sustainability

Systematic Review

A Systematic Review of Literature on Sustaining Decision-Making in Healthcare Organizations Amid Imperfect Information in the Big Data Era

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Abstract: The significance of big data analytics (BDA) has benefited the health sector by leveraging the potential insights and capabilities of big data in decision making. However, every implementation of BDA within the healthcare field faces difficulties due to incomplete or flawed information that necessitates attention and resolution. The purpose of this systematic literature review is to accomplish two main objectives. Firstly, it aims to synthesize the various elements that contribute to imperfect information in BDA and their impact on decision-making processes within the healthcare sector. This involves identifying and analyzing the factors that can result in imperfect information in BDA applications. Secondly, the review intends to create a taxonomy specifically focused on imperfect information within the context of BDA in the health sector. The study conducted a systematic review of the literature, specifically focusing on studies written in English and published up until February 2023. We also screened and retrieved the titles, abstracts, and potentially relevant studies to determine if they met the criteria for inclusion. As a result, they obtained a total of 58 primary studies. The findings displayed that the presence of uncertainty, imprecision, vagueness, incompleteness, and complexity factors in BDA significantly impacts the ability to sustain effective decision-making in the healthcare sector. Additionally, the study highlighted that the taxonomy for imperfect information in BDA provides healthcare managers with the means to utilize suitable strategies essential for successful implementation when dealing with incomplete information in big data. These findings have practical implications for BDA service providers, as they can leverage the findings to attract and promote the adoption of BDA within the healthcare sector.

Keywords: big data analytics; decision-making sustainability; healthcare organizations; imperfect information

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1. Introduction

The decision-making process is critical in both the healthcare system and medical practice. It refers to the act of selecting the best-suited plan of action from among the several possibilities available to handle a particular healthcare issue or scenario [1]. Decision making is critical in healthcare at all levels, from individual patient treatment to organizational management and policy formulation [2–4]. Making healthcare decisions has an impact on a variety of domains, including diagnosis, treatment selection, resource allocation, risk assessment, and healthcare policy creation [5–7]. Medical practitioners rely on their expertise, knowledge, evidence-based recommendations, and patient preferences to make well-informed decisions that improve patients' well-being and achieve the best possible outcomes.

The continual difficulty of selecting the best choices that benefit patient care and the industry as a whole is another challenge faced by healthcare providers and politicians [8]. Decision makers continually consider many variables affecting health outcomes and costs, from choosing the most effective therapies to determining efficient resource utilization. Big data analytics (BDA) has become increasingly important in healthcare decision making due to the complexity of these variables [9,10]. BDA has become an essential tool for improving healthcare outcomes, which benefits all parties when used in healthcare decision making [11–13]. It can help organizations make better decisions while assisting policymakers in making more educated decisions about healthcare, ultimately improving population and public health outcomes. Numerous research has looked into the possible use of BDA in healthcare decision making, highlighting its ability to enhance the results of decisions [14].

The use of big data in healthcare organizations does not, however, come without risks, despite the potential advantages [15,16]. A substantial cause of mistakes or errors in the application of big data in healthcare has been found as imperfect information [17]. Studies have recognized this problem, and healthcare institutions still have a lot of work to do to resolve it [7,18]. It is concerning how BDA in the healthcare industry is affected by imperfect information [19]. Healthcare institutions deal with private patient information, and imperfect data might make it challenging to make wise decisions. As a result of the study's recognition of the importance of this problem, a method was used to solve the difficulties involved in using imperfect information to make decisions in healthcare organizations.

Until now, BDA and its advantages to healthcare organizations have been the subject of numerous studies in the literature. With each study tackling the subject from a different perspective, numerous studies have significantly advanced our understanding of BDA in healthcare. For instance, Baro [20] and Wamba [21] offered insightful analysis. Other studies, such as those by Raghupathi and Raghupathi [22] and Ward [23] have taken a more general approach by evaluating cases in the field of health analytics, focusing on particular facets of the domain. Wang [19] set out to ascertain the breadth of BDA in healthcare, including its applications and obstacles, as well as solutions to solve them. Furthermore, Jacofsky [24] expressed worry about the dangers that analytics might pose.

However, there still needs to be more research regarding the study of imperfect data in BDA for decision-making sustainability in healthcare organizations and how to manage circumstances involving imperfect data and poor information to improve decision-making processes. This research aims to fill this gap by conducting a systematic review that summarizes earlier studies on the factors that lead to imperfect information in BDA for decision-making in healthcare organizations. To support and enhance decision-making processes, notably in the healthcare industry, the study proposes an imperfect information taxonomy for BDA that may be used to identify characteristics that affect decision-making sustainability in healthcare organizations. The taxonomy of imperfect information refers to a categorization or classification system that helps in understanding and addressing different types of incomplete or uncertain data in the context of BDA for decision making in healthcare organizations (Hos) [25]. In the healthcare sector, decision making often relies on data-driven insights, and the availability of complete and accurate information is crucial for making informed decisions. However, in practice, healthcare data can be imperfect due to various reasons, such as missing values, incomplete records, data entry errors, or uncertainty in measurements. The taxonomy of imperfect information provides a framework to organize and analyze these imperfections, allowing decision makers to account for uncertainties and make appropriate choices based on the available data.

The article will follow a structured format, beginning with Section 2, which provides a comprehensive description of the review's methodology, including the search strategy, selection criteria, and data extraction process, as well as the subsequent sections covering results, discussion, and conclusion.

2. Materials and Methods

The methodology consists of four main phases (Figure 1); the planning phase, the selection phase, the extraction phase, and the data synthesis and reporting phase.

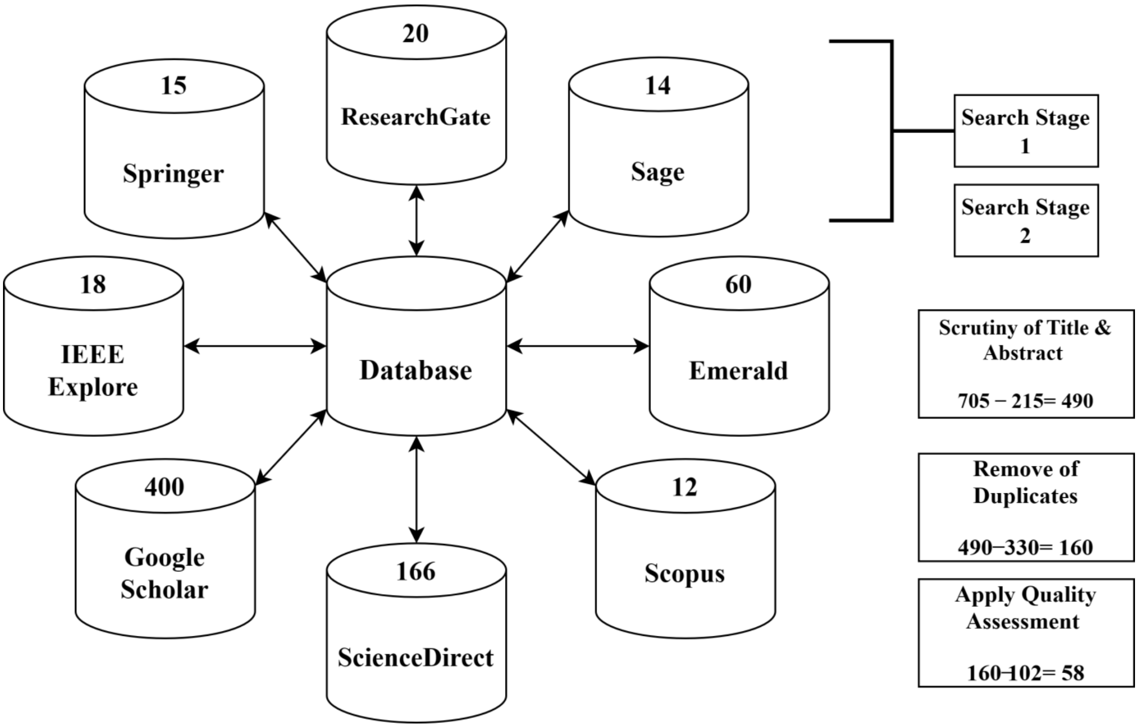

Figure 1. Search process.

2.1. Phase 1: Planning

2.1.1. Definition of Research Questions

The research questions are as follows:

- What research studies have explored the role of imperfect information in the sustainability of decision making within health organizations (HOs)?
- What factors associated with imperfect information can impede the sustainability of decision making in HOs?
- Which theoretical models are utilized to support the sustainability of decision making in HOs?
- What specific contributions have studies made in addressing the issue of imperfect information in the context of decision making sustainability within HOs?

2.1.2. Search Strategy

The following is a description of the analysis of the search methods applied in this study in terms of search words, literature sources, and the search procedure:

2.1.3. Search Terms

The selected search terms were directly related to the topic under investigation and encompassed keywords such as “big data”, “imperfect information”, and “uncertainty”. The final search terms used in the study were as follows: ([“big data” OR “big data quality” OR “big data uncertainty” OR “big data sustainability” OR “big data healthcare” OR “big data decision-making” OR “big data model”]) AND ([“imperfect information” OR “big data imperfect information” OR “imperfect information healthcare” OR “imperfect information decision-making”]).

2.1.4. Literature Resources and Existing Research Review

Google Scholar, ScienceDirect, IEEE Xplore, Scopus, Springer, Emerald, and SAGE Journals were all used in the research study. These databases were chosen to collect important information and scholarly publications on the research issue. Within these databases, several types of research information, such as review articles, research papers, systematic literature reviews (SLRs), and specific portions like "title", "abstract", and "index", were searched. The goal was to find relevant information for the research study in published journals or articles, conference proceedings, symposiums, seminars, book chapters, and IEEE bulletins.

2.2. Phase 2: Selection

The information provided covers the methodology's search procedure. The researchers conducted a systematic literature review (SLR) to acquire important information from the existing literature. The processes in this technique are depicted in Figure 1. The researchers systematically searched the eight selected digital databases in the first step of the search process. The outcomes of these searches were compiled. The current research papers were sorted through a selection process in the second stage. A list of 705 papers was first created. The titles of these papers were checked for duplicate data, resulting in a smaller list of 490 papers. Researchers then evaluated the articles' quality using particular criteria and linked them to the study questions. Finally, there are 58.

Scrutiny and Filtering Process

The initial list of 705 studies, as indicated in Figure 1, was evaluated and examined during this procedure. Several steps were taken during the filtering procedure. The titles of the studies were initially appraised concerning the primary research areas. In addition, the research content was evaluated to determine its significance. Only research that met specific requirements, such as being written in English. Only the most recent and up-to-date version was used in the analysis when duplicate papers were discovered (Figure 2).

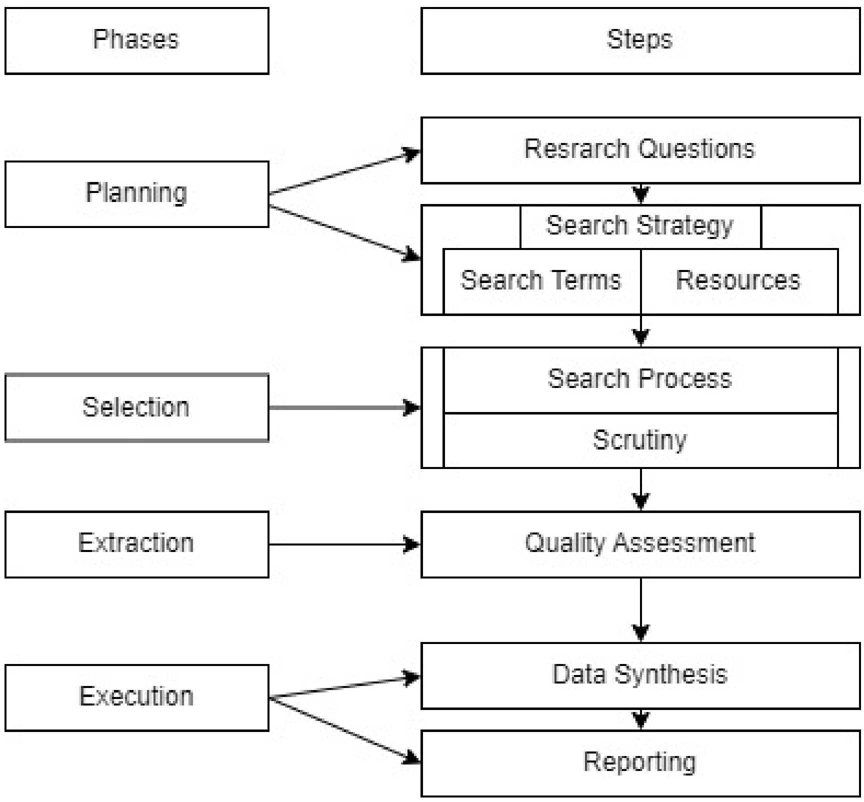

Figure 2. Phases and steps of the review protocol.

2.3. Phase 3: Extraction

Study Quality Assessment

Studies that were included in the study were given a grade for the study's quality evaluation based on their capacity to provide pertinent research topics (Table 1).

Table 1. Study quality checklist success criteria.

QA ID	Checklist Questions	Answer
QA_1	Are the study's objectives well defined?	
QA_2	Has the proposed theory/model/framework been clearly articulated and explained?	Y—Yes = 1/
QA_3	Has the chosen methodology (research approach) been appropriately applied to the subject matter?	P—Partially = 0.5/ N—No = 0.5
QA_4	Does the research information presented have value for extensive academic research or employers?	

2.4. Phase 4: Execution

Data Synthesis

The study's final phase comprised the screening of the papers (Figure 3), which included an additional validation procedure to ensure the final list's quality (Table 2).

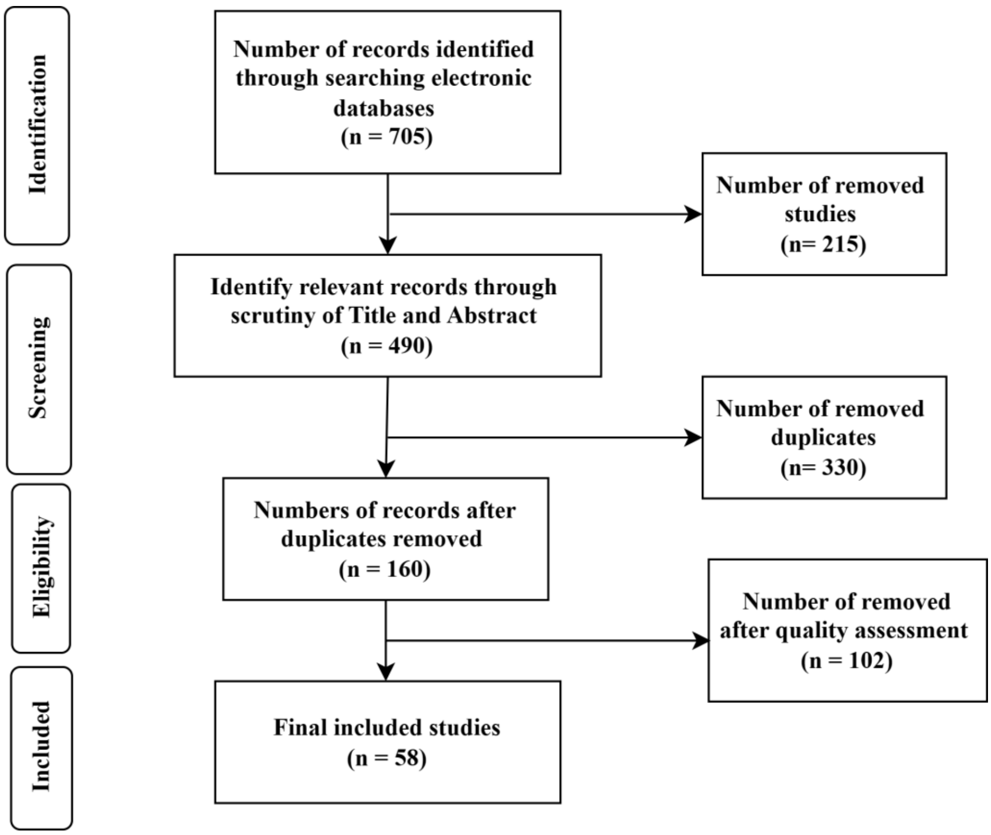

Figure 3. PRISMA flowchart.

Table 2. Inclusion and exclusion criteria.

Inclusion Criteria	Exclusion Criteria
The articles need to be written in English.	Any studies are written in other languages
All papers focus on the issues, challenges, and implications of dealing with imperfect information within the context of utilizing BDA in Hos.	Papers that had no connection to the study’s questions
Related articles released between 2013 and 2023	Unfinished studies include grey ones that do not apply to the research’s goals.
Articles that may provide insight into at least one research question.	Duplicate papers
Only empirical studies that examined factors and theories associated with imperfect information in HOs were included.	This only suggests that it is impossible to confirm the validity of articles for which search engines or authors did not make the text available.
Articles (≥3 pages)	Short articles (<3 pages)

3. Results

The final selected sample of 58 papers was read and studied further to clarify the existing research concerning this subject area (Table 3). The studies were conducted in 23 countries, indicating that the selected papers originated from research conducted in a diverse range of countries. This implies that the literature review aimed to incorporate a global perspective by considering research from different cultural, geographical, and socioeconomic contexts. These 58 papers will help to consolidate existing research on the subject, identify gaps, and contribute to a deeper understanding of the topic.

The findings of this systematic literature review highlight the introduction of a taxonomy, as demonstrated in Figure 4, which emphasizes the application of BDA for decision-making sustainability in HOs. The taxonomy is particularly considered to deal with imperfect information, recognizing the complexities and challenges associated with utilizing large-scale data in the decision-making process in many aspects of healthcare. The study goes into more detail about the traits of big data, sometimes known as the “5 V’s.” The volume describes the enormous amount of available data, encompassing data saved in many formats such as tables, files, archives, and records and ranging in size from terabytes to exabytes and zettabytes.

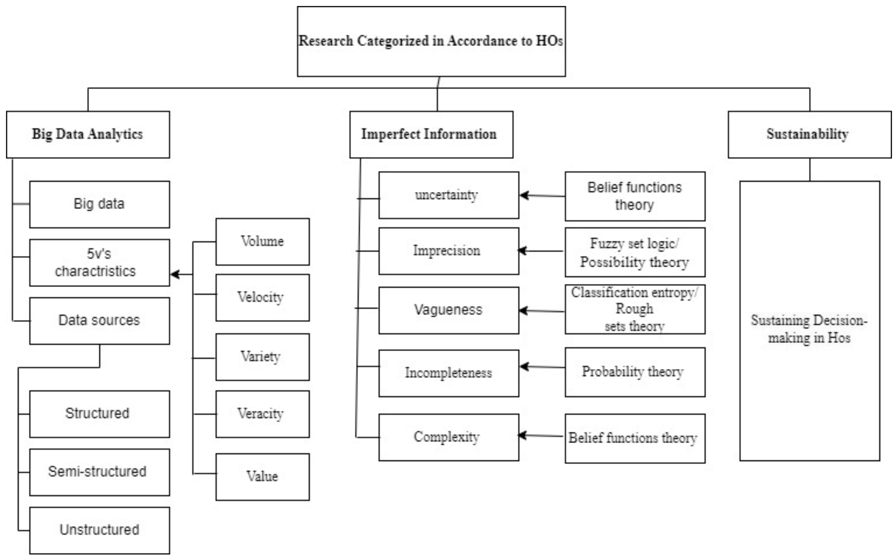

Figure 4. The research taxonomy of BDAs focusing on handling imperfect information to support sustainable decision making in healthcare organizations.

Table 3. A summary of the 58 reliable and relevant studies included in this review.

No.	Authors	Selected Studies	Location(s)
1	Alizadehsani [26]	Handling of uncertainty in medical data using machine learning and probability theory techniques: A review of 30 years (1991–2020).	Australia
2	Andreu-Perez [27]	Big data for health.	UK, USA, China
3	Bania & Halder [28]	R-Ensemble: A greedy rough set-based ensemble attribute selection algorithm with kNN imputation for classification of medical data.	India
4	Basha [29]	Utilizing machine learning and big data in healthcare systems.	India
5	Bates [30]	Why policymakers should care about "big data" in healthcare.	USA
6	Costa [31]	Big data in biomedicine.	USA, Brazil
7	Dhand [32]	Deep enriched salp swarm optimization based bidirectional long short-term memory model for healthcare monitoring system in big data.	India
8	Fatt & Ramadas [33]	The usefulness and challenges of big data in healthcare.	Malaysia
9	Ghorbel [34]	Handling data imperfection—False data inputs in applications for Alzheimer's patients.	France, Tunisia
10	Gomes [35]	Transforming healthcare with big data analytics: Technologies, techniques and prospects.	Brazil
11	Fu [36]	Disjunctive belief rule-based reasoning for decision making with incomplete information.	China
12	Han [37]	Varieties of uncertainty in health care: a conceptual taxonomy.	USA
13	Hariri [38]	Uncertainty in big data analytics: Survey, opportunities, and challenges.	USA
14	Kaur [39]	Big data analytics in healthcare: A review.	India
15	Martin-Sanchez & Verspoor [40]	Big data in medicine is driving big changes.	Australia
16	Mayston [41]	Health care reform: A study in imperfect information.	UK
17	Mehta & Pandit [42]	Concurrence of big data analytics and healthcare: A systematic review.	India
18	Nascimento [10]	Impact of big data analytics on people's health: Overview of systematic reviews and recommendations for future studies.	Brazil, USA
19	Nazir [43]	A comprehensive analysis of healthcare big data management, analytics and scientific programming.	Pakistan
20	Ola & Sedig [44]	The challenge of big data in public health: An opportunity for visual analytics.	USA
21	Palanisamy & Thirunavukarasu [45]	Implications of big data analytics in developing healthcare frameworks—A review.	India
22	Pisana [46]	Challenges and opportunities with routinely collected data on the utilization of cancer medicines: Perspectives from health authority personnel across 18 European countries.	Sweden
23	Qian [47]	Multi-label feature selection based on information entropy fusion in multi-source decision system.	China
24	Rosenfeld [48]	Big data analytics and artificial intelligence in mental healthcare.	Israel
25	Sachan [49]	Evidential reasoning for preprocessing uncertain categorical data for trustworthy decisions: An application on healthcare and finance.	UK

Table 3. *Cont.*

No.	Authors	Selected Studies	Location(s)
26	Secundo [50]	Digital technologies and collective intelligence for healthcare ecosystem: Optimizing Internet of things adoption for pandemic management.	UK
27	Singh [51]	The impact of imperfect information on the health insurance choice, health outcomes, and medical expenditures of the elderly.	USA
28	Sohail [52]	Multilevel privacy assurance evaluation of healthcare metadata.	The Netherlands
29	Yang [53]	Incomplete information management using an improved belief entropy in Dempster–Shafer evidence theory.	China
30	Chen & Zhang [54]	Explores how relative advantage and perceived credibility impact uptake of mobile health services by an organization and how environmental unpredictability alters these relationships.	China
31	Dereli [55]	Understanding risk, uncertainty, and ignorance in big data and ethics reviews for health systems research in low-income countries.	Turkey
32	Wouters [56]	Recognizing the challenges and uncertainties faced when conducting big data health research.	The Netherlands
33	Bag [57]	Investigate the influence of innovation leadership on big data analytics (BDA) on healthcare supply chain (HSC) innovation, responsiveness, and resilience in the context of the COVID-19 pandemic.	Taiwan
34	Abdel-Basset [58]	Estimating the selection of smart medical devices (SMDs) in a group decision-making (GDM) setting in a hazy decision-making setting.	Egypt
35	Pritzker [59]	The objective of precision medicine is to give patients more effective treatments that are informed by more accurate diagnoses.	Canada
36	Lv & Qiao [60]	Examine how China's healthcare system is developing as well as the privacy and security risks associated with medical data against the backdrop of big data.	China
37	Pramanik [61]	A systematic assessment of various big data and smart system technologies, a critique of cutting-edge advanced healthcare systems, and a description of the three-dimensional paradigm shift.	Hong Kong
38	Herland [62]	Cite current studies that analyze health informatics data collected at many levels, including the molecular, tissue, patient, and population levels, utilizing big data tools and methodologies.	USA
39	Dyczkowski [63]	Describe and discuss the theoretical underpinnings of the system that the author and his colleagues developed, OvaExpert.	Poland
40	Dinov [64]	Give examples of how to use distributed cloud services, automated and semi-automatic classification methods, and open science protocols to analyze heterogeneous datasets.	USA
41	Duggal [65]	Use of big data analytic methods like fuzzy matching algorithms and MapReduce is suggested as a solution to the issue of matching patient records from different systems.	India
42	Hong [66]	The purpose of the review was to enumerate the characteristics, uses, methods of analysis, and difficulties of big data in health care.	China
43	Dhiman [67]	The use of anonymity technology and differential privacy in data collecting can help avoid attacks based on background information derived through data integration and fusion.	India
44	Juddoo & George [68]	Examine the prospects for employing machine learning in the process of identifying data incompleteness and inaccuracy, since these two data quality dimensions were considered to be the most significant by the authors' prior research study.	Mauritius
45	Roski [69]	Investigates these issues as well as the prospects for integrating big data into the healthcare system.	USA
46	Viceconti [70]	Big data analytics and VPH technology may be effectively coupled to provide reliable and efficient in silico medical solutions.	Italy
47	Belle [71]	Focus on three new and promising fields of medical research, address some of the significant challenges: analytics using image, signal, and genomics.	USA

Table 3. *Cont.*

No.	Authors	Selected Studies	Location(s)
48	Zhang [72]	Examines big data mining ideas, methods, and their use in clinical practice.	China
49	Peñafiel [73]	Compare the Dempster–Shafer method's outcomes to those of other machine learning techniques.	Chile
50	Brown [74]	Showcase some of the amazing public domain materials and projects that are currently available for examination to explain big data in the context of biology, chemistry, and clinical trials.	UK
51	Sharma [75]	In intelligent information systems, large data analysis is essential.	India
52	Bikku [76]	Focuses on using deep learning to predict sickness using historical medical data.	India
53	Mardani [7]	Analyzes conventional and fuzzy decision-making approaches used in healthcare and medical concerns in a comprehensive manner.	USA
54	Straszecka [77]	Proposes a unified fuzzy-probabilistic framework for modeling medical diagnostic procedures.	Poland
55	Jindal [78]	To deliver Healthcare-as-a-Service. The suggested approach is based on the development of initial clusters, retrieval, and processing of massive data in a cloud environment.	UK
56	Majnarić [79]	Integration and deployment of effective AI technologies, notably deep learning, into clinical routines directly into medical practitioners' workflows.	Croatia
57	Li [80]	Give healthcare practitioners and government organizations with insight into the current developments in ML-based big data analytics for smart healthcare.	Vietnam
58	Rizwan [81]	Delivers a first-of-its-kind assessment of the open literature on the relevance of big data created by nano-sensors and nano-communication networks for future healthcare and biological applications.	

Velocity stresses the ever-present and overwhelming nature of data flow by describing the rate at which data appears, whether in batches or real-time/near-real-time streams. Variety highlights the necessity of handling data from multiple sources in various formats, including structured, unstructured, multi-factor, and probabilistic data. Variety also indicates the diversity of data types. Veracity investigates the data's accuracy and dependability, focusing on the value of using reliable data sources and considering elements like uncertainty, incompleteness, and inconsistency. Value, encompassing statistical data, data in action, events, connections, and hypothetical scenarios, represents the value and utility produced from the analyzed data.

Additionally, the study defines and groups three major categories of data sources inside the taxonomy. Data with a data type, format, and structure that simplifies analysis and interpretation is called structured data. Partially organized and partially structured data have some structure but only a very basic level of organization. They frequently have a self-describing nature, which allows for flexible data processing. On the other hand, unstructured data is harder to evaluate since it lacks a natural structure or pattern. Product reviews, social media posts, sensor data, supply chain data, and information from economic resource planning are a few examples of unstructured data sources in the healthcare industry.

Overall, the taxonomy displayed in Figure 4 provides a framework to help healthcare organizations use big data analytics effectively. It attempts to enhance sustainable decision-making processes in healthcare by addressing the problems caused by incomplete information, utilizing the enormous potential of big data while considering its particular characteristics and data sources.

The research's taxonomy's second column focuses on factors related to imperfect information that may jeopardize the long-term viability of decision-making in HOs. Drawing on the results of various research studies, the section stresses the variables influencing BDA in HOs (Table 4). These factors include complexity, ambiguity, imprecision, uncertainty, and vagueness. These factors relating to insufficient information threaten the long-term viability of decision making in HOs. Uncertainty, imprecision, ambiguity, incompleteness, and complexity impact both the effectiveness of BDA and the standard of healthcare services.

Table 4. The imperfect information of BDA in HOs.

Code	Factor	Description	Source
P_1	Uncertainty	The data are ambiguous when they are not well characterized. A doubt over the integrity of the information is also reflected in uncertainty.	[31,33,37,54–58]
P_2	Imprecision	Imprecision is related to the data's inherent potential for ambiguity. Additionally, it alludes to the challenge of clearly and exactly expressing knowledge.	[34,52,58,59]
P_3	Vagueness	Data that is ambiguous is related to vagueness.	[58,60–62]
P_4	Incompleteness	The absence of data is referred to as incompleteness. It also has to do with incomplete or lacking knowledge.	[61,63,65–68]
P_5	Complexity	Simple definitions of complexity include difficulty, a state of being unclear, or intricate.	[36,42,52,61,69–71]

Uncertainty is the absence of certainty or the presence of uncertainty when making decisions under complicated circumstances. When there is a lot of data to evaluate, there is uncertainty, and errors can seriously harm an organization's reputation and bottom line. Stakeholders, including managers, employees, board members, and practitioners, become anxious when uncertain. Decision-making ambiguity can hurt BDA and the effectiveness of healthcare services. To lessen this effect, practitioners should strive to have maximum control over uncertain conditions to mitigate this impact.

Imprecision refers to hazy and inaccurate estimates or lack of precision. Due to organizational uncertainty in accomplishing strategic corporate goals, imprecision frequently develops. Due to ignorance, it may go unnoticed, even if it is a typical occurrence. Healthcare professionals may face inaccurate data, and because of their inexperience or limited knowledge of handling the problem, they may be unable to analyze the data effectively. Practitioners must pay attention to how decisions are made in HOs to sustain imprecision's impact in BDA.

Vagueness describes data status as vague or imprecise, even when there may be a lot of information available. The context above shows that even while there is a wealth of information, it needs to be better defined and more complex to comprehend. The accuracy of the analysis may be jeopardized by this ambiguity, which might make it difficult to undertake efficient big data analytics (BDA). Data reliability must be carefully considered to reduce ambiguity and improve validity. The data's accuracy, relevance, and quality are assessed as part of validity considerations to ensure they are appropriate for analysis. The chance of running into ambiguity can be reduced by ensuring the data utilized in BDA is reliable.

Incomplete BDA's effects may impact healthcare organizations' goals, objectives, and service delivery on data analysis and validity. Effective decision making in HOs depends on having complete data. To keep BDA useful and sustainable in decision-making processes, incomplete data must be addressed and eliminated.

Complexity describes the challenge, perplexity, or difficulty of analyzing BDA. Increased data volume, variety, and pace are a few elements contributing to complexity. Traditional processing and management techniques may lose effectiveness when dealing with large data. It is critical to acknowledge the complexity and imprecision of data, and healthcare professionals must modify their methods to manage and make sense of such data.

Practitioners should try to address these issues by enhancing their capacity to handle uncertainty, ensuring data analysis is accurate, eliminating ambiguity and incompleteness, and adapting to the complexity of BDA in decision-making processes.

The taxonomy research demonstrates the use of numerous theories in evaluating BDA in HOs from various perspectives, and their use details the influence of these theories (Table 5). The belief function theory is one of these theories. In BDA, belief functions theory also referred to as Dempster–Shafer theory [82] plays a crucial role in managing uncertainty and complexity in the healthcare industry. Due to the inherent uncertainty and complexity of medical data and decision-making processes, it provides a mathematical framework for modeling, synthesizing, and reasoning with uncertain information. Decisions in the healthcare industry must frequently be made based on little or conflicting evidence. Medical information is frequently ill-defined, imprecise, and vulnerable to numerous causes of variation. The belief functions theory provides a systematic way to deal with these issues and supports decision making in the face of complexity and uncertainty. Medical diagnosis is one of the main areas in which belief functions theory is applied in the healthcare industry. A patient's symptoms, test results, and medical expertise must normally all be considered while diagnosing. This data is rarely exhaustive or definitive, though. According to the belief functions theory, a more thorough and reliable evaluation of the patient's condition can be produced using the combination of evidence from various sources, such as medical tests, expert opinions, and patient symptoms. It offers a method for quantifying and reasoning with ambiguous and contradictory facts, assisting in creating precise and well-informed diagnoses.

Medical decision assistance systems also make use of the belief functions theory. These systems use the framework offered by belief functions theory to aid healthcare professionals in making difficult choices, such as choosing a course of treatment or evaluating the risk. Belief functions theory facilitates the construction of decision support systems that can handle the ambiguity and complexity inherent in healthcare decisions by combining several sources of information, including patient data, medical recommendations, and research evidence. These tools can offer advice, point out potential hazards or uncertainties, and assist physicians in navigating the difficulties of providing tailored patient care.

Additionally, the analysis and interpretation of medical images use the belief functions theory. Medical imaging procedures, including MRI, CT scans, and ultrasound, produce complex and noisy data. The accuracy and dependability of image interpretation and diagnosis are increased thanks to the belief functions theory's capacity to combine data from several imaging modalities or image analysis methods. It gives medical imaging systems a mechanism to deal with picture uncertainties, like artifacts or ambiguity in tissue boundaries, improving their usefulness. The healthcare industry can gain from more reliable decision-making processes, increased diagnostic precision, and improved patient care by adding belief functions theory into BDA. Healthcare workers can use it to understand the complexities and uncertainty around medical data, resulting in more individualized and accurate treatment.

In addition, mathematical frameworks like fuzzy set logic are utilized to deal with imprecision in decision-making processes [83]. These theories can enhance sustainable decision making when used in BDA in hospitals. Although there is frequently a lot of information available in the context of BDA in hospitals, it may need to be completed, clarified, or uncertain. To address these issues, fuzzy set logic and possibility theory allow for the representation of ambiguous and uncertain information. Partial membership is a topic covered by fuzzy set logic.

Fuzzy logic offers a solution to this complexity by enabling the representation of uncertain or insufficient data. It makes it possible to model variables and ideas that lack distinct bounds or precise numerical values. Fuzzy logic permits gradations in truth values as opposed to the binary logic of the past when a proposition was either true or false [84]. The idea of fuzzy sets is introduced, in which an element may have a degree of membership ranging from 0 to 1. This membership level indicates how much an element is part of a set. Hospitals can manage imprecise information more successfully by incorporating fuzzy logic into BDA. For instance, several variables and aspects in the healthcare industry, such as patient symptoms, results of diagnostic tests, and treatment efficacy, may not have exact numerical values. These variables can be expressed as fuzzy sets using fuzzy logic, which captures their ambiguity and imprecision.

Decision-making procedures can also accommodate the inherent ambiguity in healthcare data using fuzzy logic [38]. Based on the information, fuzzy rules can be created to direct the decision-making process. These algorithms can take into account linguistic phrases and variables like "high", "medium", and "low", enabling more adaptable and human-like decision making. Fuzzy logic also makes it possible to combine data from several flawed sources. It enables the fusion of various fuzzy sets or variables to produce a thorough evaluation or judgment. This is especially helpful when several factors impact a choice, each of which may have varying degrees of imprecision. Decision-making processes in hospitals can be made more sustainable by using fuzzy logic. It enables medical practitioners to make choices based on a more thorough and complex knowledge of the information. Fuzzy logic can find patterns, trends, and linkages in large healthcare datasets, resulting in better diagnosis, choice of therapy, resource allocation, and overall decision sustainability. Overall, fuzzy set logic provides mathematical frameworks for dealing with imprecise and uncertain data, allowing for a more flexible and nuanced analysis.

Rough sets theory and categorization entropy are other theories that help healthcare organizations manage vagueness in huge data. These theories offer methods for analyzing and extracting knowledge from large and varied datasets to identify patterns and make wise judgments. A mathematical framework called rough sets theory [85] was created to deal with data's fuzziness, uncertainty, and imprecision. It seeks to arrange items according to the information at hand into discrete groups. Equivalence classes, which are collections of items that cannot be discriminated against based on the available qualities or features, are the central idea of rough sets theory. Rough sets theory enables data reduction while retaining the most important details by discovering these equivalence classes. Rough sets theory can address ambiguity and uncertainty in patient data, medical records, or clinical investigations in HOs' big data context. It makes it possible to identify pertinent characteristics or traits essential for categorizing patients or making choices. Rough sets theory makes it easier to extract knowledge and patterns that can help with medical diagnosis, therapy selection, or resource allocation by lowering the complexity and dimensionality of the dataset.

On the other hand, classification entropy [86] quantifies how imprecise a set of classes or categories is. It quantifies the quantity of data necessary to establish an object's or instance's class label. Entropy for classification seeks to maximize purity and decrease ambiguity in a dataset's classifications. Classification entropy can assess and contrast various classification models or algorithms in the context of big data in HOs. It aids in evaluating how well different strategies identify patterns and make precise predictions. HOs can choose the categorization model to maximize knowledge extraction and decision-making skills from data by calculating the entropy or information gain. Rough sets theory and classification entropy provide useful strategies for handling vagueness in big data inside HOs. They make it possible to identify pertinent patterns, lessen data complexity, and assess classification algorithms. By implementing these theories, HOs may better manage and utilize big data in clinical contexts, obtain deeper insights into their data, and make wiser decisions.

The final theory we found in earlier research is probability theory (Table 5). It is a fundamental mathematical framework that addresses incompleteness in BDA and supports decision making in HOs [38]. Data can frequently be incomplete in the context of big data analysis in HOs, indicating that not all pertinent information is available or known. By allocating probabilities to various outcomes or events, probability theory offers a formal and rigorous technique to address this incompleteness. It enables the quantification of uncertainty and offers a basis for deliberation and decision making in the face of incompleteness. Based on the information available, outcomes can be estimated and predicted using probability theory. Probability theory also makes comprehending the risk and incompleteness connected to various healthcare interventions or judgments easier. It offers a framework for calculating and managing risks, allowing HOs to analyze different outcomes and their related probability to make more informed decisions. Furthermore, statistical inference, crucial for analyzing and interpreting big data in HOs, is intimately tied to probability theory. Probability theory is used by statistical methods like hypothesis testing and confidence intervals to conclude the population from a sample of data. These methods assist HOs in making decisions and deriving insights from data. Big data analysis using probability theory can help HOs make better decisions and increase sustainability. It provides a solid foundation for statistical inference and supports evidence-based decision making in healthcare. In probability theory is important to handle incompleteness and uncertainty in big data analysis in HOs. Probability theory offers the skills to make informed decisions, sustain decision-making processes, and enhance overall data-driven practices in HOs by assigning probabilities, evaluating likelihoods, and controlling risks.

Table 5. Theoretical models for addressing the imperfect information of BDA in HOs.

Code	Factor	Theory/Model	Definition	Source
P_1	Uncertainty	Belief functions theory	Imprecision, uncertainty, incompleteness, ignorance and conflict.	[36,53,72,73]
P_2	Imprecision	Fuzzy set logic/possibility theory	Imprecision and ambiguity.	[26,32,72,77–81,87]
P_3	Vagueness	Classification entropy/rough sets theory	Handles ambiguity between the classes and vagueness.	[28,47,75,76]
P_4	Incompleteness	Probability theory	Model incompleteness of data.	[26,36,38,72,74]
P_5	Complexity	Belief functions theory	Complication; model complicated data.	[36,53,72,73,88]

The review covered several articles that examined the problems that incomplete data in BDA inside HOs presents. However, these articles did more than list the problems; they also offered remedies and implications for how to address them. Uncertainty, imprecision, vagueness, incompleteness, and complexity are the main challenges surrounding flawed information that is covered in the articles. The general sustainability of BDA in HOs may be impeded by these challenges.

The researchers presented methods for handling uncertainty and coming to wise conclusions under challenging circumstances. They emphasized the significance of retaining complete control over ambiguous situations to minimize any adverse effects on BDA and the general effectiveness of healthcare organizations.

Regarding imprecision, the studies offered several strategies for handling hazy and ill-defined estimates. They emphasized how important it is for medical professionals to have a thorough understanding of how to deal with data analysis imprecision. The negative consequences of BDA imprecision can be reduced and maintained inside HOs by giving decision-making procedures the utmost consideration. To address the vagueness issue, the researchers also underlined the relevance of clarity in data, regardless of the volume provided. They emphasized the importance of considering data validity to provide a thorough BDA analysis that yields accurate forecasts. The papers suggested actions to improve decision making in HOs by attempting to do away with vagueness in BDA. The problem of incompleteness in data was tackled by underscoring the importance of having complete and readily accessible data for effective decision making in HOs. Incompleteness can have negative implications for healthcare organizations' core values and service performance. Therefore, the papers recommended ensuring data completeness to sustain the value of BDA in decision-making processes. Lastly, the papers acknowledged the inherent complexity of BDA, particularly as data variety, volume, and velocity increase. The researchers recognized the challenges and confusion associated with analyzing complex data. They suggested accepting the complexity and inherent inaccuracies of the data and exploring alternative processing and management methods that go beyond traditional approaches.

Overall, the main aim of the included papers was to provide solutions and implications for effectively managing the challenges associated with imperfect information in BDA within HOs. By addressing uncertainty, imprecision, vagueness, incompleteness, and complexity, these proposed solutions and implications aimed to promote the extensive sustainability of BDA and its successful implementation in healthcare organizations.

4. Discussion

BDA has made an important mark on numerous HOs. Based on the vast amount of data being acquired and its impact on producing accurate records, numerous HOs have become increasingly enthusiastic about permitting BDA functions to maintain their service performance with their patients. To consistently permit the sustainability of perfect data recordings for future references significantly, HOs statistically analyze patient data using large amounts of data collected. This study aimed to examine the present state of knowledge regarding the factors that contribute to imperfect information and how they affect healthcare decision making. Thus, the aims of the study are useful for sustaining decision making in HOs. By synthesizing the factors of imperfect information in BDA and analyzing their impact on decision-making processes within HOs, the study provides valuable insights into the challenges and limitations faced by healthcare organizations when dealing with imperfect information.

One key contribution of this study is the development of a taxonomy specifically focused on imperfect information within the context of BDA in HOs. This taxonomy provides a structured framework for healthcare managers to navigate the complexities associated with incomplete information in the realm of big data. By understanding the different factors of imperfect information, managers can adopt suitable strategies that are crucial for the successful implementation of BDA. This taxonomy serves as a practical tool for healthcare managers, enabling them to make informed decisions and overcome the challenges associated with imperfect information.

The previous studies included in this review [27] emphasize the importance of understanding the traits of big data, particularly the "5 V's", as a framework to comprehend and characterize large and complex datasets. These studies also highlight the three major categories of data sources: structured, semi-structured, and unstructured, within the taxonomy. Moreover, previous research consistently underscores the significant role played by factors like uncertainty [31,33,37], imprecision [34,52,58,59], vagueness [58,60], incompleteness [61,63,65], and complexity [36,53,72] in shaping decision-making within HOs. The aim of considering these factors and data sources is to improve sustainable decision-making processes in the healthcare sector by addressing the challenges arising from incomplete information and leveraging the immense potential of big data.

Additionally, the taxonomy utilized in previous studies includes various theories that contribute to comprehending and harnessing the capabilities of BDA in HOs. Based on previous studies, these theories encompass belief functions theory [36,53,72], fuzzy set logic/possibility theory [26,32,72], classification entropy/rough sets theory [28,47,75], and probability theory [26,36,38]. These theoretical frameworks offer valuable insights and methodologies for understanding and utilizing BDA to enhance public health, improve decision-making processes, and overcome obstacles related to implementing data-driven initiatives within HOs. By incorporating these theories, the studies addressed the challenges posed by imperfect information and provided avenues for leveraging BDA in the healthcare domain.

Overall, the main aim of the taxonomy was to provide solutions and implications for effectively managing the challenges associated with imperfect information in BDA within HOs. By addressing uncertainty, imprecision, vagueness, incompleteness, and complexity, these proposed solutions and implications aimed to promote the extensive sustainability of BDA and its successful implementation in HOs.

The findings also have practical implications for BDA service providers operating in HOs. By recognizing the impact of uncertainty, imprecision, vagueness, incompleteness, and complexity on decision-making processes, service providers can tailor their offerings to address these challenges. They can develop solutions and services that assist HOs in effectively managing imperfect information, thereby enhancing the quality of decision-making. Furthermore, service providers can leverage the findings of this review to attract clients and promote the adoption of BDA within HOs. The practical implications extend to BDA service providers in terms of improving their offerings and positioning themselves as trusted partners in navigating the complexities of imperfect information in healthcare decision making.

By shedding light on the challenges and implications of imperfect information in BDA, this study contributes to the broader understanding of data-driven decision making in HOs. Decision making in healthcare relies heavily on accurate and reliable information, and addressing the factors of imperfect information identified in this review is crucial for improving the effectiveness of decision-making processes. The findings emphasize the importance of data quality, completeness, and reliability in supporting informed decision-making in HOs. This underscores the need for healthcare managers to prioritize data governance, validation processes, and quality assurance mechanisms to ensure the reliability of the data used in BDA applications.

5. Conclusions

In conclusion, this review contributes to the existing literature by shedding light on the significance of incomplete information in the context of BDA and its profound impact on decision-making processes within HOs. By integrating various factors that contribute to imperfect information and developing a specific taxonomy to address challenges such as ambiguity, imprecision, vagueness, incompleteness, and complexity, this study emphasizes the essential role of enhancing decision-making processes. Firstly, it synthesizes the elements that contribute to imperfect information in BDA and their effects on decision-making within the healthcare sector, involving the identification and analysis of factors leading to imperfect information in BDA applications. Secondly, it aims to create a focused taxonomy for imperfect information within the context of BDA in the health sector. The taxonomy research highlights the utilization of multiple theories to evaluate BDA in HOs from different perspectives, showcasing their influence. However, the study acknowledges limitations, including the exclusion of non-English studies and the cutoff date until February 2023, potentially overlooking relevant research in other languages or after the specified date. Future research should broaden the scope to encompass a wider range of studies and updated literature, deepening our understanding of the challenges and implications of imperfect information in BDA within the healthcare sector. Additionally, there is a need for further exploration of the specific impacts of imperfect information, investigation of effective techniques for improving data quality, exploration of emerging technologies, and consideration of the ethical and legal implications associated with imperfect information in BDA. By addressing these areas, future research can contribute to advancing the field and improving decision-making processes in healthcare organizations.

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