LIBERATORIA PER L'ARCHIVIAZIONE DELLA TESI DI DOTTORATO

Al Magnifico Rettore
del Politecnico di Bari

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ed essendo stato ammesso a sostenere l'esame finale con la prevista discussione della tesi dal titolo:

Inglese: Data-Driven Decision-Making in Healthcare: Unveiling the Potential of Digital Transformation in Healthcare Organizations.

Italiano: Data-Driven Decision-Making in Sanità: il Potenziale della Trasformazione Digitale nelle Organizzazioni Sanitarie.

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Luogo e data Bari, 15/12/23 Firma Luigi Jesus Basile

Department of Mechanics, Mathematics and Management
MECHANICAL AND MANAGEMENT ENGINEERING
Ph.D. Program 36°
SSD: ING-IND/35– Business and Management Engineering

Final Dissertation

Data-Driven Decision-Making in Healthcare: Unveiling the Potential of Digital Transformation in Healthcare Organizations

by

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Questo lavoro è dedicato alla mia Famiglia e a Graziana,
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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

The digital revolution, accelerated by the global COVID-19 pandemic, has brought a significant transformation in decision-making across various industries. This paradigm shift, driven by the proliferation of data, presents unprecedented opportunities to enhance decision-making in uncertain and risky environments. However, the application of data-driven decision-making in the healthcare sector remains in its early stages despite its potential to revolutionize the industry. The healthcare industry has embraced technological breakthrough, including cloud computing, big data, and the Internet of Things (IoT), ushering in the era of "Healthcare 4.0." Digital technologies, such as wearables, telemedicine, and electronic health records, have redefined the delivery of healthcare services. The COVID-19 pandemic has further accelerated the integration of digital technologies in healthcare, but decision-making in healthcare organizations remains complex and multifaceted, with far-reaching implications. This dissertation aims to explore the role of digital transformation and data-driven decision-making in healthcare by investigating how data can empower decision-making in this sector. The research is organized into five chapters.

The first chapter involves a systematic review of existing literature on data utilization in healthcare decision-making, revealing research gaps and foundational premises for further investigation.

The second and third chapter focus on collecting insights from healthcare professionals regarding the role of big data analytics and risk management practices in decision-making. The researches highlights respectively the significance of investing in big data analytics capabilities to enhance the quality of healthcare services and examines how risk management practices contribute to this improvement.

In the fourth chapter, the research investigates the potential of a decision support system model based on the exploitation of data through business intelligence to outperform traditional experience-driven practices in managing processes within the oncology domain. This analysis aims to demonstrate the practical implications of data-driven decision-making in a specific healthcare context, shedding light on the benefits and effectiveness of data-driven decision making in healthcare.

Finally, the fifth chapter investigates the potential of data to support healthcare decision-making, with a specific focus on the oncology domain and the utilization of national cancer screening programs.

These investigations contributes with valuable theoretical and practical insights into the practical applications of data-driven decision-making in healthcare, aiming to a more informed, data-driven future in healthcare, ultimately to improve the quality of healthcare services.

1. INTRODUCTION

In recent years, the world has witnessed profound changes in various industries, brought about by the pervasive digitization and the adoption of digital technologies. This transformation has fundamentally altered the landscape of decision-making across industries (Kraus, Jones et al., 2021; Nadkarni & Prügl, 2021; Oztemel & Gursev, 2020). The digital revolution, encouraged further by the urgent demands stemming from the global COVID-19 pandemic, has ushered in an era of unprecedented data creation and accessibility (Kraus, Jones et al., 2021; OECD, 2020). This proliferation of data offers a unique opportunity to bolster the decision-making (DM) processes in numerous fields, ranging from finance to healthcare (Begenau et al., 2018; Galaitsi et al., 2021; Kraus, Schiavone et al., 2021).

Digital technologies, coupled with the abundant data they generate, hold the potential to redefine the current decision-making processes, particularly in scenarios loaded with uncertainty and risk (Dicuonzo et al., 2021; PWC, 2020). The root of uncertainty in the decision-making process is often determined by the lack of information (Han et al., 2019). Leveraging data, including data from diverse sources like mobile phones and social media, can facilitate comprehensive analyses and, in turn, support decision-makers in navigating uncertain and risky environments. This process results in the accumulation of information and knowledge, which become an indispensable asset for bolstering decision-making in the face of uncertainty and risk.

While the promise of data-driven decision-making has been explored across various industries and managerial domains, its application in the healthcare organizations context remains relatively nascent (Dal Mas et al., 2023; Kraus et al., 2021b). The healthcare industry has emerged as one of the primary beneficiaries of the digital transformation revolution (Dal Mas et al., 2023; Devarajan et al., 2021; Kraus et al., 2021b; Ramzan et al., 2022). Key technological paradigms such as cloud computing, big data, and the Internet of Things (IoT) have collectively pushed healthcare into the era known as "Healthcare 4.0" (Abbate et al., 2022; Aceto et al., 2020). Within this rapidly evolving landscape, innovations such as wearables, telemedicine, and electronic health records have become instrumental in delivering timely and targeted healthcare services (Marques and Ferreira, 2020). These technologies empower healthcare providers to deliver "the right care at the right time and right place," fundamentally reshaping the way healthcare is administered (Chute and French, 2019).

Moreover, as witnessed in other industries, the COVID-19 pandemic has further increased the integration and adoption of digital technologies within healthcare, as evidenced by the growing number of research and applications (Kraus, Schiavone et al., 2021; Sechi et al., 2020). Concurrently, the healthcare sector is marked by dynamic, intricate, and uncertain decision-making environments (Brehmer, 1992; Champion et al., 2019). Decisions made within healthcare organizations have far-extensive implications, affecting professional and organizational resources, the tasks performed for patients, and the ultimate quality of care delivered (Donabedian, 1988). To address these multifaceted challenges, data-driven technologies offer a promising avenue for supporting decision-making within healthcare organizations. By dealing with the complexity of variables, environments, and their interdependencies, data-driven approaches can enhance healthcare decision-making (Champion et al., 2019; H. Chen et al., 2012). Yet, despite the increasing volume of data and the recognition of technology's role in mitigating risk and uncertainty in healthcare, a clear understanding of the interplay between data technologies and capabilities and the quality of services within healthcare organizations remains an under-investigated topic from the management literature perspective, especially when compared with healthcare and computer science ones. Therefore this dissertation aims to shed light on the role of digital transformation and data-driven decision-making in healthcare decisions, by exploring the implications of data-driven decision-making for the quality of healthcare services. By synthesizing existing knowledge and contributing with new insights, I aim to pave the way for a more informed, data-driven future in healthcare, ultimately enhancing the quality of services provided to patients, physicians and healthcare policymakers. This research has been guided by the following research question:

- *How can data empower decision-making in healthcare?*

To address this question, the whole doctorate research was organized into three phases, each comprehensively documented throughout the five chapters (from Chapter 2 to Chapter 6) comprising the main body of this dissertation.

In the first phase, the primary objective was to conduct an exhaustive review and synthesis of scholarly literature about the utilization of data within the context of decision-making processes in healthcare. In particular, based on the lack of structured reviews in the literature related to the potential of data in healthcare to support decision-making processes faced with risk and uncertainty, I defined the following research question to be answered: "How can data optimise decisions faced with risk and uncertainty in the main domains (structure, process, outcome) of healthcare organisations?". The research question guided the development of the first phase and it has been reported in the second chapter in which I systematically reviewed the literature to understand the current state of the art on the role of data in healthcare organizations' decision-making processes confronted with risk and uncertainty. I conducted the review following the PRISMA protocol for systematic review, widely adopted for its transparency. The main stages followed were: Identification (selecting databases and keywords), Screening (applying exclusion criteria), Eligibility (full-text evaluation), and Inclusion. The papers were retrieved from 3 databases: Scopus, Web of Science and PubMed. From an initial 3,240 papers, 125 were included, focusing on data-driven decision-making in healthcare without specific filters on publication year, and considering the impact factor of journals for selection. The systematic review shed light on the role of data in healthcare decisions (e.g., in predicting resource shortages, wastage, and potential complications in patient care) and revealed several research gaps within the literature, which subsequently served as foundational premises for further investigations in the subsequent chapters.

The second phase, reported in the third and fourth chapters was dedicated to the comprehensive collection and analysis of viewpoints and insights from healthcare professionals regarding the role of big data analytics technological resources and capabilities, as well as risk management practices, in dealing with risk and uncertainty within healthcare decision-making processes. This phase was concerned with showing, from a theoretical point of view, the potential of data in healthcare organisations and how to promote the quality of healthcare services by answering the following research questions: "Is the presence of BDA capabilities an explanatory mechanism of the effect of BDA technological resources in improving the quality of healthcare services domains?" and "Do risk management practices enable better use of big data analytics to inform decisions in achieving optimal quality of healthcare services?". Precisely, in the third chapter, drawing on the resource-based view theory, I explored the role of big data analytics technological resources and capabilities in the quality of healthcare services, highlighting the prominent role of developing and investing in big data analytics capabilities to ensure the quality of healthcare services. While, in the fourth chapter, drawing on the organizational information processing theory, I investigated the role of risk management practices as an explaining mechanism of the positive effect of the use of big data analytics on the quality of services in healthcare organizations. The methodology employed in the third and fourth chapters was PLS-SEM for its suitability with the collected sample and complex models without distributional assumptions.

Finally, in the third phase, I explored the potential of data to support the healthcare decision-making process, as detailed in chapters five and six. In this phase, based on the existing literature on the use of data in healthcare organisations, I defined two research questions, which were investigated in chapters 5 and 6. Specifically, the research questions are: "Can a data-driven DSS model improve healthcare process management better than a DSS model based solely on experience and literature?" and "How can big data analytics support healthcare policy makers in increasing the utilisation of healthcare services?". In the fifth chapter, I investigated through the design science research methodology framework whether a decision support system model based on the exploitation of data through business intelligence can outperform traditional experience-driven practices for managing processes in the oncology domain. Finally, in the sixth chapter, I investigated the potential of a data-driven model to support the decisions of policymakers in increasing the utilization of healthcare services, specifically the Italian national cancer screening programs.

Figure 1 shows the reasoning and the phases of the disseration, by detailing the specific subquestions.

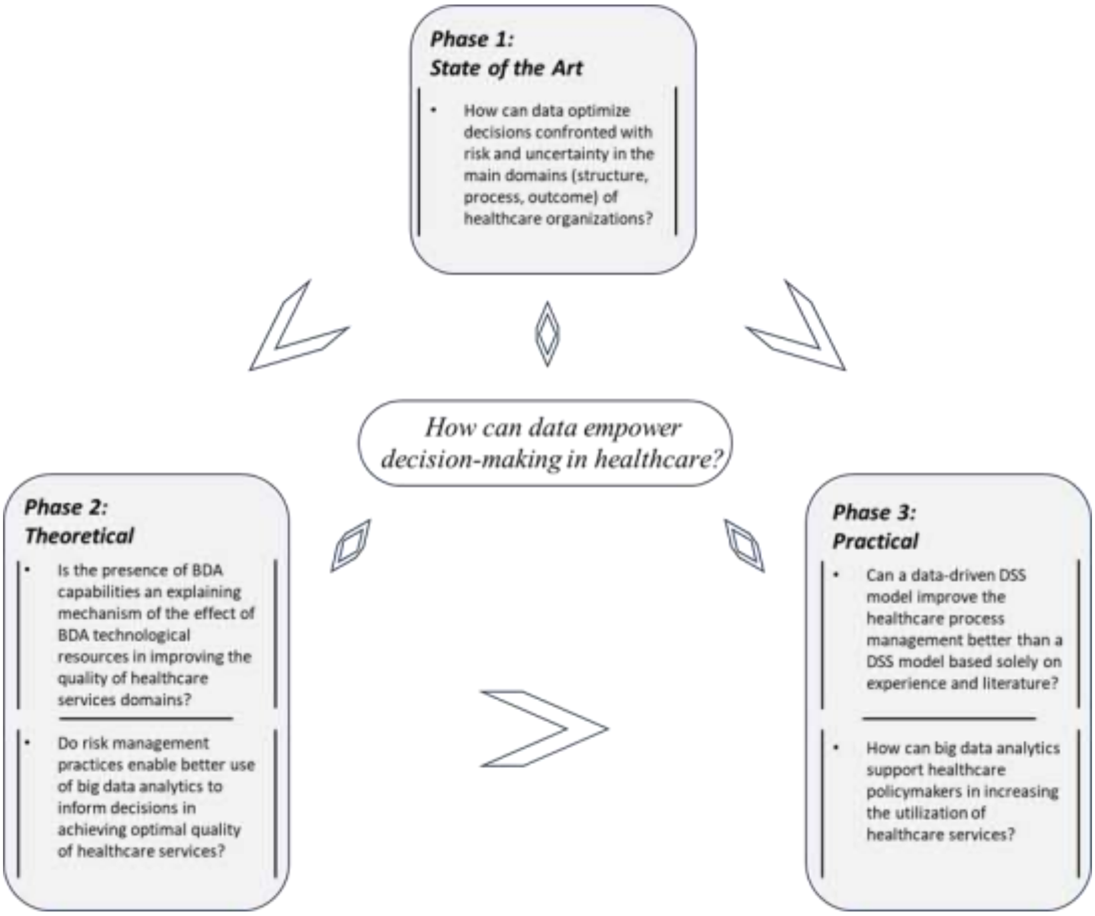

Figure 1 Reasoning and phases of the dissertation

Table 1 Research Question, Subquestions, and Publication & Presentation Outlets

2. THE EXPLOITATION OF DATA TO SUPPORT DECISION-MAKING IN HEALTHCARE: A SYSTEMATIC LITERATURE REVIEW AND FUTURE RESEARCH DIRECTIONS

2.1. ABSTRACT

The development of new technologies and their continued adoption allow data to be collected, analysed and exploited for decision-making. Data can play an important role in the healthcare industry since it is a complex system where every decision is strongly affected by risk and uncertainty. Despite the proliferation of data and the awareness of the importance of new technologies to support decision-making in the presence of risk and uncertainty, there is a lack of understanding of the interrelations between data, decision-making process and risk management in healthcare organizations and their role in delivering healthcare services. Pursued by this research gap, the objective of this study is to understand how data can optimize decisions confronted with risk and uncertainty in the main domains (structure, process, outcome) of healthcare organizations. Thus, I conducted a systematic literature review based on the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology, by selecting and analysing peer-reviewed journal articles from three databases: Scopus, Web of Science and PubMed. The paper's findings suggest that although data are widely used to optimize the decisions in the healthcare organization domains in the presence of risk and uncertainty, there are still many scientific and practice gaps that lead to the definition of a future research agenda.

2.2. INTRODUCTION

In recent years, digitisation and the diffusion of new technologies have brought in-depth changes and transformations in fostering the development of several industries and activities (Kraus, Jones, et al., 2021; Nadkarni & Prügl, 2021; Oztemel & Gursev, 2020). The digital transformation has accelerated its pace due to the needs originated by the COVID-19 pandemic, thus generating an exponential increase in data creation (Kraus et al., 2021a; OECD, 2020). Increasing the amount and quality of data means increasing the opportunities to use them for supporting the decision-making (DM) process in many industries, ranging from finance (Begenau et al., 2018) to healthcare (Galaitsi et al., 2021; Kraus et al., 2021b). Digital technologies and the subsequent proliferation of data have the potential to achieve a new value in DM support, especially when dealing with uncertainty and risky contexts (Dicuonzo et al., 2021; PWC, 2020). Indeed, the uncertainty and risk conditions in the decision-making process are generated when there is a lack of information (Han et al., 2019). In this sense, the exploitation of data could help scholars, researchers and administrators to carry on analyses and decision-making through the efficient scientific use of data sets, mobile phones, social media, etc. This leads to obtaining information, and then knowledge supporting the DM process in the presence of risk and uncertainty. In this sense, the exploitation of data provides a promising opportunity to enable decision-makers to prepare for and manage upcoming threats, challenges, risks and disasters, i.e. the risk management (RM) process. The potential of data to support DM processes under risky and uncertain conditions has been investigated in several industries (Dicuonzo et al., 2021; Tantalaki et al., 2019) and managerial domains (Ivanov et al., 2019; Liou et al., 2019). However, the investigation of the interrelations between data, DM and RM is still at a preliminary stage of its development in the healthcare organization context (Jee and Kim, 2013). Despite this, the topic has great relevance and potential due to both the increasing development of digitalisation and the complexity of the healthcare organization. Healthcare organizations are going through a period of digital transformation. The digital technologies that are most shaping these organizations are mainly related to Big Data tools, Cloud Computing and the Internet of Things, which aim to ensure the delivery of high-quality healthcare services (Aceto et al., 2020). After the pandemic, the application of digital technologies in the healthcare industry is expected to experience a real renaissance, as witnessed by the increasing number of studies in the field and applications (Kraus et al., 2021b; Sechi et al., 2020). At the same time, the healthcare industry is considered a dynamic, complex and uncertain decision-making environment (Brehmer, 1992; Champion et al., 2019), i.e., an environment in which the constraints and conditions at the moment of the choices could be completely different at another moment caused by the choices themselves (Han et al., 2019). Moreover, healthcare organizations have several stakeholders that impact their services, e.g., insurance companies, pharmaceutical firms, families, and patients, which interact on different dimensions in a non-linear way, generating unexpected and often undesirable results, e.g., re-hospitalisation, delayed hospitalisation, infections or adverse drug reactions, or even death (Lipsitz, 2012). Decisions impact different levels of a healthcare organization, which can be grouped into three main domains, concerning the professional and organizational resources (structure), the tasks done for the patient (process), and the desired outcome of the care provided by the healthcare practitioners (outcome) (Donabedian, 1988) to deliver high-quality services in the healthcare industry. To take into account the problems just mentioned, new technologies based on the exploitation of data could be used to support the decision-making process in a healthcare organization, considering the many variables, environments, and interactions between them (Champion et al., 2019; Chen et al., 2012). Although the proliferation of data and the awareness of the importance of new technologies to support DM in presence of risk and uncertainty in healthcare, enabling the assessment, treatment and monitoring of risks that may affect the quality of services, there is a lack of understanding of the interrelations between data, DM and RM in the healthcare organization and their role to deliver effective healthcare services. Pursued by this research gap, the objective of this study is to understand, through a systematic literature review, the potential of the data to support healthcare decisions. Indeed, the research question that leads this work is:

- how can data optimize decisions confronted with risk and uncertainty in the main domains (structure, process, outcome) of healthcare organizations?

The work will be organised as follows. In section 2, the theoretical background that I used to design the conceptual framework will be described. In section 3, it will be presented the methodology adopted for the systematic literature review (SLR). Then, in section 4 the findings available in the literature will be presented according to the framework proposed. In section 5, the findings will be discussed, and future research directions will be proposed. Finally, in section 6 the work will be closed with the conclusions.

2.3. THEORETICAL BACKGROUND

2.3.1. Data for Decision-Making in Healthcare

The increase in data production (Al-Ali et al., 2017; Florence and Shyamala Kumari, 2019) and the spread of analytical techniques (Ahmed et al., 2020; Tantalaki et al., 2019) are driving several industries to make data-driven decisions to achieve better outcomes and performance (OECD, 2015). For this reason, decision-makers are acquiring abilities and resources to gather, store, retrieve, and analyse the data to support their decisions (Meyer et al., 2014), and National Health Systems are promoting the learning of data-analytical skills for physicians in a healthcare organization (Howard et al., 2015). Indeed, the healthcare industry is one of the more promising industries in which decision-makers can exploit data to make decisions (Galetsi et al., 2020; Ngiam and Khor, 2019). As a result, the use of data for decision-making purposes in healthcare organizations has become an affirmed topic that has gained significant consideration from both academics' and practitioners' perspectives. Several applications have been proposed in healthcare to use data for supporting decisions (Chen et al., 2020; Weerasinghe et al., 2022). These decisions can be made by several stakeholders in different fields, which can be grouped into three main domains of the healthcare organization (Donabedian 1988), namely structure, process and outcome. At the structure level, decisions concern professional and organizational resources associated with the delivery of healthcare services (e.g., material resources, human resources and organizational activities). Using data for extracting likely trajectories or for scheduling activities based on the prediction of the length of stay (Simsek et al., 2020) are examples of the potential of the data for supporting decisions in the structure domain. At the process level, decisions regard the patient (e.g., hospital referrals) and the patient's activities to receive the services. Data could support the physicians in the decision-making process, e.g., selecting the best treatment and care pathway (Sun et al., 2021). Finally, the outcome refers to the desired outcome of the care provided by the healthcare practitioners (e.g., patient satisfaction). In this domain, data can be used to decide to improve the health of the patient, e.g., identification of at-risk patients or identification of disease in the early stage. Despite the increasing adoption of data in healthcare, its transformation into knowledge to improve the outcomes of healthcare services seems to be still limited (OECD, 2019). In this context, this paper aims at understanding how data can optimize decisions in the main domains (structure, process, outcome) of the healthcare organization.

2.3.2. Uncertainty and Risks in decisions in Healthcare

Coping with uncertainty and risks has always been a cornerstone for scholars and practitioners in many industries (Lipshitz and Strauss, 1997), considering that the condition of uncertainty differs from the condition of risk by the lack of information about the outcomes and their probabilities. Risk and uncertainty may occur in different contexts, but they have common sources such as the complexity of relationships between variables, the indeterminacy of the outcome and the lack of information (Han et al., 2011).

Healthcare organizations operate in a high-risk and uncertain environment (Babrow et al., 1998; Champion et al., 2019; Spiegelhalter, 2008). Following Han et al. (2011) the risks and uncertainties in healthcare can arise in the organization of healthcare facilities, in the processes of diagnosis and prognosis, or the psychological conditions of patients. Making decisions in this uncertain environment is a big challenge (Han et al., 2019).

In order to reduce uncertainty and risks, both clinical and non-clinical, systematic methods for risk analysis and assessment could be used (Cagliano et al., 2011; Ferroni et al., 2017; Odone et al., 2019; Tartaglia et al., 2012). The International Standard Organization (ISO) has defined a standard to apply Risk Management, aiming to decrease the probabilities and impacts related to adverse events and to increase the probabilities and impacts of positive events (ISO, 2018). According to ISO, the risk management process involves the definition of the scope, context and criteria, and it consists of different phases (ISO, 2018). In particular, the main phases are the Risk Assessment (RA), including risk identification, risk analysis, and risk evaluation, Risk Treatment (RT), and Risk Monitoring (RM). The RA phase concerns the identification of the risks that may affect the objectives of an organization, the analysis of the risks to understand their nature and characteristics, and the evaluation of risks that support the DM by making a comparison among the information acquired in the previous step. The RT phase involves the selection and implementation of optimal strategies for addressing the risks. The RM involves the monitoring of risks to assure the quality and effectiveness of the strategies adopted and the need for new actions to mitigate risks. In order to deal with risk and uncertainty in healthcare and improve the performance of the current medical systems, the integration of data into healthcare decision-making can be a breakthrough (Aceto et al., 2020; Kraus et al., 2021b). In this context, there is a continuous increase in the amount of data, although their implementation as tools to support RM is still underdeveloped (Dicuonzo et al., 2021). Even though the growing interest in research into understanding how to deal with risk and uncertainty in healthcare, there is still much to be clarified (Han et al., 2019). For these reasons, this paper aims to understand how data can help healthcare organizations optimize decisions confronted with risk and uncertainty.

2.4. METHODOLOGY

In this paper, I carry out a systematic literature review (SLR) to understand the potential of data to support decisions affected by risk and uncertainty in the healthcare organization setting, namely investigating how data can optimize decisions confronted with risk and uncertainty in the main domains (structure, process, outcome) of healthcare organizations. The systematic review methodology is based on a scientific, transparent and replicable protocol that aims to reduce biases related to the selective reporting of outcomes and arbitrariness in decision-making when extracting and using data from primary research (Moher et al., 2009), conversely, other kinds of literature review do not follow a specific and transparent protocol that could be replicated.

2.4.1. Review Process

In the current study, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) have been adopted as the protocol for the systematic review (Moher et al., 2009). This methodology has been developed in healthcare for conducting reviews, and because of its transparent and systematic approach, it has been widely adopted in other fields over time (Akhigbe et al., 2021). PRISMA provides a roadmap to report a systematic review in a transparent, objective, and explicit way, and it develops the review in four main stages: Identification, Screening, Eligibility and Inclusion. The whole review process is shown in figure 1.

Identification. As the first step, in order to ensure the comprehensiveness of the research I selected three databases to retrieve the scientific papers: Scopus, Web of Science and PubMed. Then, keywords to conduct the research on the databases have been selected. Specifically, the final set of keywords is based on the three main pillars of this research, namely: data, the healthcare industry, and the decision-making process. Concerning the first pillar, the following keywords have been selected: “business intelligence” which is the process of acquiring and analysing data to make informed decisions (Chen et al., 2012); “data-driven” was introduced because of the growing interest in data-driven decision making (Provost and Fawcett, 2013); “data mining” as it is the set of techniques and methodologies for extracting information from large amounts of data (Provost and Fawcett, 2013); finally, the last term is “big data” as it concerns the huge amount of data that could be exploited for applying complex algorithms for decision making (Galetsi et al., 2020). Regarding the second pillar, namely the context of the research, the keyword “healthcare” has been selected. Finally, to retrieve the papers concerning the decision-making process, the keywords “decision making” and “decision support system” were chosen (Chahar, 2021; Provost and Fawcett, 2013). In order to identify as many records as possible, terms relating to risk and uncertainty were not included because they would have limited the results of the research since they would have excluded papers that do not explicitly address risk and uncertainty in the healthcare organization which is implicitly characterized by them (Brehmer, 1992; Kuziemsky, 2016; Lipsitz, 2012). For the same reasons, also the keywords concerning the main domains (structure, process, outcome) of the healthcare organization have not been included since they would have excluded papers that do not explicitly use these keywords to describe them. The final research string is shown in table 1. The set of retrieved papers contained 3,240 items (1,929 items from Scopus, 802 items from Web Of Science and 509 from PubMed), running until the 31st of October 2022.

Screening. Exclusion and inclusion criteria have been used (summarized in table 1) to refine the set of papers. Initially, exclusion criteria have been applied based on the type of publication through the databases’ filters, excluding articles not written in English, books and book chapters, conference proceedings, theses and editorials, and obtaining 2065 papers. Then, the set of retrieved papers was screened in order to remove all the duplicated items, obtaining 1345 unique items, and the retrieved papers were limited to those published in a journal listed in the

2022 ISI Journal Citation Report with an impact factor of 2 or above consistently with other reviews (De Keyser et al., 2019), obtaining 995 items. It has not been used any filter about the year of publication so as not to limit the results of the literature review to a given period. Then, the screening of titles and abstracts has been conducted excluding the articles not focused on the healthcare organization, or that are focused on the development and testing of algorithms (e.g., papers concerning the performance of algorithms), or that are not concerned with the use of data to support the decision-making process. Thus, all the quantitative and qualitative papers that were focused on the exploitation of data to support the decision-making process were included, achieving 400 papers for the eligibility stage.

Eligibility. In this stage, the 400 articles retrieved in the previous stage were read and evaluated in the full text according to inclusion and exclusion criteria.

Included. Ultimately, the final set contains 125 papers.

Table 2 Criteria for Systematic Literature Review

Search string	***Inclusion Criteria***	***Exclusion Criteria***
Keywords: ("data driven" OR "data-driven" OR "big data" OR "business intelligence" OR "data mining") AND "healthcare" AND ("decision making" OR "decision support system") • **Search in: Title, Abstract and Keywords** • **Document type: Peer-reviewed Journals** • **Language: English**	• All the articles that concern the use of data to support the decision-making process in the healthcare organizations • Articles that do not limit their analysis only to the development of algorithms.	• Articles not written in English. • Journal Impact Factor < 2 • Articles not published in peer-reviewed journals • Articles not focused on healthcare organizations.

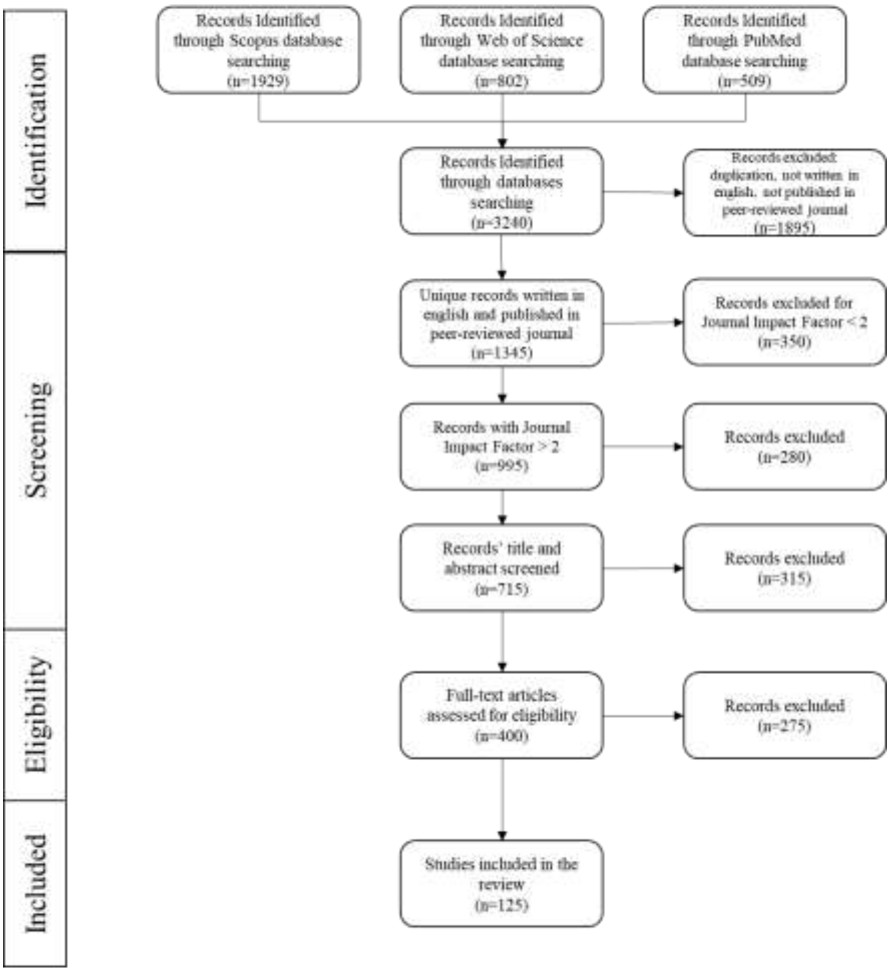

Figure 2 PRISMA flow diagram for the identification, screening, eligibility, and inclusion of studies.

2.4.2. The Framework

The framework leading this review aims to organize the collected papers and answer the research question, based on two dimensions, "Healthcare Organization Domains" and "Risk Management Phases". In particular, concerning the "Healthcare Organization Domains" the papers included in the review were examined considering the dimension "Healthcare Organization Domains", which has been borrowed from Donabedian's conceptual model of assessing the quality of healthcare organizations (1988). According to Donabedian's model, three categories of analysis have been associated with this dimension of the framework, namely structure, process and outcome. The structure refers to professional and organizational resources associated with the delivery of healthcare services (e.g., material resources, human resources and organizational structure). The process represents the tasks done for the patient (e.g., hospital referrals) and the patient's activities to receive the services. Finally, the outcome refers to the desired outcome of the care provided by the health practitioners (e.g. patient satisfaction and costs). Concerning the "Risk Management Phases", the collected papers were examined considering the dimension "Risk management process". In particular, following ISO 31000 (ISO, 2018), this dimension of the classification framework is further distinguished into three categories, that correspond to the phases of the risk management process: the Risk Assessment phase (which is composed of risk identification, risk analysis and risk evaluation), the Risk Treatment phase, and the Risk Monitoring. The Risk Assessment phase aims to identify and analyse risks in order to identify and analyse the probabilities and the magnitude of risk, and to evaluate the risk priorities for guiding further actions. The Risk Treatment phase involves the selection and implementation of optimal strategies for mitigating the risks. Risk Monitoring involves the monitoring of risks to ensure the quality and effectiveness of the strategies adopted and the need for new actions to mitigate risks. The classification framework is depicted in figure 2.

Figure 3 The classification framework

2.5. RESULTS

The final step of the systematic literature review is the critical analysis of the collected articles. The main and ultimate objective is to summarise the findings from the articles and to highlight the relevant insights that require further attention from scholars and practitioners. In the first sub-section, the descriptive findings are presented. These include the distribution and evolution of papers across time, sources, and employed research methodologies. In the second sub-section, the thematic analysis and the main findings of the systematic literature review are discussed according to the classification framework introduced in the previous section.

2.5.1. Descriptive Statistics

Figure 3 illustrates the distribution of papers per year, showing the increasing interest in the research topic. About three-quarters (70%) of the records were published in the last six years (2017-2022). The first article selected for this review is in 2007, and in the following years, the trend of articles published increased, spiking in 2021. The topic started its ascent between 2019 and 2020, doubling the number of total articles per year. In 2021, the number of selected papers (27 papers) is a third larger than in 2020 (18 papers). This shows that the reported trend is likely to continue and highlights the relevance of the research domain and the importance of reviewing the body of literature systematically.

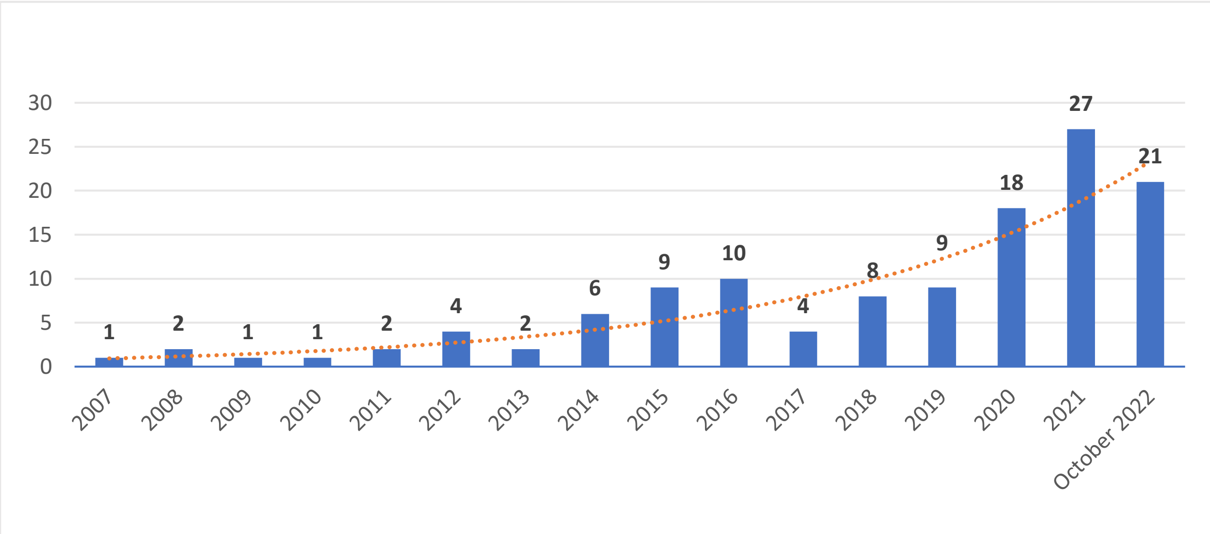

Figure 4 Articles distribution per publishing year.

The distribution of the 125 papers by research methodology employed is shown in figure 4. As for the research methodologies adopted by the selected articles, I grouped them into three different categories:

- Quantitative research (89%) – this category is characterised by studies that use quantitative research methods, such as regression models, artificial neural networks and data analysis.

- Qualitative research (8%) – in this category are grouped both studies that employ qualitative research methods and conceptual papers, such as case studies.
- Mixed method research (3%) – this category is characterised by studies that use both quantitative and qualitative research methods.

The fact that most of the papers employed a quantitative methodology is consistent with the aim of this research, namely to understand how data can optimize decisions confronted with risk and uncertainty in the main domains (structure, process, outcome) of healthcare organizations.

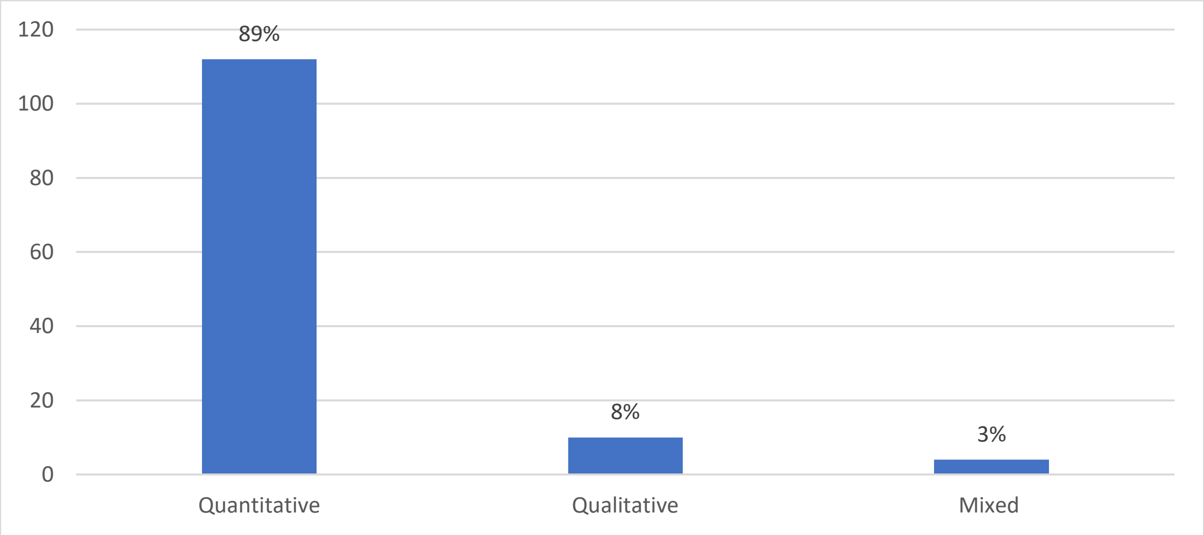

Figure 5 Paper distribution by research methodology.

Table 3 shows the journals in which the selected articles were published. In the table all journals whence at least two selected articles are listed, while all journals from which only one article was selected are grouped under the label "other". It is of particular interest to note that although more than half of the journals (64 out of 125) are represented by a single article, it was found that the journals belong mainly to three subject areas i.e., Management and Business, Medicine and Computer Science which shows the interdisciplinarity of this topic. The top contributor is “Decision Support Systems” (7 papers), followed by the Journal of Biomedical Informatics (5 papers), Artificial Intelligence in Medicine (4 papers), and IEEE Access (4 papers).

Table 3 Number of papers per Journal.

Journal	*Number of Papers*
Decision Support Systems	7
Journal of Biomedical Informatics	5
Artificial Intelligence in Medicine	4
IEEE Access	4
Big Data	3
Expert Systems with Applications	3
Health Informatics Journal	3
Industrial Management and Data Systems	3
Journal of Medical Systems	3
Scientific Reports	3
Sensors	3
BMC Health Services Research	2
BMC Medical Informatics and Decision Making	2
Computer Methods and Programs in Biomedicine	2
Enterprise Information Systems	2
Frontiers in Public Health	2
Implementation Science	2
International Journal of Medical Informatics	2
Other	*64*

2.5.2. Findings

In the following, the papers selected in the academic literature regarding how data can optimize decisions confronted with risk and uncertainty in the main domains (structure, process, outcome) of healthcare organizations are discussed.

Table 4 shows the distribution of the selected papers according to the two main dimensions of the classification framework described in section 2.4.2., namely the "Healthcare Organization Domains" and the "Risk Management Phases".

Table 4 Papers classification based on the dimensions of the framework.

		Risk Management phases			
		Risk Assessment	Risk Treatment	Risk Monitoring	***Total***
Healthcare Organization Domains	Structure	16	22	2	***40***
	Process	33	22	4	***59***
	Outcome	9	15	2	***26***
	Total	***58***	***59***	***8***	***125***

Concerning the “Risk Management Phases”, 58 of the examined papers address the risk assessment phase, in which data are used to identify, assess and prioritise risks in healthcare organizations' decisions. The second group includes 59 papers that discussed the use of data for supporting decisions related to risk treatment, where data are used to mitigate risks, while only 8 papers focus on the use of data for risk monitoring in healthcare organizations’ decisions. When it comes to the “Healthcare Organization Domains”, 59 papers investigate the use of data for supporting decisions focused on the care delivered to patients e.g. services, diagnostics or treatments (process), 40 of the reviewed papers concern the use of data for supporting decisions related to the physical and organizational settings where healthcare occurs (structure) and finally 26 papers concerns the use of data for supporting decisions about the health status of patients and populations (outcome).

2.5.2.1. Risk Assessment

Structure. In the structure domain, data are mainly used to identify and assess the risks that threaten the *optimal use of resources*, (i.e., physical facilities, human resources, equipment and Information and Communication Technology (ICT)) and *organizational activities* (e.g., staff training and resources maintenance). The use of data in the healthcare industry is opening up the optimisation of the usage and distribution of healthcare resources both through the employment of administrative (e.g., date of hospitalisation, date of discharge, medicines used) and patients’ health data (e.g. blood pressure, glucose level). For instance, it is possible to estimate the number of patients needing hospitalisation and compare them with the total number of available beds, thus identifying whether there is a risk of a shortage of available resources (i.e., beds) (Sebaa et al., 2018). In order to assess the risk of shortage of available resources, several scholars highlight the importance of administrative data to identify some managerial issues affecting the healthcare structure by predicting some important variables, such as the patients' risk of re-hospitalisation, i.e., patients who need to be re-hospitalised for further treatment after discharge (Ryan et al., 2015). The patient's length of stay affects the resources that will be used by the healthcare organizations in which the patients are hospitalised. The longer the patient is hospitalised, the more resources will be needed to treat him. Through the data, it is possible to identify and assess which are the factors that increase the length of stay (Kudyba and Gregorio, 2010) and therefore increase the consumption of resources. For instance, one of these factors identified by using data is the risk of patient re-hospitalisation which could cause an increase in the consumption of resources (Ryan et al., 2015) exposing the healthcare organization to the risk of shortage of available resources. Once the hospitalisation period is over, the patient is discharged from the healthcare organization. However, it happens that the patient's health issues have not been fully addressed and that after a short time, the patient needs to be re-hospitalised. This may lead to an excessive burden on the healthcare organization's resources, i.e., beds, medicines, and human resources. Furthermore, data are used to assess the risk of lack of available resources and also by predicting the expected number of arrivals in terms of the number of patients who will need healthcare services and thus, to plan the available resources with the expected demand (Xu et al., 2013). It is also possible to exploit data to assess the risk of waste of healthcare resources, by predicting the number of patients who do not turn up for appointments with physicians (i.e., no-show risk patients). These missed appointments imply a waste of resources that had been already scheduled, such as human resources (i.e. doctors and nurses) and the equipment needed for the visit (Simsek et al., 2021, 2020). Data have been often used for the prediction of patient disease occurrence (Phillips-Wren et al., 2008) and population disease occurrence (Hrovat et al., 2014). This can support the identification of healthcare services that will be needed, thus avoiding un-useful service (i.e. risk of waste), and permit the evaluation of the best possible allocation of resources, thus preventing the indiscriminate consumption of resources (i.e. risk of shortage of resources).

For instance, data can be used for assessing resource consumption associated with lung cancer (Phillips-Wren et al., 2008) or for supporting the assessment of the risk of waste of resources determined by the unbalanced daily workload management, by comparing the scheduling and the expected demand (Perez et al., 2016). Data can be also particularly useful in assessing risks faced by healthcare structures during health emergencies such as the recent pandemic due to COVID-19. For instance, clinical pathways in hospitals have been disrupted by the need to keep COVID-19 patients separate from each other. In this context, data have been adopted for assessing the risk of improper use of resources due to the allocation of patients to the wrong healthcare units (Sarkar et al., 2021). Also, data have been particularly useful to assess the risk of shortage and waste of healthcare resources determined by the occurrence of COVID-19, predicting the daily number of patients (Manevski et al., 2020) and vaccine willingness (Riad et al., 2021) during the pandemic emergency. Some types of healthcare services were provided in smaller numbers due to the needs created by the COVID-19 pandemic, resulting in an imbalance in resource use planning. In this context, data allow the identification of services that have been provided in lower numbers due to the pandemic and thus the associated resources. As a result, it is possible to assess the risk of shortage and abundance of resources thus supporting decisions on the sizing of resources required in healthcare organizations considering these imbalances (Segui et al., 2021). Finally, concerning organizational activities, data can support the assessment of risks that affect payment methods and medical equipment maintenance. Healthcare organizations in many countries are paid for the delivery of healthcare services provided by public healthcare organizations through the so-called health reimbursements, i.e. an amount of money paid for services and regulated by national health systems. The procedures for claiming these reimbursements can be carried out improperly and cause problems such as late payment or delayed diagnostic tests. In this context, data enable the analysis of these processes and identify the causes of delayed reimbursements (Gerhardt et al., 2018). While, concerning medical equipment maintenance, data can be used to evaluate and predict the priority of medical equipment's preventive maintenance, corrective maintenance, and replacement programs in order to identify and assess the risk of resource shortage (Zamzam et al., 2021).

Process. Data are used to identify, assess and prioritise risks at almost every stage of the *care process*: disease prevention, assessment of patient history where genetic and family status is studied, diagnosis of disease, selection of treatments, and prognosis where the likely progression is predicted and then monitored (Croft et al., 2015). In particular, the use of data to assess risks in the process domain supports the decision-making process in both cross-sectional ways and specific stages of the care process. In the first case, physicians and managers of healthcare organizations have provided data-driven tools that make information and knowledge available to assess the health risks of patients without limiting the focus to a specific stage of the care process (Chignell et al., 2013; El-Sappagh and El-Masri, 2014; Jung et al., 2015a; Lin et al., 2019; Raj et al., 2020). For instance, tools that collect and make available administrative and health data have been proposed to support physicians in managing patients affected by chronic disease (i.e. a health condition or illness that has long-term or persistent consequences, or a sickness that develops over time) (Dag et al., 2022; Yu et al., 2022), or to support the managers of healthcare organizations during epidemic outbreaks (Liu et al., 2016). Data-driven tools extract this information usually from data storage in a systematized collection of patient and population health and administrative data in digital format, the so-called electronic health records (EHRs) (Cascini et al., 2021; Dai et al., 2022; Zhang et al., 2011). To assist the decisions of physicians and healthcare managers in the risk assessment of patients' health status, it is possible to extract information from the clinical notes data stored in these EHRs (Groenhof et al., 2019). In addition, it is also possible to extract insights about patients' health from social network data (Fiaidhi, 2020). Therefore, data-driven tools are very relevant for healthcare organizations since they help to manage, analyse, and use the information extracted from data to assess the risks that threaten patients' health.

Data can also be used to support the decisions of physicians and managers of healthcare organizations along specific stages of the care process. In the disease prevention stage, data are used to support physicians in identifying and assessing the risk that a patient may develop or be affected by a disease (Lin et al., 2017; Mioshi et al., 2014; Nasir et al., 2019), e.g. to support clinicians in identifying patients at risk of acute or chronic infection disease (Zhou et al., 2022), or for the early detection of chronic disease patients (Moreira et al., 2020) or at risk of heart failure disease (Nagamine et al., 2022). Considering the diagnosis stage, data can support physicians in investigating the health status of patients (Baytas et al., 2016; Malik et al., 2020), e.g. assessing the risk of heart disease occurring (Bashir et al., 2021; Singh et al., 2021) or diabetes occurring (Bukhari et al., 2021). While, data can be used for the treatment selection stage by predicting the likely outcomes both to assess risks for patients associated with specific treatments (Basile et al., 2023; Ejaz et al., 2022; Gongora-Salazar et al., 2022; Pinto et al., 2021) and to describe treatment expected outcomes (Delen et al., 2012; Fan et al., 2022). Moreover, physicians can use information extracted from clinical trials to assess the risk of exposure for patients to a treatment (Kuang et al., 2020; Mayer et al., 2021), e.g., to predict the risk of death in kidney transplant recipients (Topuz et al., 2018).

Outcome. The analysis of selected papers reveals that data have been used in healthcare to enable the identification and assessment of *risks to patient health outcomes* and for assessing the *risk of patient dissatisfaction*. Concerning patient health outcomes, data have been adopted for identifying and assessing the risks that the healthcare service or interventions have on the health status of patients (Asaria et al., 2016; Demirbaga and Aujla, 2022), for example, to predict the probability of an in-patient falls (Lindberg et al., 2020) or to predict the long-term survival outcomes after heart transplantation (Dag et al., 2016). Data can also enable the assessment of the impact of specific organizational characteristics such as waiting time and overcrowding on hospitalised patient mortality (Clark and Normile, 2012; Soffer et al., 2021). Data have been also exploited for assessing the risks related to the satisfaction of the patients, by analysing social perceptions of healthcare service quality (C. K. H. Lee et al., 2021) or by analysing patients' feelings and emotions about their experiences in hospitals from online reviews (Abirami and Askarunisa, 2017). Through the use of data, it is also possible to assess the risk of depression that can impact the final health outcome (Jin et al., 2015).

2.5.2.2. Risk Treatment

Structure. The analysis of selected papers reveals that data are widely used in healthcare to pursue strategies to reduce some *risks that may affect the physical and organizational settings* where healthcare occurs. In particular, several scholars have used data for treating shortage risks of human, technical and organizational resources by providing information and knowledge to optimize their planning, allocation and management (Abroshan et al., 2022; Bianchin et al., 2022; Debjit et al., 2022; Delias et al., 2015; Lavrač et al., 2007). For example, it is possible to extract or predict information (e.g., number of admissions) that allows the minimization of gaps in the availability of equipment and supplies in healthcare facilities (Qiu et al., 2020; Rios-Zertuche et al., 2020) or to optimize the allocation of electric resources based on the information about healthcare facilities’ energy needs (Pakravan and Johnson, 2021). It is also possible to use the data to mitigate the risk of a shortage of available resources by optimising the number of readmissions (Demir, 2014; Y.-W. Lin et al., 2019; Zhu et al., 2015), and the length of stay (Dwyer-Matzky et al., 2020), which increase the burden on healthcare resources such as beds and medical equipment. For instance, data can be used for the simulation of the length of stay of patients, by supporting physicians and managers of healthcare organizations to reduce the risk of resource waste (Kovalchuk et al., 2018). Another way to mitigate the risk of a shortage of available resources is to use data to optimize decisions about medical equipment repair and replacement (Liao et al., 2021). In addition, the data also allows the risk of wasted resources to be mitigated by minimizing daily expected resource usage across multiple resources such as anaesthesiologists and operating room surgeries (Rath et al., 2017), by optimising the scheduling of patients (Mandelbaum et al., 2020; Nallathamby et al., 2021) or by optimising the assignment of patients to physicians in an emergency department based on the availability of resources (Rosemarin et al., 2021). Still considering the mitigation of waste of resources, physicians and managers can exploit data to select new technologies and treatments that create real value in healthcare organizations (Thompson et al., 2016). More recently, the use of data to support the mitigation of the aforementioned risks (i.e., risk of shortage and waste of available resources) was considered during the COVID-19 pandemic (Devarajan et al., 2021; Markhorst et al., 2021). In this emergency context, available resources were scarce and data were useful to optimise the capacity planning of the COVID-19 vaccination, minimising the waiting time by using data to optimise the locations of the medical hubs, the distribution of the available vaccines and healthcare professionals (Demir, 2014). Moreover, data can be used also to optimise the work of healthcare staff, for instance, Poly et al. (2020) developed a machine learning prediction model to predict the healthcare staff fatigue generated. The main concern is that these large numbers of clinically irrelevant alerts might cause alert fatigue and consume too much time and mental energy.

Process. Some of the selected papers discuss the use of data for mitigating *issues affecting the stages of the care process*, both cross-sectional and in specific stages, as observed in the risk assessment section. Concerning the cross-sectional way, data are used not only to get useful information for the assessment of health patients' conditions but also to improve it by promoting evidence-based medicine. Following these aims, physicians and managers use data to mitigate risks in healthcare organizations for particular disease conditions such as cardiovascular ones

(Raghu et al., 2015). Decision-makers of healthcare organizations can also mitigate risks in the specific stages of the care process. The disease-prevention stage is widely supported by data. Indeed, in this stage, physicians can use data to predict patients at-risk of disease occurrence and take decisions to prevent it (Dreischulte et al., 2012; Duan et al., 2011; Laila et al., 2022; Layeghian Javan and Sepehri, 2021; Wu et al., 2022); for instance using clinical notes to predict blood flow disorders (Afzal et al., 2018), using data to enable the early identification of patients to optimize the outcomes of cancer screening (Sharma et al., 2016) or using electronic health records for the early prediction of septic shock (Wang et al., 2022). In the diagnosis stages, physicians can use the information extracted from the data to make more informed decisions (Wong-Lin et al., 2020) and even to improve the existing diagnosis guidelines (Antonelli et al., 2012), for instance, data can be used to discover the conditions under which decision-making strategies produce undesired or suboptimal outcomes (Meyer et al., 2014). Concerning the selection of treatment stage, physicians can identify the optimal treatment plan based on the data about the attributes of the patients (Carey et al., 2022; Chi et al., 2022; Newland et al., 2018), e.g. to optimize anaemia treatment in hemodialysis patients (Escandell-Montero et al., 2014). Furthermore, physicians can optimize the selection of treatments using data to consider complexity among the many variables that can influence the outcome, to select treatments considering likely adverse side effects with a specific therapy (Sun et al., 2021) or in the presence of comorbidities (Zolbanin et al., 2015). In this context, data allows physicians to make a personalised treatment plan, e.g. to select the best treatment for patients with chronic diseases such as obesity, hypertension, and hyperglycemia (Valero-Ramon et al., 2020). Finally, physicians can use data to optimize treatment selection decisions by getting information about the likely course of the disease, e.g. from the likely course of oncological patients (Ji et al., 2019; Johnson et al., 2020).

Outcome. The use of data for risk treatment in the outcome domain focuses mainly *on patients'* *health and satisfaction*. The use of data enables decisions that mitigate patients' health risks, mostly by reducing the risk of complications and mortality (Bhatti et al., 2019; Kamala et al., 2021; Mahajan et al., 2019; O'Grady et al., 2021; Tao et al., 2021). For instance, data can be used to mitigate the risk of maternal and fetal mortality and morbidity rates by predicting the women at risk of developing gestational diabetes (Moreira et al., 2018) and also to minimise adverse health outcomes by analysing the reasons for medication nonadherence (i.e., the practice of patients failing to take medications as prescribed)(Xie et al., 2022). Data can also support the choice of personalised treatment to mitigate risks of hospitalization related to specific diseases (Yeh et al., 2011) or complications and side effects that may occur with certain therapies, e.g. chemotherapy (Mosa et al., 2020). Also, the Quality of Life (QoL) of the patients after treatments is of paramount importance for healthcare organizations, and data can support the decisions of physicians and managers in order to reduce the incidence of decisions-error (Faria et al., 2015). While, during the COVID-19 outbreak several scholars and organizations proposed tools to provide data-driven real-time insights to improve patients' health outcomes (Tolk et al., 2021). As an example, decision-makers used data both to formulate social distancing policy to minimize the risks of infection spread (K. Chen et al., 2021) and to predict or diagnose diabetes patients to decrease the mortality rate of COVID-19, being particularly sensitive patients (Li et al., 2021). Finally, concerning the satisfaction of the patients, for example, data can be exploited to mitigate patient dissatisfaction by improving the scheduling of healthcare activities and mitigating the risks of long waiting times (Cho et al., 2019). Moreover, it is also possible to use data to support physicians in the decision-making process to ensure elderly patients' satisfaction in delivering domestic care services (Lam et al., 2021). Another application to optimize the satisfaction of patients is the recommendation of the optimal insurance healthcare plan based on the likely expected healthcare services needs (Stein, 2016).

2.5.2.3. Risk Monitoring

Structure. Few of the selected works focused on the use of data for risk monitoring in the structure domain and they were focused on the optimal use of resources. In particular, data are used for beds, care and medical equipment by providing insights through real-time data transmission for the optimisation of resource scheduling (Wautelet et al., 2018). Furthermore, it is also possible to exploit data to monitor the impact of new organizational models for the optimal use of healthcare resources by analysing data concerning patients' conditions (Vanasse et al., 2020).

Process. Physicians and managers of a healthcare organization can use data in the process domain to monitor risks related to patients' health, by supporting the decisions throughout the care process. The whole care process can benefit from data to carry out monitoring activities in real-time, for instance, to support healthcare professionals' daily practice for patients with specific diseases (Mathe et al., 2009) or to monitor the spread of diseases enabling managers and physicians to plan actions (Chinnaswamy et al., 2019). In addition, the development of sensors and equipment for the real-time and remote collection of patient health data is enabling care process activities to be carried out without patients needing to visit facilities, as for elderly patients (Wong et al., 2017). For example, it is possible to support the diagnosis stage by analysing data obtained by monitoring patients' heart conditions (Hu et al., 2008).

Outcome. Few papers have been identified that exploit data for risk monitoring activities in the outcome domain, and they focus mainly on monitoring risks related to the health status of patients rather than their satisfaction. Both patients and physicians can benefit from the use of data collected through sensors and remote technologies for risk monitoring activities. From the patient's perspective, data enable the self-monitoring of their health status, while from the perspective of physicians, data enable the monitoring of outcomes without visiting patients. Indeed, the main goal of using data for risk monitoring in this domain is to get continuous information about the outcome of healthcare services (Rathore et al., 2016). For instance, it has been proposed a model to monitor patients' outcomes in terms of wellness, by considering lifestyle variables (Agarwal et al., 2016).

2.6. Discussion And Future Research Directions

In the following, the findings will be discussed with a focus on the specific dimensions of the framework defined in section 2 (Figure 1).

Risk Assessment. In the *structure* domain, data support the identification and assessment of risks that threaten the *optimal use of resources* and *organizational activities* in the healthcare organization. Focusing on the resources, data are used to identify and assess the risk of resource shortage and waste by making predictions on variables such as the length of stay (Kudyba and Gregorio, 2010) or the probability of re-hospitalisation (Ryan et al., 2015). While concerning organizational activities, fewer studies have been identified, and they are focused on equipment maintenance (Zamzam et al., 2021) and payment methods (Gerhardt et al., 2018). However, the risk assessment to support staff training is particularly relevant in the current era, where several new technologies and innovations have been introduced in the healthcare industry. In this context, the use of data can enable the identification of improvement areas in healthcare staff education in order to detect and assess the risk of defective training. For instance, supporting educators in the training of healthcare professionals for the use of technological innovations, such as artificial intelligence for diagnostic or telemedicine for remote delivery of healthcare services. Despite the relevance, it has not been identified qualitative or quantitative research that used data to identify areas for improvement to guide educators, managers and decision-makers in planning training pathways for healthcare professionals. *For these reasons, more research on the use of data for supporting educational managers in the development of* *staff training pathways would be needed.* In the *process* domain, data are widely used to optimise decisions affected by risk and uncertainty. It turns out that data enable risk assessment both in cross-sectional ways (Liu et al., 2016) and at specific stages of the care process. In particular, several scholars have explored risk assessment in the different stages of the care process: identification of patients at risk (Mioshi et al., 2014; Nasir et al., 2019), diagnosis (Bashir et al., 2021; Malik et al., 2020), choice of treatment (Fan et al., 2022). The relevance of these results lies in the fact that through data it is possible to identify and assess risks at various stages of the care process, thereby following the paradigm of providing the right care at the right time and in the right place. In this review, the findings highlighted how data support decisions about the stages of the care process, and thus disease-specific processes i.e., diagnosis, choice of treatment, etc. However, the process domain in the Donabedian model is not focused only on the disease-specific processes, but also on processes that are not focused on the patient's disease or non-disease-specific, e.g., physician-patient communication and nursing care. In recent years, such processes are gaining increasing interest since they can further improve healthcare service delivery. In order to support the managers and physicians in these processes, a new paradigm is spreading. This paradigm involves the *engagement of patients* throughout the care process. In this context, the role of the patient would no longer be a passive one but rather he/she can become an active member of the whole care process, as the ultimate expert in his or her own physical and psychological health status. For instance, the engagement of patients could improve the commitment to follow a suggested treatment through the improvement of physician-patient communication. Despite the *non-disease-specific* processes seems a promising topic to improve the delivery of healthcare services, papers that use data to address it have not been identified in the literature. *Thus, it is recommended to explore through the conceptual and qualitative paper the use of data for assessing risks that affect non-disease-specific processes.* Data are also used to support the risk assessment phase in the *outcome* domain by assessing the risks associated with decisions that impact both patients' health outcomes (Asaria et al., 2016; Clark and Normile, 2012) and their satisfaction (Abirami and Askarunisa, 2017; H. J. Lee et al., 2021). Focusing on patients' health outcomes, both data related to patient characteristics and organizational characteristics are used to identify and assess risks. However, the use of data to identify and assess risks related to errors in healthcare service delivery was not identified in this review. This issue has become increasingly relevant in recent years, and the World Health Organization (WHO) estimates that adverse health outcomes resulting from errors in the delivery of healthcare services are one of the leading causes of death worldwide (World Health Organization, 2019). The use of data seems to be promising to identify these risks in healthcare organizations to support the decisions of physicians and managers. For instance, data could enable the early or even real-time identification of errors in care procedures. *For the aforementioned reasons, I suggest investigating how data can help healthcare organizations in identifying and assessing the risk of errors in the delivery of healthcare services.*

Risk Treatment. In the *structure* domain, data are used to mitigate risks that threaten the physical and organizational settings in which healthcare occurs. In this context, data allow for optimised decision-making by dealing with risks of resource shortage (Dwyer-Matzky et al., 2020; Pakravan and Johnson, 2021) and resource waste (Nallathamby et al., 2021; Rosemarin et al., 2021). However, in this domain, contrary to the findings in the risk assessment, no studies have been identified that exploit data to support decisions about organizational activities (e.g., staff training, and payment methods). In a complex system such as healthcare, organizational activities play a crucial role in guaranteeing that healthcare organizations work properly in order to deliver optimal services. As already stated in this review, risk and uncertainty can lead to sub-optimal decision-making that will impact health outcomes. For instance, planning, scheduling and control of the patient flow are organizational activities in which decisions are taken under risky and uncertain conditions. Healthcare managers can use data to deal with these conditions, e.g., exploiting data to support the planning and scheduling of activities to manage effectively the flow of patients by forecasting what and how much needs to be done (i.e., planning) and defining who and when the activities will be performed (i.e., scheduling). Thus, supporting the mitigation of risk and uncertainty in decision-making is a relevant issue also for organizational activities. *Future research should be performed to explore the use of data for optimising decisions in conditions of risk and uncertainty about organizational activities.* In the *process* domain, data assist the decision-making by supporting physicians in the mitigation of risks throughout the care process: identification of patients at-risk (Afzal et al., 2018; Layeghian Javan and Sepehri, 2021), diagnosis (Meyer et al., 2014; Wong-Lin et al., 2020), selection of treatment (Newland et al., 2018). In particular, in the selection of treatment, it turns out that data about the characteristics of patients are used, i.e. health-related data. While, other kinds of data such as those related to the patients' satisfaction or the economic costs for equivalent treatments, are still overlooked. These data could enable physicians to take more aware and holistic decisions by considering not only the health-related perspective but also other ones, such as the patient's satisfaction. *It is suggested that further research should explore the combination of health-related data with other types of data, such as satisfaction, to support the selection of treatment.* Regarding the treatment of risk in the *outcome* domain, data are used to treat the risk for patients' health, e.g., to reduce complications and mortality rates (Kamala et al., 2021) and to ensure the patient's satisfaction (Cho et al., 2019; Lam et al., 2021; Stein, 2016). As emerged for risk assessment, the use of data to mitigate the risk of errors in healthcare service delivery was not identified. However, it is possible to use data to support physicians and healthcare managers to reduce the frequency of these errors. An example could be the use of data to reduce the incidence of unnecessary hospitalisation. The use of healthcare resources for unnecessary admissions deprives other patients who need those resources, leading to delays in treatment and ultimately suboptimal results. Although such an application has not been found in the literature, it is possible to predict necessary hospitalisations through data (Yeh et al., 2011). Thus, data could be a valuable support in reducing the risk of these errors. *For this reason, scholars should deeper explore the role of data to mitigate the risk of errors in the delivery of healthcare services.*

Risk Monitoring. Concerning risk monitoring, few papers have been identified (8), despite the relevance of the topic in healthcare organizations. Indeed, nowadays, the spreading of mobile and wearable technologies is enabling the collection of data to monitor several risks that threaten the domain of healthcare organizations. In the domain of *structure*, scholars have focused their attention on monitoring the use of physical facilities and equipment to support scheduling (Wautelet et al., 2018) and testing new organizational models that ensure the optimal use of resources (Vanasse et al., 2020). No studies have been identified that use data to monitor the status of human resources in healthcare organizations, a topic that has become particularly relevant after the COVID-19 pandemic. In this context, physicians and healthcare staff have been overburdened by the high number of hospitalisations and high-risk conditions related to the spread of the virus. Data could make it possible to monitor the condition of human resources, both from the psychological and physical points of view, so that action could be taken to ensure the optimal state of human resource conditions in healthcare organizations, reducing the so-called staff “burnout”. *It is recommended to explore through the conceptual and qualitative paper the use of data for monitoring risks that affect the physical and mental conditions of human resources.* In the *process* domain, scholars have focused on the use of data to support the monitoring of risks that may affect the different phases of the care process. An increasing field of application is the use of data to perform remote monitoring activities of the care process, such as in the prognosis and diagnosis (Chinnaswamy et al., 2019; Wong et al., 2017). The delivery of remote healthcare services based on monitoring patients’ health status is considered relevant both in cases where patients are not able to reach the healthcare organizations due to patient characteristics (e.g., elderly patients) and when circumstantial conditions make it hard to reach them (e.g., pandemics). An interesting and overlooked field of application for risk monitoring activities through data is the non-urbanised areas (i.e., rural areas). These areas are characterised by the scarce presence of well-equipped healthcare organizations, so it is difficult for patients to reach the healthcare facilities. The use of data for carrying on remote activities would overcome this issue, ensuring the delivery of healthcare services. *Thus, a viable future research direction is the development of empirical studies for the development of systems that allow the use of data to monitor the risk of patients' health status in rural areas.* In the *outcome* domain, I identified papers in which data are used to monitor the outcome of healthcare services on patients' health status, rather than monitoring patients' satisfaction. Patients' satisfaction is significant both for understanding performance in healthcare service delivery and because it affects patients' health status. *For these reasons, researchers should explore the use of data to monitor patient satisfaction through empirical studies in healthcare organizations.* Finally, the review unveils that data are not explicitly integrated with the risk management phases in the healthcare decision-making processes, consistent with the findings of the review performed by Dicuonzo et al., (2021) about the use of big data and artificial intelligence for supporting the risk management. This strengthens the relevance of this systematic literature review since it provides the first overview of the integration of data for decision-making under conditions of risk and uncertainty to ensure the delivery of high-quality services in healthcare organizations, exploiting risk management ideas. In addition, the lack identified in the literature encourages the development of new scientific projects to investigate the optimal integration of data into established risk management techniques.

2.7. CONCLUSION

This study aimed to provide an overview of the use of data to optimise decisions in healthcare organizations' domains and to optimise decisions made by healthcare organizations affected by risk and uncertainty.

The contributions of this study are twofold: theoretical and managerial. This study contributes to the extant literature on the use of data to optimise decisions under risk and uncertainty in healthcare organizations. It should be mentioned that the use and potential of data in the healthcare setting have been already discussed in the literature (Islam et al., 2018; Malik et al., 2018; Salazar-Reyna et al., 2020) and some studies have focused on the risks and uncertainty conditions systematically reviewing established risk management techniques (Liu et al., 2020) or on investigating emerging risks (Sardi et al., 2020) in the healthcare setting. However, to the best of the author knowledge, this is the first systematic literature review to address the problem of decision-making affected by risk and uncertainty in healthcare organizations from the perspectives of risk management, data and quality of healthcare services. Moreover, the analysis of the findings made it possible to identify gaps in the literature and thus, future research directions were defined to address them with regard to the phases of risk management and the domains of healthcare organizations where decisions are made.

Concerning managerial contribution, physicians and healthcare managers daily deal with decisions affected by risk and uncertainty in all the domains of healthcare organizations. Thus, this study offers some insights for healthcare professionals who are interested in understanding how to use data to optimize the decisions affected by risk and uncertainty. For instance, healthcare managers may understand how data can support their decisions in both planning the needs of healthcare resources and the scheduling of activities, mitigating several risks, such as the risk of shortage. While, physicians can use the findings of the study to gain a better understanding of how data-driven decisions can support them at various stages of the care process, e.g., in the selection of treatment data allow them to consider at the same time many variables that can cause adverse outcomes. Policy-makers can also use the findings of this review to guide decisions affected by risk and uncertainty, such as the decisions about social distancing policies in healthcare facilities during the Covid-19 pandemic.

Although the author used a systematic methodology to conduct this review, this work is not without limitations. The literature analyzed was identified through specific keywords, so papers that did not use the keywords defined have not been included in this review. However, to mitigate this issue, the author tested different sets of keywords in order to check that papers near the topic of interest were only eliminated after a deeper analysis of the title and abstract and not a priori. One could say that not including keywords related to risk and uncertainty is a limitation of this study. However, it is only an apparent limitation as it turns out that in the healthcare setting the conditions of risk and uncertainty are not explicitly stated in the papers' text so a research keyword-based would have not retrieved these papers. For this reason, the author preferred not to add these keywords in order to avoid a reduction of the set of selected papers, rather retrieve more papers and remove them only after reading them thoroughly. Furthermore, the filters used to perform the research on the database could also be considered a limitation. Indeed, consistently with other systematic reviews, only articles and reviews from peer-reviewed journals written in English were considered in this research. While concerning the databases used for retrieving the papers, the author selected Scopus, Web of Science and PubMed in order to ensure the review's comprehensiveness.

In conclusion, the author expect that the framework proposed to classify the papers, the findings and the research agenda represent a valuable contribution for scholars to carry on future research, as they could help to shape the increasing and progressing stream of research about the use of data to support healthcare decision-makers to take decisions affected by risk and uncertainty.

3. How can technological resources improve the quality of healthcare service? The enabling role of big data analytics capabilities

3.1. Abstract

The increasing adoption of digital technologies is revolutionising healthcare professionals' activities. These technologies generate large amounts of data that can be used by big data analytics (BDA) to extract knowledge that, if properly utilized, may support the decision-making process and ultimately improve the quality of healthcare services. Although hospitals have been investing in BDA technological resources, it seems that the quality of service has not always been improved. In recent years the academic literature has highlighted the relevance of BDA capabilities in improving organizations' performance, but their role in healthcare organizations seems overlooked. The purpose of this study is to empirically investigate the relationship between BDA technological resources and capabilities and the quality of healthcare services. It also aims to determine whether the presence of BDA capabilities in healthcare organizations can be the underlying mechanism that explains the effect of BDA technological resources on the quality of healthcare services. 114 responses from Italian healthcare professionals were collected and investigated via the lens of Resource-Based View theory using the PLS-SEM methodology. The results show the pivotal role of BDA capabilities in deploying BDA technological resources to improve the quality of healthcare services and thus the need for further investment in BDA capabilities.

3.2. INTRODUCTION

The spread of new technologies pushed the digitalization of many firms, thus generating deep changes and disruptions in recent years and driving growth in many industries (Hanelt et al., 2021; Kraus et al., 2021a). The healthcare industry is one of the main beneficiaries of this shift among others (Dal Mas et al., 2023; Devarajan et al., 2021; Kraus et al., 2021b; Ramzan et al., 2022). Technologies paradigms such as cloud computing, big data and the internet of things are leading this industry towards the so-called "Healthcare 4.0" (Abbate et al., 2022; Aceto et al., 2020). Among the most widely employed technologies in healthcare, there are wearables and portable technologies, telemedicine, and electronic health records (Marques and Ferreira, 2020). These technologies support physicians in following the paradigm of "the right care at the right time and right place" (Chute and French, 2019). Wearables and portables enable the collection of patient health data every time and everywhere (Wu et al., 2016), telemedicine is a set of technologies that assist physicians and patients in delivering and receiving healthcare services remotely (Khodadad-Saryazdi, 2021), while an electronic health record is "*a repository of patient data in digital form, stored and exchanged securely, and accessible by multiple authorized users*" (Häyrinen et al., 2008), that can be exploited for instance to support diagnosis, prognosis or treatment choices (Chen et al., 2017; Kohli and Tan, 2016; Layeghian Javan and Sepehri, 2021). These technologies are unique in their ability to generate and capture large amounts of data, e.g. patient administrative data (Kraus et al., 2021b; Wang et al., 2018). The availability of this data offers the opportunity to extract knowledge and, if properly utilized, to support decision-making (Basile et al., 2023; Weerasinghe et al., 2022; Yu et al., 2021). Big data analytics (BDA) are used to leverage these massive amounts of data. BDA refers to the technologies, processes and methodologies that analyze large amounts of data to assist an organization in taking more informed critical decisions (Bag et al., 2021; Wang et al., 2018). This is considered relevant given that healthcare decisions are characterized by high risk and uncertainty (Han et al., 2019; Lin et al., 2017), due to the lack of information (Han et al., 2011), which can be mitigated by extracting the information from the available data in healthcare organizations. Thus, in healthcare, the use of BDA seems promising to deal with risk and uncertainty in the decision-making process with the aim of increasing the quality of healthcare services, which can be assessed in three dimensions, namely professional and organizational resources (structure), tasks performed for the patient (process), and the desired outcome of the care provided by healthcare professionals (outcome) (Donabedian, 1988). Past literature mainly focused on the effective acquisition and deployment of BDA technological resources such as infrastructure, intelligence and analytics tools to support the decision-making processes (Mikalef et al., 2018). However, the mere presence of technological resources may not guarantee their optimal use (Alharthi et al., 2017; Wang et al., 2018) and consequently their impact on the quality of healthcare services. For example, the UK National Health Service lost more than £10 billion by failing to implement patient medical records that aimed to support healthcare professionals' decision-making through data analytics (Syal, 2013). One of the reasons for this failure is considered to be the lack of capabilities of the analytical team of the project, rather than the lack of technological resources (Marr, 2015). In this context, in the last few years, several researchers have focused also on the managerial and organizational aspects that impact the effective employment of these technologies (Elia et al., 2022; Mikalef et al., 2021; Vitari and Raguseo, 2020). Among these, the presence or development of digital capabilities is considered one of the factors that can lead to better organisational performance (Mikalef and Pateli, 2017; Raguseo and Vitari, 2018). However, despite the growing interest in the use of BDA technological resources and capabilities to improve decision-making in healthcare, their effect on the quality of healthcare services domains seems to be overlooked by empirical studies in the academic literature. This study aims to empirically investigate the relationship between BDA technological resources and capabilities with the quality of healthcare services domains (i.e., structure, process, and outcome), and if the presence of BDA capabilities in healthcare organizations can explain the effect that the BDA technological resources have on the quality of healthcare services domains, namely the structure, the process and the outcome. To this aim, I developed a research model grounded on the resource-based view (RBV) theory since it may provide a basis for identifying and assessing the significance of the relationship of the BDA technologies resources and capabilities with the quality of healthcare services. In light of this, the following research question is sought to be addressed:

- Is the presence of BDA capabilities an explaining mechanism of the effect of BDA technological resources in improving the quality of healthcare services domains?

The rest of this paper is organized as follows. In the next section, I presented the theoretical background and the hypotheses development. Then, I briefly presented the methodology adopted in this study. In the following, I presented results, and I subsequently elaborated the discussion of the study, highlighting the practical and academic implications as well as the limitations. Finally, I provided the concluding remarks.

3.3. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

3.3.1. Resource Based View Theory and Big data analytics

The resource-based view (RBV) is among the most relevant and discussed managerial theories (Makadok, 2001; Wade and Hulland, 2004). RBV theory is particularly useful in examining how an organization can leverage its unique resources and capabilities to achieve a sustainable competitive advantage (Barney, 1991). In particular, RBV theory emphasizes the importance of internal resources and capabilities rather than external factors such as market conditions or industry trends (Makadok, 2001). It suggests that a firm's competitive advantage is based on its ability to develop and exploit resources that are valuable, rare, inimitable, and non-substitutable (Grant, 1991). This theory is one of the most used among organizational studies about the use of big data analytics resources and capabilities (de Camargo Fiorini et al., 2018; Galetsi and Katsaliaki, 2020). Gupta & George (2016) (Gupta and George, 2016) identified the bundle of organizational resources to develop big data analytics capabilities and validated the positive relationship between capabilities and a firm's operational and market performance. In particular, big data analytics capabilities to be properly developed need technological, cultural, technical and managerial skills as basic resources [41]. Also, the big data analytics capabilities can be drawn as a composition of three main capabilities, namely technology, management, and talent capabilities, and they are considered as the discriminator of the difference in big data analytics implementation success between organizations (Akter et al., 2016). Moreover, the literature explored the relationship between big data analytics capabilities and the creation of business value pointing out the potential of big data analytics in supporting the development of new activities or in identifying areas of improvement (Mikalef et al., 2018). More recently scholars focused on the relevance of big data analytics capabilities in healthcare and their great potential in this industry, e.g. the effective exploitation of data can lead to assist and improve diagnosis processes or deliver customized health services (Galetsi and Katsaliaki, 2020; Wang and Hajli, 2017). For instance, Wang et al., (2018) (Wang et al., 2018) defined big data analytics capabilities as "the ability to acquire, store, process and analyze large amounts of health data in various forms, and deliver meaningful information to users that allow them to discover business values and insights in a timely fashion". Moreover, they explored the potential benefits it may bring to healthcare organizations such as the improvement of the accuracy of clinical decisions, reduce the time of patient travel and identify new insights about health population trends (Wang et al., 2018). In this context, Yu et al. (2021) discussed and demonstrated how culture and mindset resources are effectively managed and bundled to create big data analytics capabilities in order to obtain optimal operational performance in healthcare organizations.

3.3.2. Theoretical Model And Research Hypotheses

BDA technologies are revolutionizing service delivery in healthcare organizations, e.g. by ensuring patient-centred services and operational efficiencies (Dal Mas et al., 2023; Kraus et al., 2021b). Despite their promising relevance, the academic literature on healthcare services points out that the investment and acquisition of these technologies do not guarantee their effective use to gain strategic knowledge and insights to ultimately improve the quality of services (Mikalef et al., 2018). In this regard, quality performance improvement could be achieved with the development of big data analytics capabilities (Mikalef et al., 2018), which can be outlined as the ability to collect, analyze and visualize big data (Galetsi et al., 2020). However, to date, there is limited empirical research in the healthcare organizations setting that investigates the role of BDA technological resources and capabilities in ensuring the quality of healthcare services from the perspective of healthcare professionals. Thus, in this context, this study proposes a research model grounded on RBV theory that investigates the effect of BDA technological resources and BDA capabilities in improving the quality of services' domains (i.e., quality of structure, process and outcome) and whether the presence of BDA capabilities could be an enabling factor that explains the effect of the BDA technological resources on the quality of healthcare services' domains. In the following, the hypotheses will be developed.

Effects of BDA Technological Resources and BDA Capabilities on the quality of healthcare services' domains. In the current years, the use of digital technologies in healthcare organizations is boosting the quality of healthcare services (Kraus et al., 2021b; Salazar-Reyna et al., 2020). Among the most promising technologies, there are BDA (Aceto et al., 2020; Wang et al., 2018). Healthcare organizations produce large amounts of data by performing simple daily activities, which can be leveraged by BDA to ultimately improve the quality of healthcare services (Wang et al., 2018). The quality of these services can be drawn from three main domains: structure, process and outcome (Donabedian, 1988). For instance, in the structure domain, it is possible to have information about the resources needed (e.g., medical equipment) by predicting the number of patients that require hospitalization (Sebaa et al., 2018). In the process domain, BDA can support physicians in the diagnosis and treatment decisions (Bukhari et al., 2021; Meid et al., 2022) or in the outcome domain to understand what affects in-patient mortality (Soffer et al., 2021). Drawing on the RBV theory, healthcare organizations need both BDA technological resources and BDA capabilities to ensure the optimal performance of healthcare services.

Considering the technological resources, healthcare organizations are investing in digital technologies to collect, store and exploit large amounts of data (Kohli and Tan, 2016; Kraus et al., 2021b). For instance, among the most adopted technologies in healthcare, there are electronic health records, telemedicine and wearable devices (Marques and Ferreira, 2020). There is a growing awareness among healthcare organizations that adopting these resources may provide better care and services to patients (Khodadad-Saryazdi, 2021; Kraus et al., 2021b; Wu et al., 2016). Therefore, I proposed the following hypotheses:

- *BDA Technological Resources have a positive impact on the domains of healthcare service quality, in terms of structure (**H1a**), process (**H1b**) and outcome (**H1c**).*

Considering the capabilities, BDA capabilities can also be defined as the organization's unique and inimitable abilities to efficiently use big data to gain strategic knowledge and insights (Mikalef and Pateli, 2017). Particularly, in the academic literature, the role of BDA capabilities is proposed as a leading factor of success in the implementation of big data projects rather than the result of investments in resources (Gupta and George, 2016; Vidgen et al., 2017). Thus, this capability could be considered as an enabler of the effective use of data to inform the decision-making process in healthcare (Wang et al., 2018; Weerasinghe et al., 2022) and ultimately leading an impact on the healthcare organization's performance in terms of quality of services. The following hypothesis is formulated:

- *BDA Capabilities have a positive impact on the domains of healthcare service quality, in terms of structure (**H2a**), process (**H2b**) and outcome (**H2c**).*

Effects of BDA Technological Resources on BDA Capabilities. The successful employment of BDA technological resources is more than just the consequence of data technologies and procedures employment, it encompasses a larger variety of factors (Galetsi et al., 2020; Mikalef et al., 2018). In this sense, following the RBV theory and specifically considering the capability-building lens, the technological resources represent the “starting point” for ensuring the improvement of the organizational performance, while capability is the capacity to deploy these resources in the most effective way (Gupta and George, 2016; Makadok, 2001). As a consequence, the main premise for the effective use of big data analytics is that an organization has invested in all the necessary technological resources (Mikalef et al., 2018; Wade and Hulland, 2004). Thus, I devised the following hypothesis:

- *BDA Technological Resources have a positive impact on BDA Capabilities (**H3**)*

The role of BDA capabilities on the relationship between BDA technological resources and the quality of healthcare services' domains. The role of technological resources is relevant to the effective use of BDA (Gupta and George, 2016). However, the literature points out that the technological resources themselves could not explain the difference in the success of the use of BDA in organizations with the same technological equipment (Alharthi et al., 2017; Gupta and George, 2016; Wang and Hajli, 2017; Ward et al., 2014), although technological resources are considered among the most relevant resources that an organization needs to effectively employ BDA (Gupta and George, 2016). Therefore, the presence of BDA capabilities can be considered as the ground and the boost for BDA technological resources to have an impact on healthcare services (Makadok, 2001; Wang et al., 2018). For the aforementioned reasons, I hypothesized the following:

- *BDA Capabilities mediate the relationship between BDA Resources and the domains of healthcare service quality, in terms of structure (**H4a**), process (**H4b**) and outcome (**H4c**).*

Figure 5 shows the research model and the hypotheses that will be tested in the following section.

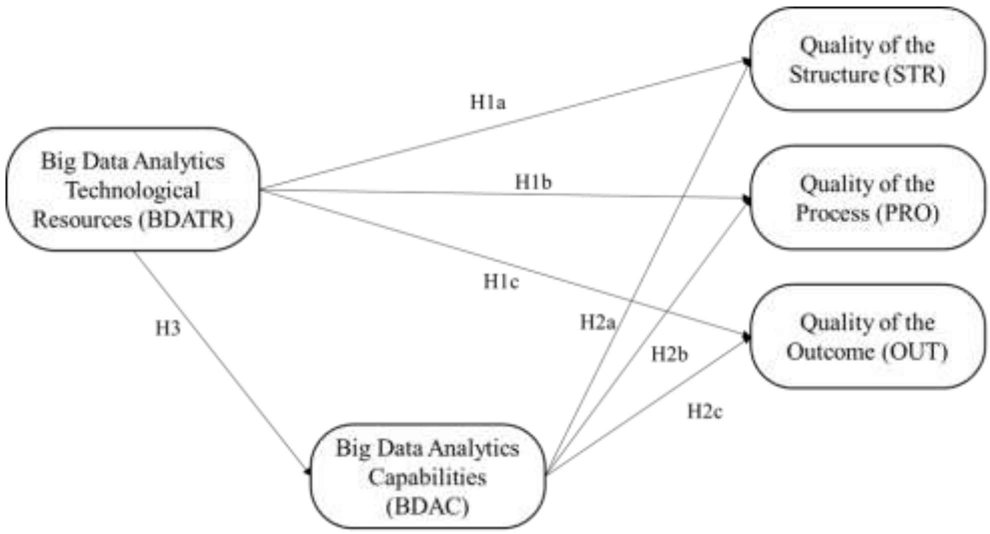

Figure 6 The research model.

3.4. RESEARCH METHODS

Aiming to test the hypotheses and consequently answer the research questions, in this study I adopted a questionnaire-based methodology. The questionnaire was built based on a deep literature review of the topic of the research. Then it was tested and verified by healthcare professionals. The constructs of the research model are 5, namely BDA technological resources (BDATR), BDA capabilities (BDAC), Quality of the Structure (STR), Quality of Process (PRO) and Quality of Outcome (OUT). The BDATR is represented by 4 items that describe the availability of descriptive statistics on informatics tools, information systems up to date for data collection, and the availability of tools to make analysis and visualize data (Benzidia et al., 2021; Dubey et al., 2019a; Gupta and George, 2016). BDAC is described by the actual use of data to support decision-making, the mindset about the usefulness of data, the willingness to use data and the performance of their utilization in daily activities (Ashaari et al., 2021; Gupta and George, 2016; Mikalef et al., 2018). The STR is described by the availability of adequate environments, appropriate medical equipment and devices, and an adequate number of human resources for patient care (Donabedian, 1988; Wu and Hsieh, 2015). The PRO is described by the physicians' willingness to follow the guidelines for the diagnosis and treatment selection phases, the implementation of prevention activities, patients monitoring afterwards a treatment, physicians discussing the pros and cons with patients for treatment choice, physicians' willingness to consult and discuss with others physicians before making the decisions (Donabedian, 1988; Santry et al., 2020; Wu and Hsieh, 2015). Finally, OUT is described by the outcome obtained by the healthcare organization's activities in terms of the patient's physical well-being and chances of survival, the patient's emotional well-being and quality of life and patient satisfaction with their living conditions (Donabedian, 1988; Wu and Hsieh, 2015). Table 7 in appendix A shows the constructs and the respective items. For each item, a statement was used to understand how strongly the respondent agreed and a Likert scale from 1 (absolutely disagree) to 5 (absolutely agree) was used to measure the healthcare professional perspective. Moreover, the respondents were assured that their personal information would remain confidential. Afterwards, the questionnaire was administered through email to the selected sample which consists of healthcare professionals from Italian healthcare organizations (e.g., physicians, medical directors and general managers). A sample of 2,474 healthcare professionals were selected to be representative of the Italian national healthcare system (NHS). In particular, we selected the five most relevant hospitals for each Italian region based on the number of operational units and inpatient hospital beds. To test the hypotheses of the proposed research model, healthcare professionals (e.g., physicians, medical directors, and general managers) were selected because they were more likely to objectively assess the current impact of the use of BDA technological resources and capabilities on the quality of healthcare services domains. Moreover, the data analysis was performed using the partial least square structural equation modelling (PLS-SEM) methodology (Hair et al., 2013). This approach was chosen because, according to Hair et al. (2013) (Hair et al., 2013), it is more appropriate for small samples and allows for the estimate of complicated models with several constructs, indicator variables, and structural paths without imposing any distributional assumptions on the data (Hair et al., 2019).

3.4.1. Analysis of Results

I collected a final set of 114 responses from healthcare professionals in Italian healthcare organizations. Following Cohen (1988) (Cohen, 1988) and Hair et al. (2013) (Hair et al., 2013), the recommended sample size for the PLS-SEM analysis for the model investigated in this paper is 110 with a minimum R2 value of 0.10 and a statistical power of 80%, therefore, the study's sample size exceeds the recommended threshold confirming the validity of the sample. Table 5 shows the characteristics of the sample.

Table 5 Sample demographic characteristics.

Demographic characteristics	Number of respondents	Percentage of respondents
Gender		
Female	45	39%
Male	67	59%
Not specified	2	2%
Experience		
< 5 years	5	4%
Between 5 and 10 years	9	8%
>10 years	100	88%
Role		
Healthcare manager	4	4%
Administrative manager	2	2%
Department manager	2	2%
Operational Unit Manager	59	52%
Medical Executive	42	37%
Physician	5	4%

I performed a non-response bias test to guarantee the data's validity. Following Werner et al. (2007) (Werner et al., 2007), I investigated the differences between early and late respondents based on the date of receipt of the questionnaire ($N = 59$ and $N = 55$, respectively), and after applying the t-test to the responses of the two sub-samples, I discovered no significant statistical difference ($p > 0.05$). As a consequence, I determined that non-response is not a major concern in this study. Moreover, I tested the common method bias, i.e., the bias caused by systematic error variance shared by variables assessed or collected with the same source or technique. Thus, I tested the common method bias through Harman's single-factor test and Kock's collinearity test (Tehseen et al., 2017). In the single-factor test developed by Harman, the items were subjected to an exploratory factor analysis in which each item was grouped into a single dimension. According to the results, there is not any single factor explaining all of the items' variances, and the first factor did not account for the majority of the variance. While following Kock’s collinearity test I checked the variance inflation factors (VIF) for each pair of constructs. In the literature, VIF values are considered acceptable if less than 5 (Ko et al., 2021) and in this study, all the VIFs were lower than the suggested threshold. Therefore, the results of Harman’s single-factor test and Kock's collinearity test showed that the common method bias was not an issue in this study.

3.4.2. Items and internal consistency reliability

The item’s loadings reflect how much of an item's variation is explained by the construct and is known as the variance extracted from the item. Item loadings should be greater than 0.708 because they imply that the construct explains more than half of the variation in the items, resulting in adequate item reliability (Hair et al., 2019). All items in this study are above the threshold of 0.708, ensuring the item's reliability. Internal consistency reliability can be defined as the extent to which the items measuring the same construct are associated with each other (Hair et al., 2013). To test the internal consistency reliability, I used two measures Cronbach’s alpha and Composite Reliability. The Cronbach’s alpha value and Composite Reliability of 0.7 are considered benchmark values (Hair et al., 2019). At this level and higher, the items are sufficiently consistent to indicate the construct is reliable. The results revealed that Cronbach’s alpha and Composite Reliability are all above the 0.7 thresholds for each construct. Table 8 in appendix A shows the items’ loadings, Cronbach’s alpha, and Composite Reliability for each construct.

3.4.3. Convergent and discriminant validity

Convergent validity is demonstrated when measurement items converge to represent the construct itself. The mean of the squared loadings of each item linked with a construct is used to compute the average variance extracted (AVE) and the convergent validity is demonstrated statistically when the AVE is greater than 0.5 (Hair et al., 2019). In this study, all constructs have corresponding AVE well above the threshold of 0.5. Table 8 in appendix A shows the AVE for each construct. To determine the distinctness of the constructs in the study, the discriminant validity is determined. It demonstrates that the constructs in the study have their own distinct identities and are not strictly associated with other constructs in the study. To test the discriminant validity, I used the Fornell and Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio (Hair et al., 2019). The Fornell and Larcker Criterion states that discriminant validity is demonstrated if the square root of AVE for a certain concept exceeds its correlation with all other constructs, while the HTMT ratio value above 0.9 represents a lack of discriminant validity. In this study, both tests demonstrated the discriminant validity between the constructs. Table 9 in appendix A shows the results of the discriminant validity tests.

3.4.4. Hypotheses testing

I assessed the model's hypotheses by using the bootstrap resampling method with 5,000 iterations to determine the statistical significance of the results. The results of the R^2 demonstrated that the model can adequately account for the variation of the constructs, coherently with Cohen (1988) (Cohen, 1988) and Falk & Miller (1992) (Falk and Miller, 1992) (R^2 for Big Data Analytics Capabilities is 0.146, R^2 for Quality of Structure is 0.234, R^2 for Quality of Process is 0.219 and R^2 for Quality of Outcome is 0.303). Concerning the hypotheses testing, Table 6 shows the results of the performed PLS-SEM. In particular, the results showed that the BDA Technological Resources have a positive and significant direct effect on the Quality of the Structure (H1a), but the direct effect on the quality of process (H1b) and outcome (H1c) was not found significant. BDA Capabilities have a positive and significant impact on all the quality of healthcare services' domains, namely structure (H2a), process (H2b) and outcome (H2c). Moreover, the direct effect of the BDA Technological Resources on the BDA

Capabilities (H3) was found to be positive and significant. It is also interesting to point out that all the mediating hypotheses (H4a, H4b, H4c) were found positive and significant. In particular, the mediating effect of BDA capabilities between BDA technological resources and the quality of structure is known as complementary mediation, i.e. when the indirect effect is significant (H4a) and the direct effect is positive and significant (H1a) (Nitzl et al., 2016), implying that BDA capabilities explain the connections between the independent (i.e., quality of structure) and dependent variables (i.e., BDA technological resources). The mediating effect of BDA capabilities on the relationship between BDA resources and the quality of process and outcome is found to be a full mediation since the direct effect (H1b, H1c) is not significant whereas the indirect effect (H4b, H4c) is significant. This type of mediation infers that the effect of BDA technological resources on the quality of process and outcome is completely conveyed through the BDA capabilities (Nitzl et al., 2016). Figure 6 shows the results obtained in the research model.

Table 6 Results of hypotheses testing.

Hypotheses	**Path coefficients**	**Standard deviation**	**T values**	**P values**	**Result**
H1a: BDATR -> STR	0.209	0.085	2.451	0.014**	Supported
H1b: BDATR -> PRO	0.093	0.092	1.014	0.310	Not Supported
H1c: BDATR -> OUT	0.030	0.079	0.378	0.706	Not Supported
H2a: BDAC -> STR	0.364	0.095	3.831	0.000***	Supported
H2b: BDAC -> PRO	0.424	0.109	3.903	0.000***	Supported
H2c: BDAC -> OUT	0.538	0.100	5.386	0.000***	Supported
H3: BDATR -> BDAC	0.382	0.079	4.840	0.000***	Supported
H4a: BDATR -> BDAC -> STR	0.139	0.054	2.588	0.010**	Supported
H4b: BDATR -> BDAC -> PRO	0.162	0.063	2.580	0.010**	Supported
H4c: BDATR -> BDAC -> OUT	0.205	0.068	3.023	0.003***	Supported

*****p<0.01; **p<0.05; *p<0.1**

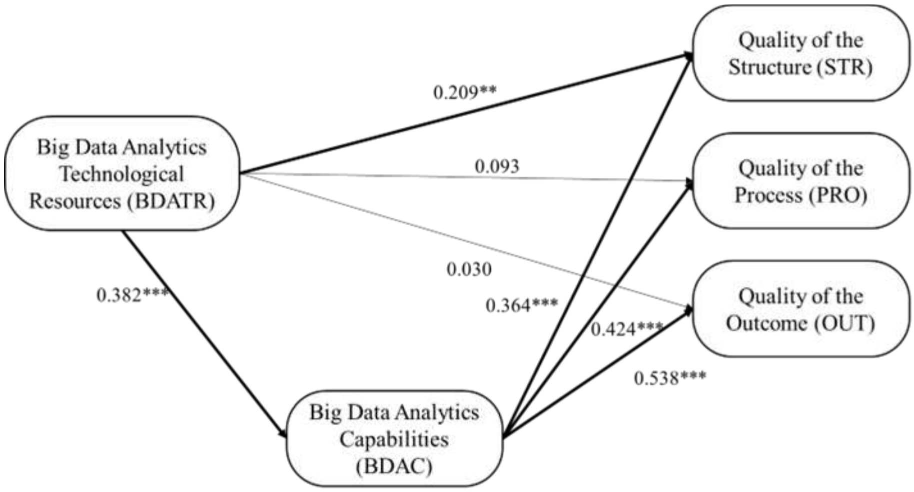

Figure 7 The research model results

3.5. DISCUSSION

In this study, the author investigated how BDA resources and capabilities influence the quality of healthcare services' domain (i.e., structure, process, and outcome) in the context of healthcare organizations from the perspective of RBV theory. Moreover, the mediating effect of the use of BDA capabilities is proposed and investigated. The findings presented in this study have significant implications for scholars as well as for practitioners' perspectives. From an academic perspective, in line with the RBV theory, the findings show that the resources represent only the "starting point" and an organization needs to develop the capabilities to effectively deploy these resources (Makadok, 2001). Moreover, to the best of the author's knowledge, this study is the first to empirically demonstrate the actual impact of BDA capabilities on the quality of service, with its different domains, in healthcare organizations. Also, the study advances the existing knowledge by empirically demonstrating what has been mostly theoretically formulated so far, namely the role of BDA technological resources in strengthening a healthcare organization's quality of services. Infrastructure, technologies, software, data and other basic resources are considered crucial pillars for success in the context of BDA deployments (Gupta and George, 2016). The current study found that the presence of BDA technological resources affects positively and significantly only the quality of structure (H1a). Thus, the presence of BDA resources impacts positively only the managerial characteristics of the healthcare quality services' domains, such as the availability of adequate equipment, facilities and staff dimension, while the positive effect of BDA technological resources on the quality of process (H1b) and outcome (H1c) was not found to be significant. The effect of BDA technological resources on the quality of the structure is quite intuitive since the quality of the structure is determined by the presence of facilities, equipment and human resources whose effective use can be monitored by BDA technological resources. Hence, their presence may ensure higher quality. Contrarily, the process and outcome quality are determined by abstract factors (e.g., relationship with patients, and willingness to follow the guidelines). Thus, an effective application of BDA technological resources requires an effort to analyze and interpret data beyond their mere presence. These results point out that the presence of BDA technological resources does not ensure the healthcare services' quality alone, coherently with the RBV theory. This finding suggests the need to develop capabilities to make resources have an impact on the organization's performance (Makadok, 2001; Mikalef et al., 2018). In contrast to the findings for BDA technological resources, the BDA capabilities affect positively and significantly all the domains of healthcare service quality (H2a, H2b, H2c). This result is perfectly coherent with the academic literature about the RBV theory, pointing out that the capabilities need to be developed to make investments in technological resources relevant to the organization's performance. In this context, capabilities for effectively storing, analyzing, and exploiting data to turn data into insights are relevant for ensuring the quality of service leading to optimal healthcare organization performance (Mikalef et al., 2018; Wang and Hajli, 2017; Yu et al., 2021). Finally, I tested whether the BDA capabilities could be the underlying mechanism that explains the positive effect of the BDA technological resources on the domains of healthcare service quality. The findings show that the BDA capabilities mediate these relationships but in two different ways. I found that BDA capabilities are one of the explaining mechanisms of the positive relationship between BDA technological resources and quality of structure, while the presence of BDA capabilities is imperative to improve the quality of process and outcome through BDA technological resources. The findings present also valuable contributions to healthcare decision-makers and practitioners interested in the use of BDA in their organizations. This study clarifies the impact of BDA capabilities in enabling the positive effect of BDA technological resources on healthcare service quality domains. This finding suggests healthcare managers and policymakers focus on BDA capabilities development rather than focusing exclusively on the acquisition of BDA technological resources, hence guiding their investment decisions. Considering this perspective, this study could encourage the concurrent investment in BDA technologies and capabilities to effectively improve the performance of healthcare organizations, in terms of quality of services. Besides, the BDA capabilities also need technical skills as well as technological resources to be properly developed (Grant, 1991; Gupta and George, 2016; Mikalef and Krogstie, 2020). Therefore, the acquisition of BDA technical skills or skilled human resources is now a necessity for healthcare organizations in this technology disruption and digital transformation era (World Economic Forum, 2020). Based on these findings, healthcare managers and policymakers should invest in BDA technological resources alongside BDA technical skills acquisition to develop BDA capabilities in order to have an impact on the quality of healthcare services.

3.6. CONCLUSIONS

Big data analytics is revolutionizing the healthcare industry and their potential is still not entirely exploited. The amount of investments in BDA technological resources is increasingly growing. These investments aim to improve the quality of healthcare services enabling the support of the decision-making processes of healthcare professionals (e.g., healthcare managers, physicians, and policymakers). However, the effectiveness of BDA seems not guaranteed by the acquisition of BDA technological resources (Gupta and George, 2016; Marr, 2015; Syal, 2013). This study aimed to examine the relationship between BDA technological resources and capabilities with the quality of healthcare services domains (i.e., structure, process, and outcome), and if the presence of BDA capabilities in healthcare organizations can explain the effect of the BDA technological resources on the quality of healthcare services' domains. This study empirically proved that the mere presence of technologies does not lead to an improvement in the quality performance of healthcare services, coherently with the RBV theory. Moreover, the findings show that the presence of BDA capabilities explains the effectiveness of technological resources on the performance of healthcare organizations. This result highlights the necessity to develop BDA capabilities concurrently with investments in technological resources. The academic literature points out that one of the main factors that lead to the development of BDA capabilities is the acquisition of technical skills to properly exploit technological resources. Based on the findings of this study, the mere acquisition of technological resources is not enough for performance improvement, consequently, the acquisition of skilled human resources or the development of skills in this era of digital disruption could be relevant to obtaining an organization's performance improvement. While providing an opportunity to further explore the proposed model, this study is not without limitations. Firstly, the cross-sectional rather than longitudinal nature of the data collection means that the generalizability of the results is subject to limitations. Secondly, this study focuses on the opinions of Italian healthcare professionals, so it might be interesting to examine the proposed model in other countries to identify similarities and differences. Finally, as I did not examine other resources that could have an impact on the quality domains of healthcare services such as the organization's culture, there is room for further investigation on the relationship between BDA resources and capabilities with healthcare quality services domains.

3.7. APPENDIX A

Table 7 Constructs and items

Construct	Item	Indicator	Adapted from
Big Data Analytics Technological Resources (BDATR)	Data are available in the form of descriptive statistics and reports	BDATR1	Benzidia et al., 2021; Dubey et al., 2019; Gupta & George, 2016
	I have easy access to descriptive statistics and reports (e.g., through PC or smartphone)	BDATR2	
	Our information systems are up to date for data collection, storage and management	BDATR3	
	The instrumentation to visualize and use the data is up to date	BDATR4	
Big Data Analytics Capabilities (BDAC)	We use data to support decision making	BDAC1	Ashaari et al., 2021; Gupta & George, 2016; Mikalef et al., 2018
	We believe that collecting, analyzing, and using data is important to our organization	BDAC2	
	We are open to new ideas and approaches based on data as decision support	BDAC3	
	The use of data enables better performance of daily activities	BDAC4	
Quality of the Structure (Str)	There are adequate environments for patient care (inpatient rooms, emergency room environments, operating rooms)	STR1	Donabedian, 1988; Wu and Hsieh, 2015
	Appropriate medical equipment and devices are available for patient care (dressing kits, medicines, instrumentation for invasive and non-invasive operations)	STR2	
	An adequate number of staff is employed for patients care	STR3	
Quality of the Process (Pro)	Physicians follow guidelines for making the diagnosis	PRO1	Donabedian, 1988; Santry et al., 2020
	Physicians follow guidelines for treatment selection	PRO2	
	Prevention activities are carried out to protect the health and safety of the community and patients (e.g., from infectious risks or unhealthy lifestyles)	PRO3	
	Physicians perform patient monitoring activities following an intervention or prescription of therapy	PRO4	
	Physicians discuss the pros and cons with patients for treatment choice	PRO5	Donabedian, 1988; Wu and Hsieh, 2015
	Physicians are willing to consult and discuss with other physicians before making decisions	PRO6	
Quality of the Outcome (Out)	The activities carried out by my healthcare organization improve the patient's physical well-being and chances of survival	OUT1	Donabedian, 1988; Wu and Hsieh, 2015
	The activities carried out by my healthcare organization improve the patient's emotional well-being and quality of life	OUT2	
	The activities carried out by my healthcare organization make it possible to improve patient satisfaction with their living conditions	OUT3	

Table 8 Loadings, internal consistency and convergent validity

Construct	Items	Loadings	Composite Reliability (CR)	Cronbach's alpha	Average Variance Extracted (AVE)
Big Data Analytics Technological Resources (BDATR)	BDATR1	0,862	0.875	0.874	0.725
	BDATR2	0,874			
	BDATR3	0,830			
	BDATR4	0,839			
Big Data Analytics Capabilities (BDAC)	BDAC1	0,713	0.887	0.878	0.739
	BDAC2	0,915			
	BDAC3	0,920			
	BDAC4	0,875			
Quality of Structure (STR)	STR1	0,904	0.906	0.848	0.765
	STR2	0,932			
	STR3	0,781			
Quality of Process (PRO)	PRO1	0,829	0.905	0.902	0.670
	PRO2	0,853			
	PRO3	0,784			

	PRO4	0,777			
	PRO5	0,815			
	PRO6	0,851			
Quality of Outcome (OUT)	OUT1	0,895	0.912	0.891	0.819
	OUT2	0,897			

Table 9 Discriminant Validity

Construct	**BDATR**	**BDAC**	**STR**	**PRO**	**OUT**
Fornell-Larcker criterion					
Big Data Analytics Technological Resources (BDATR)	0.852				
Big Data Analytics Capabilities (BDAC)	0.382	0.860			
Quality of Structure (STR)	0.348	0.443	0.875		
Quality of Process (PRO)	0.255	0.459	0.618	0.819	
Quality of Outcome (OUT)	0.235	0.550	0.476	0.589	0.905
Heterotrait-monotrait ratio (HTMT)					
Big Data Analytics Technological Resources (BDATR)	-				
Big Data Analytics Capabilities (BDAC)	0.440	-			
Quality of Structure (STR)	0.397	0.490	-		
Quality of Process (PRO)	0.281	0.510	0.699	-	
Quality of Outcome (OUT)	0.263	0.605	0.542	0.650	-

4. THE ROLE OF BIG DATA ANALYTICS IN IMPROVING THE QUALITY OF HEALTHCARE SERVICES: THE MEDIATING ROLE OF RISK MANAGEMENT

4.1. ABSTRACT

Digital transformation is revolutionizing many industries and increasingly more organizations are adopting digital technologies in their processes. The adoption and integration of digital technologies are boosting the production of data that can be collected, analyzed, and exploited for decision-making through big data analytics. Data can play a significant role in healthcare since it is a complex system where every decision is affected by risk and uncertainty. This study investigates how big data analytics (BDA) enables the use of risk management (RM) practices, resulting in improving the quality of healthcare services (QoHS). It also analyses the indirect effect of BDA on the QoHS through the use of RM practices. To this aim, 204 responses from healthcare professionals were collected and investigated via the lens of Organizational Information Processing Theory using PLS-SEM methodology. The results revealed that BDA contributed positively and significantly to the use of RM practices, while only the use of risk identification and monitoring practices impacted healthcare service quality significantly and mediated the relationship between BDA and QoHS. The results provide managerial insights about the use of data to support the decision-making process in healthcare showing that decision-makers should focus their effort on integrating data-driven tools and capabilities with RM practices to reduce the uncertainty surrounding this environment and ensure a higher quality of healthcare services.

4.2. INTRODUCTION

Digital transformation can be defined as "a fundamental change process enabled by digital technologies that aim to bring radical improvement and innovation to an entity (e.g., an organization,
a business network, an industry, or society) to create value for its stakeholders by strategically leveraging its key resources and capabilities" (Gong and Ribiere, 2021). Many industries are experiencing a renaissance as a result of digital transformation (Kraus et al., 2021a). The academic literature about digital transformation pointed out that the adoption of technologies such as IoT, Artificial Intelligence and Blockchain is leading to several benefits for organizations, including increased agility and adaptability, innovation in business models, and improved efficiency and productivity (Hanelt et al., 2021; Hess et al., 2016; Troise et al., 2022). In this context, the healthcare industry is considered one of the most beneficiaries of digital transformation (Kraus et al., 2021b). The Internet of Things (IoT), big data, and cloud computing are considered the most widely used and impactful digital technologies in healthcare (Aceto et al., 2020). These technologies have the potential to assist physicians and policymakers in addressing large-scale healthcare issues such as population ageing and disease spread (Dal Mas et al., 2023; Kraus et al., 2021b). For instance, they are revolutionizing how healthcare providers deliver care, ranging from remote patient monitoring to personalized medicine (Cannavacciuolo et al., 2022; Secundo et al., 2021). They also can lead to an improvement of hospital management practices, the efficiency of services, and cost reduction, to increase the engagement of patients and in general to enhance patient outcomes (Bardhan and Thouin, 2013; Dal Mas et al., 2023; Marques and Ferreira, 2020). As in other industries, the implementation of these technologies increases the availability and usability of data, which has raised the importance of big data analytics (BDA) (Chen et al., 2012; Hanelt et al., 2021). BDA refers to the technologies, processes and methodologies that analyze large amounts of data to assist an organization in taking more informed critical decisions (Wang et al., 2018). BDA support

healthcare professionals by providing knowledge and insights to cope with the lack of information, which is one of the main drivers of risk and uncertainty in healthcare (Han et al., 2019). Indeed, risk and uncertain conditions characterize this industry since it is a complex system, in which decisions are influenced by many variables, such as the complexity of the patient's disease and the involvement of various actors in the decision-making process, e.g., physicians, families and patients. Therefore, in order to consider the complexity of the decision-making process in healthcare, new technologies based on the exploitation of data are being used to take into account many variables, environments and interactions between them (Chen et al., 2012). These can be used to achieve several objectives, such as the development of a data-driven model for optimal drug administration (Tsoukalas et al., 2015) or for supporting the treatment selection (Basile et al., 2023). Thus, in an environment of high complexity, such as the healthcare one, the role of BDA in supporting decision-making becomes increasingly interesting to cope with risk and uncertainty (Provost and Fawcett, 2013). Nevertheless, one must consider that the issue of uncertainty in healthcare decision-making does not arise with digital transformation but is an intrinsic characteristic of this industry that has historically been addressed with other managerial approaches. In this regard, risk management (RM) is one of the most established. RM aims to reduce risk and uncertainty in decision outcomes, ultimately leading to an improvement of the QoHS, through practices designed to identify and prevent adverse events, i.e., an unexpected event related to the care process that could expose a patient, physician, nurse or healthcare facility to the risk of an unintentional and undesirable damage (Odone et al., 2019; Schwendimann et al., 2018; Tartaglia et al., 2012). Despite the growing number of studies in the literature focusing on the use of BDA in healthcare (Galetsi et al., 2019; Malik et al., 2018) and the more established topic of the use of RM practices (Cagliano et al., 2011) to support decision-making under conditions of risk and uncertainty, to the best of the author's knowledge, no empirical study has examined the actual effect of BDA on the use of RM practices, resulting in improved QoHS, and whether the use of RM practices may foster the role of BDA to improve the QoHS. In order to examine these relationships, I developed a research model grounded on the Organizational Information Processing Theory (OIPT) (Yu et al., 2021). OIPT suggests that organizations need to collect, analyze, and use information and knowledge efficiently, mostly when executing activities and tasks with extensive levels of risk and uncertainty (Srinivasan and Swink, 2018). In this context, BDA might be a relevant instrument to obtain information and knowledge to cope with risk and uncertainty and finally to impact the QoHS. Therefore, grounded on OIPT, this study contributes to understanding the potential benefits of digital transformation in healthcare. In particular, I investigate the effect of big data analytics on the use of risk management practices and the quality of healthcare services, and on the indirect effect of big data analytics on the quality of healthcare services through the use of risk management practices, from the perspective of healthcare professionals. Coherently with other studies (Benzidia et al., 2021), this study extends the classical model of OIPT considering BDA as an innovative technology that improves the decision-making processes in healthcare organizations leading to data-driven decision-making.

Consequently, this study seeks to answer the following research question:

- How does the use of big data analytics impact the quality of healthcare services, and do risk management practices enable better use of big data analytics to inform decisions in achieving optimal quality of healthcare services?

This paper is organized as follows: section 2 describes the theoretical background. Section 3 presents the research model and the hypothesis leading this study. Section 4 details the data sources, data analysis and research methodology. Section 5 describes the empirical results, and section 6 discusses the results before concluding with limitations and proposing future research directions.

4.3. THEORETICAL BACKGROUND

4.3.1. Digital transformation and healthcare

Existing literature indicates that digital transformation is revolutionizing organizations' activities and processes in many industries (Hanelt et al., 2021; Kraus et al., 2021b). The benefits of Digital transformation have been discussed in academic literature among others for business model innovation, customer relationship management and healthcare management (Gaglio et al., 2022; Hanelt et al., 2021). Moreover, these studies investigate the role of digital transformation from both the organizational transformation and the technological impact perspective. The healthcare industry is one of the most beneficiaries of digital transformation, as proofed by the increase in the number of publications about this topic, such that the literature considers the concepts of digital health and digital transformation to be overlapping (Baudier et al., 2022; Dal Mas et al., 2023; Kraus et al., 2021b; Massaro, 2021). The current discussion of digital transformation in healthcare began with an examination of the adoption of information and communication technologies (ICT) (Kraus et al., 2021b). However, it has since expanded to include the use of new digital technologies such as artificial intelligence, the internet of things, blockchain and other emerging technologies to improve the performance of healthcare organizations in terms of patient engagement, patient outcomes, streamline operations, and enhance the overall healthcare experience (Biancone et al., 2021; Drago et al., 2021; Massaro, 2021). The potential impact of these technologies on healthcare is significant and continues to be a topic of exploration and innovation (Dal Mas et al., 2023; Marques and Ferreira, 2020). One of the most discussed opportunities determined by the adoption and use of digital technologies is the generation of a huge amount of data (Chen et al., 2020; Hanelt et al., 2021). Currently, these data can be exploited through big data analytics in order to enable data-driven decision-making, i.e., a decision-making process in which the uncertainty due to the lack of evidence is reduced by the information extracted from available data (Malik et al., 2018; Wang et al., 2018; Weerasinghe et al., 2022). BDA enables the collecting, handling and merging of huge amounts of various types of data obtained from different sources (McAfee et al., 2012; Provost and Fawcett, 2013) and using several analysis techniques to deal with the huge amount of available data to produce descriptive, informative, and prescriptive results (Hagerty, 2017; Provost and Fawcett, 2013). BDA gained acceptance because it supports decision-makers in making more informed decisions based on data rather than human judgment or intuition (Brynjolfsson et al., 2011). The recent deployment of technologies to collect big data and use data analytics seems to be a turning point in supporting healthcare decision-making (Basile et al., 2023; Malik et al., 2018; Simsek et al., 2021), as witnessed in the scientific literature, where the topic of using BDA in healthcare to support healthcare decision-making is increasingly growing (Islam et al., 2018; Salazar-Reyna et al., 2020). Big data can come in different formats, for example, images or X-rays, structured datasets, and medical records, and to eventually get data analytics there are several algorithms and techniques to extract meaningful information from big data, that could lead the improvements in the QoHS in different domains of healthcare (Galetsi et al., 2019; Salazar-Reyna et al., 2020). These domains can be outlined in the professional and organizational resources associated with healthcare services (e.g., material resources, human resources, and organizational activities), the activities to deliver the healthcare service (e.g., for hospital admissions), and the desired result of the care provided (e.g., patient satisfaction)(Donabedian, 1988). For example, BDA benefits the resources by providing insights and knowledge about the availability and optimal use of resources (Augustin et al., 2022; Liao et al., 2021; Simsek et al., 2021). While BDA could support the activities to deliver the healthcare service by informing decision-makers about treatment pathways (Basile et al. 2023) or the diagnosis (Kavitha et al., 2022) of breast cancer. Finally, BDA could also be used to identify patterns in disease occurrence in order to reduce patient mortality and morbidity (O'Grady et al., 2021; Tao et al., 2021). Although the literature on the use of big data analytics to support healthcare decision-making is growing, seems more focused on finding technological improvements and new areas of application rather than testing their effectiveness in improving the quality of healthcare services.

4.3.2. Risk Management Practices in Healthcare

According to the International Standard Organization (ISO), risk is "the effect of uncertainty on objectives", i.e. a positive or negative deviation from what is expected; while risk management is the "systematic application of management policies, procedures and practices to the tasks of communication, consultation, establishing the context, identifying, analyzing, evaluating, treating, monitoring and reviewing risk" (ISO, 2018). The concept of risk is related to the outcome of a decision, often referring to possible adverse events (Cagliano et al., 2011). These decisions can be more or less complex depending on the context in which they are made, and the healthcare industry is considered one of the most complex industries in which to make decisions (Han et al., 2019). The complexity of decision-making processes in the healthcare industry lies in the great uncertainty faced by decision-makers, due to the multitude of diseases, actionable treatments and actors involved in decisions (Carroll and McSherry, 2021; Han et al., 2011). Therefore, given that risk and uncertainty are part of the healthcare decision-making process, the use of techniques and tools to manage it is of paramount importance considering that in healthcare organizations poor risk management can lead to adverse events, up to the loss of the patient's life (Cohen et al., 2009; La Russa and Ferracuti, 2022). In the literature, it is possible to find several works dealing with the topic of risk management in healthcare. For example, Sardi et al. (2020) proposed a risk assessment tool for analyzing incidents in the maternal and child pathway. Cagliano et al. (2011) defined a systemic methodology to study the risks that impact not only directly but also indirectly on patients, thus enhancing the quality of healthcare services. Tricarico et al. (2016) proposed an assessment tool to measure the performance of healthcare organizations in risk management and to promote improvements over time. Festa et al. (2021) contributed to the literature by developing a case study on a healthcare organization that adopted a tool to manage drug logistics risks.

Hence, according to the literature, the objective of risk management in healthcare is to avoid deviations from the correct and effective delivery of healthcare services, which eventually might lead to deviations from the optimal QoHS. The RM practices would be relevant not only from the perspective of QoHS but also from that of healthcare costs. In fact, the use of RM practices would reduce the frequency and impact of adverse events both on the quality and costs of healthcare services (Schwendimann et al., 2018; Wang et al., 2021). In this paper, I considered the 31000 standard defined by the International Standard Organization (ISO) (ISO, 2018) to guide the development of risk management practices constructs.

4.3.3. Organizational Information Processing Theory

OIPT provides a theoretical foundation for the use of RM practices and BDA as a support for decision-making under uncertainty (Benzidia et al., 2021; Yu et al., 2021). OIPT has been grounded on the paper of Galbraith (1974). This theory states that an organization needs quality information and insight to cope with uncertainty and improve its decision-making process. In OIPT Galbraith defines uncertainty as "the difference between the amount of information required to perform the task and the amount of information already possessed by the organization" (Galbraith, 1974). The uncertainty stems from the complexity of the environment and the dynamism of various environmental variables. OIPT suggests that organizations should face complexity and uncertainty through the employment of information processing capabilities and practices that improve information quality and flow (Galbraith, 1974). Among the most complex environments in which to make decisions, there is the healthcare one (Han et al., 2019; Kuziemsky, 2016). Following Han et al. (2011), the risks and uncertainties in healthcare can arise in the processes of care, such as in diagnosis and prognosis, in the healthcare organization, such as in the activities schedule, or the patients-centered aspects, such as in the patient's psychological conditions. In these domains, many variables compete and interact with each other in the creation of possible adverse events which influence the decision-making process. This theory is used in the healthcare sector also to explain the positive effects that new information technologies have on healthcare organizations, such as BDA (Gupta et al., 2022; Yu et al., 2021). The use of BDA seems to be promising in the healthcare decision-making process by fulfilling the information gaps that lead to uncertainty (Han et al., 2019; Spiegelhalter, 2008), for instance by providing information about the optimal follow-up appointment scheduling to reduce the probability of an adverse event in chronic disease patients (Nenova and Shang, 2022). However, even though this field seems to be very promising, to the best of the author's knowledge, no empirical studies have been identified in the literature grounded on the OIPT that investigates the perspective of healthcare professionals on the use of both BDA and RM practices to improve the healthcare decision-making process, thus leading to an impact on the QoHS.

4.4. RESEARCH MODEL AND HYPOTHESES

4.4.1. Research model

Guaranteeing the quality of service is a central issue in the healthcare industry (Arah et al., 2006; Donabedian, 1988; Kim et al., 2016). However, quality is threatened by the complexity of the sector, which leads to uncertainty in decision-making processes (Han et al., 2019; Kuziemsky, 2016). Uncertainty does not allow healthcare professionals to make optimal decisions, which ultimately results in suboptimal healthcare outcomes (Mandelbaum et al., 2020; Mishel, 1988; Wray and Loo, 2015). In this paper, I suggest that BDA could influence the use of RM practices resulting in improved QoHS. The use of RM practices would indicate that healthcare professionals already use structured models to manage risk and uncertainty in the healthcare decision-making process. Therefore, BDA could facilitate the use of RM to inform healthcare decision-making resulting in improving the quality of healthcare services. Furthermore, I investigate whether the use of RM practices can foster the role of BDA in improving QoHS. The proposed research model is based on the OIPT theory which states that an organization could achieve optimal performance despite complexity and uncertainty by trying to ensure a flow of information and knowledge (Galbraith, 1974). Moreover, I used the Donabedian model to draw the construct of the QoHS, since it is the most established model in the healthcare industry to assess the quality of healthcare services (Donabedian, 1988).

4.4.2. Hypotheses Development

Effects of the use of BDA on QoHS.

In recent years several healthcare organizations have invested to improve their information technology departments by acquiring clinical and operational information systems (e.g., medical health record systems), aiming to create an infrastructure to enable the collection and exploitation of BDA (Aceto et al., 2020; Bardhan and Thouin, 2013; Nenova and Shang, 2022). Indeed, BDA can enable a healthcare organization to handle multiple data formats to provide healthcare decision-makers with information and knowledge to cope with the organization's information needs (Islam et al., 2018; Malik et al., 2018; Weerasinghe et al., 2022), seeking to have an impact on the QoHS (Donabedian, 1988). As such, BDA can be a relevant tool to cope with the complex decision-making process for healthcare professionals (Asante-Korang and Jacobs, 2016; Salazar-Reyna et al., 2020). Because of the potential benefits, I expect that the use of BDA enables a healthcare organization to improve the QoHS. Hence, I hypothesize the following:

H1. The use of BDA has a positive effect on the QoHS.

Influence of BDA on the use of RM practices.

According to the International Standard Organization (ISO), the RM process consists of different phases. The main phases are Risk Identification, Risk Assessment, Risk Treatment, and Risk Monitoring (ISO, 2018). The risk identification phase concerns the identification of the risks that may affect the objectives of an organization, while the risk assessment concerns the analysis of the risks to understand their nature and characteristics, and the evaluation of risk likelihood and impact. The risk treatment phase involves the selection and implementation of optimal strategies for addressing the risks. Risk monitoring aims to assure the quality and effectiveness of the strategies adopted. In all these phases, RM practices are used to identify and prevent circumstances that could be exposed to an adverse event. The use of BDA enables the collection of information and the creation of knowledge that can be exploited in RM practices (Dicuonzo et al., 2021), namely for identifying, analysing and selecting proper strategies to prevent and control an adverse event (Nenova and Shang, 2022; Schwendimann et al., 2018; Tartaglia et al., 2012), reducing the lack of knowledge which results in an uncertainty decrease (Han et al., 2019). Therefore, I propose the following hypothesis:

H2. BDA has a positive influence on the use of RM practices in the different phases: (H2a) Risk Identification, (H2b) Risk Analysis, (H2c) Risk Treatment, and (H2d) Risk Monitoring.

Effects of RM practices on QoHS.

The goal of RM practices in the healthcare industry is to limit the effects of adverse events that can jeopardize QoHS (Odone et al., 2019; Schwendimann et al., 2018). RM practices have been widely adopted in healthcare to guarantee that risk and uncertainty do not compromise the QoHS (La Russa and Ferracuti, 2022; Odone et al., 2019; Vincent et al., 2000). RM focuses not only on the outcome of services but also on the activities performed for the patient, such as diagnosis or prognosis, and on hospital resources, such as staff and equipment. For instance, by preventing errors and their negative effects on patient health outcomes, physician activities (e.g., diagnosis) and also on healthcare resources (e.g., staff) (La Pietra et al., 2005; Simsek et al., 2020). Based on the above arguments, I propose the following hypothesis:

H3. The use of RM practices in the different phases ((H3a) Risk Identification, (H3b) Risk Analysis, (H3c) Risk Treatment, and (H3d) Risk Monitoring) has a positive effect on QoHS.

The mediating role of RM practices

New technologies and techniques are spreading in the digital transformation era for the delivery of healthcare services (Abdel-Basset et al., 2021; Dalal and Ingle, 2019; Papa et al., 2020). These technologies and techniques, such as the BDA, have the potential to further enhance the QoHS by providing valuable support for healthcare services, providing knowledge and insights to cope with the lack of information (Aceto et al., 2020; Weerasinghe et al., 2022). The higher use of big data analytics means that healthcare organizations that seek to use structured practices for supporting healthcare professionals' decisions in a condition of uncertainty can quickly leverage their data and achieve improved QoHS (Weerasinghe et al., 2022). Healthcare organizations which use structured RM practices to support the healthcare professionals' decisions in a condition of uncertainty can be expected to deliver higher QoHS (Cagliano et al., 2011; La Russa and Ferracuti, 2022) and to be better at utilizing BDA toward the improvement of services since structured RM practices for supporting healthcare professionals' decisions in a condition of uncertainty underline a healthcare organization's capacity to use BDA to foster more informed decisions under uncertainty and improve the QoHS because the use of these practices underlines a healthcare organization's ability to use BDA to promote more informed decisions under uncertainty. As such, higher use of structured RM practices can be expected to enhance QoHS and enable better leveraging of BDA to inform decisions under uncertainty in achieving QoHS. In other words, I expect that structured RM practices for supporting the healthcare professionals' decisions in a condition of uncertainty operate as a linking pin between BDA and QoHS and convey the influence of BDA on QoHS. Hence, I draw the following hypothesis:

H4. The use of RM practices in healthcare organizations can mediate the relationship between the use of BDA and the QoHS.

Figure 7 shows the research model that leads this paper.

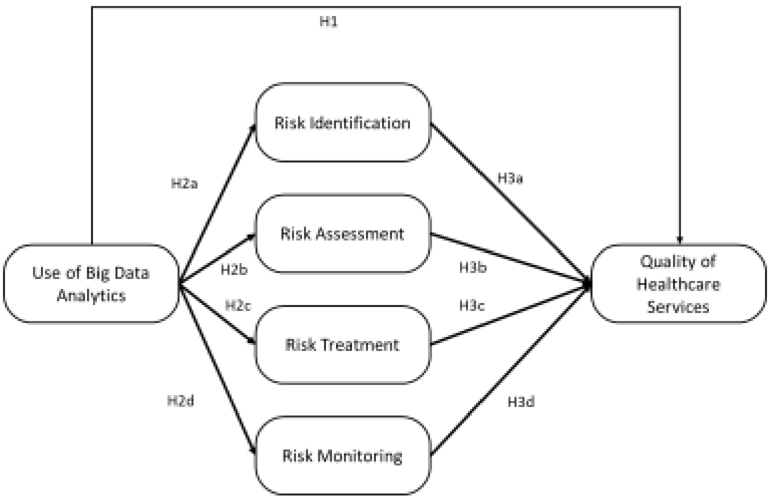

Figure 8 Research model

4.5. METHODOLOGY

4.5.1. Survey design

This study uses a survey-based approach to assess the hypotheses of the research model (figure 7). A questionnaire was designed by developing each section following the reasoning of the basic constructs of the research model, in order to gather the primary data from healthcare organizations in Italy to test the research model. Several stages were followed, and a pre-test was carried out in order to build the survey. Firstly, the items for each construct of the research model were defined based on an in-depth literature review, and a Likert scale from 1 (absolutely disagree) to 5 (absolutely agree) was used to measure the healthcare professional perspective. Secondly, to validate the items for each construct, the first version of the questionnaire was evaluated and modified through several discussion sessions with healthcare professionals and experienced scholars. In addition, the survey was assessed by 6 healthcare professionals to ensure that all the questions were clear and adequately represented the topic under investigation. After the implementation of the suggested improvements, the survey was administered via email to healthcare professionals (e.g., administrative manager, general manager, healthcare manager, etc.) with a message presenting the aim of the study. Respondents were assured that their personal information would be kept confidential. The surveys were returned via email. Table 10 shows the items and the references for each construct.

Table 10 Construct and Items

Construct	Item	Indicator	References
The use of Big Data Analytics (BDA)	Data are available from administrative sources (e.g., regional information systems), electronic medical records, or questionnaires (e.g., administered to obtain patient opinions)	BDA1	Benzidia et al., 2021; Dubey et al., 2019; Srinivasan and Swink, 2018
	We use data analysis techniques (e.g., statistical analysis, simulations, regressions)	BDA2	
	Data are available in the form of descriptive statistics and reports	BDA3	
	I have easy access to descriptive statistics and reports (e.g., through PC or smartphone)	BDA4	
	Our information systems are up to date for data collection, storage, and management	BDA5	Hooi et al., 2018; Singh and El-Kassar, 2019
	The instrumentation to visualize and use the data is up to date	BDA6	
	Databases can be interrogated to obtain additional information	BDA7	
	We use data to support decision making	BDA8	
The use of Risk Identification practices (RI)	I am aware of possible adverse events that may affect the patient care	RI1	El Baz et al., 2020
	I know the "sentinel events" that may affect the patient care	RI2	Gama et al., 2020
	We use indicators or selection criteria to identify adverse events that may affect the patient care	RI3	
	We use checklists to identify adverse events	RI4	
The use of Risk Assessment practices (RA)	We use qualitative analysis tools to assess adverse events (e.g., flowcharts, cause-and-effect diagram, brainstorming)	RA1	Gama et al., 2020
	We use quantitative analysis tools to assess adverse events (e.g., histogram, Pareto chart, control chart)	RA2	
	We assess the probability of an adverse event occurring	RA3	Gama et al. 2020; El Baz et al. 2020; Ramesh and Sarmah, 2020
	We assess the impact of the occurrence of an adverse event	RA4	
	We classify risks according to the probability and impact of the adverse event	RA5	
The use of Risk Treatment practices (RT)	We identify possible actions to prevent and control the adverse event (e.g., by making clinical recommendations)	RT1	El Baz et al. 2020; Ramesh et al. 2020
	We evaluate the effectiveness of actions to prevent and control the adverse event	RT2	
	Over the past 3 years, we have reduced the frequency of occurrence of adverse events through prevention and control actions	RT3	

	Over the past 3 years, we have reduced the impact of occurrence of adverse events through prevention and control actions	RT4	
The use of Risk Monitoring practices (RMo)	We use sentinel events to monitor situations/events that may affect the patients care	RMo1	Gama et al., 2020
	We have reduced the frequency of adverse events through risk-monitoring actions	RMo2	El Baz et al. 2020
	We have reduced the impact of adverse events through risk-monitoring actions	RMo3	Ramesh et al., 2020
Quality of Healthcare Services (QoHS)	There are adequate environments for patient care (inpatient rooms, emergency room environments, operating rooms)	QoHS1	Donabedian, 1988; Wu and Hsieh, 2015
	Appropriate medical equipment and devices are available for patient care (dressing kits, medicines, instrumentation for invasive and non-invasive operations)	QoHS2	
	Physicians follow guidelines for making the diagnosis	QoHS3	Donabedian, 1988; Santry et al., 2020
	Physicians follow guidelines for treatment selection	QoHS4	
	Prevention activities are carried out to protect the health and safety of the community and patients (e.g., from infectious risks or unhealthy lifestyles)	QoHS5	
	Physicians perform patient monitoring activities following an intervention or prescription of therapy	QoHS6	
	Physicians discuss the pros and cons with patients for treatment choice	QoHS7	Donabedian, 1988; Wu and Hsieh, 2015
	Physicians are willing to consult and discuss with other physicians before making decisions	QoHS8	
	The activities carried out by my healthcare organization improves the patient's physical well-being and chances of survival	QoHS9	
	The activities carried out by my healthcare organization improves the patient's emotional well-being and quality of life	QoHS10	

4.5.2. Sample and data collection

The selected sample is composed of healthcare professionals from Italian healthcare organizations. A sample of 2,474 healthcare professionals were selected to be representative of the Italian national healthcare system (NHS). In particular, we selected the five most relevant hospitals for each Italian region based on the number of operational units and inpatient hospital beds. To build the sample we relied on the email contacts provided by the selected Healthcare Organizations' websites. To test the hypotheses of the proposed research model, healthcare professionals (e.g., physicians, medical directors, and general managers) were selected because they were more likely to objectively assess the current effect of the use of BDA and RM practices on the QoHS. To build the sample I relied on the email contacts provided by the selected Healthcare Organizations' websites. I focused on the data collection from Italian organizations since after the COVID-19 pandemic, several researchers and public organizations observed the relevance of the use of BDA in supporting healthcare decisions in the Italian context (Lv et al., 2021; Perrella et al., 2022; Villanustre et al., 2021), encouraging the adoption and spread of the use of data in healthcare. The data were collected from October to December 2022.

4.6. RESULTS

4.6.1. Sample characteristics

I received 204 answers from the 2474 healthcare professionals reached, indicating an 8.2% response rate. According to Dillman (2000), a response rate ranging from 6% to 16% is considered acceptable and the collected responses exceed the sufficient range for partial least squares structural equation modelling (PLS-SEM) analysis (Chin, 2010). I did not include the non-complete answers, including in the final sample 173 answers.

Furthermore, following the recommendations of Cohen (1988) and Hair et al. (2013), the recommended sample size for the PLS-SEM analysis with a minimum R2 value of 0.10 and a statistical power of 80% for the model investigated in this paper is 147. Therefore, the study’s sample size (i.e., 173) is well above the sample size recommendation. Table 11 shows the study's sample characteristics, which were based on responses from 173 participants. According to the results, 99 of respondents were male, and the majority (88%) of respondents have more than 10 years of working experience in healthcare. According to the data about the healthcare professional's role in the healthcare organization, 51% of respondents hold the position of the *operational unit manager*, implying that the majority of respondents have a role of responsibility in their organization.

Table 11 Sample characteristics

Demographic characteristics	Number of respondents	Percentage of respondents
Gender		

Female	71	41%
Male	99	57%
Non specifies	3	2%
Experience		
< 5 years	5	3%
Between 5 and 10 years	15	9%
>10 years	153	88%
Role		
Healthcare manager	7	4%
Administrative manager	2	1%
Department manager	4	2%
Operational Unit Manager	88	51%
Medical Executive	63	37%
Physician	4	2%
Nursing coordinator	5	3%

4.6.2. Non-response bias and common method bias

To ensure the data's validity, I conducted a non-response bias test. Following Werner et al., (2007), I investigated the differences between early and late respondents according to the receipt date of the questionnaire (respectively, N = 83 and N = 90) and after applying the t-test to the responses of the two sub-samples I discovered that there was no significant statistical difference ($p > 0.05$). As a result, I concluded that non-response bias was not an issue in this study.

In applied statistics, the common method bias (CMB) is defined as the bias caused by systematic error variance shared by variables assessed or collected with the same source or technique (i.e., the survey). In the presence of CMB, the variance is a result of the measuring process rather than the structures it is believed the constructs of the research model reflect. The issue of CMB is common for all research projects that employ a survey-based tool to acquire the data (Podsakoff et al., 2003; Podsakoff and Organ, 1986). Following the review of Tehseen et al. (2017), there are two main categories of remedies for dealing with CMB: procedural remedies and statistical remedies. The procedural remedies must be used in the "survey design" phase to reduce the likelihood that CMB occurs. In this research, as procedural remedies suggested by Podsakoff et al., 2003, I separated the sections for each construct in the survey, protected the privacy of the respondents and pre-tested the survey to avoid ambiguity in the constructs' items.

While concerning the statistical remedies, I applied the most used tests for CMB coherently with the existing literature: Harman's single-factor test and Kock's collinearity test. In Harman's single-factor test, the key components were subjected to an exploratory factor analysis in which all indicators were clustered into a single dimension. The Harman test revealed that no one factor explained all of the item variations and that the first factor did not account for the majority of the variance (37.28%). Thus, CMB did not appear to be a concern according to the accepted parameters for Harman's single-factor test. Finally, Using Kock's collinearity test, I expanded the prior tests with one for pathological collinearity, as an indication of CMB. Pathological collinearity is suggested by variance inflation factors (VIF) greater than 3.3, indicating that the model might be loaded with CMB according to Kock and Lynn (2012). Moreover, in the literature, VIF values are also considered acceptable if less than 5 (Ko et al., 2021). Almost all VIFs in this work are below 3.3 and all are below the threshold of 5. Table 12 shows the VIF for each pair of constructs. Based on these findings, I concluded that CMB had no major impact on this study.

Table 12 Common Method Bias: collinearity test

Construct	BDA	RI	RA	RT	RMo	QoHS
The use of Big Data Analytics (BDA)		-	-	-	-	-
Risk Identification (RI)	1.000	-	-	-	-	-
Risk Assessment (RA)	1.000	-	-	-	-	-
Risk Treatment (RT)	1.000	-	-	-	-	-
Risk Monitoring (RMo)	1.000	-	-	-	-	-
Quality of Healthcare Services (QoHS)	1.396	2.266	2.161	3.544	2.982	-

4.6.3. Data analysis

To test the hypotheses about the relationships between the constructs of the research model (Figure 7) and finally answer the research questions, this study employed the Partial Least Square Structural Equation Modelling (PLS-SEM) method (Hair et al., 2019), using the software SmartPLS (v. 4.0.8.4). This methodology has been selected since it is more suitable for small samples (Hair et al., 2013) and enables the estimation of complex models with a large number of constructs, indicator variables, and structural paths without imposing any distributional assumptions on the data (Hair et al., 2019). The methodology consists of two stages: the measurement model assessment and the structural model assessment. The first stage is devoted to examining and assessing the relationship between the latent variables (or constructs) and their measures (or items), while the second stage is focused on the relationship between the latent variables.

The Measurement Model. In this stage, the measurement model was assessed on the reliability of the items, the internal consistency and converging validity among the constructs and their items, and the discriminant validity among the constructs. Table 13 shows the summary of the parameters used to test the measurement model. The reliability of the items was proven since all the loadings were greater than 0.5 and almost all of them were greater than 0.708 (Hair et al. 2013). The internal consistency was established by checking both Cronbach's alpha and the composite reliability since they were all above the lower limit of 0.60 (Hair Jr et al., 2017). To check the discriminant validity, the author used the Fornell Larcker criterion and the heterotrait-monotrait ratio (HTMT) approach (Henseler et al., 2015). Moreover, as shown in Table 14 the average extracted variance (AVE) between the latent variable and its indicators was more than the variances (squared correlation) of each variable with the other latent variables, confirming the discriminant validity (Fornell and Larcker, 1981). Table 14 shows also that the HTMT ratio was found to be always less than 0.9 verifying the discriminant validity among the constructs.

Table 13 Measurement Model Summary.

Construct	Items	Loadings	Composite Reliability (CR)	Cronbach's alpha	Average Variance Extracted (AVE)
The use of Big Data Analytics	BDA1	0.697	0.888	0.887	0.560
	BDA2	0.708			
	BDA3	0.785			
	BDA4	0.781			
	BDA5	0.785			
	BDA6	0.786			
	BDA7	0.697			
	BDA8	0.739			
Risk Identification	RI1	0.697	0.789	0.763	0.573
	RI2	0.736			

	RI3	0.823			
	RI4	0.765			
Risk Assessment	RA1	0.820	0.911	0.908	0.732
	RA2	0.820			
	RA3	0.867			
	RA4	0.870			
	RA5	0.900			
Risk Treatment	RT1	0.870	0.904	0.895	0.758
	RT2	0.857			
	RT3	0.870			
	RT4	0.884			
Risk Monitoring	RMo1	0.775	0.905	0.882	0.815
	RMo2	0.962			
	RMo3	0.959			
Quality of Healthcare Services	QoHS1	0.674	0.907	0.902	0.533
	QoHS2	0.701			
	QoHS3	0.801			
	QoHS4	0.811			
	QoHS5	0.769			
	QoHS6	0.750			
	QoHS7	0.745			
	QoHS8	0.746			
	QoHS9	0.635			
	QoHS10	0.648			

Table 14 Discriminant Validity

Construct	BDA	RI	RA	RT	RMo	QoHS
Fornell-Larcker criterion						
The use of Big Data Analytics (BDA)	0.748					
Risk Identification (RI)	0.447	0.757				
Risk Assessment (RA)	0.489	0.635	0.856			
Risk Treatment (RT)	0.423	0.697	0.670	0.870		
Risk Monitoring (RMo)	0.440	0.649	0.606	0.800	0.903	
Quality of Healthcare Services (QoHS)	0.435	0.506	0.402	0.504	0.522	0.730
Heterotrait-monotrait ratio (HTMT)						
The use of Big Data Analytics (BDA)	-					
Risk Identification (RI)	0.481	-				
Risk Assessment (RA)	0.535	0.708	-			
Risk Treatment (RT)	0.458	0.785	0.731	-		
Risk Monitoring (RMo)	0.493	0.752	0.674	0.896	-	
Quality of Healthcare Services (QoHS)	0.469	0.576	0.428	0.544	0.571	-

The structural model. Once I had corroborated the goodness of the measurement model, I assessed the model's hypotheses by using the bootstrap resampling method to determine the statistical significance of the results. The first analysis was about the R^2 results of the model. Accordingly, with Cohen (1988) and Falk and Miller (1992), the findings showed that the model can explain an adequate portion of the variance of the constructs (R^2 for QoHS = 0.359, R^2 for RI = 0.200, R2 for RA= 0.239, R^2 for RT= 0.179 and R^2 for RMo = 0.194). Turning now to the results of the structural model analysis, figure 8 shows the relationship among the variables of the research model and Table 15 summarizes the significance of the structural relationship and the path coefficients. What stands out in Table 15 is that most of the hypotheses were supported. The results show a positive and significant direct relationship between BDA and the QoHS (H1) and between BDA and the use of RM practices (H2a, H2b, H2c, H2d). Such findings confirm that big data analytics contributed positively and significantly to the use of all the RM practices, while only the use of risk identification and monitoring practices impacts healthcare service quality substantially. Further, the connection between big data analytics and the quality of healthcare services has been influenced by risk identification and risk monitoring. In fact, the results reveal that only the risk identification and risk monitoring practices have a positive and statistically significant impact on the QoHS, respectively the hypotheses H3a and H3d. Conversely, the hypotheses on the positive impact of risk assessment (H3b) and treatment (H3c) practices on the quality of healthcare services were rejected. Finally, concerning the mediation hypotheses (H4) the results show that the risk assessment and risk treatment practices do not mediate the relationship between BDA and QoHS. Therefore, hypotheses H4b and H4c were rejected. On the contrary, the findings reveal that risk identification and risk monitoring practices mediate the relationship between BDA and the QoHS, ultimately corroborating hypotheses H4a and H4d.

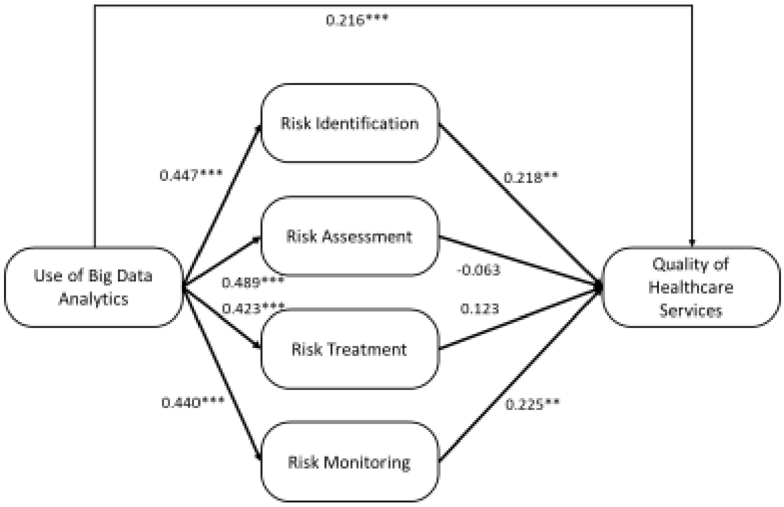

Figure 9 Research model with coefficient estimates

Table 15 Structural model summary.

Hypothesis	Path coefficients	Standard deviation	T values	P values	Result
DIRECT EFFECTS					
H1: BDA -> QoHS	0.216	0.087	2.486	0.006***	Supported
H2a: BDA -> RI	0.447	0.060	7.419	0.000***	Supported
H2b: BDA -> RA	0.489	0.065	7.511	0.000***	Supported
H2c: BDA -> RT	0.423	0.070	6.009	0.000***	Supported
H2d: BDA -> RMo	0.440	0.065	6.774	0.000***	Supported
H3a: RI -> QoHS	0.218	0.111	1.970	0.024**	Supported
H3b: RA -> QoHS	-0.063	0.098	0.642	0.260	Not supported
H3c: RT -> QoHS	0.123	0.150	0.821	0.206	Not supported
H3d: RMo -> QoHS	0.225	0.118	1.902	0.029**	Supported
INDIRECT EFFECTS					
H4a: BDA -> RI -> QoHS	0.097	0.054	1.802	0.036**	Supported
H4b: BDA -> RA -> QoHS	-0.031	0.050	0.622	0.267	Not supported
H4c: BDA -> RT -> QoHS	0.052	0.064	0.810	0.209	Not supported
H4d: BDA -> RMo -> QoHS	0.099	0.056	1.783	0.037**	Supported

***p<0.01; **p<0.05; *p<0.1

4.7. DISCUSSION

This study empirically investigates how big data analytics in the context of healthcare organizations influence the use of risk management practices and the quality of healthcare services from the perspective of OIPT. Furthermore, based on a survey administered to healthcare professionals, the mediating effect of the use of risk management practices is proposed and investigated. The findings of this study present valuable contributions to theory and healthcare decision-makers who from one side could encourage the use of BDA to improve the daily activities of healthcare organizations and on the other foster the use of BDA through the existing RM practices.

Theoretical Implications

First, the results of this study show a significant positive relationship between the use of BDA and the QoHS (H1). In the context of healthcare organizations, the use of BDA to support the decision-making process rises and thrives rapidly and in a significant way. Although researchers have discussed the use of BDA in healthcare organizations to support their organizational and operational activities (Wang et al., 2018; Weerasinghe et al., 2022), the actual effect of BDA on the QoHS seemed to be an under-investigated theme. Thus, drawing on the OIPT this study empirically demonstrates that BDA are valuable tools to obtain quality information to cope with the complexity and uncertainty that affect the outcome of healthcare services.

Second, the findings show that the use of BDA has a positive effect on the use of risk management practices (H2). The results are coherent with OIPT theory and previous studies that discussed the use of big data analytics for supporting internal processes in an uncertain environment (Bahri et al., 2019; Wang et al., 2018). This study provides a novel contribution to the positive impact of the use of BDA on the practices devoted to coping with risk and uncertainty in healthcare organizations, i.e., risk management practices. More specifically, the findings show a positive and significant impact on all the risk management practices: risk identification (H2a), risk assessment (H2b), risk treatment (H2c) and risk monitoring (H2d). Based on these findings, BDA has a positive impact on the use of RM practices, which confirms the need for the integration of BDA into RM practices, as stated in the academic literature, in order to fully exploit their potential (Dicuonzo et al., 2021). For these reasons, researchers should focus on the transformation of healthcare operations, and in particular on the integration of BDA into RM practices with the aim of providing useful information to users of these practices in order to improve the quality of services.

Third, this study suggests that the use of RM practices has a positive effect on the QoHS (H3). In particular, the risk identification (H3a) and the risk monitoring (H3d) practices show a positive and significant influence on the QoHS, confirming that the RM practices have a primary role in ensuring the QoHS in healthcare organizations, coherently with academic literature. However, the effect of risk assessment (H3b) and treatment (H3c) procedures on the QoHS was not demonstrated. This finding can be explained by the level of use of risk management practices in healthcare organizations. The responses from healthcare professionals indicate that these procedures are carried out, but less frequently than risk identification and monitoring procedures. Results showed that 66% of healthcare professionals do not use or know whether they use RA practices, while 40% said the same for RT practices, on the contrary, only 27% and 30% of healthcare professionals affirmed that do not use or know whether they use respectively RI and RMo practices. This might be because healthcare organizations and their professionals still lack the advanced managerial knowledge and infrastructure strictly required to effectively apply and implement risk assessment and treatment practices, thus preventing their adoption. Based on the findings for RI and RMo practices, I suggest that researchers and healthcare practitioners should work on how to address the proposed gaps in knowledge and infrastructure to promote and facilitate RA and RT effective adoption, aiming to improve the quality of healthcare services. Moreover, in this study, I propose and validate the mediating role of risk management practices, which serves as the underlying mechanism to explain the relationship between the use of BDA and the QoHS. The findings reveal that the effectiveness of the use of BDA on the QoHS should be realized through the exploitation of existing RM practices, i.e., risk identification and risk monitoring practices. Overall, the empirical findings are consistent with the OIPT, suggesting that this theory can be used to characterize the effects of BDA and RM practices on the QoHS. Indeed, these can leverage the effect of uncertainty on the decision-making process in healthcare, leading to an impact on the QoHS. Moreover, in the context of healthcare organizations to the best of the author's knowledge, this is the first study to propose and confirm the mediating role of RM practices in the effect of BDA on QoHS. This result seems promising and nurtures a scientific debate on the use of established practices to effectively employ new technologies in healthcare organizations.

Practical Implications

This study provides some practical implications for decision-makers in healthcare organizations. Firstly, the finding shows that the BDA positively influences the RM practices (H2) and QoHS (H1), pointing out that the investment in acquiring technologies and capabilities leads to an actual impact on the performance of healthcare organizations. Indeed, the BDA can be used to provide insightful information to support several activities in these organizations, from organizational activities to patient care activities, thus, healthcare managers should continue along the path of digital transformation by acquiring big data technologies and promoting the acquisition of capabilities to exploit them.

Secondly, the statistical analysis demonstrates that RM practices have a positive impact on the QoHS. This result suggests to healthcare decision-makers that although the implementation and use of data-driven technologies is one of the most currently discussed and promising themes, they should not take other organizational and strategic practices for granted as they impact their performance. This is even more relevant given that this work demonstrates that RM practices play a mediating role in the relationship between BDA and QoHS. Consequently, healthcare managers should use these practices to effectively employ the BDA for their potential benefits on the QoHS.

4.8. CONCLUSION

The results of this research are relevant from both a practitioner and an academic perspective. Healthcare managers can benefit from this study to understand which is the current relationship between the use of BDA and RM practices to improve the QoHS, and if the RM practices can mediate the relationship between the use of BDA and the QoHS. The relevance lies in the fact that in recent years the development of innovative technologies to generate and extract data offers a great potential to optimize decision-making in the healthcare industry confronted with uncertainty. The use of BDA is spreading and revolutionizing decision-making in healthcare (Malik et al., 2018), fostering more informed decisions to improve the QoHS, but no study has been identified in the literature that tests empirically this relationship. From an academic point of view to the best of the author's knowledge, this is the first attempt to examine how the use of BDA directly influences RM practices and QoHS and to examine how the use of RM practices mediate the relationship between BDA and QoHS. Therefore, this contribution is an important step toward a better understanding of the current role of BDA and RM practices in supporting the healthcare professional's decision-making process. Moreover, this study contributes to the body of knowledge about QoHS by providing empirical research to unveil the actual effect of the use of BDA and RM practices on the quality of service. The QoHS can be affected by the risk and uncertain conditions in the decision-making process and the use of BDA and RM practices can address these issues. This study also contributes to testing OIPT in the healthcare organization setting, since the use of BDA can enable the improvement of the use of information extracted to cope with risk and uncertainty in the decision-making process.

This study, like any other, has limitations that provide opportunities for additional investigation. This study employs a cross-sectional approach and focuses on Italian healthcare professionals. As a result, future research can be carried out in other countries, that may give information about similarities and differences. I only gathered data at one moment in time and did not have access to longitudinal data needed to investigate causation over a longer period. Accordingly, completing a longitudinal study may give important insights into the connection between the variables and their relationship investigated in this study.

5. BUSINESS INTELLIGENCE IN THE HEALTHCARE INDUSTRY: THE UTILIZATION OF A DATA-DRIVEN APPROACH TO SUPPORT CLINICAL DECISION MAKING.

5.1. ABSTRACT

The pandemic has forced people to use digital technologies and accelerated the digitalization of many businesses. Using digital technologies generates a huge amount of data that is exploited by Business Intelligence (BI) to make decisions and improve the management of firms. This becomes particularly relevant in the healthcare sector where decisions are traditionally made on the physicians' experience. Much work has been done on applying BI in the healthcare industry. Most of these studies were focused only on IT or medical aspects, while the usage of BI for improving the management of healthcare processes is an under-investigated field. This research aims to fill this gap by investigating whether a decision support system (DSS) model based on the exploitation of data through BI can outperform traditional experience-driven practices for managing processes in the healthcare domain. Focusing on the managing process of the therapeutic path of oncological patients, specifically BRCA-mutated women with breast cancer, a DSS model for benchmarking the costs of various treatment paths was developed in two versions: the first is experience-driven while the second is data-driven. I found that the data-driven version of the DSS model leads to a more accurate estimation of the costs that could potentially be prevented in the treatment of oncological patients, thus enabling significant cost savings. A more informed decision due to a more accurate cost estimation becomes crucial in a context where optimal treatment and unique clinical recommendations for patients are absent, thus permitting a substantial improvement of the decision-making in the healthcare industry.

5.2. INTRODUCTION

The Covid-19 pandemic has generated deep transformations in several industries around the world. While from a human and social point of view, the changes are dramatic, many new opportunities have emerged in business and education (Fernandez et al., 2020; Ienca and Vayena, 2020). The need to maintain the social distance caused by the pandemic and, at the same time, keep working has forced companies, employees, students, and different professionals to accelerate digital transformation. McKinsey professionals have estimated that because of COVID-19, digital technology adoption in Europe has jumped from 81% to 95% and that this change would have only been achieved in 2-3 years at pre-pandemic growth rates (Fernandez et al., 2020). Moreover, the issues raised during the pandemic highlighted the need to innovate policies and regulations under emergency conditions to speed up government response times (Reale, 2021). One of the industries more impacted by digitalization is the healthcare industry. In the U.S., telemedicine usage has grown from 0.1% of users in February 2020 to 43.5% in April 2020 (Bosworth et al., 2020), despite the challenges associated with its implementation (Khodadad-Saryazdi, 2021). Applications that leverage digital technologies are multiplying day by day. Recently, digitalization in the healthcare industry has enabled the adoption of antifragile strategies, i.e. strategies that enable the healthcare industry to become stronger during and after a crisis such as the COVID-19 pandemic (Cobianchi et al., 2020). Other interesting examples come from the development of new wearable technologies which make it possible to monitor and analyse clinical data in real-time (Yilmaz et al., 2020). All new forms of digitalization are based on the massive use of data for knowledge extraction. The business process that deals with this is the Business Intelligence (BI), defined as a combination of processes, policies, culture, and technologies for gathering, manipulating, storing, and analysing huge collections of data (the so-called “big data”) coming from internal and external sources, to communicate information, create knowledge, and inform decision making. BI helps report business performance, uncover new business opportunities, and make better business decisions regarding competitors, suppliers, customers, financial issues, strategic issues, products, and services (Foley and Guillemette, 2010). Therefore, the recent massive use of digital technologies opens many opportunities for BI and generally for the exploitation of big data for different purposes, but with the common goal of making better-informed decisions.

After the pandemic, the application of BI in the healthcare industry is expected to experience a real renaissance, as witnessed by the increasing number of studies in the field and applications (Sechi et al., 2020). In this sector, BI is considered a real boost to improve traditional decisions made by physicians (i.e. medical doctors) (E.R. Safwan et al., 2016). However, even if there are plenty of applications based on the use of data to improve medical processes (i.e., supporting physicians in selecting and monitoring prognosis and diagnosis) (Methaila et al., 2014; Topuz et al., 2018) or the ICT architectures and the data management systems (Ahmad et al., 2016; Ali et al., 2013; Meyer et al., 2014; Swarna Priya et al., 2020), the use of data for improving healthcare management processes seems to be still limited (Liu and Lu, 2009; Patil et al., 2010). Despite the limited attention, this topic seems to be very promising. Decision-making in healthcare is challenging because of the high complexity of decisions due to a high level of uncertainty, a huge number of interacting and unpredictable variables (Han et al., 2019; Kuziemsky, 2016; Massaro, 2021) and a multitude of heterogeneous actors involved (Secundo et al., 2019). In this highly complex context, physicians can be supported in decision-making through new technologies such as decision support systems (DSSs) (Bright et al., 2012; Kawamoto et al., 2005), which may provide suggestions for diagnoses, patient management, screening and management of treatment pathways (Garg et al., 2005). Hence, integrating BI into the decision-making process enables saving time and costs, thus avoiding waste of resources (Foshay and Kuziemsky, 2014; Safwan et al., 2016b). Although the high potential of the use of data in DSS (data-driven DSS), many decisions are still made based on experience and clinical practices rather than on rigorous approaches integrating BI into the decision-making process, and the use of data-driven DSS, from both a research and application perspective, still appears to be under-researched (Sperger et al., 2020; Wang et al., 2018).

This paper contributes to this under-investigated field by exploring whether the exploitation of data through BI in the decision-making process can outperform experience-driven practices for managing processes in the healthcare domain. Ultimately, the research question is: "Can a data-driven DSS model improve the healthcare process management better than a DSS model based solely on experience and literature?". To answer the research question, a DSS model was developed to support physicians in benchmarking the costs of various treatment strategies for oncological patients (i.e., BRCA-mutated women with breast cancer). This specific domain is a good candidate for testing the potentiality of data-driven DSS since it is characterized by high complexity and uncertainty of decisions that should consider the risks and complications that may arise in each treatment strategy throughout the lifetime of the patient. The DSS model was developed in two versions: the experience-driven model and the data-driven model. The input data for the experience-driven model were collected through interviews with physicians and from the academic literature. Data input for the data-driven DSS model was extracted from a database built on data reported on the clinical records of oncological patients. A simulation study was carried out to compare the two versions of the DSS model. Simulation results revealed that the use of BI improves decision-making in the healthcare domain. In particular, it was found that the data-driven version of the DSS model leads to a more accurate estimation of the costs that could potentially be prevented in the treatment of oncological patients. This improved cost estimation of alternative treatment strategies permits a more informed decision by the physician in the absence of optimal treatment and unique clinical recommendations for patients, thus permitting a substantial improvement of the healthcare processes. This type of decision-making, if applied systematically on a large scale, would lead to significant economic savings and optimization of resources. At the same time, a better awareness of the economic burden associated with cancer treatment strategy along with information about the effectiveness of each strategy may support policymakers in the decisions of resources allocation within the healthcare system.

The paper is organized as follows. In the second section, the theoretical background on the usage of BI in the healthcare industry and on the decision-making for BRCA mutated patients is presented. The third section, it has been describes the methodology used in this work while discussing the main results and conclusions in the remaining two sections.

5.3. Theoretical Background

5.3.1. Business intelligence for decision-making in healthcare

Digital transformation has now spread to all sectors and the healthcare industry is not excluded (Gong and Ribiere, 2021). Several new technologies, such as telemedicine and e-health (Khodadad-Saryazdi, 2021; Wong et al., 2017), are increasingly embedded in healthcare processes and several studies analyse their impact and evolution from different perspectives (Biancone et al., 2021; Drago et al., 2021; Massaro, 2021; Tortorella et al., 2021). One of the main effects of digital transformation is the generation of a huge amount of data. As a consequence, Business Intelligence is established as the process of obtaining information and then knowledge for decision-makers by collecting data from different sources, analysing the data through data mining techniques, and finally creating reports that allow easy visualization (Foley and Guillemette, 2010; Llave, 2019). The BI process leverages large data sets and analytical techniques for data repository, management, analysis, and visualization which are usually defined as big data and data analytics (Chen et al., 2012; Niu et al., 2021; Provost and Fawcett, 2013).

Much work has been done in the domain of BI applied to the healthcare industry where data are used to support decision-making not only by predicting clinical conditions (Sousa et al., 2019) but also by enabling more informed decisions by doctors (Goienetxea Uriarte et al., 2017; Larson and Chang, 2016).

These works can be grouped depending on their focus (Campbell et al., 2000; Mashinchi et al., 2019). By reviewing the literature, three main focuses can be identified (Table 16). The first focus includes studies centred on applying BI to refine prognoses and diagnoses and select the best treatments, by using medical informatics, data mining, and machine learning algorithms (Delen et al., 2012; Topuz et al., 2018). An application of these algorithms can improve the early diagnosis of diseases (Methaila et al., 2014), reduce physician errors and improve patient outcomes (Bashir et al., 2021).

The second group of studies is on improving data management and communication performance through the usage of ICT to ensure health services (Ahmad et al., 2016; Ali et al., 2013; Meyer et al., 2014; Swarna Priya et al., 2020). Chen et al. (2021) proposed a scheme for sharing data between IoT (Internet of Things) technologies in an attempt to preserve privacy, and thus be able to use these technologies to deliver health services.

The third group of studies focuses on how to apply BI in the healthcare industry to improve the managerial processes, the prediction of operational information, such as length of stay and no-show patients, and to develop indicators related to the quality of clinical services and expected life (Gastaldi et al., 2018; C. K. H. Lee et al., 2021; Shahid Ansari et al., 2021; Simsek et al., 2020). However, to the best of author’s knowledge, no work has demonstrated whether the exploitation of data through BI in the decision-making process can outperform experience-driven practices for managing processes in the healthcare domain. This paper aims to contribute to the third category of studies by filling this gap.

Table 16 A classification of studies on BI in the healthcare industry.

Topic Area	Reference	The objective of the study
Applying data to refine prognoses and diagnoses	(Bashir et al., 2021)	Improving the accuracy of heart disease prediction.
	(Delen et al., 2012)	Development of predictive models to explain the surgical outcome of a patient undergoing a surgical operation.
	(Methaila et al., 2014)	Early heart disease prediction.
	(Topuz et al., 2018)	Prediction of the survivability of kidney transplant recipients.
Improving data management and communication	(Ahmad et al., 2016)	Identifying requirements to apply Business intelligence.
	(Ali et al., 2013)	Transforming a traditional online transactional processing (OLTP) system towards online analytical processing (OLAP) solution.
	(Meyer et al., 2014)	Approach to collect data to improve the decision-making
	(Swarna Priya et al., 2020)	Preserving privacy from cyber attacks.
	(Chen et al., 2021)	Development of a blockchain system to share data.
Improving the management of the processes through data	(Gastaldi et al., 2018)	Improving the implementation of BI applications.
	(C. K. H. Lee et al., 2021)	Supporting the cervical cancer screening strategies.
	(Shahid Ansari et al., 2021)	Improving the management of resources by predicting Length of Stay.
	(Simsek et al., 2020)	Improving the management of resources by predicting No-show patients.

5.3.2. Decision-making for BRCA mutated patients

BRCA1 (BReast CAncer gene 1) and BRCA2 (BReast CAncer gene 2) are genes that produce proteins that help repair damaged DNA. A woman's lifetime risk of developing breast and/or ovarian cancer is markedly increased if she inherits a harmful variant in BRCA1 or BRCA2 ("BRCA Gene Mutations," 2020). For this reason, patients with BRCA gene mutations are considered high-risk patients, whose clinical treatment must be properly evaluated and chosen by physicians. Therefore, both physicians, who must decide on the treatments to be performed, and policymakers, when deciding on screening and awareness campaigns, should take the BRCA mutation into account. The complexity of the decision-making process on the appropriate treatment of BRCA-mutated patients and the proper screening campaign is increased by the fact that the incidence of genetic mutations is not uniform but relates to ethnicity and territory. Several scientific articles found that the incidence of BRCA gene mutation varies between different ethnicities, varying from 9.4% for the Middle East to 15.6% for the African ethnic group (“BRCA Gene Mutations,” 2020; Hall et al., 2009).

The literature on clinical management of BRCA-mutated patients with breast cancer shows that there exist different possibilities to treat these high-risk patients and reduce their risk of new tumours (Mehrgou and Akouchekian, 2016). Although they are all equally feasible, none of the clinical guidelines suggest specific treatment pathways for BRCA-mutated patients with breast cancer (Forbes et al., 2019). Yet, they consume different resources, drugs, radiotherapy, surgery, diagnostics, etc., thus burdening the healthcare system cost differently (van der Nat et al., 2020). Therefore, improving the decision-making process supporting the selection of treatment strategies for high-risk women already diagnosed with breast cancer may produce advantages for the healthcare systems, in terms of cost and effectiveness of the processes. Nevertheless, only a few studies have developed models to support decision-making in this field. Recently, Carbonara et al. (2021) proposed a cost decision-making model that compares the costs for diverse treatment strategies for BRCA-mutated women with breast cancer. Focusing on breast cancer screening in BRCA1/2 mutation carriers, Pataky et al. (2013) proposed a cost-effectiveness decision model that evaluates the cost-effectiveness of using magnetic resonance imaging and mammography in combination to screen for breast cancer in patients with mutated BRCA genes.

On the other hand, in this context, it is crucial to use data because it allows decisions to be made in real time and based on the patient's overall condition. For instance, to support physicians in predicting breast cancer (Eletter et al., 2021) and patient survival probability for breast cancer (Zolbanin et al., 2015). Nonetheless, scientific literature lacks data-driven DSS models that support physicians' decisions in choosing treatment pathways for BRCA-mutated patients, taking into account the costs to the healthcare system. Trying to fill this gap, this paper develops a DSS model to support decision-making in choosing treatment strategies for BRCA mutated patients by demonstrating that a data-driven DSS model allows for a more accurate estimation of the costs that could potentially be prevented in the treatment of oncological patients concerning an experience-based DSS model.

5.4. METHODOLOGY

In order to investigate whether a data-driven DSS model improves healthcare process management better than a DSS model based solely on experience and literature, the work has been conducted by following the Design Science Research Methodology (DSRM) (Peffers et al., 2007). DSRM aims to address either an unsolved problem in a unique and innovative way or a solved problem more effectively or efficiently (Hevner et al., 2004). DSRM enables the balance between research rigour and practical relevance, thus addressing both practice-driven and research-driven goals (March and Smith, 1995; Simon, 1996). Moreover, in the healthcare industry, this methodology is currently used to implement “artefacts” and create models based on new technologies to support physicians and health professionals, e.g. pharmacists through online services for drug dispensing (Lapão et al., 2017) or doctors through clinical decision support systems (CDSS) for disease monitoring and assessment (Casal-Guisande et al., 2020).

DSRM consists of six steps (Peffers et al., 2007): the first step is the identification of the problem, the second step is the definition of the objectives to be achieved, the third step is the design and development of the so-called “artefact” which can be of various nature such as a model, a process or a new technique, the fourth step is the demonstration on the use the model to solve the problem identified in the first step, the fifth step is the evaluation of the proposed solution concerning the objectives defined in the second step, and finally there is the phase of communication of the solution in terms of effectiveness for both academics and practitioners (Hevner et al., 2004).

The following describes the steps of the DSRM (Figure 9) for developing the two versions of the DSS model for benchmarking the costs of various treatment strategies for oncological patients (i.e., BRCA-mutated women with breast cancer), considering, throughout the lifetime of the patient, the risks and complications that may arise in each strategy and, therefore, the costs associated with the management of such events.

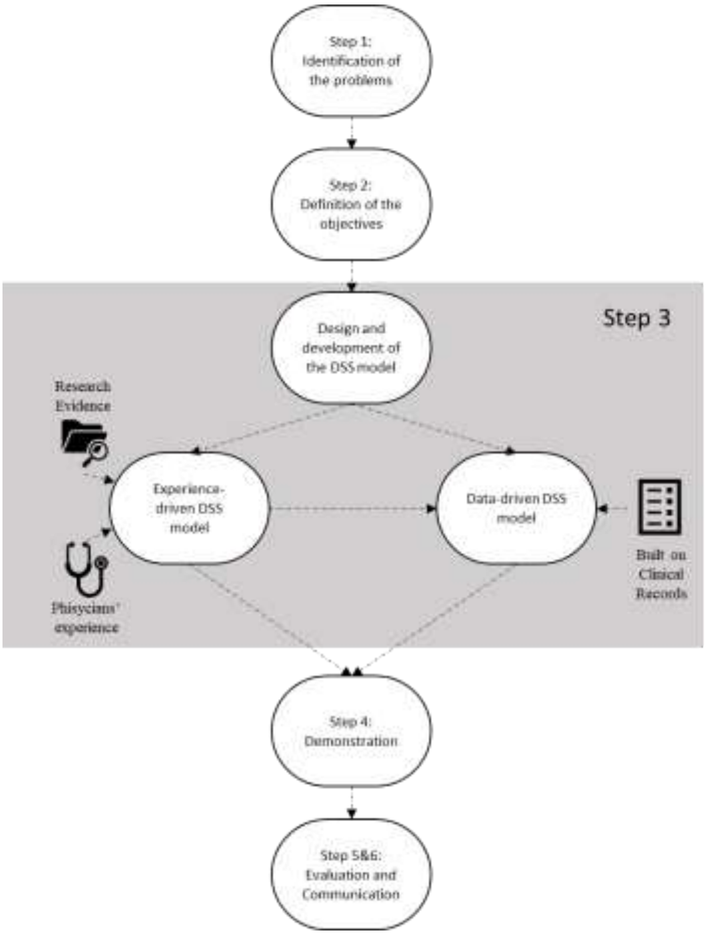

Figure 10 DSRM flowchart

5.4.1. Identification of the problem

The research problem comes from the observation of a gap in the existing literature on clinical management of BRCA-mutated patients with breast cancer where, although there exist different possibilities to treat high-risk patients and reduce their risk of new tumours, none of the clinical guidelines suggests a unique treatment pathway for these patients. Yet, they consume different resources, thus burdening the healthcare system differently. Therefore, improving the decision-making process supporting the selection of treatment strategies for high-risk women already diagnosed with breast cancer may produce advantages for the healthcare systems, in terms of cost and effectiveness of the processes. Nevertheless, only a few studies have developed models to support decision-making in this field. This problem has been confirmed by informal interviews with professionals and doctors operating in the field of oncology, and in particular with patients affected by BRCA gene mutations, which explained that they currently make decisions mainly based on their experience. Furthermore, another problem that emerged from the interviews is that decisions are often based on generic data from scientific literature or historical data that are not always up-to-date, and even based exclusively on the experience of doctors. Indeed, the use of literature data and experience in this context clashes with the need to decide the presence of a high degree of uncertainty, caused by the risks and complications that may arise in each strategy throughout the lifetime of the patient and with the need to control the costs associated with the management of such events.

5.4.2. Definition of the objectives

Having identified the problems, the study benchmarks two versions of a DSS model comparing the costs for diverse treatment strategies for BRCA-mutated women with breast cancer. The first version of the DSS model, I call it experience-driven, uses data coming from academic literature and interviews with physicians. The second version, I call it data-driven, uses a database built on data reported on the clinical records of oncological patients. The ultimate goal is to understand whether the DSS model performs differently when it is supported by data extracted from clinical records and when it uses data derived from experience or the literature. Hence, the objective of this study is not to find the best DSS model, but to understand if a DSS model based on clinical data and one based solely on experience and literature data behave differently, and specifically whether the data-driven one performs better.

5.4.3. Design and development of the artefact

4.4.3.1 Design of the DSS model

Firstly, it has been designed a DSS model which compares the costs for diverse treatment strategies for BRCA mutated women with breast cancer and calculates the cancer treatment costs that could potentially be prevented if the treatment strategy with minimum cost is chosen for treating high-risk women with breast cancer. Figure 10 shows a flowchart representing the current practice of the possible therapeutic pathways that the patients would follow. Appendix B details possible therapeutic pathways for affected patients with a BRCA mutation.

The DSS model assesses and computes the cost of each possible treatment strategy throughout the lifetime of the BRCA mutated patient, and thus defines the therapeutic pathway with the lowest cost. The DSS model works under conditions of uncertainty, taking into account the risks and complications that may arise throughout the patient's life and therefore the costs associated with the management of such events. The study examines the diagnostic and therapeutic care pathway of BRCA mutated patients receiving the first diagnosis at 40 years of age, e.g., two clinical pathways are: women opting for intensive radiological follow-up and those of women opting for prophylactic mastectomy and subsequent ultrasound follow-up, both of the options have been considered over 35 years, in accordance with the first eligible age for the testing program from 40 to 75 years. DSS model allows to simulate the different clinical pathways under uncertainty and obtaining the associated costs, thus identifying the clinical pathway that minimizes costs, called the “optimal therapeutic path”. Then, based on the actual practice, the therapeutic pathway that the patient would follow without the DSS model is considered and the associated cost is calculated. The difference between the two costs of the two therapeutic paths (with the DSS model versus the current practice of the physicians) represents the net unit savings per affected patient, which is the main output of the model along with the optimal therapeutic path.

The logic of the DSS model may be summarized in the following steps:

1. Calculation of the costs associated with the therapeutic pathways.
2. Comparison of costs of alternative therapeutic pathways and choice of the one with the lowest cost (“optimal therapeutic path”).

3. Calculation of the cost of the therapeutic pathways in the current practice - the therapeutic pathway, that the patient would follow without the DSS model.
4. Comparison of the cost of the "optimal therapeutic pathway" with the cost of the current practice therapeutic pathway.
5. Calculation of the net cost saving per affected patient: the unit cost savings that would be obtained by choosing the optimal therapeutic path, throughout the patient's entire residual life. To this end, it is calculated by considering all the net potential savings (or costs) generated by the optimal path in each year, until the end of the life of the patient, discounted with a predefined discount rate, identified from the literature. Specifically, the Net Present Value (NPV) has been used to calculate the present value (actual unit "saving" per affected patient) of a series of future payments (with a discount rate of 3%) (Gamble et al., 2017).
6. Identification of the most cost-effective therapeutic pathway.

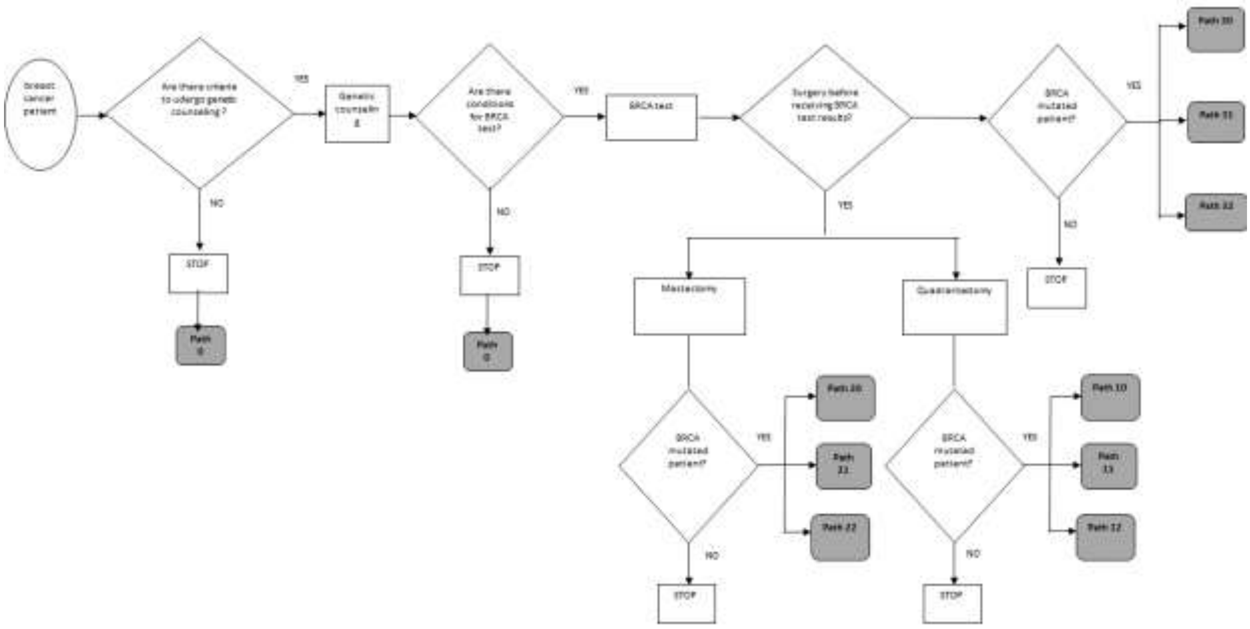

Figure 11 DSS model flowchart.

4.4.3.2 *Development of the two versions of the DSS model: experience-driven versus data-driven version*

In order to answer the research question of the paper "Can a data-driven DSS model improve the management of healthcare processes better than a DSS model based solely on experience and literature?", two versions of the DSS model have been considered. The first one is the experience-driven one, which uses data based on the physicians' experience and collected through interviews and literature and on the review of the scientific literature on the topic.

The second is the data-driven one and it uses data extracted from a database with information on female patients with cancer who underwent genetic testing to detect mutations in the BRCA genes, as detailed in the following.

4.4.3.3 *Experience-driven version*

The experience-driven version of the DSS model was built by collecting data through interviews with a multidisciplinary team of doctors at the "Giovanni Paolo II" Cancer Institute, located in Bari (Apulia region – Southern Italy), which is one of the most relevant centres on genetic oncological pathologies in that geographic area. In addition, other input values were extracted from the scientific literature (Table 17) on the topic, and data on the probability of occurrence of alternative therapeutic paths in the current practice was collected during the interviews (Table 18). The costs and their sources are summarised in table 22 Appendix B.

Table 17 Experience-driven variables for the DSS model.

Variables	**Distribution**	**Values**	**Sources**
Starting age (Affected)	Normal	Mean = 40 Std. Dev. = 2.5	(Chen et al., 2009; Fostira et al., 2018; Palma et al., 2006; Tuffaha et al., 2018)
The probability of BRCA mutation-positive in affected individuals	Uniform	Min = 10% Max = 20%	(Chen et al., 2009; Fostira et al., 2018; Palma et al., 2006; Tuffaha et al., 2018)
The annual risk of new incidence of breast cancer if BRCA-positive	20-29 30-39 40-49 50-59	0.005 0.015 0.03 0.026	(Tuffaha et al., 2018)

	60-69 70-79	0.012 0.012	
The annual risk of contralateral breast cancer if BRCA positive	20-29 30-39 40-49 50-59 60-69 70-79	0 0.05 0.04 0.03 0.03 0.03	(Tuffaha et al., 2018)
The probability that the patient is treated with radiotherapy after mastectomy		40%	Physicians' experience
The probability that the patient is treated with radiotherapy after quadrantectomy		95%	Physicians' experience
The probability to undergo genetic counselling	Bernoulli	45%	Physicians' experience
The probability to undergo BRCA genetic testing	Bernoulli	45%	Physicians' experience
Probability of detecting suspected local recurrence (skin or lymph node recurrences)		5%	Physicians' experience
Risk of surgery complications	Uniform	Min = 10% Max = 20%	Physicians' experience
Positive biopsy rate	Bernoulli	60%	Physicians' experience

Table 18 Probability of occurrence of alternative therapeutic paths in the current practice.

Variables	**Values**
% affected patients undergoing surgery after receiving BRCA test results	15%
% affected patients undergoing mastectomy before receiving BRCA test results	26%
% affected patients, BRCA-positive, choosing contralateral mastectomy (RRM) and ultrasound follow-up after mastectomy	30%
% affected patients undergoing quadrantectomy before receiving BRCA test results	70%
% affected patients, BRCA-positive, choosing intensive breast screening (intensive follow up) after quadrantectomy (Chance 1a)	20%
% affected patients, BRCA-positive, choosing bilateral mastectomy (RRM) and ultrasound follow-up after quadrantectomy (Chance 1b)	80%
% affected patients undergoing monolateral mastectomy after receiving BRCA test results, if BRCA positive	70%
% affected patients undergoing bilateral mastectomy after receiving BRCA test results, if BRCA positive	30%

4.4.3.4 Data-driven version

The construction of the data-driven version involved the creation of a database for the extraction of the input variable. The database used for estimating the probability of BRCA mutation-positive in affected individuals in the data-driven DSS model contains information on female patients with cancer who underwent genetic testing to detect mutations in the BRCA genes during the period 2004-2019 in the Apulia region. All data were provided either by laboratories performing the genetic analysis on-site or by pathology clinicians (oncologists, gynaecologists) who requested the genetic analysis from laboratories outside the region. In particular, data were collected from four institutions, IRCCS Cancer Institute "Giovanni Paolo II" in Bari, Policlinico of Bari, Ospedale Riuniti in Foggia, and PO Vito Fazzi Hospital in Lecce. The so built database contains information on 2,255 patients from the Apulia region in Italy. In Table 19 the schematization of the attributes and the typology of data in the database are reported.

Table 19 Attributes of the dataset for the data-driven DSS model.

Attribute	**Type**	**Values And Meaning**
Patient condition	Binomial categorical	Identify whether the patient is healthy or sick.
Sex	Binomial categorical	F=female; M=male
Date of birth	Range numeric	day/month/year
Place of birth	Nominal categorical	Municipalities of Apulia or other Italian regions
Residence	Nominal categorical	Municipalities of Apulia or other Italian regions
Age at diagnosis	Numeric ratio	Age at which a tumour was contracted
Post-test year	Numeric ratio	Year in which the patient received the result of the test
Histotype	Nominal categorical	Result of histological examination related to the location of the neoplasm
Neoplasm place	Nominal categorical	Where the tumour is located
Outcome Test BRCA	Nominal categorical	C(*Carrier*)=carrier of a pathogenic mutation in one of the two genes; *VUS* (a *variant of uncertain significance*) = carrier of a mutation of uncertain meaning in one of the two genes; NC (*Non-Carrier*) = non-carrier
BRCA1	Nominal categorical	Alphanumeric mutation identification code in the BRCA1 gene
BRCA2	Nominal categorical	Alphanumeric mutation identification code in the BRCA2 gene

Taking into account the evidence on the relationship between the incidence of genetic mutations and ethnicity and territory, reported by several scientific articles BRCA Gene Mutations, 2020), the probability of BRCA mutation in affected individuals has been measured for each Apulia province by using information about the province of birth. For the same reason, I eliminated the records about patients not belonging to the Apulia region, thus reaching a final database containing 1,873 individuals. The 382 excluded individuals were born either in other Italian regions or in other countries.

Table 20 shows the values of the probability of BRCA mutation in affected patients for each Apulia province, measured as the frequency of occurrence of the positive outcome of the genetic test.

Table 20 Probability of BRCA mutation in affected patients.

		Total of Patients	Probability of BRCA mutation in affected patients
Provinces	Bari	739	20.43%
	BAT	172	43.02%
	Brindisi	121	28.93%
	Foggia	39	41.03%
	Lecce	555	24.68%
	Taranto	247	26.72%
Region	Apulia	1873	25.57%

5.4.4. Demonstration

In order to demonstrate how to use the DSS model to solve the identified problem, I simulated the functioning of the two proposed versions of the DSS model. Simulation may be considered a valid research method when it is not possible to experiment with the actual system and when the complexity of the system itself precludes the possibility of developing an analytical solution (Lamé and Simmons, 2020). In order to take into account the uncertainties that characterize the input data, the Monte Carlo simulation has been used. It is a numerical method that can consider multiple sources of uncertainty in the estimation and decision problems, as they are in the actual environment (Mun, 2006). The simulation was done in the @Risk for Excel environment, with 1000 sample iterations. Using the data reported in the previous section (baseline case), I got, as a result of the simulation, the probability distribution of the cost saving of using the DSS model compared to current practice and the most cost-effective therapeutic pathway, either in case of the data-driven version or in case of the experience-driven version. Also, the cost savings obtained by using the two versions of the DSS model were compared in order to assess which version performs better.

In addition to the baseline case, I have considered alternative scenarios which reflect different choices by the policymaker about the planning of the screening and testing campaigns. These two scenarios differ from the baseline case for the values of two input parameters, representing the percentage of patients who have undergone genetic counselling and the percentage of patients who undergo BRCA testing. By varying these two parameters, I designed a plan of experiments, resulting in the following two scenarios: the first scenario is the one in which genetic counselling is extended to all patients, and the second is the one in which the BRCA genetic test is extended to all patients.

5.4.5. Evaluation and Communication

The evaluation of the DSS model has been made by calculating the output of the model in the two versions (i.e the probability distribution of the cost-saving), thus assessing whether the usage of the DSS model improves the current practice and comparing the difference between the outputs in the two versions, thus assessing whether the data-driven version outperforms the experience-driven one. The methodology applied to analyse the difference among the results obtained for the two versions of the DSS model in statistical terms uses the definition of "confidence interval". It has been calculated the confidence interval associated with a confidence level of 95% for the data-driven version and the experience-driven version.

As for further development of the research project, the DSS model will be implemented as a DSS to be used in a real case. To this aim, a pilot project in the hospitals that collaborated for this research, or in other medical fields with similar decision complexity, would be carried out.

5.5. RESULTS

This section will present the results obtained from simulations and statistical comparisons.

Table 21 reports the results of the simulation in the baseline case and the other two scenarios.

Table 21 Statistics of the probability distribution of the net cost-savings per affected patient and confidence interval estimation.

Baseline case								
			Net cost saving per affected patient			Confidence intervals		
DSS Version	Geographical area	Probability of BRCA mutation	Mean	Std. Dev.	Prob. (Net cost saving >0)	Confidence	Lower bound	Upper bound
Data-driven	**Apulia region**	25.57%	€ 1,568.76	€ 4,602.99	16.4%	€ 285.29	€ 1,283.47	€ 1,854.05
	Province of Bari	20.43%	€1,377.95	€ 4,417.11	14.5%	€ 273.77	€ 1,104.18	€ 1,651.72
	Pr. of BAT	43.02%	€ 1,811.95	€ 5,057.70	17.0%	€ 313.47	€ 1,498.48	€ 2,125.42
	Pr. of Brindisi	28.93%	€ 1,555.72	€ 4,425.92	16.5 %	€ 274.32	€ 1,281.40	€ 1,830.04
	Pr. of Foggia	41.03%	€ 1,887.48	€ 5,400.93	17.2%	€ 334.75	€ 1,552.73	€ 2,222.23
	Pr. of Lecce	24.68%	€ 1,514.16	€ 4,530.43	15.9%	€ 280.79	€ 1,233.37	€ 1,794.95
	Pr. of Taranto	26.72%	€ 1,555.91	€ 4,760.37	14.8%	€ 295.05	€ 1,260.86	€ 1,850.96
Experience-driven	**Not specified**	Uniform Distribution (10%-20%)	€ 1,388.50	€ 3,836.37	16.3%	€ 237.78	€ 1,150.72	€ 1,626.28
First Scenario								
			Net cost saving per affected patient			Confidence intervals		
Version	Geographical area	Probability of BRCA mutation	Mean	Std. Dev.	Prob. (Net cost saving >0)	Confidence	Lower bound	Upper bound
Data-driven	**Apulia region**	25.57%	€ 3,593.96	€ 6,640.63	34.6%.	€ 411.58	€ 3,182.38	€ 4,005.54
	Province of Bari	20.43%	€ 3,011.27	€ 5,307.66	35.1%	€ 328.97	€ 2,682.30	€ 3,340.24
	Pr. of BAT	43.02%	€ 4,118.40*	€ 7,368.89	36.6%,	€ 456.72	€ 3,661.68	€ 4,575.12
	Pr. of Brindisi	28.93%	€ 3,306.63	€ 6,812.43	34.2%	€ 422.23	€ 2,884.40	€ 3,728.86
	Pr. of Foggia	41.03%	€ 4,109.61*	€ 7,649.24	32.2%	€ 474.10	€ 3,635.51	€ 4,583.71
	Pr. of Lecce	24.68%	€ 3,883.75*	€ 5,959.52	36.6%	€ 369.37	€ 3,514.38	€ 4,253.12
	Pr. of Taranto	26.72%	€ 3,872.25*	€ 6,926.86	36.1%	€ 429.32	€ 3,442.93	€ 4,301.57
Experience-driven	**Not specified**	Uniform Distribution (10%-20%)	€ 2,982.77	€ 5,564.84	34.6%.	€ 344.91	€ 2,637.86	€ 3,327.68
Second Scenario								
			Net cost saving per affected patient			Confidence intervals		
Version	Geographical area	Probability of BRCA mutation	Mean	Std. Dev.	Prob. (Net cost saving >0)	Confidence	Lower bound	Upper bound
Data-driven	**Apulia region**	25.57%	€ 7,783.12*	€ 8,003.45	77.1%	€ 496.05	€ 7,287.07	€ 8,279.17
	Province of Bari	20.43%	€ 6,922.94	€ 6,922.94	77.8%	€ 429.08	€ 6,493.86	€ 7,352.02
	Pr. of BAT	43.02%	€ 9,549.42*	€ 8,893.74	81.5%	€ 551.23	€ 8,998.19	€ 10,100.65

	Pr. of Brindisi	28.93%	€ 7,872.31*	€ 7,834.62	77.3%	€ 485.59	€ 7,386.72	€ 8,357.90
	Pr. of Foggia	41.03%	€ 9,114.14*	€ 8,866.50	77.7%	€ 549.54	€ 8,564.60	€ 9,663.68
	Pr. of Lecce	24.68%	€ 7,412.29*	€ 7,563.05	76.9%	€ 468.75	€ 6,943.54	€ 7,881.04
	Pr. of Taranto	26.72%	€ 7,919.19*	€ 7,770.73	78.3 %	€ 481.63	€ 7,437.56	€ 8,400.82
Experience-driven	**Not specified**	Uniform Distribution (10%-20%)	€ 6,360.68	€ 6,458.55	75.7%	€ 400.30	€ 5,960.38	€ 6,760.98

*Statistical significance at 95% confidence.

Simulation results show that all the mean values of the net cost saving per affected patient are positive, thus proving that the application of the DSS model leads to cost savings compared to the current practice. In other words, adopting the DSS model for benchmarking the costs of diverse treatment strategies for BRCA-mutated women with breast cancer improves the current practice and shows a clear economic advantage.

In cases in which there is a statistically significant difference between the outputs in the two versions, the mean value of the net cost saving is higher when the data-driven DSS is adopted. This means that the data-driven version of the DSS model results in higher cost savings as compared to the experience-driven one. For these cases, it is observed that the mean value of the net cost-saving changes as the probability of being BRCA mutated changes as well.

A further advantage of the data-driven version of the DSS model relies on the fact that by using disaggregated input data, specifically the probability of BRCA mutation in affected individuals measured for each Apulia province, it allows for obtaining a more accurate estimation of the cost savings. On the contrary, the experience-driven version of the DSS model relies on aggregated data available in the literature, thus providing a rough estimate of the net cost saving per affected patient.

In addition, the number of statistically significant differences between the outputs in the two versions of the DSS model increases moving from the baseline to the second scenario. In particular, the higher number of statistically significant differences are in the second scenario. These results make it possible to highlight that the economic advantage of using BI increases as its usage increases as well since the DSS model is applied to a larger population. This finding is in line with the results reported by some previous studies (Collins et al., 2013; Slade et al., 2016) highlighting the economic advantage of extending the test to the wider population.

5.6. DISCUSSION

The adoption of digital technologies has increased the amount of data available to make decisions (Goienetxea Uriarte et al., 2017; Sousa et al., 2019; Yilmaz et al., 2020), thus spreading the use of Business Intelligence (BI) in several sectors (Safwan et al., 2016; Sechi et al., 2020). Even in the healthcare industry where decisions are traditionally made on the physicians' experience, BI may be promising because it allows decisions to be made in real-time and based on the patient's overall condition (Chen et al., 2012; Khodadad-Saryazdi, 2021). The use of BI in the healthcare decision-making process is raising in the current era of technological advancements, but from both a research and practical perspective it has not yet reached its full potential (Sperger et al., 2020; Wang et al., 2018). This paper contributes to this under-investigated field by exploring whether the exploitation of data through BI in the decision-making process can outperform experience-driven practices for managing processes in the healthcare domain. Ultimately, the research question is: "Can a data-driven DSS model improve the healthcare process management better than a DSS model based solely on experience and literature?".

Focusing on the managing process of the therapeutic path of oncological patients, specifically, BRCA-mutated women with breast cancer, a DSS model for benchmarking the costs of various treatment paths was developed in two versions: the first is experience-driven (i.e., based only on physicians' experience and literature data), and the second is data-driven (i.e., based on additional information coming from clinical records). The evaluation of the DSS model has been made by calculating the unit cost savings that would be obtained by choosing the optimal therapeutic path, thus assessing whether the usage of the DSS model improves the current practice and comparing the difference between the outputs in the two versions, thus assessing whether the data-driven version outperforms the experience-driven one. Adoption of the developed DSS model has shown an improvement in current practice and a significant economic advantage. In addition, it was found that the data-driven version of the DSS model leads to greater cost savings than the experience-driven version. The results show that the economic advantage of using BI increases as the DSS model is applied to a larger population, i.e., when genetic counselling and testing is extended to all patients.

From a theoretical perspective, this paper proves that the exploitation of data through BI in the decision-making process can outperform experience-driven practices for managing processes in the healthcare domain, filling the gap identified in the literature. While at a practical level, the implications are twofold. From a managerial perspective, the DSS model demonstrated that BI could improve the management of the decision-making process by providing physicians with a mapping of all possible pathways, thus helping them make the best decision. The DSS model also demonstrated that BI can improve the effectiveness of the decision-making process, thus leading to financial savings. Therefore, physicians can consult the DSS model to identify the decision that will save money on the treatment pathway. As a result, the adoption of the DSS model can contribute to cutting unnecessary waste of money that can be allocated to an alternative use such as the expansion of hospitals' clinical offerings.

Finally, the results also have policy implications. The proof that the data-driven DSS model leads to more efficient decisions should encourage policymakers to launch initiatives and campaigns aimed at collecting patients' health data in order to facilitate the employment of DSS models and data-driven technologies. In fact, one of the long-standing problems in the use of data-driven technologies is the availability of data. This issue is particularly relevant in the healthcare industry, where data about the patient's health conditions are not always available despite their relevance, such as in the oncology domain where data on the patient's health conditions are mostly collected through non-routine examinations, i.e. examinations that are only carried out on explicit request. For instance, in the specific domain of breast cancer, awareness campaigns for genetic screening can be used for gathering patients' data about the outcome of genetic counselling and BRCA genetic testing, thus favouring the adoption of the DSS model.

5.7. CONCLUSIONS

This study contributes to the academic literature on the use of BI for decision-making in the healthcare industry, by demonstrating that the exploitation of data through BI in the decision-making process can outperform experience-driven practices for managing processes in the healthcare domain.

The study also contributes to the scientific literature on the decision-making for BRCA mutated patients, by proposing a DSS model which supports physicians in choosing treatment pathways where optimal treatment and unique clinical recommendations are absent, and by also demonstrating that a data-driven DSS model leads to a more accurate estimation of the cancer treatment costs that could potentially be prevented if the optimal treatment pathway is chosen.

This study contributes to the managerial practice by demonstrating that the usage of rigorous approaches integrating BI into the decision-making process may support physicians' decisions, such as diagnosis, screening, and treatment pathways, even in a context where decisions are highly complex due to their high level of uncertainty and a huge number of interactive and unpredictable variables. The findings of the study show that the data-driven version of the DSS model enables cost-saving, thus avoiding waste of resources. This improved cost estimation of alternative treatment strategies permits a more informed decision by the physician in the absence of optimal treatment and unique clinical recommendations for patients, thus permitting a substantial improvement of the healthcare processes. This type of decision-making, if applied systematically on a large scale, would lead to significant economic savings and optimization of resources. At the same time, a better awareness of the economic burden associated with cancer treatment strategy may support policymakers in resource allocation within the healthcare system. In particular, I found that the data-driven version of the DSS model allows policymakers to make more informed healthcare policy decisions in the oncological field, such as the planning of screening campaigns.

This work is not without limitations. One could say that in a domain like the medical one, an automated decision system cannot, and should not, substitute doctors. Such criticism derives from the fact that people often confuse data-driven technologies with artificial intelligence (AI) technologies. In reality, these two are different because data-driven technologies are used to improve the cognitive and calculation capability of humans, while AI tries to mimic the capability of humans (Di Nucci, 2019). This limitation is however apparent because the aim of the work is not to create a DSS that substitutes the physicians but to support them in the choice of diagnoses, treatments, etc., demonstrating that integrating data into the decision-making process leads to a more informed decision, avoids the waste of resources, and lets the doctor keep full control on the decision-making process by achieving a full comprehension of the problem.

Another limitation of the study is that in this work I focus on a specific DSS, without providing a comparison between different DSS models or searching for the best-performing one. Such a limitation is only apparent because the objective of this study was not to find the best DSS model but to understand if a DSS model based on clinical data and one based solely on experience and literature data behave differently, and specifically whether the data-driven one performs better. Further research will be devoted to extending the comparison between a data-driven and an experience-driven version to other DSS, even in different fields characterized by similar managerial and organizational complexity, thus increasing the robustness of the findings.

Another limitation lies in the fact that I set a laboratory experiment with static data extracted from existing databases while it can be interesting to set a live experiment with a DSS model fed with real and live data.

This would be an objective of future research consisting of the development of a DSS tool, including its architecture, KPIs, dashboards and data warehouses, which will make it possible to use it in a real-case scenario involving a hosting hospital. Finally, the model could be further improved by considering not only the views of experts but also those of patients, to manage the whole healthcare decision-making process.

5.8. APPENDIX B

Path 0: Patient not subjected to genetic counselling and/or BRCA test;

Path 10: Quadrantectomy surgery without preference for chances (quadrantectomy + intensive follow-up or quadrantectomy + bilateral mastectomy) before receiving BRCA test results;

Path 11: Quadrantectomy + intensive radiological follow-up, before receiving BRCA test results;

Path 12: Quadrantectomy + bilateral mastectomy, before receiving BRCA test results;

Path 20: Mastectomy surgery with no preference for chances (unilateral mastectomy + intensive follow-up or unilateral mastectomy + contralateral prophylactic), before receiving BRCA test results;

Path 21: Unilateral curative mastectomy surgery + intensive radiological follow-up, before receiving BRCA test results;

Path 22: Unilateral curative mastectomy surgery + mastectomy contralateral prophylactic, before receiving BRCA test results;

Path 30: Surgery without preference for therapeutic chance (mastectomy unilateral + radiological follow-up or bilateral mastectomy) after receiving BRCA test results;

Path 31: Unilateral curative mastectomy surgery + intensive follow-up after receiving BRCA test results;

Path 32: Bilateral mastectomy surgery + ultrasound follow-up after receiving BRCA test results.

Table 22 Model input parameters: costs.

Activity	Cost (€)	Notes	Reference
Quadrantectomy	2,354.00	Without complications	NHS: DRG code 259
	2,717.00	With complications	NHS: DRG code 260
Intensive breast screening (intensive follow up)	263.31	mammography and breast magnetic resonance imaging (MRI)	NHS: DRG codes 8737 – 88929 – 897
Biopsy	52.08	core-biopsy	NHS: DRG code 8511
Mastectomy including reconstructive surgery	8,265.00	Without complications	NHS: DRG codes 258 461
	8,872. 00	With complications	NHS: DRG codes 257 461
Bilateral mastectomy including reconstructive surgery	16,530.00	Without complications	NHS: DRG codes 258 461
	17,744.00	With complications	NHS: DRG codes 257 461
Ultrasound follow-up	56.55	Breast examination and ultrasound	NHS: DRG codes 8873 897
Surgery for local recurrences (skin or lymph node recurrences)	4,583.00		NHS: DRG code 1988
Plastic surgery after complications or for breast implant replacement after 15 years	4,924.00		NHS: DRG code 461
Radiotherapy	2,936.00	cost per regimen in combination with systemic therapy	NHS: DRG code 409
Genetic counselling	20.76		NHS: DRG
BRCA testing	1,107.00		Primary data collectio

6. HOW DIGITAL TRANSFORMATION MAY OPTIMIZE THE UTILIZATION OF HEALTHCARE SERVICES: THE CASE OF ITALIAN SCREENING PROGRAMS

6.1. ABSTRACT

Digital transformation is revolutionizing the healthcare industry, and the use of digital technologies is generating large amounts of data that can be used to support the healthcare decision-making process. The use of data leads to several improvements in healthcare, such as treatment selection or diagnosis process. The utilization of healthcare services is one of the prominent topics in healthcare, but it is still in its infancy in the digital transformation literature. This study aims to investigate the use of big data analytics to improve the utilization of healthcare services, specifically the Italian national cancer screening programs, through a two-step methodology. First, I investigate the relationship between patient characteristics and the utilization of the healthcare services under consideration. In the second step, the collected data are used to build a data-driven model to identify patients who are more likely not to use healthcare services based on their characteristics. This study contributes to the existing literature on digital transformation in healthcare by proposing a data-driven model to improve healthcare service utilization. I contribute to the practitioner perspective by proposing a real-world data-driven methodology that overcomes the disadvantages of the most common methods to identify patients who will not utilise healthcare services (i.e., survey-based methods).

6.2. INTRODUCTION

Digital transformation is shaping the future of organizations in many industries (Hanelt et al., 2021). Gong and Ribiere (2021) defined it as “a fundamental change process enabled by digital technologies that aim to bring radical improvement and innovation to an entity (e.g., an organization, a business network, an industry, or society) to create value for its stakeholders by strategically leveraging its key resources and capabilities”. The adoption and proper use of digital technologies have many positive impacts on organizations (Gaglio et al., 2022). These range from improved productivity and efficiency, through the automation of activities, to the creation of new business opportunities (Hanelt et al., 2021; Kraus et al., 2021a). Moreover, the adoption and use of digital technologies are opening up new ways to further improve the performance of organizations. In this regard, digital technologies generate a large amount of data that can be exploited to extract insightful information to support decisions in different domains (Aceto et al., 2020; Chen et al., 2012). One important trend of digital transformation is the increasing use of big data analytics to analyze large amounts of data and generate these insights (Ashaari et al., 2021; Wang et al., 2018). The major beneficiaries of this breakthrough are those industries characterized by highly complex decision-making processes with uncertain outcomes, certainly including the healthcare industry. The healthcare industry is characterized by highly complex and uncertain decisions, whose outcome is influenced by multiple and different variables and issues, such as the complexity of the patient’s disease and the involvement of various actors in the decision-making process, e.g., physicians, families, and patients (Han et al., 2019; Kraus et al., 2021b). As such, the healthcare industry can gain great advantages from digital transformation and in particular through the use and exploitation of big data. In the academic literature, the use of big data analytics in healthcare has been widely investigated for delivering personalized care, supporting the diagnosis or treatment selection, identifying patients at risk of developing a disease and improving the use of resources (Galetsi and Katsaliaki, 2020; Kraus et al., 2021b). Despite the growing literature on the use of big data analytics to support decision-making in healthcare, it is clear that it has not yet reached its full potential and there is still room for further investigation (Galetsi and Katsaliaki, 2020). In this regard, the potentiality of big data analytics for improving the utilization of healthcare services is a promising topic (Dal Mas et al., 2023; Hu et al., 2021; LaVeist et al., 2009) and at the same time, it seems to be overlooked by the literature about digital transformation in healthcare. Underutilization of healthcare services refers to the unwillingness to use a healthcare service that has the potential to improve the patient's quantity and quality of life (Elshaug et al., 2017). The underutilization of healthcare services can be due to contingency factors, such as financial barriers, and the patient's characteristics, such as lack of knowledge, lack of awareness, and risk attitude (Glasziou et al., 2017).

A pivotal example of the underutilization of healthcare services regards the screening programs aimed at preventing and detecting diseases at an early stage. Data on the screening programs for breast, cervical, and colorectal cancer provided by the Italian National Healthcare System (NHS) in the 2019 campaigns show that only 60.7%, 39.1%, and 41.6% respectively, of the target population, access to these services (ONS, 2020). Since the screening programs are free of charge for all the citizens who are in the at-risk age group, the patients' characteristics can be considered as a main explanatory factor of the underutilization of these healthcare services.

Therefore, healthcare policymakers need to take into account these characteristics to understand how a patient will act with respect to using a healthcare service and to develop strategies to lead the patient's behaviour towards optimal choices. However, acquiring information about these characteristics is a big challenge. In fact, it requires interviewing individuals through questionnaires, which makes this information difficult to exploit as the process would be costly and time-consuming (Houston et al., 2021; Regmi et al., 2016). In this regard, digital transformation can support healthcare policymakers by enabling the extraction of information about the patients' characteristics in real-time without any relevant additional costs.

Despite this topic seems promising to support healthcare policymakers, to the best of the author's knowledge, the use of data to improve the utilization of healthcare services seems overlooked by academic literature. Pursued by this research gap, this study investigates how big data analytics could support policymakers in optimising the utilization of healthcare services. Consequently, this study seeks to answer the following research question:

- How can big data analytics support healthcare policymakers in increasing the utilization of healthcare services?

Aiming to answer the research question I developed a methodology consisting of two steps. In the first step the relationship between patients' characteristics and utilization of healthcare services has been deeply investigated in the academic literature, and a survey has been developed and administered. In the second step, the data collected in the first step are used to build a big data analytics model to classify patient characteristics that lead to underutilization of healthcare resources. The remainder of this paper is structured as follows: section 2 describes the theoretical background. Section 3 presents the research design and the methodology. Section 4 presents the results, and section 5 discusses the results before concluding with limitations and future research avenues.

6.3. THEORETICAL BACKGROUND

6.3.1. Digital transformation and big data analytics in healthcare

One of the main beneficiaries of digital transformation is the healthcare industry (Baudier et al., 2023; Kraus et al., 2021b). Technology concepts such as big data, the Internet of Things and cloud processing are driving this sector towards 'Healthcare 4.0' (Aceto et al., 2020). Wearable and portable devices, telemedicine and electronic health records are some of the most widely used technologies in healthcare (Marques and Ferreira, 2020). Digital technologies are characterized by their ability to generate and collect large amounts of data (i.e. big data) (Dal Mas et al., 2023; Kraus et al., 2021b). The availability of these data provides an opportunity to extract information and, if used correctly, provide decision support (Basile et al., 2023; Weerasinghe et al., 2022). The information is extracted through big data analytics (BDA). BDA refers to technologies, processes, and methods that evaluate large amounts of data to help an organisation make more informed, critical decisions (Wang et al., 2018). Big data can come in different formats, for example, images or X-rays, structured datasets, and medical records, and to eventually get data analytics there are several algorithms and techniques to extract meaningful information (Chen et al., 2012; Dicuonzo et al., 2021; McAfee et al., 2012). Big data analytics can have an impact on several domains of healthcare. Disease surveillance is one of the domains addressed by the big data analytics literature. For example, BDA can be used to ensure a rapid reaction to disease outbreaks, for instance, to identify the need for new vaccines (Abdel-Basset et al., 2021; Baudier et al., 2023). Another prominent topic is the use of BDA in disease management. In this regard, BDA can support the physicians' decisions to identify patients at risk, and for diagnosis and treatment selection (Bukhari et al., 2021; Chi et al., 2022; Eletter et al., 2021). Moreover, the use of BDA has also proven successful in improving healthcare processes in terms of organizational performance by assessing resource efficiency, tracking workload, and reducing human error (Augustin et al., 2022; Demir, 2014; Zhu et al., 2015). Considering the utilization of healthcare services, the academic literature focused mainly on how to ensure basic healthcare services and the continuity of care by using data collected through telemedicine and wearable technologies (Cannavacciuolo et al., 2022; Khodadad-Saryazdi, 2021; Wu et al., 2016). Telemedicine allows patients to communicate with healthcare professionals remotely via videoconferencing or other digital platforms, while wearable and portable devices enable remote tools to monitor patient health data. However, the current focus seems to be on overcoming issues such as the inaccessibility of services by delivering services remotely through the use of digital technologies, rather than using big data analytics to increase the use of healthcare services (e.g., screening and prevention programmes). To the best of author's knowledge, no work has proven whether the use of BDA to support healthcare policymakers' decision-making process can lead to an increase in the utilization of healthcare services. This paper aims to contribute to the academic literature about the use of big data analytics in healthcare by filling this gap.

6.3.2. Utilization of healthcare services and risk attitude

The main causes of underutilization of healthcare services can be outlined in inadequate access, healthcare system failures, physicians' decisions and competencies in delivering care, and patient behaviour (Glasziou et al., 2017). These aspects have been widely studied in the literature (Elshaug et al., 2017; Saini et al., 2017; Titaley et al., 2010). Among others, the patients' risk attitude (RA) is considered a key determinant of the decision-making process and a leading cause of patients' behaviour in healthcare (Lutter et al., 2019; Zhu et al., 2020). RA can be defined as the individual's characteristic that explains the willingness of people to prefer decisions with lower or higher risk, depending on whether they are risk-averse or risk-seeking, respectively (Weber, 2010). According to the scientific literature, RA may also change over time, for instance, as people age, they may become more risk-averse (Massin et al., 2018; Lisa A. Prosser et al., 2002; Rosen et al., 2003). In this context, the information about an individual's RA could support the healthcare professionals' decision-making. For example, physicians could use the patients' RA to identify patients who need to be encouraged in treatment adherence (Zhu et al., 2020). Moreover, it is possible to inform healthcare policymakers to properly design vaccine campaigns considering patients' RA since risk-averse patients tend to avoid vaccination (Diza et al., 2022). In accordance with these results, Lutter et al. (2019) found that "risk-seeking" patients have lower odds of attending medical check-ups. The most used methods to measure RA are questionnaire-based: lotteries, assessment of hypothetical or actual behaviour and self-reports based on situational questions and rating scales (Lutter et al., 2019; Weber, 2010). These methods have several limitations including the administration and answer time, patients may not be interested in filling them out due to their attributes (including RA), and finally considering the changing nature of RA in individuals the answer to a questionnaire may no longer be valid a short time later. In this paper, following the academic literature, I maintain that RA is a relevant patient characteristic that can inform healthcare policymakers about healthcare utilization. However, current measurement methods do not enable easy measurement of risk attitude and therefore its use. Despite the availability of data (e.g., electronic health records) and the spreading of big data analytics, academic literature did not explore the potential of big data analytics in improving the utilization of healthcare services through the use of patient characteristics (i.e., risk attitude).

6.4. METHODOLOGY

In this research project, I investigated whether the use of information about the patient's risk attitude obtained through the use of big data analytics could support the healthcare policymakers' decision-making in increasing the utilization of healthcare services, and the research methodology is based on the Design Science Research Methodology (DSRM) (Peffers et al., 2007), since this methodology supports researchers in addressing both practice-driven and research-driven goals (Hevner et al., 2004). Moreover, this methodology supports researchers in implementing "artefacts" based on digital technologies to support healthcare decision-makers, e.g. to support physicians in treatment selection (Basile et al., 2021) and for disease assessment and monitoring (Casal-Guisande et al., 2020). The process of the DSRM consists of six steps (Peffers et al., 2007). The first step is devoted to the identification and definition of the problem. The second step includes the definition of the research's goals. The third step provides the design and development of the artefact. The fourth step is focused on demonstrating how the model can solve the problem identified in the first step. The last steps are the evaluation of the proposed solution and the communication of the objectives and performance reached by the proposed artefact.

6.4.1. Identification of the problem

In the current era, technological and medical advancement is driving an increase in average life expectancy. The ageing of the world's population is increasing and it is bringing out more and more diseases related to genetics and lifestyles (World Health Organization, 2022). In this context, cancer is the second leading cause of death, accounting for roughly 10 million deaths in 2020 (Ferlay et al., 2020), consequently, it represents a significant social and economic burden in all countries, reflecting premature mortality, morbidity and high healthcare expenditures. As the cost of cancer care increases, attempts to prevent and detect cancer at an early stage through screening programmes become more and more relevant (Abati et al., 2020; Xi and Xu, 2021). Despite their relevance, the screening programs are underutilized healthcare services (Baird, 2022; Nuche-Berenguer and Sakellariou, 2019). The underutilization can be determined by financial issues, lack of awareness and patients' behavioural characteristics (Glasziou et al., 2017). In this research project, I considered the screening programme for breast, cervical and colorectal cancer provided by the Italian national healthcare system (NHS) for three reasons. Firstly, the Italian NHS provides these healthcare services free of charge for all the citizens who are in the at-risk age group (i.e., women aged 50-69 for breast cancer, women aged 25-64 for cervical cancer and women and men aged 50-69 for colorectal cancer), as a result in the Italian case the financial barrier to access healthcare services can be excluded from the causes of underutilization (ONS, 2020). Secondly, the Italian NHS has for many years been committed to campaigns to raise awareness of the importance of screening, so it is reasonable to assume that the lack of awareness among its citizens has diminished over the years. Third, despite the efforts of the Italian NHS, the utilization of these services is still low and has considerable room for improvement (ONS, 2020). Therefore, the case of the Italian NHS can provide the proper context to investigate whether the use of big data analytics to identify patients at risk of not participating in screening programs due to their behavioural characteristics (i.e., risk attitude) can support the policymakers' decision-making process leading to an improvement of the healthcare utilization.

6.4.2. Definition of the objectives

This study aims to investigate the use of big data analytics to improve the utilization of healthcare services, specifically the utilization of screening programmes in Italy. Therefore, firstly this study investigates the utilization of breast, cervical and colorectal cancer screening programmes and the role of patients' risk attitude in the use of these services. Secondly, I investigate the potential of big data analytics in informing policymakers and healthcare policymakers about the patient's risk attitude in order to enable data-driven decision-making to improve the utilization of healthcare services.

6.4.3. Design and development of the artefact

Aiming to answer the research question and achieve the research project's goal I designed and tested a decision support model following two steps. In the first step, I developed and administered a survey to investigate the relationship between patient characteristics and utilization of the healthcare services under consideration. In the second stage through a process of big data analytics, a model will be defined to predict the risk attitude of patients with respect to their characteristics collected in the first step. This paper presents the results of the investigation of patient characteristics and utilization of healthcare services.

6.4.4. Demonstration

The information collected through the survey will be used to build a model that compares the performance of screening programs in terms of costs and time savings in three scenarios: the real scenario (baseline), the scenario in which healthcare policymakers use the risk attitude information from the questionnaire (first scenario) and the scenario in which they use the risk attitude information extracted through the model. The demonstration of the effectiveness of the model will be carried out by means of Monte Carlo simulations under the three reference scenarios.

6.4.5. Evaluation and Communication

The evaluation will be carried out by analysing the results of the proposed model in the three scenarios in terms of utilization of healthcare services utilization and costs. As for communication, the model will be implemented to be used in a real case. To this aim, a pilot project in a hospital would be carried out.

6.5. RESULTS

To collect information about patients and investigate the relationship between patients' risk attitude and screening programme utilization I developed a survey consisting of three sections. In the first section, the questions aim to assess the risk attitude of respondents through a self-assessment question and the DOSPERT scale (Blais and Weber, 2006). I selected these assessment methodologies because they are considered among the most reliable for the assessment of respondents' risk attitudes (Lutter et al., 2019). In particular, I considered only the health and general domains of the DOSPERT scale since the academic literature highlights the need to measure risk attitudes in the area where the decision-makers have to make the decision (Rosen et al., 2003; Weber, 2010). Considering the DOSPERT scale, the survey developed in this research project investigates the patient's risk attitude in two domains. The first is the general domain in which the respondents were asked general questions about their willingness to take risks in the situation as the betting of their salary in different scenarios. The second is the health domain, where the respondents were asked to indicate their preference in engaging in risky activities for their health such as not carrying a helmet on a motorcycle or not using sunscreen when they are sunbathing. In the second section, the survey aims to collect respondents' personal information that is at the same time available in hospital electronic health records and which, according to the scientific literature, is related to risk attitudes. For instance, I collected data about their age, gender, height and general health status. Finally, in the third section, I investigated the current use of healthcare services and in particular of cancer screening programs under investigation. Table 23 shows the sections and questions of the survey.

Table 23 The survey

Section	Item	References
Risk Attitude	In general, in the different domains of your daily life, where do you situate yourself between 0 and 7, where 0 means “not at all willing to take risks” and 7 means “fully prepared to take risks”?	Lutter et al., 2019
	Admitting that your tastes are different from those of a friend.	DOSPERT (Blais and Weber, 2006)
	Betting a day’s income at the horse races.	
	Drinking heavily at a social function.	
	Disagreeing with an authority figure on a major issue.	
	Betting a day’s income at a high-stakes poker game.	
	Betting a day’s income on the outcome of a sporting event	
	Engaging in unprotected sex.	
	Driving a car without wearing a seat belt.	
	Riding a motorcycle without a helmet.	
	Sunbathing without sunscreen.	
	Walking home alone at night in an unsafe area of town.	
Respondents’ Characteristics	What is your age?	(Arrieta et al., 2017; Dohmen et al., 2011; Lutter et al., 2019; Massin et al., 2018; Prosser et al., 2002; Rosen et al., 2003; Weber, 2010; Zhu et al., 2020)
	What is your gender?	
	How tall are you?	
	How much do you weigh?	
	What is your city of residence?	
	Are you married?	
	Are you divorced?	
	Are you widowed?	
	Do you have children?	
	How many children do you have?	
	How old is your youngest child?	

	What is your educational qualification?	
	Are you a smoker?	
	What is your occupation?	
	How would you define your general health status?	
	Has one or more of the following diagnosed chronic conditions: [ALS (Lou Gehrig's disease); Alzheimer's disease or other dementias; Arthritis; Asthma; Cancer; Chronic obstructive pulmonary disease (COPD); Crohn's disease, ulcerative colitis or another inflammatory bowel disease; Cystic fibrosis; Diabetes; Eating disorders; Cardiovascular disease; Obesity; Osteoporosis]	
	Have you ever had surgery?	
	How long ago did you have the most recent surgery?	
	Are you taking any drug therapy (excluding dietary supplements)?	
Healthcare services utilization	When you had your last visit	Lutter et al., 2019; Dohmen et al., 2011
	When did you have your last checkup?	
	Have you ever participated in a screening program?	
	Have you ever participated in a breast cancer screening program?	
	Have you ever participated in a cervical cancer screening program?	
	Have you ever participated in a colorectal cancer screening program?	

6.6. CONCLUSION

Digital transformation is reshaping the activities in several industries, and healthcare is considered one of the most beneficiaries. The use of digital technologies produces data that can be exploited to support the decision-making process in healthcare. In this regard, the underutilization of healthcare services is one of the most discussed topics in healthcare, and the academic literature points out several causes of underutilization. The patients' behaviour decision-making is considered one of the main causes and it can be caused by patients' characteristics (i.e., risk attitude). However, the use of data for the identification of patients who will not use healthcare services is an under-investigated topic in the literature on data-driven digital transformation. Therefore, this study examines the potential of data-driven decision-making in improving the utilization of healthcare services, and in particular, the Italian national cancer screening program, through a two-step methodology. In the first step, I investigated the relationship between risk attitude and patients' personal information through a literature review and consequently, I developed a survey which was administered to potential users of the screening programme. The second step concerns the development and testing of a data-driven model to identify patients who will not participate in the screening programme. This paper shows the results of the first step, by describing the survey developed. In this regard, the academic literature points out that there are several methods to measure the individual's risk attitude, but the self-assessment and the assessment of hypothetical or actual behaviour (i.e., DOSPERT scale) are considered the most reliable (Lutter et al., 2019; Massin et al., 2018). Moreover, I identified the patients' information that is related to the risk attitude according to the academic literature. The results presented in this paper contribute to both theory and practice. From a theoretical perspective, this paper contributes to the extant literature about data-driven decision-making in healthcare by proposing the use of big data analytics to improve the utilization of healthcare services. I contribute to the practitioners' perspective by proposing a data-driven methodology to exploit the information about patients' risk attitudes that overcomes the disadvantages of the most common measurement methodologies that are survey-based. Despite the relevance and potential of this topic, researchers and practitioners must consider that patients' data privacy is of paramount importance. In recent years, artificial intelligence (AI) and machine learning have opened up several opportunities for automated decision-making that at the same time raised relevant concerns about the use of these tools. Therefore, it is crucial to develop ethical guidelines and regulations that ensure the responsible use of AI and machine learning in healthcare, protecting patients' privacy while harnessing the benefits of these technologies. Additionally, educating healthcare professionals and patients about the implications of AI and machine learning in healthcare can foster a better understanding of these tools potential and limitations. However, in this paper, I did not propose a model for automated decision-making but only a data-driven tools to support healthcare policymakers decision-making. Thus, since I maintain a human direct intervention in the decision-making process the issues related to automated decision-making are not a primary concern of this study. Despite this, in accordance with Art. 22 of the General Data Protection Regulation (GDPR) (art. 22 GDPR, 2018), the proposed model could only be used for patients who have authorized healthcare organizations to use their personal information.

7. CONCLUSION

Digital transformation is rising as a tremendous opportunity to deal with risk and uncertainty in the decision-making process. The adoption of digital technologies led to the growing creation and collection of data that can be exploited to extract information and insight to guide the decision-making process. In the rapidly evolving landscape of healthcare, the integration of data-driven decision-making processes has become imperative. The coupling of innovative digital technologies and data-driven approaches has the potential to redefine how healthcare professionals, managers, and policymakers tackle complex challenges. In this thesis, I delve into the evolving landscape of digital transformation and its profound implications for decision-making in healthcare and I examine how data can empower the healthcare organizations decision-making processes in the digital transformation era. By analysing the benefits and challenges associated with these advancements, I provided insights into how healthcare organizations can effectively explore and exploit this changing landscape and harness the power of data-driven decision-making to improve the quality of healthcare services.

This thesis started with a systematic literature review (please refer to Chapter 2) aimed to provide an overview of the use of data to optimize decisions affected by risk and uncertainty in healthcare organizations' quality domains. While the use and potential of data in the healthcare setting have been already discussed in the literature, this is the first systematic literature review to address the problem of decision-making affected by risk and uncertainty in healthcare organizations from the perspectives of risk management, data, and quality of healthcare services. Therefore, this study contributed to the extant literature on the use of data to optimise decisions under risk and uncertainty in healthcare organizations. While the main contributions are related to the academic literature, this study offers also some insights for healthcare professionals who are interested in understanding how to use data to optimize the decisions affected by risk and uncertainty. For instance, healthcare managers may extract useful insights about how data can support their decisions in both planning the needs of healthcare resources and scheduling activities, mitigating several risks, such as the risk of shortage. Also, physicians can use the findings of the study to gain a better understanding of how data-driven decisions can support them at various stages of the care process, e.g., in the selection of treatment data. Moreover, the analysis of the state of the art offered the opportunity to shed light on current relevant research gaps that have been used as ground to develop the research directions of this thesis. Indeed, the reviewed body of research has revealed notable gaps in empirical studies concerning firstly the influence of data-related technological resources and capabilities on the quality of healthcare services, and secondly, if the effect of managerial practices (i.e., risk management practices) have an impact on the relationship between the use of data and the quality of healthcare services. These gaps were discussed respectively in the third and fourth chapters.

In detail, in the third chapter, I argued that despite the growing investments in technological resources their impact on the quality of healthcare services is not guaranteed by their acquisition. In this chapter, I examined the relationship between big data analytics (BDA) technological resources and capabilities with the quality of healthcare services domains. The results showed that the mere presence of technologies does not lead to a positive impact on the quality of healthcare services, aligning with the resource-based view theory. Moreover, the presence of BDA capabilities was found to be a major explaining mechanism of the effectiveness of technological resources on the quality of healthcare services. This shed light on the paramount relevance of the investments in BDA capabilities acquisition and development concurrently with investments in technological resources. The acquisition of technical skills is a key factor in developing BDA capabilities. Drawing on the finding that the mere acquisition of technological resources is not enough to ensure a positive effect on the quality of healthcare services, I highlighted that the acquisition of skilled human resources or skills in this era of digital disruption could be relevant.

Turning the attention to the second gap identified, I explored the effect of BDA and risk management practices on the quality of healthcare services. In presented the results of this study in the fourth chapter. Under the lens of the organizational information processing theory (OIPT), I discussed the use of BDA as a breakthrough for supporting decision-making in the healthcare industry, fostering more informed decisions to improve the quality of healthcare services. This study was the first attempt to examine how BDA directly influences risk management practices and quality of healthcare services, and if the use of risk management practices can foster the relationship between BDA and quality of healthcare services. The findings showed the positive influence of BDA on the quality of healthcare services and unveiled the role of risk identification and risk monitoring practices as explaining mechanisms of this positive relationship. In this study, I contributed to the body of knowledge about the quality of healthcare services by providing empirical evidence that shows the effect of the use of BDA and risk management practices on the quality of healthcare services. Moreover, I also contributed to testing OIPT in the healthcare organization setting, as the use of BDA can enable the improvement of the use of information extracted to cope with risk and uncertainty in the decision-making process.

In combination with academic literature and healthcare professionals' needs, I explored the potential of data in real decision-making processes and the results have been presented in the last two chapters. In the fifth chapter, I examined through the design science research methodology the use of Business Intelligence (BI) in healthcare decision-making, ultimately demonstrating that data-driven approaches can outperform experience-driven practices. Moreover, the study also contributed to the decision-making for BRCA mutated patients by proposing a Decision Support System (DSS) model that helps physicians choose treatment pathways when optimal treatment and unique clinical recommendations are absent. The proposed data-driven DSS model leads to a more accurate estimation of cancer treatment costs, potentially preventing them if the optimal treatment pathway is chosen. The findings of this chapter contribute to managerial practice by demonstrating that rigorous approaches integrating data-driven insights into the decision-making process can support physicians' decisions, such as diagnosis, screening, and treatment pathways, even in complex contexts with high uncertainty and unpredictable variables. The findings show also that the data-driven version of the DSS model enables cost-saving, avoids resource waste, and allows more informed decisions by physicians. Based on this evidence, I discussed that this type of decision-making, if applied systematically on a large scale, would lead to significant economic savings and optimization of resources. A better awareness of the economic burden associated with cancer treatment strategy may support policymakers in resource allocation within the healthcare system. In particular, the data-driven version of the DSS model allows policymakers to make more informed healthcare policy decisions in the oncological field, such as the planning of screening campaigns. Moreover, I highlighted that the relevance of such a model lies in their assistive role in the decision-making process, rather than substitute physician’s decision-making. In this regard, the proposed model aims to support physicians in the choice of treatments, demonstrating that integrating data into the decision-making process leads to more informed decisions, avoids resource waste, and allows doctors to maintain full control over the decision-making process. Future research will focus on extending comparisons between data-driven and experience-driven models across different fields, ensuring the robustness of findings. Additionally, future research will consider integrating the views of patients to manage the entire healthcare decision-making process.

In the final chapter, I presented the preliminary results of an ongoing research project about the potential of data-driven decision-making in improving healthcare service utilization, particularly the Italian national cancer screening program. As the first step, I investigated the reasons for the underutilization of healthcare services. Among others, patients' risk attitude (RA) emerged as a key determinant of the decision-making process and a leading cause of patients' behaviour in healthcare. Therefore, I investigated the relationship between patients' risk attitudes and utilization of healthcare services through a literature review. Subsequently, I developed a survey that collects information about patients' risk attitudes, patient's descriptive characteristics and utilization of cancer screening programs. The following steps will be devoted to developing and testing a data-driven model to identify patients who will not participate in the screening program. From a theoretical perspective, this study contributes to the extant literature about data-driven decision-making in healthcare by proposing the use of data analytics to improve the utilization of healthcare services. It contributes to the practitioners' perspectives by proposing a data-driven methodology to exploit the information about patients' risk attitudes that overcomes the disadvantages of the most common measurement methodologies that are survey-based.

Finally, in this thesis, I aimed to shed light on the crucial role of data in optimizing decision-making processes within healthcare organizations and their impact on the quality of healthcare services. The presented studies offer a comprehensive overview, revealing both theoretical and practical contributions in tackling the under-explored topic of decision-making under risk and uncertainty, emphasizing the vital intersection of data, risk management, and healthcare services quality. In an era where digital transformation is reshaping healthcare, I discussed and demonstrated the role of data-driven insights as the compass to guide healthcare professionals, managers, and policymakers towards a more informed and efficient decision-making process.

These studies represent a theoretical and practical foundation towards leveraging the power of data to empower the decision-making processes in healthcare organizations.

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