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Digital Innovation, challenge and policy evolution in the Italian National Healthcare System (INHS)

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Abstract

This thesis explores the evolution and challenges in Italian healthcare by analyzing:

i) the key factors influencing the adoption of Artificial Intelligence (AI) in healthcare through a systematic literature review, highlighting critical barriers and enablers;

ii) the opportunities and issues related to the implementation of AI in three major Italian hospitals, focusing on its impact on public health outcomes, diagnostic accuracy, and operational efficiency;

iii) the policy implications of introducing regional "differentiated autonomy" in the Italian National Healthcare System (INHS), examining stakeholder perspectives and the potential advantages and risks associated with decentralization.

The research aims to contribute to the discourse on healthcare innovation by providing insights into the interplay between technological advancements, organizational dynamics, and policy frameworks. The thesis is structured into three chapters: the first offers an overview of the research; the second conducts a systematic literature review to identify and categorize factors affecting AI adoption; the third presents a multiple case study of AI integration in healthcare facilities using semi-structured interviews analyzed through the CFIR framework; the fourth evaluates the potential impact of differentiated autonomy on regional healthcare systems using a document-based stakeholder analysis. The findings emphasize the relevance of aligning technological innovation and policy decisions with healthcare performance, addressing organizational and economic challenges, and offering managerial insights into adopting AI and policy reforms in healthcare systems.

Keywords: Artificial Intelligence, Healthcare Performance, Differentiated Autonomy, Public Health.

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1.Introduction

This thesis entitled “Digital Innovation, challenge and policy evolution in the Italian National Healthcare System (INHS)” is the result of an in-depth research activity carried out during the three years of my PhD in Accounting, Management and Business Economics (AMBE) at the Department of Management and Business Administration of the University Gabriele D'Annunzio Chieti-Pescara Italy. The research activities were carried out under the supervision of Prof. Ianni Luca. The research topic was also explored during a visiting period at the Business Department of the University of Girona (Spain) under the supervision of guest Prof. Marc Carreras Pijuan.

The main topic of the thesis explores the evolution of Italian healthcare, combining empirical analyses of technological innovation and studies on the political-institutional dynamics impacting its performance.

Today, in fact, the growing challenges in global health have made technological innovation necessary to improve efficiency in healthcare delivery (Akinwale & AboAlsamh, 2023). This thesis analyzes how economic, technological, and political institutional factors influence and impact the performance of the healthcare system, with a particular focus on the Italian healthcare system.

To achieve this goal, three chapters are proposed. The second chapter addresses a need that has emerged from the existing literature and analyses the factors influencing the adoption of Artificial Intelligence (AI) in healthcare. The third chapter empirically analyses, through multiple case studies and semi-structured interviews, the effects, impact and barriers resulting from AI adoption in three major Italian hospitals. The fourth chapter, on the other hand, explores the probable effects on Italian healthcare of the government maneuver called ‘differentiated autonomy,’ which aims at a fractioning of some competencies (including healthcare) to the regions.

Within the scope of this thesis, various methodologies are adopted to study the research areas. In particular, the Systematic Literature Review is used to obtain a comprehensive and systematic view of the topic. This method is generally considered as a main practice to methodically discover, identify, and synthesize the existing literature in a rigorous and replicable method, leading to robust conclusions based on the current literature. Moreover, Systematic Literature Reviews (SLRs) have proven to be extremely relevant and valuable in the field of healthcare, particularly in the context of AI implementation and institutional policy development. These reviews can provide a comprehensive and structured approach to synthesizing existing research, offering crucial insights for decision-makers and researchers.

As a qualitative instrument, a multiple-case study with semi-structured interviews with directors and managers of important hospital facilities in Italy was used in chapter three as reported above. This tool allowed us to examine the phenomenon investigated in detail, returning important qualitative data. Conversely, the fourth chapter deals with the Italian health situation and the possible effects of approving differentiated autonomy through document analysis. In this case one of the main research outputs was to intercept stakeholders' sentiments through the use of a stakeholder's map. All these methodologies, which are presented in the following chapters, are used as tools to develop the thesis and study this field of research. The research results and manuscripts are presented in the following three chapters. In the second chapter (Key factors Influencing the adoption of Artificial Intelligence in healthcare: A systematic Review; co-authored paper) the authors explore the key factors influencing the adoption of Artificial Intelligence (AI) in healthcare, focusing on the identification and categorization of these factors through a rigorous analysis of 18 peer-reviewed studies selected through the PRISMA protocol. The results show a tendency for heterogeneity among the factors, however, through in-depth analysis, they highlight five main macro-categories: technological, human and psychological, organizational, social and economic factors.

Trust stands out as a pivotal element, deeply intertwined with other factors such as ease of use, social influence, and external pressures. Although barriers such as regulatory challenges and resistance to change are briefly discussed, the main objective of this review is to provide a clear picture of the critical factors driving AI adoption. The results obtained could provide a good basis for further investigating these factors, creating qualitative scales of impact, and refining strategies for integrating AI into healthcare practices.

In the third chapter (Will artificial intelligence become a good doctor? Opportunities and issues to implementing artificial intelligence in healthcare and its impact on public health: The case of the Italian NHS; co-authored paper) the authors explore the implementation of artificial intelligence (AI) within the Italian National Health Service (NHS), examining both the opportunities and challenges it presents, as well as its impact on public health outcomes. The study was conducted in three large hospitals in Italy that have integrated AI technologies into their healthcare systems. Data sources included interviews with key stakeholders, observations and relevant institutional documents. A qualitative multiple case study approach was employed, using the Consolidated Framework for Implementation Research (CFIR) to guide the analysis. This framework was selected to systematically evaluate factors influencing the implementation of AI in healthcare settings. Data

were collected through semi-structured interviews with hospital administrators, healthcare professionals, and technical staff. In addition, direct observations of AI implementation processes and an analysis of hospital documents provided further context and insights. Implementing AI technologies in selected hospitals resulted in significant improvements in diagnostic accuracy, personalization of treatment, and operational efficiency. Machine learning algorithms facilitated advanced data analysis, supporting clinical decision-making and improving patient outcomes. However, barriers were identified, particularly in the areas of technical integration, data management, and stakeholder resistance, particularly among healthcare professionals. Despite these challenges, perceived benefits included increased automation, accuracy, and efficiency in both diagnostics and healthcare management. The findings highlight the multifaceted role of AI in healthcare, offering substantial benefits but also presenting considerable challenges. Addressing these barriers through strategic planning, comprehensive training programs, and stakeholder engagement is critical to maximizing the potential of AI in improving public health outcomes. Finally, in the fourth chapter (Italian healthcare in transition: Examining the role of differential autonomy in policy evolution; co-authored paper) the authors examine the effects of differential autonomy, as it seems to be the only solution to make the nation and the regions effective and efficient, simplifying the former and holding the latter accountable.

In detail, this chapter explores the introduction of differentiated autonomy in the Italian National Health System, analyzing this reform's policy and management implications. The literature analysed and the authors' previous studies have shown how regional governance can significantly influence the adoption of technological innovations in healthcare, including Artificial Intelligence. Regions _.with greater decision-making autonomy and a stronger administrative structure tend to experiment and introduce new healthcare technologies more quickly than regions with more stringent constraints and more limited resources.

The analysis conducted in the three hospitals studied (Chapter 3) suggests that the regional context plays a key role. For example, the presence of specific funding and regional healthcare innovation strategies could explain the differences observed in the levels of AI implementation among the facilities analyzed. This dynamic is consistent with what has been reported in other studies on Italian healthcare, which highlight how administrative decentralization can lead to inequalities in the levels of digitalization and innovation. The integration of AI in the Italian healthcare system could, therefore, depend not only on the technological capabilities of individual hospital structures but also on the institutional set-up and regional policies adopted.

Differentiated autonomy appears to be the only solution to make a country and regions effective and efficient, streamlining the former while holding the latter accountable. The “legislative framework” is based on the reformed Article 116, paragraph three, Title V, of the Italian Constitution, according to which it is possible, upon request, to provide regions with increased autonomy. This autonomy encompasses twenty-three areas (including healthcare) while retaining the remaining matters under the central State's control to ensure system unity and sustainability. This issue is still debated, where virtuous regions and their respective local institutions are pressing for the implementation of differentiated autonomy, while the worst regions, having further experienced bad conditions due to regional federalism, take positions against that. In general terms, perhaps there is no stakeholder group capable of obstructing this ongoing reform; at most, they may further delay it. Beyond the opportunities and risks outlined for stakeholders, along with their respective positions and influences, what is concerning currently is the lack of determinants for success and cautions against potential undesirable effects. Without addressing these aspects, reform may jeopardize its sustainability over time, making, at the same time, worse the multi-tier situation featuring the NHS in Italy and the related struggle among Italian regions.

This thesis follows a logical progression connecting the three articles. The second chapter provides a theoretical foundation through a systematic literature review, identifying the key factors influencing the adoption of Artificial Intelligence (AI) in healthcare. The third chapter translates these theoretical findings into an empirical analysis, exploring the implementation process of AI in three major Italian hospitals and its impact on public health. Finally, the fourth chapter broadens the perspective by examining the political and institutional implications of the differentiated autonomy reform and its potential effects on the Italian healthcare system."

2. **Key factors influencing the adoption of Artificial Intelligence in healthcare: A Systematic Review**

2.1 Introduction

Artificial intelligence (AI) has a rich history and has made exponential developments in various fields despite being around for less than a century. The birth of AI stems from concepts such as the Turing machine and the Turing Test, which laid the foundation for the development of modern AI. Over time, branches have taken many paths, from the first expert systems to more advanced Big Data,

robotics, and machine learning applications (Prasad & Choudhary, 2021).

Despite debates over terminology, as some researchers prefer the term Augmented Human Intelligence (AHI) to specify how computers function as a support and not a replacement for human decision-making (Romero-Brufau et al., 2020), today, AI is often defined as "the ability of a system to correctly interpret external data, learn from such data, and use that knowledge to achieve specific goals and tasks through flexible adaptation" (Haenlein & Kaplan, 2019). To distinguish AI from traditional computing, it is essential to note that AI has evolved with a "bottom-up" approach, contrasting the "top-down" structure of classical computing systems that rely on "if-then" functions. This evolution includes incorporating artificial neural networks and deep learning, enabling AI to learn from its environment analogous to a child learning through sensory experience (Minsky & Papert, 1969) (Silver et al., 2016).

Before delving into the various types of AI available today, a fundamental question persists: when can we classify a system as truly intelligent? The boundary is fluid, but the Turing test remains a valid metric. If a human cannot reliably distinguish between a machine and a human counterpart, the machine can be said to demonstrate intelligent behavior equivalent to that of a human (Turing, 1950).

Over time, AI has progressed from systems designed for language decoding and chess to a broad spectrum of applications. AI's role in healthcare, for instance, rapidly expands, transforming medical practices and care delivery. AI's contributions include early disease detection, drug development, personalized treatments, and remote monitoring (Mohan et al., 2023). Machine learning algorithms, such as deep learning and natural language processing, are pivotal in analyzing medical data, supporting clinical decision-making, and improving patient outcomes (Fatima et al., 2023). Additionally, integrating AI into mobile health (m-health) platforms and using diverse datasets have been identified as promising advancements for genetic therapy and healthcare efficiency (Saxena et al., 2024). AI can enhance various healthcare services, including machine learning to process vast quantities of medical data, natural language processing to refine medical diagnoses, and robotic systems to assist in surgeries (Davenport & Kalakota, 2019).

The literature highlights the benefits AI has brought to healthcare, with one study focusing on 62 physicians examining the challenges and opportunities in adopting AI. The study explored strategies physicians might employ to navigate the dilemmas presented by AI integration in hospitals, using paradox theory as a framework (N. Singh et al., 2024). The identified benefits include ease of use, facilitating more efficient medical care and quicker diagnoses, a conclusion supported by numerous

studies (Laï et al., 2020), automation, which enables systems to perform multiple functions autonomously (Reddy et al., 2020), and accurate diagnosis, with AI systems demonstrating reliability in interpreting complex data, such as radiological images (Dicuonzo et al., 2023) (Al Badi et al., 2022) . A further advantage concerns cost efficiency, which relates to the expenses tied to developing, installing, and implementing AI technologies. Findings suggest that costs are often closely linked to treatment procedures and long-term patient outcomes, frequently reducing operational costs (Bamel et al., 2023).

Algorithms contribute to more accurate medical information, help predict future outcomes, and improve the chances of alleviating long-term financial pressures on patients (Vučinić, 2020). Nevertheless, the implementation of AI in healthcare is accompanied by challenges. Ethical concerns, the need for transparency in algorithms, and the importance of safeguarding patient privacy and safety are critical issues that must be addressed as AI becomes more integrated into healthcare systems (Sivaguru R et al., 2024) (Talati, 2023). In previous cases, the discrepancy between expectations and actual results has hampered AI adoption, and such challenges continue to pose risks in the healthcare sector (Shaw et al., 2019).

The barriers to AI Integration In healthcare are varied and complex, with studies identifying several technical, ethical, and organizational obstacles. These include data availability, model reusability, concerns about patient privacy, data security, algorithmic bias, resistance to change, and the need for education and resources (Babajide Tolulope Familoni, 2024; Shifan Khanday et al., 2024). Additionally, issues such as patient acceptance, regulatory compliance, and data protection must be considered to ensure the responsible implementation of AI (Student, Bal Bharati Public School. & Gupta, 2023).

Moreover, the surrounding environment, including technological infrastructure, socio-economic factors, and regulatory frameworks, plays a significant role in AI implementation in healthcare (Chafai et al., 2024). Technological readiness, such as data availability and processing capabilities, is critical. Socio-economic factors, including healthcare institutions' financial capacity and healthcare professionals' willingness to adopt new technologies, are also essential considerations (Thakkar & Bharathi, 2023).

While specific barriers, such as the ethical implications of diagnostic and treatment decisions, are specific to healthcare, others, like technical and organizational challenges, are shared across industries (Cubric, 2020). Despite the many benefits of AI in healthcare, large-scale adoption remains a complex challenge. The existing literature focuses heavily on the benefits but lacks a

systematic analysis of the factors influencing adoption. Indeed, the literature has highlighted the need to investigate the factors that might influence AI adoption. In detail, it's useful for a better understanding and, for future empirical testing, to identify the critical factors (N. Singh et al., 2024). Today, we know that various organizational, professional, and patient factors influence AI adoption in healthcare. Organizational characteristics play a crucial role in AI adoption. Significant factors include organization size, workflow, training programs, and safety measures. Professional characteristics that influence the adoption of AI can be classified into psychosocial, experiential, and background elements(Khanijahani et al., 2022). At this level, key factors include perceived ease of use, usefulness, performance expectation, and social influence (Alanzi et al., 2023; Khanijahani et al., 2022). Safety measures focus on the unclear legal relationships between AI and users(Arnold, 2021). Finally, an empirical study indicated that the most important factors, across all groups, are 'AI ability to learn from patient data', 'insufficient data privacy measures for patients', 'availability of technical support and maintenance services', 'physicians' acceptance of AI in healthcare', "reliability and uptime of AI systems" and "ability to reduce medical errors"(Alnasser et al., 2024).

To fill the gap in the literature, our study systematically examines these factors, providing insights into organizational, professional, and patient-related elements that play pivotal roles in shaping the adoption process. This review identifies critical factors and examines their prevalence and impact across different healthcare systems, offering a nuanced understanding of how context shapes AI adoption.

2.2 Methodology

We've adopted the PRISMA Protocol to guide our analysis. The PRISMA protocol is the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol, which has been widely used in systematic reviews examining the implementation of artificial intelligence (AI) in healthcare.

Several studies have used this methodology to ensure a comprehensive and transparent review process.

PRISMA has been used to investigate several aspects of AI implementation in healthcare. For example, one scoping review mapped nurses' approaches to influencing AI implementation in healthcare (Sodeau & Fox, 2022). Another study used PRISMA to analyze AI's current status and

future prospects in medicine (Bitkina et al., 2023).

This demonstrates the versatility of the PRISMA Protocol, which has also been used to systematically analyze explainable artificial intelligence (XAI) models in healthcare (Bharati et al., 2024).

The PRISMA protocol has proven valuable for conducting systematic reviews on the implementation of AI in healthcare. Several studies have consistently used it to ensure rigorous and transparent reporting of research findings, contributing to the growing body of knowledge in this rapidly evolving field.

To conduct the analysis (figure 1), we collected all articles concerning artificial intelligence (AI) in healthcare and used the main search engines, such as Scopus and Web of Science. We've decided not to include the grey literature as Google Scholar because the three databases selected can perfectly represent the complex situation and provide us with all the instruments necessary for investigating the phenomenon. Indeed, Scopus has been widely used as a database to conduct systematic reviews on AI in healthcare, as evidenced in several studies analyzed.

A systematic review examined medical students' attitudes, knowledge, and skills regarding AI using Scopus and other databases such as Embase and Web of Science (Mousavi Baigi et al., 2023).

On Scopus, we found 1539 articles, and on WoS, 2187 articles. These were found by entering a keyword string suitable for selecting articles relevant to our objective, namely "artificial intelligence OR AI AND adoption OR implementation OR acceptance OR diffusion OR uptake AND healthcare OR health care OR hospitals OR medical practice OR clinical practice AND factors OR barriers OR drivers OR enablers OR challenges OR facilitators OR determinants". The extracted articles were already the result of an initial filtering phase, i.e., we selected only research articles, consequently eliminating books, book chapters, reviews, and anything else that differed from the articles by only selecting articles written in English and Italian. The merged database consisted of 3726 articles. To ensure the inclusion of studies of high quality and academic relevance, we adopted the ABS (2021) & ABCD (2022) Journal Ranking as the selection criteria for the papers. This ranking, recognized in business economics and management, ranks journals according to their scientific reputation, methodological rigor, and academic impact. As our review explores the implementation of artificial intelligence in healthcare, a topic involving economic management aspects, this ranking allowed us to focus on studies published in A-ranked journals, ensuring greater scientific soundness and relevance to our analysis. This second process led us to a total database of 105 articles.

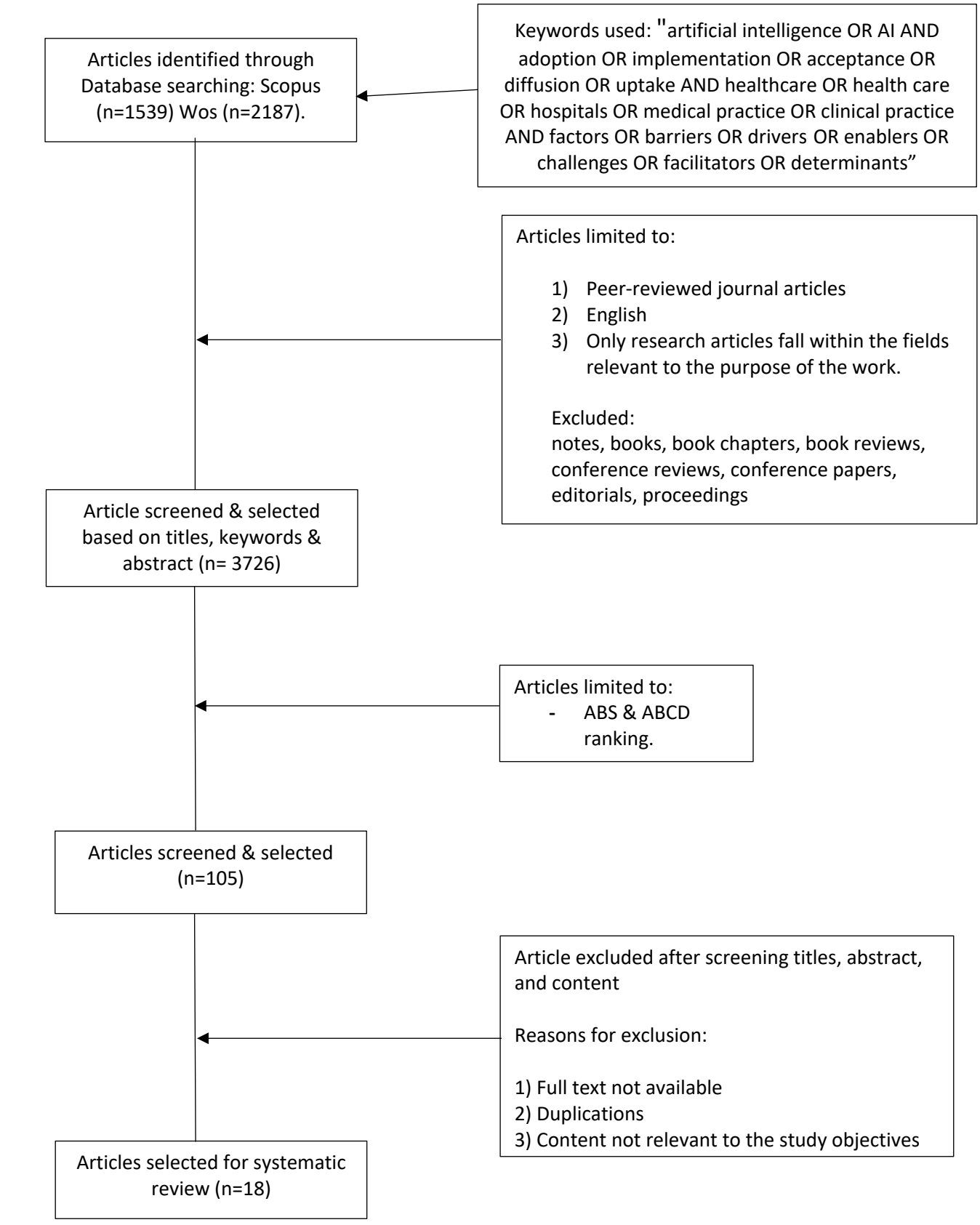
In the final filtering phase, we manually reviewed each article, eliminating articles irrelevant to our objective. The final database suitable for our review consists of 18 articles.

We've also clustered the papers based on the country where the IA was studied. In detail, we have divided the geographical locations into the rest of the World (in case the nation where AI was studied is not identified), the Rest of Europe, Australia, U.S.A, and the U.K. This subdivision was made because the rest of Europe, as well as in many countries of the world, the system is Civil Law. In contrast, the U.S., U.K. and Australia (and other Anglo-Saxon countries) have a common law system. Implementing new technologies like artificial intelligence (AI) in healthcare presents unique challenges and opportunities within civil law and common law systems.

In civil law jurisdictions, the focus tends to be on codified statutes and regulations, which may struggle to keep pace with rapidly evolving AI technologies. This can create gaps in governance and liability frameworks for AI in healthcare. On the other hand, common law systems rely more heavily on case law and precedent, potentially allowing for more flexible adaptation to novel AI applications through judicial interpretation (Capowski, 2009) (Gomes, 2018).

We divided the articles among the various authors for a timely and effective analysis. We read and analyzed each article and then reported the results and other important elements of the article in an Excel file where the graphs in the results section were plotted.

Figure 1 Prisma Protocol



2.3 Results

Following the method underlined in the previous section,3726 potentially relevant records were identified by searching the database. Finally, after some filter stage, 18 papers were included in the systematic review. The findings were organized as follows: (a) cumulative frequency analysis of included papers intended to show the trend of publications in the field object of study (Fig 2; Tab. 1); (b) data matrix analysis of papers (tab.2).

Figure 2 Accumulated frequency analysis of the papers included in the review

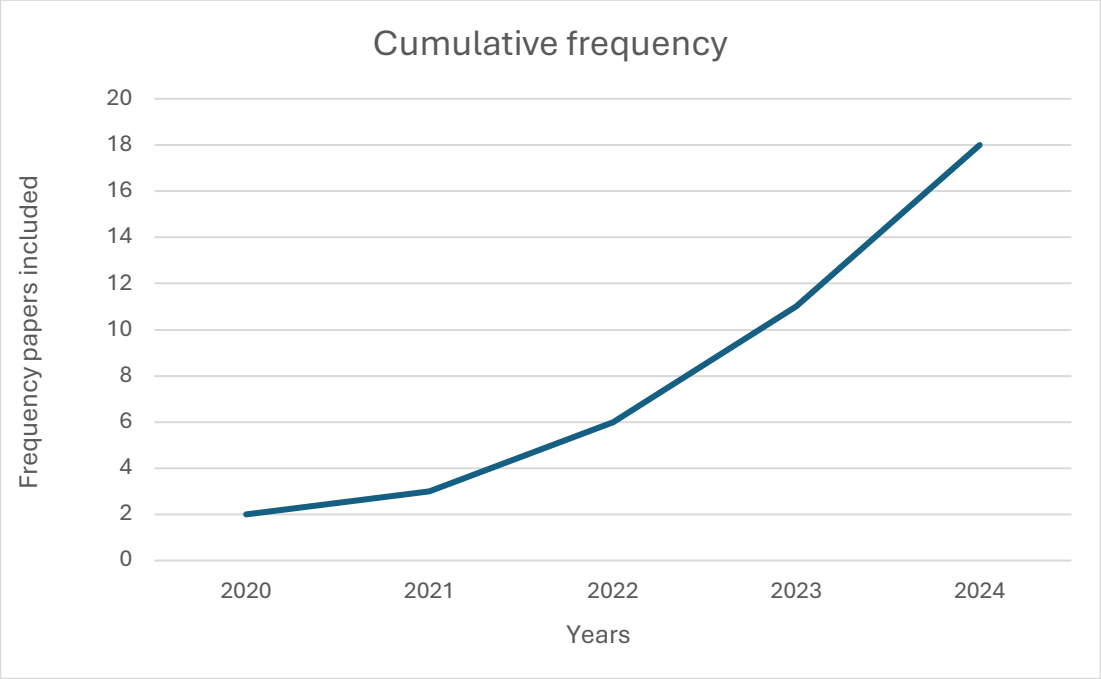


Table 1 Accumulated frequency analysis of the papers included in the review

Year	Frequency	Cumulative frequency
2020	**2**	**2**
2021	**1**	**3**
2022	**3**	**6**
2023	**5**	**11**
2024	**7**	**18**

Despite the rich literature on AI in healthcare, only a few works have focused on analyzing the factors influencing the adoption of AI. However, the graph clearly shows an exponential increase over the last five years.

2.3.1 Main factors

Our analysis revealed many factors, which is the reason why we considered it appropriate, for the purpose of greater clarity of presentation, to group the factors into macro-categories created by the authors based on the relevance of the individual factor. We have, therefore, included (tab. 2) the main evidence in terms of services and factors. We then explored in detail in the macro-categories what emerged from the literature analysis under investigation.

Table 2 Data matrix analysis of papers

Focus/Countries	Rest of the world (or not well-specified country)	Rest of Europe	Australia	USA	UK	Total
AI Services						
Diagnostic	4	4	0	0	1	**9**
Pharmaceutical Development & Education	0	1	0	0	0	**1**
Clinical Decision Support	1	2	0	0	0	**3**
Therapy Management	1	1	0	0	0	**2**
Patient Support	2	1	0	0	0	**3**
Other Services	2	0	0	1	0	**3**
Subtotal	10	9	0	1	1	**21**
Factors						
Technologies						
Ease of Use/Effort Expectancy	1	0	0	1	1	**3**
IT Experience	2	0	0	0	0	**2**
Perceived Usefulness	2	0	0	0	0	**2**
Other Technologies factors	5	2	0	0	2	**9**
Subtotal	10	2	0	1	3	**16**
Organizational						
Workplace Readiness	1	0	0	0	0	**1**
Business plan	1	0	0	0	0	**1**
Organizational Redesign	0	1	0	0	0	**1**

Other organizational factors	1	5	0	4	0	**10**
Subtotal	3	6	0	4	0	**13**
Human & Psychological						
Trust	4	0	0	1	0	**5**
Anthropomorphism	2	0	0	0	0	**2**
Motivation	1	0	0	0	0	**1**
Other Human & Psychological factors	7	1	0	0	0	**8**
Subtotal	14	1	0	1	0	**16**
Social						
External Factors	3	0	0	0	0	**3**
Social Influence	1	0	0	0	0	**1**
Social Value	1	0	0	0	0	**1**
Other Social	6	0	0	0	0	**6**
Subtotal	11	0	0	0	0	**11**
Economic, Functional & Operational						
Cost efficiency	0	0	0	0	1	**1**
Functional Value	1	0	0	0	0	**1**
Other Economic, functional & Operational	3	2	0	0	0	**5**
Subtotal	4	2	0	0	1	**7**

2.3.2 Technologies factors

Our first macro-category analyzed several factors incorporated into technological factors, the most relevant in the literature being Ease of Use/Effort Expectancy, Perceived Usefulness, and IT Experience. In detail, Ease of Use represents the convenience of using AI-based technologies for medical care, data management, and rapid diagnosis. It is considered a key predictor of AI adoption. Indeed, ease of use can lead to increased satisfaction, which favors the initial and continued adoption of AI services. In particular, the ability of AI technologies to simplify the management of large patient datasets and offer more efficient services has been observed.

Such systems also make it possible to reduce the complexity of procedures, improving transparency and outcomes for patients.

Ease of use, therefore, improves operational effectiveness and encourages greater adoption by younger generations, who are more inclined to use advanced technologies (N. Singh et al., 2024). Instead, effort expectancy can be defined as 'the degree of ease associated with using a system'

derived from the concept of ease of use proposed in the original TAM model (Venkatesh et al., 2003). The easier a system is to use, the greater the propensity of physicians to use it. Furthermore, effort expectancy directly impacts behavioral intention and positively correlates with performance expectancy, thus improving initial confidence in AIMDSS (Artificial Intelligence-Based Medical Diagnosis Support System) (Fan et al., 2020). The third factor that emerged in relevance relates to IT experience, with prior experience with IT positively influencing the adoption of AI technologies. Users with more IT experience perceive systems as less complex and easier to use. This experience helps reduce initial barriers, promoting more effective and confident use of technologies (Cao et al., 2020) (Liu & Tao, 2022). There may be doubts whether this factor falls under technological factors rather than human factors. However, it has been included in the category of the following paragraph as it refers to how a technological system requires a certain level of IT skills to be used effectively.

2.3.3 Organizational factors

In the organizational context, the factors were heterogeneous; as seen from the table above, there is no clear predominance in the factors that emerged. However, below are those that have emerged in the literature as particularly influential in adopting AI in the organizational context. The first factor concerns workplace readiness. It is crucial in facilitating the adoption of AI technologies in healthcare. It involves ensuring stakeholder acceptance and involvement, which are vital to the success of the implementation itself. For example, a high degree of stakeholder acceptance has been linked to more effective use of AI systems, as it aligns organizational goals with individual tasks and professional expectations. The literature emphasizes the importance of involving end-users, such as nurses and physicians, early in the process to foster acceptance and reduce resistance. This readiness also involves adapting workflows and professional roles, ensuring that AI tools fit seamlessly into existing practices without overwhelming staff (Alami et al., 2020).

AI implementation finds another critical issue in the lack of a clear business plan, in fact, it is essential for the sustainable adoption of AI. The plan should outline financial requirements for infrastructure improvements, ongoing training and technical support. Some studies suggest that inadequate funding and unclear financial strategies may hinder the long-term success of AI initiatives (Alami et al., 2020).

There is a need to invest in data integration and infrastructure upgrades to support the operational needs of AI systems. Moreover, ensuring sufficient resources for these initiatives is crucial to avoid the risk of failure of pilot projects and to ensure the scalability of AI applications (Manetti et al.,

2022). Finally, our analysis showed that integrating AI often requires a complete organizational redesign, framing it as a third factor, we emphasize how it is especially useful for adapting clinical pathways and workflows.

In one case study, introducing a machine learning algorithm for early sepsis detection required the redesign of the clinical workflow to accommodate the new diagnostic tools while maintaining efficiency and quality of care. Organizational redesign helps overcome structural challenges and align new technologies with broader organizational goals, thus enabling a more efficient and effective healthcare delivery system (Manetti et al., 2022).

2.3.4 Human & Psychological factors

Of all the factors investigated, trust is certainly the key factor. We found a strong presence of this factor in the macro-category of human factors and overall. Some studies place trust, especially initial trust, as a factor that can most accurately explain the rationale behind the evolution of the behavior of doctors adopting AI-assisted diagnosis systems. It refers to the degree to which an individual believes in another party and is willing to depend on it (Mc Knight, 2005). A study shows that initial confidence positively impacts the willingness to use AI-assisted diagnostics (Wang & Wang, 2024) (Choudhury et al., 2022) (Liu & Tao, 2022). The propensity to trust has the highest impact on initial trust. The propensity to trust is a personal characteristic of physicians, and the higher the propensity to trust, the easier it is to establish trust when dealing with AI-assisted diagnostic systems (Wang & Wang, 2024). Importantly, trust not only acts as a critical factor for initial acceptance but also as a catalyst for AI technologies continued use and perceived value. Initial trust is crucial to overcome natural resistance to technological change. Users become more reliant on AI systems when they perceive that they meet accuracy and reliability expectations. Studies such as the one on AIMDSS show that transparency in decision-making and perceived reliability of the system significantly increase trust, reducing the perception of risk (Fan et al., 2020) (Choudhury et al., 2022).

To improve and maintain trust, some studies suggest the importance of specific strategies, such as continuous training and clear communication on system reliability. Anthropomorphism, or using more human-like interfaces, can also play an important role, creating an emotional connection with the user and fostering a positive experience(Prakash & Das, 2024).

In fact, our review shows how Anthropomorphism, or the ability of AI systems to imitate human traits, significantly improves user confidence by making the technology more acceptable (Fan et al., 2020; Liu & Tao, 2022).

As a final factor, we find motivation in improving understanding and training using AI. This plausible and practical solution enables healthcare professionals to use AI continuously (Al-Dhaen et al., 2023).

2.3.5 Social factors

The main social factors that emerged were external factors, social influence, and individual characteristics and occupation. External factors include environmental and structural stimuli influencing healthcare professionals' decision-making behavior. According to the S-O-R model, these stimuli act as triggers that modify cognitive and affective states, ultimately determining behavioral responses (Dalvi-Esfahani et al., 2023). A crucial aspect of these factors is conformism, the tendency of users to conform to the technological choices adopted by reference groups (Wang & Wang, 2024).

Hospital environments can optimize operational efficiency through collaborative design with technology developers. This approach has been shown to reduce patient waiting times and improve user satisfaction, highlighting how the management of external operational settings can positively influence adoption (Cao et al., 2020).

Social influence, on the other hand, can be defined as “the degree to which an individual perceives that significant others believe that he or she should use the new system“(Venkatesh et al., 2003) and a study shows how this factor may influence the intention to adopt AI towards AIMDSS use (Fan et al., 2020).

Social value refers to the perceived usefulness of associating an alternative with a specific social group, a study shows that it has a positive effect on the physician's intention to use AI-assisted diagnosis (Hsieh, 2023).

2.3.6 Economic, Functional & Operational

Two factors stand out and are related to cost and functional value. The results suggest that cost is directly associated with treatment procedures and long-term patient outcomes (Bamel et al., 2023). However, the cost could be controlled by using well-tested and accurate technology in the healthcare system to reduce operational and routine costs. Artificial intelligence techniques could be used to conduct clinical drug trials, using deep learning techniques for planning, processing, and data collection. This could reduce operational costs and save time. Interviewees discussed how artificial intelligence services improve procedural efficiency, speed up the process, and save costs.

On the other hand, artificial intelligence techniques can be used to conduct clinical drug trials, using deep learning techniques for planning, processing and data collection. This could reduce operational costs and save time. Several studies have indicated that AI-based services have high investment and maintenance costs, which are difficult to maintain due to the system's funding constraints and lack of financial support. Moreover, some constraints, including financial support, lack of investors, and high investment costs, may not apply to developed markets compared to developing systems (N. Singh et al., 2024).

Functional value, on the other hand, refers to an individual's rational and economic assessment of the quality of a product or service (Sheth et al., 1991). One study found that if physicians perceive that the use of AI-assisted diagnosis can help them quickly identify, for example, an injured area and reduce the problem of misdiagnosis, this will increase the physician's intention to use AI-assisted diagnosis.

Furthermore, functional and emotional values significantly impact doctors' intentions to use AI-assisted diagnosis (Hsieh, 2023).

2.4. Discussion

Based on the themes highlighted in the previous sections, this part presents the evidence that has emerged concerning the factors influencing the adoption of AI in healthcare. Founded on the compilation of factors, what emerges as a first aspect is that the literature is rather divergent and heterogeneous as to what the crucial factors might be to effectively adopt AI in healthcare, therefore, although it is an absolutely correct approach to explore the whole multitude of factors that might influence adoption, one should also focus more on what the literature has brought out to firmly determine some factors that have a major impact on AI adoption. Going in chronological order of the data that emerged, what appears from our review is first of all, the discrepancy in the nations that investigated the phenomenon. As the results suggest, almost all the investigations were conducted in Civil Law nations, where the implementation of AI could be more ‘problematic’ due to legislative frameworks that could slow the adoption of AI. It is a different story regarding the services for which AI implementation has been requested; almost all the work is focused on diagnostic support services. This result could be the result of the wide range of applications within the diagnosis branch. Diagnosis usually refers to identifying the nature or cause of a possible pathological condition with many tools (e.g. X-ray imaging, ultrasound, blood tests, etc.).

However, it remains valid information on the services for which the factors influencing the adoption of AI technologies are being investigated. As stated at the beginning of this section, given the multitude and non-convergence of the factors, we considered it appropriate, for the sake of clarity and cleanliness, to consider only the main factors and to summarize them by grouping them into macro-categories to avoid a dispersive phenomenon. The factors were selected according to the criteria of importance that emerged in the articles and the number of times a factor emerged in the literature review. Before discussing the factors that emerged, it is useful to specify that almost all the factors were investigated in the face of problems and barriers encountered in adopting AI. Given the non-specific relevance to the focus of this paper, the authors agreed not to put the problems encountered in the results section under a magnifying glass, however, for the sake of clarity of exposition, it is appropriate to specify some of the main barriers under discussion. The main critical issue encountered is related to trust in AI. This barrier is present in both protagonists involved, i.e., Patients and Doctors. Regarding the first group, mistrust occurs mainly due to privacy issues, lack of transparency towards those who manage the data and on the functioning of the technology itself, and the undecidedness of AI's ability to make diagnoses as well as or better than a human doctor (Wang & Wang, 2024) (Al-Dhaen et al., 2023; Gaube et al., 2024, 2024; Hsieh, 2023; N. Singh et al., 2024). On the physicians' side, concerns are directed at security and privacy issues and lack of national and international standards and regulations in the field of AI, but also at ethical issues or the fear of an AI dependency developing or that over time, they may lose their decision-making autonomy with the consequent loss of professional competence. In addition, not fully understanding the dynamics, the processes, and the lack of demonstrability of results leads to framing AI as a black box and increases mistrust (Apell & Eriksson, 2023; Fan et al., 2020; Guo et al., 2024; Manetti et al., 2022; N. Singh et al., 2024). Additionally to these personal aspects, organizational barriers are given by resistance to change, technical problems by poor interoperability with other software, and high infrastructure and implementation costs that lead to adoption favoring mainly by resource-intensive organizations (Alami et al., 2020; Al-Dhaen et al., 2023; Apell & Eriksson, 2023; Manetti et al., 2022; N. Singh et al., 2024; Wenderott et al., 2024).

The exposed barriers and the wealth of literature on the subject underline even more the importance of understanding what factors are needed to overcome the various problems.

About the factors investigated, therefore, what particularly stands out is the factor of trust we found that it is often cited as a key factor behind the willingness to adopt an AI technology. However, it would be a mistake to consider it as an isolated factor.

Although analyzed in isolation, each factor is part of a directly or indirectly connected and mutually influential system involving factors of different categories. For example, trust itself often changes according to the functional value a physician attributes to AI or with the perception of value (Prakash & Das, 2024; Wang & Wang, 2024) and is influenced and affected by several barriers in the literature. Working on the trust factor would mean solving the multiple barriers mentioned above. Working on ease of use and IT experiences would be appropriate concerning the technology macro-categories. In fact, the greater the ease of use of an AI technology, the more confidence a user has in the possibility of additional value in using it.

IT experience also falls into this category, as competence is given by the extent of the interaction between the user and the technology and not merely by the user's previous accumulated competence in similar technologies. These two factors, although belonging to different macro-categories, would have a positive impact on trust and also on perceived usefulness.

Another critical aspect is implementation costs, which exacerbate inequalities between healthcare facilities. Organizations with limited resources may find it difficult to cover the initial costs of adopting AI and, for example, to bear the costs associated with the maintenance or ongoing updating of systems. This leads to slower or partial adoption, further widening the gap between facilities with different technological capabilities.

Workplace readiness emerges as a crucial organizational factor in facilitating AI integration. Active stakeholder involvement is essential to foster a collaborative environment and reduce resistance to change. Although the documents emphasize the importance of organizational readiness, reflecting on how this can be translated into concrete actions to improve technology acceptance remains crucial.

In parallel, a clear business plan addresses the economic challenges associated with AI implementation. Although the articles analyzed do not provide specific details, it seems clear that a structured plan could help organizations manage investments, training resources, and infrastructural adjustments. The social macro-category highlighted how external factors play an active role and significantly influence the decision-making process in AI adoption in healthcare. These external stimuli act as triggers that alter organizational and individual AI technology adoption decisions. The literature has also highlighted how collaborations between hospitals and technology developers can improve the interoperability and efficiency of systems, helping to reduce technical and organizational barriers. These environmental factors stimulate trust and value perception of AI systems, enhancing acceptance by healthcare professionals.

2.5 Conclusion

The application of artificial intelligence in healthcare is a rapidly growing phenomenon in terms of academic interest; however, as reported at the beginning of our work, the literature is not particularly rich in studying the factors influencing the adoption of AI in healthcare. Accepting the suggestion from the literature, we decided to investigate this phenomenon to bridge the existing gap by analyzing the existing literature to establish the most influential factors in AI adoption. After discussing the results, the authors recommend focusing efforts on continuous education and positive awareness of AI among medical personnel and users to increase trust towards AI by breaking down multiple barriers. By doing so, both actors involved would have a greater awareness of how AI does not lend itself as a medical replacement but more as an effective assistance allowing doctors to focus on more demanding practices with reduced workload and increased healthcare facility efficiency. On the other hand, users would have greater confidence in the processing of diagnoses by AI. In addition, legislation should intervene by setting policies and standards to overcome privacy issues and the lack of transparency of AI results and data. Furthermore, a gradual integration is recommended to overcome barriers such as interoperability of systems and to identify and correct any issues, as well as positively affecting organizational readiness and a greater readiness to change. Our results align with the existing literature, in particular, an interesting paper identified 46 factors, and among them is the confirmation of ethical deficiencies, privacy, and security issues. The other main factors in our review are how greater trust and positive acceptance foster collaboration between healthcare professionals and AI technologies and the other main factors that emerged (Alnasser et al., 2024). This study followed an implicit research question (RQ), namely, to provide an overview of the most influential factors on AI adoption in healthcare. However, the same is not without its limitations. The first concerns the failure to create a qualitative scale of factors with relevant empirical data. We believe that although this aspect is fundamental to the literature, our work can provide an important starting point for the creation of the same. The second limitation is dictated by not including the secondary factors. Despite the perspective provided, including secondary factors could provide even more insight into the factors that emerged during our analysis. We consider it useful to continue investigating the influence of the factors, starting from the analysis of individual macro-categories until we arrive at a qualitative scale with empirical data from questionnaires or semi-structured interviews, which is comprehensive and can provide with certainty the importance and impact of certain factors so that we can effectively intervene on them and arrive at an effective adoption of AI in healthcare.

3. Will artificial intelligence become a good doctor? Opportunities and issues to implementing artificial intelligence in healthcare and its impact on public health: a multiple case study of Italian hospitals.

3.1 Introduction

Artificial intelligence (AI) is older than one might think, even though it has only been a few years since the term and knowledge became mainstream. Its official origin dates back to 1956 when John McCarthy and Marvin Minsky were the creators of the workshop "Dartmouth Summer Research Project on Artificial Intelligence (DSRPAI)" at Dartmouth College in New Hampshire, intending to bring together all the great minds working on similar projects and creating a unique network for the development of machines capable of mimicking human intelligence and artificial intelligence (McCarthy et al., 2006). Before this event, AI had more blurred characteristics; during World War II, Alan Turing, a British mathematician serving the British government, created "the bombe," the first official trace of computer science and artificial intelligence. "The bombe" could break the Enigma code used by the German army, and no human mind could replicate the work in the limited time taken by the machine. However, it was too early in those years to talk about artificial intelligence.
Nevertheless, what is artificial intelligence, and how is it defined? From the view of human intelligence as the biopsychological potential to process information, solve problems, or create products that have value in culture (Gardner, 1999), Minsky defined artificial intelligence as a machine that behaves in intelligent ways if a human behaves like that(McCarthy et al., 2006). Today, AI is commonly defined as "the ability of a system to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Haenlein & Kaplan, 2019). To distinguish AI from computer activities, it is useful to specify that artificial intelligence, over time, has evolved and is currently equipped with a "bottom-up" system, different from the "top-down" computer systems based on the "if-then" function, with artificial neural networks and deep learning at its core, which provide the ability to flexibly learn from the surroundings (such as a child learning about life through the development of its own senses) (Minsky & Papert, 1969; Silver et al., 2016). Before exploring the different categories of AI currently available, one question remains: when can artificial intelligence be defined? The boundary is extremely fluid, and the Turing test is still a valid tool for identification: If the human interacting with the entities cannot reliably distinguish between the machine and the human, the machine can be said to exhibit

intelligent behavior equivalent to, or indistinguishable from, that of a human (Turing, 1950).

We started with the first artificial intelligence systems used to decode languages and win chess games. Today, we have a panorama of broad and interesting opportunities.

This study will particularly focus on using artificial intelligence in healthcare. The uses are many and evolving and cover different areas of healthcare, starting from online appointment scheduling services to drug interaction alerts when doctors prescribe more than one drug, to research development (Akyon et al., 2023), and ending with an interesting classification of the role of AI in healthcare that encapsulates the uses in four macro-categories (Poalelungi et al., 2023). The first relates to disease detection and diagnosis and medical imaging, in particular in this field, AI-based diagnoses can help doctors decipher medical images such as X-rays, magnetic resonance imaging, and computed tomography scans, all of which produce faster and more accurate diagnoses, in addition, algorithms are adept at examining patient information, symptoms, and medical background (Umapathy et al., 2023). There are also several uses for imaging, for example, in the case of pancreaticobiliary disease. AI is useful in disease detection, risk stratification, and diagnosis prediction (Barat et al., 2021).

The second category involves treatment planning and personalized medicine. By rapidly analyzing large amounts of patient-specific data, AI systems can offer tailor-made healthcare recommendations to aid the physician in clinical decision-making (Parekh et al., 2023).

The third category encompasses drug discovery and development. Here, the role of AI contributes both by accelerating and actively contributing to the drug discovery process and by accurately predicting drug efficacy (S. Singh et al., 2023).

The fourth category concerns predictive analytics and risk assessment. Both contribute to the healthcare revolution through improved clinical outputs and optimized resource allocation. Predictive analytics can identify patients at risk in advance by providing early warnings and improving situational awareness. These tools have also shown uses beyond their initial training; in fact, they can provide real-time feedback on the effectiveness of treatments (Keim-Malpass et al., 2023).

Once the role of AI has been defined, we shift our attention to what are the advantages and barriers encountered so far. Given the different objectives of this work, which aims to investigate with case studies what are the effects produced by the implementation of AI and the barriers that have emerged in Italian healthcare, we quickly expose the main benefits and barriers that have emerged so far. In detail, the literature analyzed is rich in the benefits produced, some studies frame AI as a

real breakthrough in providing better and safer care for their patients (Laï et al., 2020), while others point to more far-reaching benefits focusing not only on better patient care with the consequent reduction of clinical risk, but also find significant improvements in administrative processes within organizations leading to optimization of healthcare resources (Dicuonzo et al., 2023). On the barrier front, the literature points to some critical issues, such as ethical and privacy concerns arising from protecting patient privacy and gaining the trust of physicians and the public in the use of AI in healthcare AI biases arise when data used for training are not representative of the target population and when inadequate or incomplete data are used (Vayena et al., 2018). Or barriers arising from transparency, accountability, and responsibility that are directly related to each other. For example, transparency in medicine is crucial, and when this is lacking, it can reduce the reliability of artificial intelligence models in healthcare (Whittelestone et al., 2019). Furthermore, organizational barriers are present; in fact, these, such as the availability of skilled resources, strategic roadmap, and corporate culture, have influenced the adoption of AI (Radhakrishnan et al., 2022).

This study aims to analyze in depth the implementation of AI in healthcare, using the Italian context as a reference. This will provide the literature with the benefits and obstacles produced and a perspective on the implementation processes. Lastly, it aims to provide practical indications for overcoming the barriers.

3.2 Methodology

The methodology section of this research focuses on the multiple case study approach, a qualitative research method particularly suited for a more in-depth understanding of the phenomenon through comparing similarities and differences within and between cases (Heale & Twycross, 2018). In this study, we selected three major hospitals in Italy that have implemented artificial intelligence (AI) technologies and are recognized internationally. These hospitals represent critical cases for understanding the complexities of AI integration in healthcare contexts. The choice of a multiple case study methodology allows us to explore each case in detail while also providing a comparative analysis across different contexts. The methodology is structured to capture each case's complexity, considering the hospitals' unique context, the AI technologies implemented, and the observed outcomes. In fact, each case study will be conducted following a consistent protocol to ensure reliability and comparability.

We collected the data through a combination of interviews (semi-structured interviews) with key stakeholders (AI managers or implementers), observations of AI in use, and analysis of relevant documents such as implementation reports and performance metrics. Furthermore, we considered it appropriate to conduct the interviews following the conceptual lens of the CFIR (Consolidated Framework for Implementation Research). The Consolidated Framework for Implementation Research (CFIR) is a meta-framework designed to guide systematic assessment of multifaceted influences on implementing evidence-based practices. It integrates constructs from various theories into a comprehensive taxonomy, facilitating the exploration of factors that may affect implementation success across different contexts (Smith et al., 2015). CFIR categorizes these factors into five domains: innovation characteristics, outer setting, inner setting, individuals involved, and implementation process, each encompassing specific constructs that can act as barriers or facilitators to implementation (Damschroder et al., 2022).

3.2.1 Cases Involved

For case selection, as outlined above, we opted for a multicase comparison to be able to offer a more reliable and valid overview by providing interesting insights from the comparison of the three cases under analysis. We undertook a step-by-step process. First, we created a list listing all the Italian hospitals implementing AI in their facilities. After this preliminary research phase, we filtered the list by excluding all the facilities that, at the time of the research, had not yet obtained results from the implementation of AI. Subsequently, we chose three different hospitals to represent the whole Italian situation, which sees the existence of public and private hospitals, some of which may be scientific and are called IRCSS (Scientific Hospitals and Care Institutions), which can be either public or private. Once this classification had been made, we proceeded to select the hospitals using both the criterion of the highest documented results produced and by consulting the important magazine 'Newsweek' on the best hospitals in the world, which chose, among the various selection factors, precisely those facilities that showed an intriguing use of artificial intelligence (Newsweek, 2024):

- **[CASE 1] Niguarda Metropolitan Hospital (Grande Ospedale Metropolitano Niguarda):** This is a public institute of hospitalization and care with scientific character (IRCCS) located in Milan, Italy. It is one of the largest hospitals in Europe, with 1167 beds and an estimated 6,000 employees. The hospital is recognized as a center of excellence for research, innovation, and patient care in several specialist areas. Founded in 1939, Niguarda has a long and rich history of quality healthcare. Over the years, hospitals have evolved and expanded, becoming a benchmark for medicine in Italy and internationally. Innovation and technology have proven to be at the forefront of using innovative technologies to improve the quality of patient care. The hospital has implemented telemedicine, surgical robotics, and artificial intelligence systems. Ranked 52nd in Newsweek magazine's ranking of the 250 best hospitals in the world, it was selected especially for its 'Data Lake' project(*ASST Grande Ospedale Metropolitano Niguarda*, 2024).

- **[CASE 2] Gemelli University Hospital (Policlinico Gemelli):** Is a private Institute for Hospital and Scientific Care (IRCCS) located in Rome, Italy. It is one of Europe's largest and most important hospitals, with 1,526 beds, approximately 5300 employees, and 2500 scientific publications. Founded in 1964 by the Catholic University of the Sacred Heart, the Gemelli University Hospital was the first university hospital in Italy. Over the years, hospitals have evolved and expanded, becoming a point of reference for medicine in Italy and internationally. In terms of innovation and technology is at the forefront of using innovative technologies to improve the quality of patient care. The hospital has implemented telemedicine, surgical robotics, and artificial intelligence systems. Ranked 35th in the list of the world's top 250 hospitals, it was chosen because of its in-house artificial intelligence center (Gemelli Generator) («Policlinico Gemelli», 2024).

- **[CASE 3] Sant'Orsola-Malpighi Polyclinic Hospital (Ospedale Policlinico Sant'Orsola-Malpighi):** The Sant'Orsola-Malpighi Polyclinic Hospital in Bologna is one of the leading public hospitals and research centers in Italy. Founded in 1592, it covers an area of more than 223,000 square meters and houses approximately 1,535 beds. With a staff of 6,807 employees, including 857 physicians, the hospital handles approximately 69,000 ordinary admissions, 139,000 emergencies, 33,000 surgeries, and over 3 million specialist examinations annually. Sant'Orsola-Malpighi Polyclinic Hospital is at the forefront of using

technology and artificial intelligence (AI) in the medical field. AI is used to improve diagnostic accuracy, optimize care pathways, and support clinical research. It was ranked 66th in the list of the 250 best hospitals in the world and was chosen precisely for its breadth in the use of AI(P. Sant'Orsola, 2024).

3.2.2 Semi-structured interviews

We selected semi-structured interviews as they are widely used research methods that are particularly appreciated in the literature for their in-depth explorations of participants' perspectives and for the flexibility to adapt to the flow of conversation, leading to a greater understanding of what is being investigated. Once the case studies had been selected, we searched for contacts by contacting the directors or persons responsible for the IA process in the various facilities via e-mail. Upon authorization was received, we proceeded to the pretesting phase by sending the interview questions to conduct a cognitive interview to provide the participants with the interview guidelines. This phase is useful because it contributes to better efficiency and validity and helps improve the quality of the data collected. The preparation phase ensured that interviewees were well-informed about the study's topics and objectives, enhancing the responses' relevance and depth. In fact, by doing so, we received feedback from the interviewees, possible clarification questions, and more complete and elaborate answers. In the next phase, we conducted the interviews by meeting the stakeholders online. In the first case (Niguarda Metropolitan Hospital), we interviewed a director of nuclear medicine who has worked in the facility for twenty-three years, knowing every internal, external, and technical aspect of the facility and the implementation of AI, which is why we were able to investigate the implementation of Ai in the facility thoroughly. In the second case (Gemelli University Hospital), we interviewed the scientific director of the artificial intelligence laboratory as well as the IRCCS Vice Director in charge of Big Data, Director of the Imaging Diagnostics, Oncological Radiotherapy and Hematology Department, who, with his many years of experience provided broad and detailed overviews of the entire process that has evolved over time. In the last case (Sant'Orsola-Malpighi Polyclinic Hospital), we interviewed the Director of the Sanitary Physics Department with more than five years of experience, who provided us with technical data that was very important for our purposes. All interviews have been recorded in the original language, transcript by specific software to avoid possible errors and mistakes, translated into English directly by the interviewer and then checked by other research team members to ensure agreement of a

“correct” version of the text. The interviews lasted, on average, approximately forty minutes, during which we explored all the points necessary to obtain quality data.

3.3 Results

In the following section, we will illustrate the results of the interviews by dividing them into cases. Each case study will be presented following the points of the CFIR outlined in the methodology section. In the context of AI implementation in healthcare, the innovation characteristics domain considers the description and attributes of AI applications, such as their relative advantage over existing solutions, the complexity of the technology, and the quality and strength of evidence supporting their effectiveness. The outer setting refers to the economic, political, and social context within which an organization resides, including patient needs and resources, which can influence the implementation of AI in healthcare settings.

The inner setting domain encompasses features of the implementing organization, such as the organization's culture, readiness for implementation, issues, and availability of resources such as data quality, which are crucial for AI applications. The characteristics of individuals involve their attributes in the implementation process, including their beliefs and attitudes toward AI innovation, which can significantly affect the uptake and use of AI in clinical practice.

Finally, the process domain involves the steps taken to implement AI applications, including planning, engaging, executing, and reflecting on implementation efforts. Effective engagement with and management of the implementation process are cited as facilitators of the successful adoption of AI in healthcare (Chomutare et al., 2022). Subsequently, (Tab. 3), a table of the three cases will be shown in which we will report the AI implemented, obstacles encountered, the results produced, and the impact on public health for each of them that emerged during the interview. Consequently (Fig. 3), we have elaborated a conceptual map from the analysis of the interview data on how the barriers preventing or limiting the implementation of artificial intelligence can be overcome.

3.3.1 [CASE 1] Niguarda Metropolitan Hospital (Grande Ospedale Metropolitano Niguarda)

Innovation Characteristics:

In this case, we observe the initial stage of AI implementation. An external IT partner supports the AI implementation and its adaptation, with a focus on smart platform design and data collection. Data collection unveiled higher complexity and higher time, due to the limited interplay between different data sources and to lexical misalignment in the queries.

<<*The start-up was especially complex, especially the connection to our 19 different connectors, because there were local databases that had to be integrated into the single data lake. Moreover, not all these databases were owned by the hospital, or in any case belonged only to the hospital, some were regional, so it was complex and continues to be so. Another critical aspect is the definition of medical terms in the query. We faced with many problems of vocabulary and interpretation, because the same parameter could be defined in the medical records differently and therefore there was a risk, as we have seen, of having wrong results because they did not consider all the possible declinations and definitions of the same parameter. A sure obstacle that we have therefore seen is lexical alignment and homogenization to align definitions and therefore manage data in a more coherent way*>>.

Another critical process was data entry due to the limited technical skills of internal staff involved in data analysis. The smart technologies adopted include data collection and archival structure, i.e., databases oriented toward different objectives, and forecasting tools to predict the performance of some processes and related therapy. AI applications focus on these goals: supporting management decisions, health monitoring and therapeutic decisions, improving scientific research, and forecasting patients' clinical trends.

Outer setting

The external context of this organization is the metropolitan area, which encounters many different social contexts and patients. The main driver for AI adoption was the COVID-19 pandemic, which greatly affected this organization and changed its habitual operating pattern.

<<*We can certainly say that the main determinant of AI was the COVID-19 emergency. During the pandemic wave, we made a hospital-wide register of 80 items that we had taken from the medical records of the different departments to assess the progress of the epidemic and the follow-up of patients. The external context was, in general, totally different from the common patterns in which hospital used to operate*>>.

Inner setting

The organization did not have all the requested technical resources to create and manage the AI processes. There were many local databases, not all owned by hospital, many records with lexical misalignments that requested to manage data more consistently. Also, technical skills for data interrogation were underdeveloped. The hospital provided training to implement and deliver the innovation within the organization.

<< *We were used to data analysis and to having a phase in which data managers had a big job called data entry. This has obviously changed, as querying the data is much more important than querying the sources. People will be trained, rather than going to find and enter data, they can go and interrogate it.*>>

The AI innovation seems to align with the overarching commitment. It fits with general goals and is supported by coordination and convergent intentions.

<<*The process began and progressed positively thanks to this convergence of intentions, coordination, and understanding between external teams and internal teams*>>.

Individual domain

High-level and mid-level leaders who promoted and supervised the implementation processes recognize as main actors the innovation deliverers working in departments affected by pandemic. Also relevant are and the implementation facilitators, those internal experts who support the implementation.

<<It's not easy to draw a picture of all the individuals involved. Certainly, all people working in the departments affected by pandemic infection, i.e. infectious diseases, emergency rooms, radiology and laboratories, were actively involved.>>

A homogeneous culture and positive attitude toward AI promoted the change, and the reliability of innovation was reinforced during the time motivation for the AI implementation. Leader's motivation stimulates confidence in AI innovation, focusing on future improvement of technologies and communicating advantages and challenges clearly.

<<All of us, albeit with different expectations, had a good attitude toward AI innovation. Even now, the feelings are the same. In the assessment of the forecasting reliability we had some problems..[..], but over time and with appropriate changes, clearer and more marked advantages may come>>

Process:

The organization adopted tailored strategies to implement AI innovation, applying a lean approach and external support to overcome barriers and monitoring each stage through performance indicators. External technical staff supported the start-up stage by working on the convergence of multiple data sources and tools.

<< To have a complete ability to implement and manage everything effectively and efficiently, we turned to a company, a software house, which implemented what we called the Smart Data Platform, which required some technical connection work. We were several providers that had to be conveyed on a single data lake. […] There was a joint effort between the external team (suppliers and system consultants) and internal ones (teams from many departments)>>

Collection and audit of clinical performance data over a defined period addressed the evaluation of reliability of innovation and the diffusion toward other departments. Mid-level leaders checked barriers that impeded the implementation, reinforcing motivation and communication goals. Other implementation' strategy refers to initial centralization of data and skills. After capturing local knowledge from implementation departments, organization shared it with other sites.

<<We decided to intervene with AI first for Covid-19 and nosocomial infections. Then other departments were involved, such as laboratory, anatomopathological, medicine, radiology and other areas, so the aim was to make them converge. We collected data on 15 projects from all departments to implement the system. We evaluated clinical data on infection trends, discussing the appropriateness of treatment to predict patients who may progress toward infection. Another project was the assessing of emergency room flows to predict which patients will need to be admitted>>.

The analysis unveils some innovative outcomes according to the possible evolution of the framework. The main advantage clearly assessed by the respondent was forecasting patient trends and detecting criticalities in clinical treatment compared to traditional analysis. To adjust the prediction model to clinical evaluation linked to other factors not detected by data, internal teams discussed with external teams to improve the flexibility of the tools.

<<In hospital infections, some criticalities have been identified. There is antibiotic therapy in patients with negative antibiogram, which was discussed and assessed with the clinical need for antibiotic treatment even in the presence of negative antibiogram that had other justifications, but this leads us to discuss the appropriateness of these treatments.>>

3.3.2 [CASE 2] Gemelli University Hospital (Policlinico Gemelli):

Innovation Characteristics:

A laboratory named 'generator' was set up to bring together clinical data scientists to create a system for processing and analysis through automated data collection. Starting from this central node, the characteristics of the innovation traveled in four specific directions: the creation of predictive models, data clustering, creation of synthetic data, and finally, distributed learning.

<< Artificial intelligence is an umbrella word where inside there are multiple indications alongside everything that supports diagnostics and process automation in laboratories. What I would like to focus on, however, which is specific to this hospital of ours, is the enhancement of the Data Warehouse. We have activated by setting up a value chain which from the vault of data that

originates within daily practice because almost all the operations we perform on patients rely on IT resources, feed the hospital's data warehouse. We have set up a laboratory called 'generator', which has brought together clinical data scientists to create a system of exploitation of these data through automated collection, using mini bots, and programs that have various levels of sophistication, also relying on NLP (natural language processing), i.e., text reading systems with ontological encodings formalized through standard encodings that create a second-level Data Mart layer of qualified data. From these qualified data, all the analytics lines then start to pull out services that go roughly in four directions: the first is to create predictive models; the second direction is to clusterize data according to demanding clinical contexts, where the multiplicity of information resources leads to the need to have specific aggregations of data; the third direction is the creation of synthetic data for possible second- to third-level studies and clinical simulations; and finally, the fourth trajectory is all that is a network of predispositions for distributed learning, then to be able to use an interconnection with other centers for specific topics, rare diseases, etc..., which does not involve the mobilization of data but only of intermediate results. It should be emphasized that all this is an architecture that remains within the protection systems of the data warehouse, so it is all very much guaranteed within the GDPR; we have different layers of authorizations by the DPO (Data Protection Officer) of the supervisory mechanisms >>.

Outer Setting:

The structural size and time duration make it difficult to frame a well-defined external environment, however, the greatest influence comes from regulatory bodies as they require sustainability of the laboratory itself and concrete evidence to validate the work in the scientific world.

<< Starting from 2009, it is complex to indicate a clear external context, as it has undergone several changes over time. Certainly, Gemelli University Hospital is one of the most important in Italy and beyond, and it has had a prominent place in the world for many years due to its many advantages. It is a structure of considerable size; we are talking about over 1,500 beds. As far as the generator is concerned, the descriptions of the external environment can be framed as 'pressures' on the sustainability of the project and the results. From the beginning when the external environment was under pressure, many regulators were asking (they still do) for evidence from prospective trials to be able to obtain drug approval or quality of evidence. Therefore, in the beginning, many were skeptical that the evidence we produced could be relevant to the scientific world. Then, as the world realized,

the sustainability of the clinical and prospective trials that were being introduced could be very relevant. These were not real pressures but rather high expectations that were rightly placed on a project as important and ambitious as ours. Over time, we found the key to creating extremely favorable contexts for our work >>.

Inner Setting:

The organization has an extremely structured and well-resourced internal environment. This environment allows the pursuit of numerous and diverse projects, which leads the Gemelli Generator to achieve high scientific publications and interface directly with industry through co-creation and co-development programs, developing and testing prototypes created within the laboratory.

<< We have about twenty-five engineers and data scientists; it is a project that has won several European tenders, and it is a project that is highly regarded by the industry and especially by our clinicians. We have more than ninety active projects and a prototype structure that creates this value chain. If, from this value chain, research leads to prototypes, we also have a start-up, again owned by Gemelli University Hospital, which takes care of the transferability of these prototypes to the world of industry and therefore has a focus on the valorization for the certification for the commercialization of these prototypes, turning them into products through programs also of cocreation and co-development with industry itself. The areas of application are therefore all from neuroscience to cardiology, neurology, oncology, etc., so they are all departments, and ninety-two to ninety-three studies in progress involve many branches of clinical applications >>

The inner environment is so well-developed that it allows the organization to work on processes internally without using third parties for data development and analysis.

<< The peculiarity of this architecture is that we have the data and expertise to process it, and therefore, we have an in-house system that does not make us dependent on anyone. We have over a billion granular data points, and CT or MRI reports contain granular data >>

Individual involved:

The individuals involved in the different processes are numerous; the laboratory has twenty-six people with medical-engineering skills. It is reductive to limit the number of individuals involved to internal staff only, as the projects also involve people from different departments.

<< It is a complex question, at the moment we have about twenty-six people involved in the generator, and certainly an advantage, with respect to the human qualities they have, we call them 'mutants', i.e., they have a doctor's brain lobe and an engineer's brain lobe. In many universities such as Gemelli, there are almost every clinic these people with this talent of having these two brain lobes specialize differently, so we made a call to these people and found them here. However, as mentioned, we have approximately ninety open projects that also involve people from the different departments involved; in this case, providing a precise number of people is expensive and is not relevant. Certainly, all the people who participated in this project had an extremely positive attitude toward Ai but, in general, toward all the objectives of the structure. You do not have to be extremely visionary or dreamy concerning AI; you must be concrete and pragmatic. If AI performs a function with an extremely reduced time and cost, consequently freeing up resources that can be used in other, more opportune and delicate ways and do not perform a task at least 'worse than you would do it', it makes sense to invest and believe in it >>.

Process:

The implementation process started in the internal area of radio-oncology, where data mining and radionics chains were activated. In-house laboratories were created, and engineers, bioengineers, and mathematicians were selected. The scope of these chains was based on predictive modelling, distributed learning, and semantic web.

"In 2009, the radiotherapy of the Gemelli had been classified as a Knowledge-Based Oncology Center, i.e., a center where the exploitation of data as part of the architectural aspect of radiotherapy of the kind and, being the director of the radiotherapy, at that time we had activated data mining and radionics chains with two internal laboratories, within these two laboratories, we had accrued part of a series of research contracts but above all, the selection of engineers, bioengineers, and mathematicians who worked in our radiotherapy for research purposes on these chains of data

mining, predictive modeling, distributed learning and semantic web. Therefore, it was all an internal activity in radio oncology >>.

Over time, the structure has mutated to become IRCCS. From this point onwards, a division of the research groups evolved the data mining center. The prior knowledge of the data scientists led the center to a natural internal growth that led the structure to expand its staff from the initial six people to the current twenty-six within a few years.

<< Then, when the IRCCS was started seven years ago, we started to think about a valorization for the whole IRCCS of this asset. There were six-seven people working in our laboratories, and by splitting them up between data mining and radiomics, thus separating them into two research groups, the radiomic data remained here in the radiotherapy and radiology house, while we evolved the data mining internally with an IRCCS laboratory for the entire Gemelli Hospital. This type of operation was approved in 2019, and the COVID-19 pandemic began in 2020. These were the main operational phases; there was a mechanism in which we were already familiar with this type of technology because we had a hard core of data scientists who had already obtained PhDs and teaching degrees and therefore had a natural evolution. We had a particular situation in which a very senior executive at the age of sixty decided he wanted to quit the business world and work in the social sector, coming to us and bringing a great deal of organizational engineering ability. In the latter case, the contribution is that we have effectively gone from a structure of five people to the twenty-five/twenty-six people we currently have >>.

3.3.3 [CASE 3]: Sant'Orsola-Malpighi Polyclinic Hospital (Ospedale Policlinico Sant'Orsola-Malpighi)

Innovation Characteristics:

Artificial intelligence was introduced seven years ago in the hospital, this long period has allowed AI to be applied to almost all hospital areas. What is proving most successful is the imaging associated with radiotherapy and the surgical department.

<< We have been implementing AI at our facility for seven years now. We use artificial intelligence in almost all areas of application, especially those related to imaging; we have one area of application that is related precisely to improving imaging. We have applied artificial intelligence to radiotherapy with radioisotopes, radionuclides, and radiotherapy in short of the very technical aspects related to treatments. We have applied artificial intelligence to the field of surgery to determine which patients need surgical demolition removal or whether more sparing of tissues is not affected by the tumor or particular problems because we have applied it to various aspects concerning predictive treatment models. We have also used artificial intelligence for management purposes, for example, to see if the machine delivers well, if they are fully utilized, if the machine retains geometric characteristics over time, and much more. We are now accepting a PET scan called the "U Explorer", which has a length of 194 cm, as a detector and, in one to two minutes, a PET scan of the entire patient, and if we keep him under observation for longer, we perform a dynamic study in which we go and predict the pharmacokinetics of organs and tissues. Now we are also in clinical trials to test in AI systems that go and see if a patient has lung cancer before he knows he is in a control group, i.e., with an image that he does for other reasons and still goes and predicts if he will have lung cancer. >>

Outer Setting:

The outer setting hardly ever produced any influence on the hospital, noteworthy was the COVID pandemic that compromised the organization and functionality of the hospital itself, artificial intelligence made it possible, however, to minimize the negative impact produced by the pandemic.

<< The external context only influenced during the period of the COVID-19 pandemic. At that time and in the post-COVID-19 phase, there was a need for many people to be physically present for radiotherapy planning. We had implemented these AI solutions before COVID-19, but during COVID-19, we were able to compensate for the absences of indirect family members for direct health reasons, which allowed us to maintain the same work rate because we were part of those groups of people who never stopped during COVID-19. Therefore, it is this external environment that somehow is worthy of demarcation that has let us say indirectly brought a reduction in personnel and then let us say our internal resource has been to compensate with the implementation of these automation tools.>>

Inner Setting:

The inner setting is quite disconnected regarding artificial intelligence. Not everyone knows what it is and does not know how to fully exploit its potential.

<< As far as it is inherent with the internal organization, it is still very disconnected from AI, in the sense that within these institutes, many people do not even know what they are talking about, that is, everyone talks about it but let us say except for a few figures who are more technical, in my opinion, many do not understand. Even academics may know what the system does, but they do not understand what the impact is on the clinical part because, for them, let us say working on an AI model means "I can extract features common to the various patients", but maybe we treat the patient because he is not common, because he is something particular. For example, "if one uses an AI system on a patient where we have implanted seeds in the prostate to be able to give me imaging during radiotherapy, these scientists have created an AI model to improve the image quality of this prostate district, the best model was a model that deleted the seeds to aim the radiation at the specific point instead. Therefore, the image improvement is useless. Basically, if there is a disconnect between those who make the models and those who use them and you do not talk to these people, you do a lot of useless work.>>

Individual involved:

The range of people involved in the implementation process is wide. This group includes specialists, doctors, academics, and external consultants, as each role requires interaction with others to fully understand and exploit AI.

<< The individuals involved are all those who take an active or passive part in the implementation process. This group includes specialists, academics, external consultants and physicians. In our case, a key role is certainly that of health physics. Because the problem lies in conscious use, i.e., those who use it as if it were a black box many times do not know where they can trust it and instead cannot trust it. As medical physicists, on the other hand, we have the expertise to act as an intermediary interface that allows academics and AI experts to talk to doctors.

There are such issues that if an AI specialist talks to the doctor, they most likely end up not having a full understanding. When we have a specialist we have to translate for the clinician what he has to

do, we have to translate the clinician's question to the specialist, so our role is to be a facilitator in this respect.>>

Process:

An internal core sets up the AI model. Then, there is the study design, development, testing, and monitoring of the test over time.

<< We have to specify how we started this implementation activity for research reasons, and it was always supported by the fact that software already available already implemented these AI systems; therefore, we worked on benchmarking the models, on development robustness, and so on. We started about seven years ago, always as a research activity, and then every time we found a positive test, we confronted it with the multicenter and then with clinical practice. We always have a small core that does the setup of the model, so we design the study, develop the time plan, and divide the data into trading, verification, testing, and monitoring the tests. Let us say over time, this thing goes into clinical practice to support the clinician. The implementation phase happens either internally or via projects at the European level, and in developing the European model, everyone brings input. >>

As mentioned at the beginning of the results section, below is a table containing the AI applications, emerging barriers, results produced, and public health impact for each of the three cases.

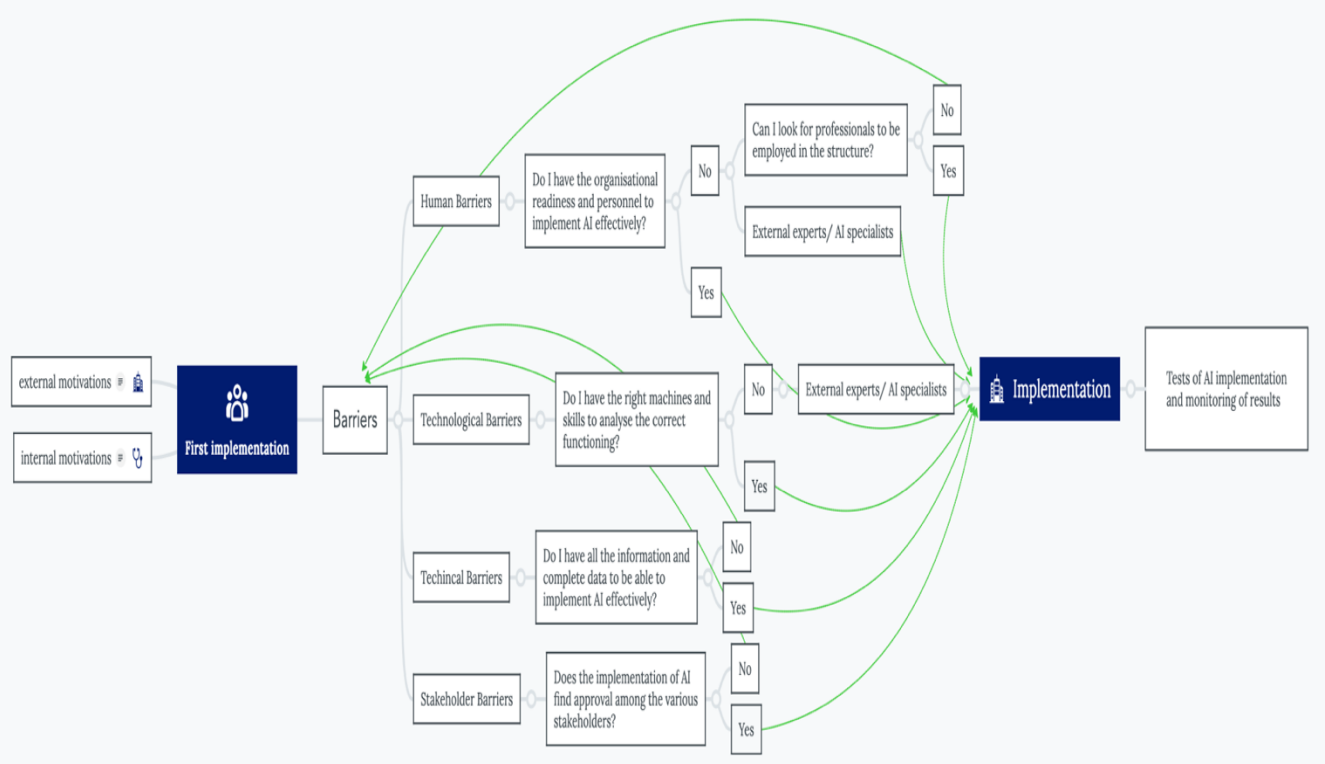
Table 3 Summary of implementations, barriers, results, and impacts on public health.

Case	*AI Implementation*	*Barriers*	*Results*	*Public Health*
Case 1 - Niguarda Metropolitan Hospital	**AI is used for multiple purposes, *i.e.*, with a managerial nature, to monitor the activities of the various departments; with the purpose of research and in the medical health field with predictive objectives**	**Difficulties in merging data from different databases into one central database (DataLake) dictated by not having the structure of all databases (Technical barriers)** **Problems of vocabulary and interpretation dictated by the criticality of language as the same parameter may be defined differently in medical records. This leads to a possible misreading of results. (Human Barriers)**	**More streamlined and effective emergency care(+)** **More appropriate care(+)** **More effective and efficient infection monitoring(+)**	**More targeted and specific treatment and care** **Shorter waiting times resulting in timelier treatments** **Better medical care**
Case 2 – Gemelli University Hospital	**"AI Gemelli Generator": In-house laboratory for the creation and implementation of AI systems that enables the facility to implement AI in every department and purpose. At the time of the interview, there are approximately 93+ studies involving**	**Many regulators ask for evidence from prospective trials in order to be able to arrive at drug approvals or quality of evidence (Stakeholder barrier)** **Recruitment of personnel suited**	**Scientific impact of the highest quality (+)** **Activation of top-level funds, tenders and investors(+)** **Over 1 billion granular data as a basis for analysis(+)**	**Greater effectiveness in diagnostics (including predictive) and treatment** **Personalization of care** **New breakthroughs in medicine and healthcare** **Better medical care**

	branches of clinical applications	**to the scope of the project (Human barrier)** **Showing economic sustainability to stakeholders (stakeholder barrier)**	**93+ active studies(+)** **Laboratory sustainability(+)**	
Case 3 - Sant'Orsola-Malpighi Polyclinic Hospital	**Artificial intelligence is used in almost all fields of application, especially in imaging.** **It is also used for management purposes, *i.e.*, to control the proper functioning of machinery (even over time) and to automate processes**	**Identification of AI limits with risk of artifact creation (Technological Barriers)** **Lack of homogenization between AI software with machines not suited to support such technology (technological barriers)** **Not all staff have full knowledge of AI and its applicability (human barriers)**	**High-quality scientific impact(+)** **High-quality healthcare services and surgery in terms of effectiveness and appropriateness (+)** **Strong predictive activity especially in the field of imaging with the possibility of predicting cancer conditions well in advance (+)**	**Better medical care** **More targeted preventive care** **More accurate and timely diagnoses**

Based on the evidence gathered from the interviews and, therefore, from the processes used by the facilities to overcome the three case studies, we created a conceptual map in the section below in which we created a pathway for overcoming the barriers that emerged in the interview phase.

Figure 3 Concept map on overcoming barriers.



3.4 Discussion

Our study details the status of the adoption of artificial intelligence in Italian healthcare, its potential, the challenges faced, and the impact caused by them. This section will present the main findings and some practical recommendations on how to overcome the identified barriers. As previously mentioned, the study followed the method of the multicase study with the conceptual perspective of the CFIR, this aspect allowed for a full understanding of the dynamics of the implementation processes, the motivations that prompted the implementation, the influence of the external and internal environment, the people involved and how the implementation process unfolded in detail.

Subsequently, a table was created (in Table 3) in which all the applications of AI that emerged during the interviews, the barriers that emerged, the results produced and the impact on public health were listed.

Finally, a conceptual map was created in the graph below the table (in Figure 3) to create a road map for overcoming barriers and understanding the hindering fact. Again, the line was drawn thanks

to the information that emerged during the interview.

After breaking down the results via case analysis, from an overall perspective, we find that AI has been implemented on all fronts of the healthcare chain, from first aid to management uses to the creation of an in-house AI research center. Therefore, currently, the multifaceted capability of AI is taking root in every use. This allows for a complete and well-representative analysis of the phenomenon. This, however, is not without encountering barriers. The prevalence of barriers to date is dictated by human expertise (human barriers). Human barriers in implementing AI technology in healthcare usually refer to the challenges associated with human factors that impede the successful adoption and integration of AI systems within healthcare settings. Critical to our analysis was the lack of full knowledge of the technology and its applicability and validity. The lack of full knowledge of AI due to cultural misalignment of medical-technological fields is imposing and certainly represents a barrier to implementing and fully using this technology. Continuing with the analysis, the second barriers are the technical barrier (technical barrier) and the technological barrier (technological barrier). The technical barriers to implementing AI technologies in healthcare revolve mainly around challenges such as the complexity of data integration, trust issues, and the time and energy constraints of healthcare personnel adapting to new technologies (Chomutare et al., 2022). Technological barriers in the implementation of AI technologies in healthcare include several challenges. These include the complexity of data integration, data scarcity, model interpretability issues, and the reliability and security of AI applications (Sangeetha et al., 2023). In the three case studies, inherent barriers emerged in the incompatibility of the AI software used in unsuitable machines due to "obsolescence", which does not mean that the machine is no longer suitable for its diagnostic function but rather that it has problems supporting AI software. These machines, as well as newer ones that are fully compatible with AI implementation, showed barriers in producing diagnostic results, returning artifacts as clinical output. In detail, tests were carried out using "shapes" reproducing a human body condition, and the tests showed that AI could lead to incorrect learning and reading, thus leading to unreliable clinical results. It should be pointed out that in one case study, the AI had a technical barrier dictated by the fact that the data were not fully analyzed since they came from different databases, some of which were not in the hospital's possession and were incomplete, resulting in possible deviations due to incorrect data management. The last barrier encountered concerns stakeholders. Stakeholder barriers in implementing artificial intelligence (AI) in the healthcare sector refer to the challenges and obstacles stakeholders face in adopting AI technologies. These barriers can stem from various sources,

including technical, organizational, cultural, and regulatory issues. Several studies have identified specific stakeholder barriers. For instance, concerns about data quality and management, resistance to change, and a lack of understanding and trust in AI have been noted as significant barriers(Cubric, 2020). In the case studies, stakeholder requests emerged concerning the assurance of the economic viability of the AI center and the receipt of evidence from prospective trials to be able to arrive at drug approvals or quality of evidence. The results produced by the implementation of AI in the three case studies were extremely satisfying and varied. The common front is scientific impact, and the hospitals highlighted the importance of being able to obtain high-impact scientific publications. This, in one case, enabled the activation of funds, calls and investors and collaboration at the highest national and international levels. It should be emphasized that the implementation of AI is of a medical-healthcare nature, given its applicability to all departments, including those of a managerial nature. In fact, AI also allows autonomous programming of machinery; in one case, this approach made it possible to compensate for the absence of human resources in the radiotherapy department due to pandemic causes because it was able to rely on the automation of diagnostic processes. Another case showed, more generally, how the possibilities for implementation are so varied that in just a few years, more than ninety-three active studies have produced over a billion data points as a basis for analysis. Moreover, depending on the application of artificial intelligence systems, all three hospitals have produced results in terms of more targeted, effective, and timely treatment. On this last point, there are important results from a predictive perspective, which make it possible to investigate and discover pathologies before they occur. In one case, a system was implemented in which a simple lung scan performed for non-oncological reasons was used to predict whether the subject would be prone to tumor development in the lungs. At the same time, it provides accurate data that allow high-quality surgery in terms of efficiency and appropriateness. AI enables more effective and efficient monitoring of infections. In one case, AI is used when monitoring infections, thus enabling doctors to have a more complete and timelier picture of the progress of infections that may affect an individual or an entire population. As specified above, this process involves not only individual departments but also a constant connection with the whole hospital structure; for example, in one case, AI is used for emergency room access. The result is that it allows for a streamlining of the emergency room itself with precise targeting of the patient accessing the emergency room, reducing error margins and waiting times for diagnosis. As an effect of all these applications, patients can receive more targeted, effective and specific treatment and care, significantly reducing waiting times for better medical care. In addition, the various discoveries

have a public impact, and better diagnostics, in predictive terms, provide patients with the possibility of receiving personalized care. Our studies also created a pathway, drawn from the analyzed cases, of how barriers can be overcome. Figure 3 shows a simplified road map in which we start with the motivations, which can be external or internal. The first refers to political or social pressures or, as in one highlighted case, a pandemic that pushes doctors and hospitals to find innovative and rapid solutions to better manage the epidemic/pandemic trend by finding and providing more effective and efficient treatments, while the second refers to internal motivations that can be of a research nature. Once this process is set in motion, we find ourselves in the 'first implementation' phase, i.e., where we try to understand how to implement practically; from this point, there are several branches depending on the nature of the barrier encountered. Our study revealed the presence of four types of barriers. The first relates to human barriers, in which case a hospital has to answer whether it has the organizational readiness and the right personnel inside to implement AI effectively. The concept of a "readiness organization" in the context of implementing AI in the healthcare sector and hospitals refers to the preparedness of healthcare institutions to adopt and integrate AI technologies effectively. This encompasses the organizational infrastructure, culture, and the willingness of stakeholders to embrace change and innovation(Roppelt et al., 2024). In cases where facilities lacked one or both of these factors, they found a solution to the barrier by turning to experienced external specialists or consultants who could not only provide better knowledge of how IA works but also practical advice for better internal organization. In the case studies where only suitable personnel and available resources were needed, an internal recruitment search was carried out.

The second barrier encountered was of a technological nature, in this case, the questions to be asked in the analysis were whether one had the right equipment for the implementation of AI and whether one had sufficient in-depth knowledge to understand the analysis of its correct use. In the case studies where such barriers were encountered, the solution was to turn to external specialists who could support in-house staff. Unfortunately, when faced with technological machinery unsuitable for supporting AI functions, as is, for example, obsolete, the solution is to change the machinery where the resources are available; otherwise, imperfect matching between AI and machinery could lead to errors in the output provided. The technical barrier emerged in a case study where the hospital did not have complete data and did not possess all the hospital's databases. In this case, the barrier remains important and present, as it does not allow the full exploitation of information analysis.

The last barrier is the stakeholders; often, the implementation of AI raises many expectations and concerns about reliability and sustainability. However, the latter is not a real barrier in the initial stages of implementation as much as it is in the later stages when the results are to be presented.

3.5 Conclusion

This study explored the application of artificial intelligence in Italian healthcare to understand the current status and the barriers limiting or preventing such adoption, to analyze the results produced and to verify the impact of artificial intelligence on public health. After summarizing the literature and detailing the meaning of artificial intelligence by providing a background consistent with the purposes of the study and presenting the case studies, the reasons why they were selected and the details of the interviews, we opted for the methodological selection of multiple cases to provide direct and extremely reliable data that could better illustrate this phenomenon. The selection of the case studies followed a search for the best Italian hospitals on the international scene that had already effectively implemented AI to be able to give a clear direction both to the phenomenon and to the realities of deciding to implement AI in their facilities. The study followed the conceptual lens of the CFIR (Consolidated Framework for Implementation Research) to provide a clearer explanation of the process and the personnel involved and provide a full and complete overview of the environment in which it took place. The results showed that AI is currently multifaceted in nature and can be used in almost all healthcare departments, not only for medical purposes but also for management purposes. Furthermore, AI was shown to be extremely versatile, being able to perform predictive activities, monitor, automate processes, analyze data, and provide useful outputs for innovative medical and scientific research purposes. At the same time, however, the study emphasized the presence of barriers, mainly human, technological, technical, and stakeholder factors. Organizational non-readiness, cultural factors inherent in being unaware of the phenomenon and resistance to change are the most prevalent. Therefore, it is crucial to address human barriers both through training programs and cultural changes that promote the adoption of AI and through being mentored and supported by AI specialists and external consultants when available resources prevent in-house recruitment. At the same time, investments in technology infrastructure and technical support can facilitate a smoother transition. Furthermore, the active involvement of stakeholders at an early stage can reduce resistance and increase the acceptance of AI in daily practice. In addition, for each barrier encountered, we analyzed the dynamics and resolution methods adopted by the case studies to construct a roadmap to follow in the early stages

of implementation for successful implementation where possible. Despite the presence of barriers, important impacts regarding public health emerged from the study. These can be summarized as a more efficient and effective healthcare system in terms of the utilization of resources and medical care, which spills over into a positive impact for the community, as patients can receive timely, better, personalized care and greater operational efficiency in medical treatment. In conclusion, after analyzing all the various aspects, we feel that we can answer the initial question “Will artificial intelligence become a good doctor?” with “Most likely yes, for now, it’s a good facilitator in routine practices and diagnosis for doctors.”.

3.6 Limitations and Future Directions

Some of the limitations include the fact that the interviews are qualitative in nature and few cases were analyzed, which may have biased the results obtained from this study to be generalized. Also, without quantitative data, measuring AI's exact impact on health and health outcomes is impossible. Furthermore, the analysis focuses on a few contexts that may not represent the various experiences that occur in various regions or health systems. Other future studies could be conducted with respect to the long-term effect that AI will have on quality of care and patient satisfaction, adopting a quantitative approach to integrate the types of evidence. Furthermore, comparative studies between different regions or health systems could integrate knowledge of the contextual variables that influence AI implementation.

Finally, future research should focus on how national and international health policies can also facilitate or hinder AI adoption and call for a more cultural approach that emphasizes organizational readiness for change. Once the identified barriers are mitigated, artificial intelligence's opportunities can substantially improve and future-orient the healthcare system by rapidly integrating important scientific discoveries.

4. The introduction of regional "differentiated autonomy" in the Italian National Healthcare System (INHS). Issues and ongoing developments.

4.1 Introduction

We can identify differentiated autonomy as the process of fiscal and administrative decentralisation with significant implications for regional disparities and governance. This process influences the composition of public expenditure at regional level (Grisorio & Prota, 2015).

The topic is extremely controversial and sensitive, in fact, even in the literature we do not find a single side that is either for or against, some argue that differentiated autonomy could extremely increase disparities between regions, others see the potential to reduce them through targeted interventions. Probably the most worrying consequence is not only related to regional disparities, but to the central state that would lose much of its ability to tax and spend to the benefit of the regions. Not only that, some studies point out that differentiated autonomy leads to a strong weakening of the state's ability to make budgetary policies, increasing the risk of bankruptcy (Silipo, 2023a).

The reorganization of healthcare structures has been a crucial topic in European administrations for years. Since the Second World War, healthcare policies have increasingly pushed towards a process of decentralization to lower levels of government, extending to regions and private sector organizations(Saltman et al., 2007). However, the direction is far from clear and defined. In the European context, some state institutions have reversed course, reassuming political and fiscal decision-making (Saltman, 2007) responsibility. In Italy, there has been a shift from a central state towards regional federalism, which has encountered many critical issues. Italian Regions have never enjoyed true financial and decision-making autonomy, a factor that has become even more important in times of crisis. From 2013 to 2015, the central government imposed public spending control policies to address the economic crisis, cutting, for example, spending on financing the LEAs (Essential Levels of Assistance), or again, during the more recent crisis due to the Covid-19 pandemic, the government regained its central role to provide uniformity of action within the nation and respond to the inefficiency and irrationality of some regional maneuvers. Thus, one key reason driving the differentiated autonomy process is to achieve recognized economic and financial autonomy (Angelini, 2019; Chessa, 2017; Dini & Zilli, 2020). On October 22, 2017, Lombardy and Veneto held a consultative referendum for greater autonomy. Previously, Emilia-Romagna had moved in the same direction but without resorting to popular consultation. On February 28, 2018,

all three regions signed a preliminary agreement with the government. However, while Veneto, in July 2018, officially launched negotiations with the new government by proposing, in a new enabling law, all twenty-three matters provided for in the Constitution, Lombardy, as early as mid-May, also expressed the desire to extend autonomy to all matters covered by Art. 116.

The attitude of Emilia-Romagna, on the other hand, was more cautious, with its Legislative Assembly, in September, slightly expanding the formulation of some requests and introducing three other matters into the negotiations (for a total of fifteen) (Greco & Messina, 2019). The March 23, 2023 bill, presented by the Minister for Regional Affairs and Autonomies, regulates the provisions for implementing differentiated autonomy for ordinary statute Regions. The bill stems from Article 116, third paragraph of the Italian Constitution, which reads: *"Additional forms and particular conditions of autonomy, concerning the matters referred to in the third paragraph of Article 117 and the matters indicated in the second paragraph of the same article under letters l), limited to the organization of peace justice, n), and s), can be attributed to other Regions, by law of the State, at the initiative of the interested Region, after hearing the local authorities, in compliance with the principles laid down in Article 119. The law is passed by the Chambers by an absolute majority of the members, based on agreement between the State and the Region concerned" (Costituzione della Repubblica Italiana, 1947)*. The proposal leverages the aforementioned article to lay the groundwork for a transfer of powers from the State to the Regions in specifically identified areas, including public health. The subjects themselves have been chosen based on those that were deemed capable, more than others, of projecting the region's political-institutional action towards the highest standards of efficiency, thus allowing the region itself to compete with the most developed territories in Europe and internationally, leaving in the hands of the central state matters that guarantee the unity of the system (such as the essential levels of performance concerning civil and social rights and civil law) (Tubertini, 2018). The goal is to create more regional autonomies, drawing inspiration from the Iberian model with the *Comunidades autonomas*, making them like small 'nations' or autonomous communities obliged to cooperate with the central state itself and with other regions (Calabria, 2020). Spain is an interesting point of reference because it has become one of the most decentralized countries in the world in just over three decades, starting from a highly centralized institutional framework. The first thing that the Spanish decentralization process demonstrates is that a deep decentralization process can be achieved quickly, even from a highly centralized state and with a strong preference for equality in access to decentralized public services(Lago-Peñas et al., 2017).

Fiscal equalization has set aside initial fears of inequality due to substantial interregional divergences in fiscal capacity (Lago- Penas, 2014).

Spain's approach to decentralization, particularly in healthcare, was characterized by incremental implementation. Negotiations between the central state and the autonomous communities allowed for a gradual transfer of responsibilities. By 2002, the devolution process had been completed, enabling innovative reforms by autonomous regions, though it also led to comparative grievances and increased expenditures. These reforms highlight the potential and challenges of decentralization, showcasing a balance between regional autonomy and national unity in ensuring essential healthcare standards.

The broader Mediterranean paradigm situates Spain within a shared Southern European context, marked by transitions from centralized systems to more decentralized models, shaped by socio-political and economic factors. Spain's ability to align decentralization with fiscal equity offers valuable insights for Italy, which is considering implementing differentiated autonomy (Giarelli, 2021).

Fiscal federalism entails the distribution of fiscal functions among various government levels (Agrawal et al., 2024). In the case of Italy, this means dividing the funding of healthcare and decision-making authority between national and regional governments. Decentralization may result in the creation of more effective and responsive healthcare services that address the specific needs of the local population (Ahmad & Brosio, 2007).

Still, fiscal federalism has certain disadvantages. Evidence from other nations demonstrates that decentralized arrangements can be afflicted with inadequate budget constraints, thus resulting in inefficiencies in the event of poor design (Sorens, 2016). For the Italian context, this phenomenon would be detectable in terms of regional differences in healthcare accessibility and quality, particularly if a few regions suffer from financial handling problems or have reduced resources.

In summary, though fiscal federalism may enhance the delivery of healthcare through the ability of areas to design services as per local demand, it has the potential of enhancing variations in access to healthcare across regions. Whether fiscal federalism in the context of Italian healthcare will succeed relies on the actual structure of the system, where equalization devices are incorporated and national standards are preserved (Weingast, 2009).

4.2 Policy background

The Italian National Health Service (SSN) was established in 1978 with Law 833/1978 in response to the fragmentation and disorganization prevalent at that time, involving various national and local institutions and organizations. For years, the healthcare system had been centrally managed by the state. However, after numerous challenges emerged, Legislative Decree No. 56 of February 18, 2000, marked a fundamental transition in the institutional structure of the SSN, initiating it towards fiscal federalism. This process aimed to empower each region with the capacity to self-sustain through its own revenue autonomy. Specifically, the measures to achieve this included regional participation in VAT, increasing regional surtax rates for IRPEF and IRAP, and increasing the share of participation in gasoline excise duties (Ianni, 2008). This represented only a small but significant step towards federalism, as the central level ensured the integration of state resources to ensure the health of the entire community. In particular, the CIPE (Interministerial Committee for Economic Planning), a collegiate body of the Government, acts as a controller of resources and foresees their allocation to the different regions. The measure also provided for the establishment of a healthcare expenditure monitoring system through the verification of compliance with standards associated with indicators aimed at measuring the achievement of essential levels. Law 405/2001, particularly, introduced important precepts concerning managing and monitoring healthcare expenditure. These included(Ianni, 2008):

- Regions must adopt all necessary initiatives and provisions to ensure that hospitals and local authorities undertake measures to contain spending approved by the CIPE. Additionally, the regions must adopt sanctions established by law, against administrators who do not comply;
- Within the framework of monitoring regional healthcare expenditure, it is necessary to distinguish expenditures relating to purchases of goods outside agreements and those exceeding reference prices;
- Regions adopt the monitoring of medical, pharmaceutical, specialist, and hospital prescriptions to ensure timely availability of information, also electronically, to the relevant Ministries.

All these measures aimed to increase the responsibility of each region; however, this was threatened by a multi-level situation in the SSN, as some regions were facing financial difficulties.

Historically, northern regions are usually more efficient in developing administrative capacities compared to southern regions (Tediosi et al., 2009). Other reforms aimed to reduce costs, increasingly empower regions (as envisaged in the State-Regions agreement of March 23, 2005), monitor healthcare expenditure, introduce a governance structure to change healthcare provision by inserting competitive dynamics between public and private providers, and implement various forms of payment systems linked to performance to achieve cost reduction, performance improvement, and increased quality of the healthcare system(Fetter et al., 1976; Ianni, 2008; Mauro & Giancotti, 2021). Additionally, planning, accounting, and control measures were added to the transition from traditional cash-based accounting to accrual accounting and the adoption of management accounting (Anessi-Pessina & Cantù, 2006). As specified at the beginning of the article, the system has never received full approval; several challenges have emerged over time, such as a lack of cooperation between regions, centrally controlled monitoring mechanisms, and historical and administrative differences between northern and southern regions, leading to the Italian federalist system being termed "hybrid." A factor that has further strained the federalist system is the Covid-19 pandemic, which has highlighted the need for central public management with democratic coordination of healthcare, as there have been inadequacies in regional intervention actions with untimely, approximate and contradictory policies due to the malfunctioning of the machinery at various territorial levels and the varying speeds of different regions(Dini & Zilli, 2020). In Figure 4, we have presented a reconstruction of the chronological stages of the implementation process of differentiated autonomy.

Figure 4 Timeline of differentiated autonomy

- **October 2017.** During the 17th Legislature, Emilia-Romagna, Lombardia and Veneto began negotiations with the Gentiloni government for the recognition of differentiated autonomy. Emilia-Romagna after the approval of a resolution of the Regional Assembly to start the process (3 October 2017); Lombardy and Veneto following consultative referendums on the attribution of additional special forms and conditions of autonomy (22 October 2017).
- **21 November 2017.** The bicameral Commission for Regional Issues launches a fact-finding investigation that concludes with the drafting of a document**.**
- **28 February 2018**. Emilia-Romagna, Lombardia and Veneto sign three different preliminary agreements on differentiated regionalism with the Gentiloni Government. The three regions indicate the same subjects of priority interest subject to negotiation (protection of the environment and the ecosystem; protection of health; education; labour protection; international relations and with the European Union), reserving the possibility of later extending the negotiation to other subjects.
- **17 May 2018**. The Contract for the Government of Change, signed by the League and the 5 Star Movement, reaffirms as a 'priority issue [...] the attribution, for all the Regions that justifiably request it, of greater autonomy in implementation of Article 116 of the Constitution, also bringing to a rapid conclusion the negotiations between the Government and the Regions that are currently open'.
- **February 2019**. At the beginning of the XVIII Legislature (Conte I Government), the signatory Regions request an extension of the list of subjects on which to activate asymmetrical regionalism, while other Regions (Piedmont, Liguria, Tuscany, Umbria, Marche) formalize their request to start negotiations.
- **21 March 2019**. The Parliamentary Commission for Regional Issues starts conducting a fact-finding investigation into the process of implementing differentiated regionalism.
- **25 June 2021**. The Minister for Regional Affairs and Autonomies establishes by Ministerial Decree of 25 June 2021 a Commission to study, support and advise on differentiated autonomy, chaired by the late Prof. Beniamino Caravita.
- **28 April 2022**. The Ministry for Regional Affairs and Autonomies prepares a draft DdI on the implementation of differentiated autonomy, which is never presented in Parliament.
- **12 July 2022**. The Parliamentary Commission for Regional Affairs approves a final document on the implementation process of 'differentiated regionalism', to which we refer for a detailed chronological analysis of the various stages.
- **September 2022**. The programme of the center-right coalition, which emerged victorious from the last elections, envisages "implementing the path already started for the recognition of the Autonomies pursuant to Article 116, paragraph 3 of the Constitution, guaranteeing all the equalization mechanisms envisaged by Article 119 of the Constitution", as well as the "Full implementation of the law on fiscal federalism [...]".
- **17 November 2022**. The Minister for Regional Affairs and Autonomies presents a draft DdL to the Regions: 'Provisions for the implementation of differentiated autonomy pursuant to Article 116, paragraph 3 of the Constitution'.
- **29 Dicember 2022**. The Minister for Regional Affairs and Autonomies transmits the Draft Law on Autonomy to the Presidency of the Council.
- **11 January 2023**. The Minister for Regional Affairs and Autonomies accepts all the requests for changes to the draft DdL sent on 17 November 2022 made by the Regions.
- **2 February 2023.** The draft DdL, dated 30 January 2023, is placed on the agenda of the Council of Ministers.

Source: (Cartabellotta et al., 2023)

4.3 Content of the new policy

The Italian regions (except for those with a special statute) that request autonomy will be enabled to exercise autonomy over twenty-three matters (institution, healthcare, environmental protection, ecosystem and cultural heritage safeguarding, scientific and technological research, etc.). Alongside the transfer of functions, the regions will also receive the corresponding human, instrumental, and financial resources necessary to implement autonomy in the requested areas. The regions may retain equivalent taxes to manage the matters subject to autonomy.

The transfer of functions related to the realization of civil and social rights (education, employment, social security, etc.) is tied to determining the Essential Levels of Assistance (LEP) and their associated costs and standard requirements, to be defined within one year (Silipo, 2023b). Conversely, the transfer of functions in other areas (infrastructure, ports, airports, special economic zones, railways, civil protection, energy) can occur independently of the definition of the LEP. This action is driven by the desire to surpass the mere territorial fulfillment of rights by capitalizing on the inherent potential of territorial autonomies. The role of the State will be to safeguard the interests and rights of citizens through the management of remaining matters within the exclusive competence of the State (Senato della Repubblica, 2023). In practical terms, focusing our efforts on healthcare, differentiated autonomy will empower each region to manage resources derived from direct rather than centralized state revenues, autonomously handling all aspects of healthcare, with the central state acting as guarantor and controller of the Essential Levels of Assistance (LEP). These correspond to the Essential Levels of Care (LEA), namely the services concerning civil and social rights services that must be guaranteed across the national territory (Viesti, 2019). Indeed, the regulatory framework related to LEP will remain unchanged from what is already governed by LEA. To ensure this, the State will bridge the gaps of less virtuous regions through financing, thus assuming a function resembling the current Equalization Fund. That the politically most relevant motivation for regional differentiated autonomy is the distributive conflict between different areas of our country is evident when considering, on the one hand, the emphasis placed by proponents on the issue of fiscal residuals and, conversely, the idea of secession of the wealthy that the various drafts of agreements between the State and the interested regions have raised in certain institutional circles and in meridional list literature (Caruso, 2022).

4.4. Stakeholders' position and their influence

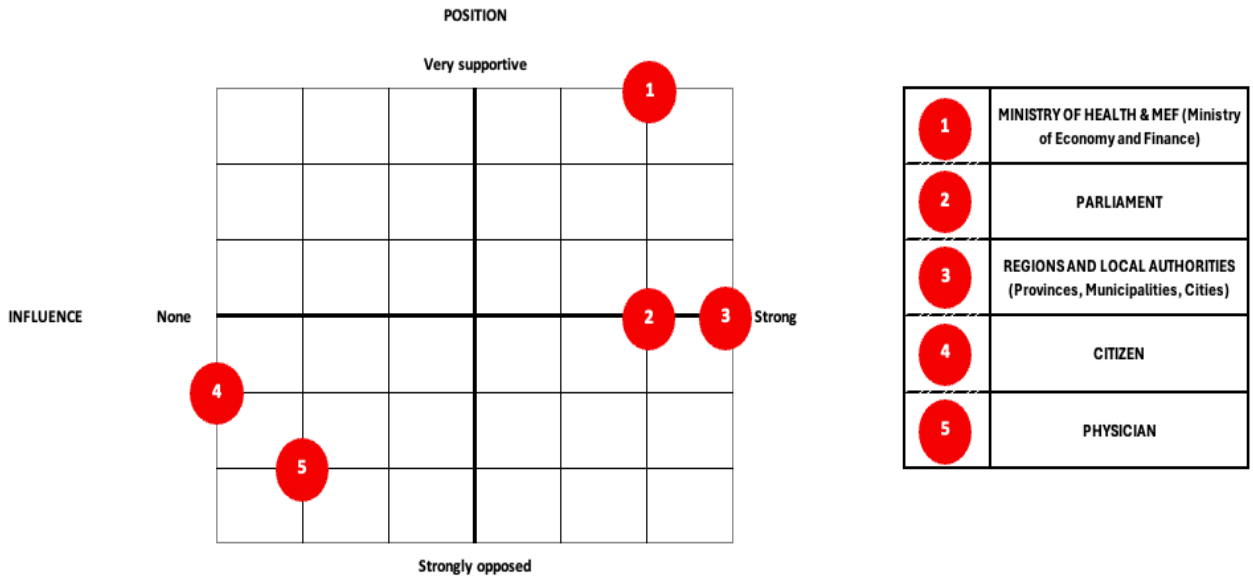
The various stakeholders' concerns are directed towards the divisions that such legislation could bring about. In our field, it could lead to an effective and efficient elite healthcare system in Northern Italy, while in Central and Southern Italy, it might result in a survival-based healthcare approach. Differentiated autonomy could mark a point of no return for the decentralized system. We have compiled a table containing a series of opportunities and risks for different stakeholders regarding the impact that differentiated autonomy could have on Italy and Italian healthcare (Tab. 4). Subsequently, we have outlined the various positions of the stakeholders (Fig. 5).

Table 4 Opportunity and risk of differentiated autonomy (expected benefits – potential problem)

OPPORTUNITIES	RISKS
Retaining most tax revenues automatically translates into greater efficiency in the delivery of services to citizens.	The diversion of tax revenues from redistribution to all territories would then violate the principle of economic and social solidarity enshrined in the Constitution, leading to an increase in disparities between North and South, with a consequent social and economic collapse of the most disadvantaged regions that could easily destabilize the whole of Italy.
Overcoming the 'historical expenditure criterion' and moving to the standard expenditure criterion'.	The state may be forced to continue borrowing to finance ailing health systems in order to maintain the provision of essential public services ("LEP").
The regions can manage the resources obtained from their citizens directly and independently. This would make regional policy more responsible.	There is no objective or technical criterion to determine whether a region is better equipped than the state to manage the areas of competence that will be transferred.
The most dynamic territories could boost the productivity of the territorial economy by creating a knock-on effect on the others.	In an already highly asymmetrical situation, the implementation of differentiated regionalism in the field of health protection runs the risk of leading to even greater differentiation in the already very unequal models of the regional health services.
Differentiated autonomy can strengthen the incentives of regional governments and the national government to innovate in public service delivery models.	The state would lose control over a significant portion of expenditure, potentially compromising its ability to plan effectively, i.e. to make decisions that promote growth and counteract the damaging effects of a global economic downturn or crisis. Moreover, overall spending could be affected by fragmentation in the delivery of public services and increased costs due to economies of scale.
With greater autonomy, regions can have more flexibility in managing administrative and bureaucratic procedures, simplifying decision-making processes and reducing administrative burdens.	Analyzing the experience of various developed and emerging countries, the economic literature tends to refute the hypothesis that fiscal decentralization (symmetrical or asymmetrical) has a positive effect on economic growth.
	There could be a shift in the healthcare labour market towards more adequate remuneration and better working conditions. This could create a domino effect on citizens who will be increasingly driven to leave their region for better living and treatment conditions.
	During the Covid-19 pandemic, the choices made to mitigate the damage caused by the spread of the virus and the resulting relationships between central and regional administrations showed that, at the moment, it is not possible to manage Italy based on the identified network of metropolitan cities or on a multi-speed structure with differentiated autonomies. Faced with a health crisis, the system as a whole has shown its inefficiency. The approval of differentiated autonomies in the form demanded by Lombardy, Veneto and Emilia-Romagna runs the risk of bringing the entire system to collapse if faced with a new crisis.
	The regions would have an incentive to claim autonomy only in those areas where tax revenues exceed expenditure, relying on the central state to cover the remaining matters where the opposite is the case.
	The region, being able to rely directly on the tax revenues of its residents, in the event of inefficiencies in the system, it would be the citizens themselves who would pay the consequences with increased taxation.

Source: Own authors' compilation

Figure 5 Position of stakeholders and their influence



Source: Own authors' compilation

On one side, some argue that differentiated autonomy could be the turning point for a system that currently faces too many critical issues. They see differentiated autonomy as a process of holding regional politicians accountable, increasing transparency and accountability so that citizens, at the end of the local government's mandate, can evaluate the performance of the regional and local governments. Retaining the majority of tax revenue automatically translates into greater efficiency. On the other hand, some associate differentiated autonomy with the death knell of the National Health Service (SSN), with Italy divided into two, specifying how the experience with special statute regions (which benefit from autonomy) has not led to any overall reduction in public spending; indeed, the central government, to finance new debt or cope with exogenous shocks, would have to resort to new taxation, to be imposed nationwide, or it would have to reduce transfers to those regions that do not meet the essential levels of service. Regions would resort to local tax leverage by increasing regional income tax surcharge and the IRAP surcharge (mandatory flexibility in case of lack of coverage from regional budgets). In other words, it is the residents' pockets in a given territory that bear the inefficiencies of the system (Carboni, 2023; Cartabellotta et al., 2023; Caruso,

2022; Silipo, 2023b).

What emerges from Table 4 is that currently, the risks far outweigh the opportunities that differentiated autonomy would bring to the Italian context. The stakeholders' positions reflect a nation divided in two; indeed, as one might easily imagine, the most virtuous regions generally favor implementing differentiated autonomy, while regions facing difficulties with federalism are more opposed. The Minister of Health and the Minister of Economy and Finance (MEF), who enjoy strong influence, did not oppose it, specifying how differentiated autonomy does not call into question the unity of the right to health protection and that the LEAs will always be ensured in each region, while the MEF specifies how differentiated autonomy can contribute to generating positive spillover effects on the territory in terms of functionality, sustainability, and competitiveness of the socio-productive system(MEF, 2023; Quotidiano Sanità, 2024b). Physicians have little influence on the current policy action, with the trend being to frame it negatively, specifying that there is no evidence confirming an increase in the efficiency of services provided in the face of further degrees of autonomy in the availability and management of resources; above all, there are no economic conditions that allow all regions to start from the same starting line (Quotidiano Sanità, 2024a). Most citizens, who nonetheless have no influence, are concerned about the conditions in which the less wealthy regions could find themselves since resources would be diverted from less wealthy regions(Vento & Titone, 2024).

Therefore, the fear is that an elite healthcare system will be created in the most virtuous regions and a survival-based one, forcing wealthier patients towards passive mobility to the detriment of their own region, which, with fewer direct revenues and fewer tax contributions would find itself asking for funding from a leaner but more indebted state. Lastly, the parliament has already voted on financial autonomy; 110 votes were in favor, 64 against, and 3 abstained (Baldolini, 2024).

4.5 Conclusion

Differentiated autonomy appears to be the only currently available solution to make both the Nation and Regions effective and efficient, streamlining the former and holding the latter accountable. However, as highlighted in the article, there are currently far more risks than opportunities. In the clash between political forces and stakeholders, however, a fundamental aspect is missing that goes beyond the individual aspects of contention: how will the success or failure of this maneuver be measured? For example, would a divided and probably more indebted

Italy be considered a victory if some regions were to improve their situation? Or again, can it be considered a victory for Italy to have less than half of the already virtuous regions shining even brighter, while the others continue to decline? These questions seek to investigate an aspect that currently seems lacking, given the freedom to choose the subjects of autonomy, and the fact that each region is inevitably more inclined to request autonomy in those areas where it excels, leaving failed areas in the hands of the state. Currently, there are not many determinants for success or precautions to mitigate the undesired effects that the reform could generate.

The unintended consequences are numerous and worrying; they could lead to elite healthcare systems and others based on survival, potentially resulting in a catastrophe regarding costs, access, and quality of care. National equity, already compromised today, could face a new abyss.

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