization resources (58%), information quality (50%), analytical skills (42%), government regulation (42%), and data governance (33%). Other factors including system quality, organization support, training, and training, evidence-based decision making, accounted for 25% each.

4.3.1. Person

In this study, the person component refers to the characteristics of professionals involved in BDA tasks within healthcare. This includes data analysts, engineers, scientists, managers, and even healthcare professionals with BDA expertise [38]. Among these characteristics, analytical skills stand out as a key factor influencing BDA adoption. Analytical skills encompass a professional's ability to effectively utilize data and technology to extract valuable insights (e.g., capturing and analyzing information) [29], [39]. In the context of BDA for healthcare, this involves techniques for rapidly processing large and diverse datasets. These techniques often leverage specialized technologies for data storage, management, analysis, and visualization

[1]. By harnessing analytical capabilities, healthcare professionals can uncover care patterns and correlations within extensive medical records, ultimately informing evidence-based clinical practices [33]. Healthcare analytical systems are specifically designed to address the challenge of processing massive datasets, including real-time patient visual data and electronic medical records. However, the success of data analysis hinges on the ability to analyze all stored data effectively. Deficiencies in analytical skills can lead to errors during data input, resulting in misplaced information and the loss of valuable insights [40], [41]. This, in turn, diminishes the potential benefits an organization can reap from its BDA initiatives. In conclusion, the analytical skills of individuals directly impact the success of BDA adoption in healthcare settings.

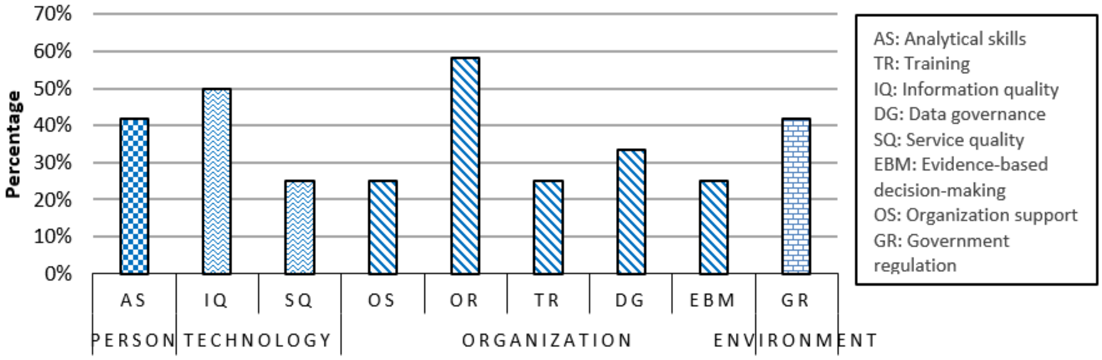

Figure 6. BDA adoption factors extracted from the include studies

4.3.2. Technology

In this study, technology refers to computerized healthcare systems supporting BDA for healthcare services. Adoption factors are derived from the ISSM [23], namely information quality and system quality. These factors are crucial because they influence how well healthcare professionals receive and utilize the insights generated by BDA. High information quality ensures data accuracy, completeness, and relevance, leading to more reliable analytics. System quality focuses on user-friendliness, ease of use, and overall system performance, ultimately impacting user satisfaction and willingness to adopt the technology.

a. Information quality

Information accuracy, data integration, data privacy and data security are crucial information quality factors influencing BDA adoption in healthcare services. In the era of big data, data emerges from diverse sources and requires a unified platform for comprehensive organization-wide information generation [42]. This underscores the importance of information quality in decision-making. Information accuracy is particularly important in BDA because big data algorithms can amplify the effects of even small errors in the data. For example, if a BDA algorithm is used to predict patient outcomes and the data is inaccurate, the algorithm may identify incorrect patients as at risk of poor outcomes [43]. This can lead to unnecessary interventions and wasted resources. Furthermore, incomplete data or a lack of user understanding can also significantly compromise information quality. Users without a deep grasp of BDA systems might misinterpret information, leading to flawed decision-making across operational, tactical, and strategic levels [44], [45]. Incomplete data sets can also skew results, hindering effective decision-making processes [39].

Data integration is another critical information quality factor in healthcare's big data landscape, marked by its massive and fragmented nature. Challenges arise in integrating data from older systems into big data analytics platforms [3], [15]. A robust data integration strategy, advocating for standardized formats to ensure interoperability and efficient integration of diverse healthcare data sources are important. Integrating structured and unstructured data from various sources like electronic health records (EHRs), medical devices, wearable technology, and patient-generated data is challenging. Advanced integration methods like data cleaning and transformation are vital for insightful analysis and informed decision-making.

Data privacy and security focus on secure management of distributed data and enabling safe data sharing, emerging as a pivotal factor impacting the success of big data projects, particularly in healthcare [19], [21]. Healthcare data, being profoundly sensitive, demands safeguarding against unauthorized access to prevent public exposure and to deter potential healthcare fraud by attackers. This is closely tied to ethical and legal considerations given the personal nature of healthcare's big data [30]. Traditional security measures are insufficient for the diverse scenarios in BDA, making data privacy and security a critical factor influencing the adoption of BDA in healthcare services.

b. System quality

System reliability, complexity, and compatibility are the crucial system quality factors influencing BDA adoption in the healthcare sector. Reliability ensures consistent, error-free performance over time, yielding accurate outcomes [10]. Unreliable BDA systems can produce inaccurate or misleading results, which can lead to adverse consequences for patients and the healthcare system. An expert review of a BDA quality model highlighted reliability as the highest-rated factor for enhancing healthcare organizational performance [37]. Reliable BDA systems are essential for effective decision-making and optimal performance in healthcare organizations.

Complexity is defined as a dynamic set of interacting processes and objects [46]. BDA tools are highly complex, demanding extensive programming expertise and a diverse range of skills [3]. Perceived complexity can lead to resistance due to a lack of skills and knowledge [47]. Public hospitals, serving diverse patient classes, create complex systems with varied medical treatments, adding to the challenge. Consequently, this creates a complex system and a complicated environment [48].

Compatibility, a key factor influencing BDA adoption in healthcare, refers to the ease with which a new technology integrates with existing systems, processes, and workflows [49]. It essentially measures how well BDA aligns with an organization’s existing infrastructure, user needs, and information-sharing requirements. High compatibility facilitates a smoother integration process, minimizing disruptions and reducing resistance to change among users [36]. A study by Kapoor *et al.* [50] support this notion, highlighting compatibility as a major driver of technology adoption in general. In the context of healthcare, this translates to a greater willingness from organizations to embrace BDA if it seamlessly integrates with existing workflows and adheres to established standards [36]. Healthcare organizations' receptiveness to BDA adoption if it aligns with existing processes and standards [36].Therefore, ensuring compatibility during BDA implementation is crucial for promoting user acceptance and ultimately, successful adoption within healthcare institutions.

4.3.3. Organization

Organization refers to the organizational condition of the work system. The organization factors identified from the review encompass organizational support, resources, training, data governance, and evidence-based decision-making (EBM). The factors influenced the organization's decision-making process.

a. Organization support

Organizational support involves managers' understanding and positive attitudes toward technological capabilities. The commitment from top management is essential for providing a consistent and meaningful direction to BDA [35]. The leadership needs to establish a common and well-defined purpose for the use of BDA. Organizational leadership plays a vital role in providing long-term commitment to employees for carrying out new changes in the organization. Top management should provide sufficient resources such as human, financial, and material required for change implementation [36].

b. Resources

Infrastructure, financial support, and BDA expertise are pivotal organizational resources for successful BDA adoption. A scalable IT infrastructure is important to perform data analytic tasks from vast healthcare data [3], [35]. High-performance servers and specialized tools are essential for efficient processing and analysis. The absence of these tools poses a significant challenge.

Besides, healthcare organizations must allocate capital and skilled staff to transform raw data into valuable insights. Previous study has consistently pointed out that the time and costs of medical big data applications stand as significant obstacles to establishing a comprehensive big data warehouse [51]. Integrating medical big data incurs high costs, with expenses related to data standardization, handling vast data volumes, and addressing system connectivity challenges [3].

Moreover, managing real-time data requires not only new tools and techniques but also cultivating knowledge and expertise for transforming data into a strategic asset and instilling new management practices or organizational culture. Data scientists equipped with the necessary expertise to utilize sophisticated analytics methods for evidence-driven decisions play a significant role in effective BDA in healthcare organizations. However, the healthcare sector faces challenges in bridging the expertise gap related to BDA, both in quality and quantity, hindering progress in medical big data technology [30].

c. Training

Training is vital for the sustained growth of healthcare organizations as it provides individuals with essential skills and enhances preparedness for BDA adoption. It represents an investment in human capital, fostering continuous learning and information sharing among employees. Formal training for all employees is crucial to ensure their preparedness for job performance and promote innovation within the organization. In the context of BDA adoption, training courses in areas like basic statistics, data mining, and business intelligence are essential to prevent errors in judgment and flawed decisions [15].

d. Data governance

Data governance is an organizational approach to managing data and information through formalized policies and procedures covering the entire data life cycle. In the healthcare industry, information governance becomes crucial as personalized medicine advances through big data analysis of genomics and electronic health record data. Agrawal and Madaan [35] identified five challenges tied to data governance include the lack of health policies and regulations, security and privacy concerns, insufficient health data sharing, lack of standardization and integration, and concerns about data quality. A strong data governance protocol, as outlined by [15], provides clear guidelines for handling data in terms of availability, importance, authenticity, sharing, and retention. This protocol facilitates the effective management and utilization of diverse data, information, and insights from internal systems (e.g., EHRs) and broader healthcare network applications for BDA purposes. These guidelines enable healthcare organizations to use BDA appropriately, leading to long-term competitive advantages.

e. Evidence-based decision-making

Evidence-based decision-making (EBM) involves making decisions based on the best available evidence. BDA enables healthcare professionals to make informed decisions by enhancing their understanding of data and identifying valuable insights for present and future decision-making [3]. It also assists in pinpointing data that offers valuable insights for both present and future decision-making. Empowering healthcare organizations with evidence-based decisions and real-time data would lead to improved diagnoses, treatment choices, and ultimately enhanced patient care [33]. This synergy between EBM and BDA enhances the efficacy and applicability of EBM in healthcare services [32].

4.3.4. Environment

Government regulation is a significant environmental factor influencing BDA adoption in healthcare. It encompasses the support provided by governmental authorities to promote the integration of IT innovations within companies. Government rules can act as both deterrents and encouragements for businesses to adopt new technologies [19]. These regulations may include incentives, technology standards, and laws influencing BDA adoption. Government regulation significantly impact the healthcare sector's readiness for big data adoption [36]. When government regulations stipulate that businesses must adhere to specific big data standards and protocols, companies are more likely to embrace BDA [36]. However, challenges arise when laws hinder big data adoption in healthcare, as seen in Korea [30]. There's a call for refining existing laws and introducing new legislation to encourage responsible data practices and prevent misuse.

4.4. Discussion

This review aimed to explore how socio-technical including person, technology, organization, and environment components influence the BDA adoption in healthcare services. While earlier studies have explored technologies employed in BDA [12], the advantages provided by BDA [8], and the obstacles associated with BDA in the healthcare field. Our review revealed that analytical skill is the person-related factor that influences BDA adoption. Similarly, previous studies have underscored the significance of analytical skill in enabling organizations to perceive and transform data to enhance the quality of decision-making and attain competitive advantages [52], [53]. The evidence suggests that employees with good analytical skills can analyze the high volume, diverse type, and velocity of medical data into valuable insights and informed decision-making. In contrast, deficiency in analytical skills leads to misinterpretation of medical data and failure to extract valuable insights from the medical data [33]. As a result, healthcare organizations will be unable to realize the full potential of their BDA initiatives.

From the technology perspective, information quality and system quality are critical factors. Information quality is particularly crucial due to the complexity and heterogeneity of healthcare data originating from diverse sources such as EHR, clinical trials, and medical devices. In the same vein, information quality and system quality has been recognized as a determinant impacting the success of BDA in literature review [54]. The accuracy, completeness, integration, and security of this data are vital for deriving valuable insights into patient care and treatment effectiveness. Inaccurate data can lead to misinformed decisions, especially as big data algorithms can magnify small errors, potentially resulting in unnecessary interventions [43]. Healthcare organizations can improve information quality by implementing data quality management processes and tools to ensure accurate and consistent data collection, entry, and storage. Moreover, data integration is critical due to the diverse formats and structures of medical data from various sources. Healthcare organizations can invest in data integration solutions to integrate data from different sources into a single, unified view. Additionally, data privacy and security are essential to building trust with patients and employees, as a lack of trust may impede data sharing. Healthcare organizations need to have robust measures in place to protect the privacy and security of that data. System quality, on the other hand, is influenced by factors like reliability, complexity, and compatibility. Reliable BDA systems are crucial for making informed decisions in patient care, while overly complex systems can hinder adoption by healthcare professionals [47]. Healthcare organizations should look for BDA systems with a high uptime, robust backup, and recovery procedures. The systems should also have intuitive user interfaces and clear documentation so that they are easy to learn and use. Besides, compatibility with existing systems, such as EHRs, is vital to ensure seamless integration and utilization. Incompatibility between BDA systems and existing infrastructure can result in challenging and costly integration, which can lead to adoption challenges.

Moreover, BDA adoption in healthcare is shaped by organizational factors, including top management support, resource allocation, training, data governance, and EBM. Top management support is crucial, as it facilitates the allocation of resources, cultural transformation, and long-term commitment necessary for success. When top management comprehends and embraces BDA's technological capabilities, they are more likely to foster a culture of innovation and integration of BDA into the strategic plan, ensuring sustained efforts to improve healthcare services. A SLR conducted by Surbakti *et al.* [55] highlighted that top management support stands out as the most frequently cited element within organizational category. Additionally, critical resources for successful BDA adoption in healthcare encompass infrastructure, financial support, and BDA expertise. A scalable and robust IT infrastructure is essential to handle the vast volume, velocity, and variety of healthcare data. It requires investments in high-performance servers, storage, and networking [56]. Specialized BDA tools can enhance data processing efficiency. Financial resources are crucial for funding BDA systems, infrastructure, and staff training. Moreover, access to skilled professionals, including data analysts and scientists, is imperative for managing complex data integration and utilizing sophisticated analytics methods. Combining resources across organizations improves decision-making efficiency, leading to superior services and a sustainable competitive advantage. This finding extended the findings of Maroufkhani *et al.* [57], who emphasized that preparedness with requisite resources and infrastructure serves as a crucial facilitator for the adoption of BDA. Training is also identified as a critical factor, helping staff effectively use BDA tools, interpret analysis results, and apply BDA insights to their work, ultimately fostering a culture of innovation within healthcare organizations. BDA systems can be complex and require specialized skills to be used effectively. Healthcare organizations that invest in training their staff on BDA are more likely to be successful in reaping the benefits of this technology [58]. Training can help healthcare staff with how to use BDA tools and technologies, how to interpret the results of BDA analysis, and how to apply BDA insights to their work. Training can also help to overcome resistance to BDA adoption and create a culture of innovation within the healthcare organization. By investing in training, healthcare organizations can ensure that their staff have the skills and knowledge they need to use BDA effectively.

Data governance is another crucial factor because BDA systems need to efficiently access and analyze diverse data from various sources [35]. This data can be heterogeneous, meaning that it is in different formats and structures. Data governance can help to ensure that data is standardized in a format that is compatible with BDA tools and technologies. This makes it easier to collect, integrate, and analyze data from different sources. It also helps to ensure that data is accessible to those who need it to do their jobs and helps to facilitate the sharing of data between different departments and organizations. This is important for BDA because BDA often requires access to data from multiple sources. In addition, data governance helps to protect data from unauthorized access, use, disclosure, disruption, modification, or destruction [59]. This is important for healthcare because BDA often involves the use of sensitive patient data. Besides, it helps to ensure that data is accurate, complete, and consistent. This is important for BDA because BDA algorithms are only as good as the data they are trained on. Healthcare organizations can enhance data governance for BDA adoption by establishing and implementing a comprehensive framework outlining policies and procedures for data management, including aspects such as data access, security, privacy, and the implementation of data standards. Furthermore, evidence-based medicine establishes a foundation for maximizing the potential of BDA. BDA enables the extraction of meaningful insights from extensive clinical data, uncovering hidden patterns and valuable information. This synergy between evidence-based medicine and BDA enhances decision-making, ultimately improving the effectiveness and applicability of evidence-based medicine. To boost BDA adoption within the context of evidence-based medicine, healthcare organizations can facilitate collaboration between healthcare professionals and data scientists. This ensures that BDA initiatives align with evidence-based medicine principles, promoting effective and efficient implementation.

From the environmental perspective, government regulations significantly influence the adoption of BDA in healthcare. Policies offering financial incentives or regulatory relief can motivate healthcare organizations to invest in BDA technologies. These measures help offset upfront costs, making BDA adoption more appealing. Governments should also balance encouraging innovation with safeguarding patient privacy and data security. Clear and tailored regulations can achieve this balance. Additionally, governments can work with healthcare organizations and industry experts to develop best practices for BDA implementation. Thorough consideration of the key factors outlined in this study enables successful adoption of BDA. By providing financial support, clear regulations, and collaborative knowledge-sharing initiatives, governments can empower healthcare institutions to navigate the challenges of BDA adoption.

A systematic literature review (SLR) was conducted to identify the BDA adoption factors in healthcare. SLR is a rigorous method for assessing existing research on a specific topic. However, SLR has some limitations that should be considered when interpreting the findings. One of the limitations is that the SLR may be limited by the availability of published research. Keywords “big data” or “big data analytics” along with “healthcare”, “medicine”, or “biomedicine” were used to search the articles on only six databases including ScienceDirect, PubMed, Emerald Insight, ResearchGate, ProQuest, and IEEE Xplore published between 2013 and 2023. Additionally, the availability of relevant literature may be influenced by publication biases, potentially excluding valuable insights from unpublished or non-peer-reviewed sources. Moreover, the review's focus on English-language articles may omit valuable research from other languages. Another limitation is that BDA adoption in healthcare is a relatively new research area, limiting the number of high-quality studies. Besides, the scope of this SLR may not cover every aspect of BDA adoption due to challenges in defining and categorizing the dynamic field. Hence, the SLR may be unable to provide a comprehensive overview of the current state of knowledge. Despite these limitations, the review provides a robust foundation for understanding BDA adoption factors in healthcare, acknowledging the need for ongoing exploration as the field continues to evolve. Nevertheless, the limitations do not invalidate the study findings. Readers should consider the limitations when interpreting results and making informed decisions based on the SLR.

5. CONCLUSION

In conclusion, our review revealed that socio-technical factors including analytical skills, system quality, information quality, organization support, organization resources, training, data governance, evidence-based decision-making, and government regulations are the key factors influencing BDA adoption in healthcare services. This review contributes valuable insights by emphasizing key socio-technical factors critical for BDA adoption in healthcare services. Successful adoption necessitates a comprehensive approach, addressing factors like analytical skill, information quality, system quality, organization support, resources, training, data governance, EBM, and government regulation. Decision-makers in healthcare organizations should carefully consider these factors when formulating a tailored BDA adoption strategy. Acknowledging these factors during the initial stages of adoption is crucial. A well-crafted BDA strategy can lead to enhanced patient care, cost reduction, and increased satisfaction. Future studies may explore the significance of these factors in influencing BDA adoption in healthcare by conducting empirical studies such as questionnaire surveys. In addition, conceptual models integrating all the socio-technical factors can be developed in future studies.

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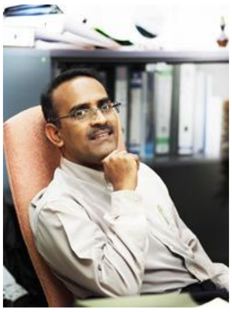

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