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Artificial intelligence in healthcare institutions: A systematic literature review on influencing factors

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ABSTRACT

The purpose of this review is integrating and contextualizing relevant literature on the factors influencing the adoption of AI in the healthcare industry into a comprehensive framework. Health systems are considered fundamental to creating societal value. However, global health systems are challenged by the increasing number of patients due to population aging and the growing prevalence of chronic diseases and cancer. Meanwhile, the United Nations calls for equal access to healthcare, tackling costs, and addressing resource constraints to foster the sustainable development of societies. In this context, artificial intelligence (AI) is gaining attention as it constitutes a promising technology to address these burgeoning challenges. Despite opportunities, the literature specifically on the adoption of AI in the healthcare industry is fragmented across various research fields, lacking a comprehensive overview. It lacks theoretically grounded research integrating, for example, the factors that influence the adoption of AI in healthcare institutions.

Derived from a multi-disciplinary systematic literature review, building on 130 studies, we propose the *Adoption of AI in the Healthcare Industry Model*. This model encompasses five dimensions influencing the adoption of AI in the healthcare industry and contextualizes them. We propose that *macro-economic*, *regulatory*, and *technological readiness* serve as external antecedents whereas *organizational* and *individual readiness* constitute internal antecedents influencing adoption of AI in healthcare institutions.

Our review has implications for research on technology acceptance related to AI in healthcare. Further, we provide hands-on guidance for AI providers, health institutions, and official bodies such as governments to foster the adoption of AI to leverage value.

1. Introduction

Global health systems are challenged by a growing number of patients due to population growth and increased prevalence of cancer and chronic diseases, increasing healthcare costs, as well as staff shortages [e. g. Refs. [1,2]]. At the same time, the United Nations calls for promoting good health, well-being, and reducing inequalities to foster the sustainable development of societies globally. These factors motivate key stakeholders in the healthcare industry, including governments, clinical institutions, and corporations, to rethink current practices and boost innovation [3–5].

One technology with the potential to tackle the burgeoning challenges faced by global health systems and therefore attracting increasing interest among practitioners and academics is artificial intelligence (AI). AI is a technology that, through rules-based logic, can help to significantly speed up the process of analyzing vast amounts of data and leverage patterns by mimicking human intelligence [6]. In contrast to human-based analysis, AI may result in fast and often better-advised decisions [7]. Thus, as it pertains to the healthcare industry, AI has the potential to overcome staff shortages in developing and developed countries, enhance organizational efficiency, and maximize diagnostic accuracy as well as patient outcomes by providing at least comparable results in terms of quality compared to human based assessments. Consequently, AI may reduce costs due to avoidance of

Abbreviations: TAM, Technology Acceptance Model; UTAUT, Unified Theory of Acceptance and Use of Technology; TOE, Technology – Organization – Environment.

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inefficiencies, unnecessary treatments, and late diagnoses [8–10].

This potential explains the growth of the AI health market [4], which is projected to reach a market size of USD 6.6 billion with a compound annual growth rate of 40 % [11]. On a more granular level, it is estimated that the healthcare industry may see 20 % of unmet clinical demands fulfilled by the adoption of AI. In addition, the industry is expected to save USD 150 billion annually by 2026 after the adoption of AI [9].

This considerable potential of AI has also been recognized by the academic community, and the number of publications on AI in healthcare has recently risen exponentially as more and more health institutions consider AI and provide grounds for research [12–15]. Research to date focuses particularly on the development of AI algorithms, new technical models, and clinical studies [e. g. Ref. [16]]. Besides, scholars examine ethical considerations around the topic of AI [e. g. Refs. [17–19]]. However, to fully benefit from the potential of AI in the healthcare domain and create societal value, insights into the adoption of AI in healthcare are crucial as both the implementation and adoption of this technology in the real world has proven challenging and most health institutions seem not yet ready to adopt AI [20,21]. For example, half of all studies on clinical support systems for triage in emergency departments lack an implementation phase [22].

The literature on factors influencing the adoption of AI in healthcare has been very fragmented, dispersed, and scattered over several research fields. The factors influencing the adoption of AI in the healthcare industry are outlined as side products of clinical and technical studies as well as analyzed from an ethical and end user's perspective. However, a holistic framework incorporating the factors affecting the adoption of AI in healthcare is lacking. As a result, various scholars have called for research that outlines how health institutions can successfully adopt AI in healthcare [20,22]. To fill this research gap and pave the way for future studies, this paper aims to review and integrate the respective literature.

2. Background

2.1. Theoretical background

Technology acceptance theory – in conjunction with contingency theory – provides a fruitful ground for analyzing and integrating the factors influencing the adoption of AI in the healthcare industry. Adoption describes the decision of an individual to adopt an innovation such as a new product [23] and goes beyond its sole implementation. In the scope of this paper, we describe innovation adoption as having occurred once a technological solution is accessible to an intended user group, and the solution is used in practice routinely.

Various approaches exist in information systems research to analyze the acceptance and adoption of technologies. Scholars distinguish between models explaining the adoption of technology on the individual and organizational levels. On the individual level, the most widespread model for explaining the adoption of AI in the healthcare industry is the technology acceptance model (TAM) introduced by Fred Davis in 1985 [24,25]. Venkatesh and Zhang [26] extended the well-established TAM and mitigated its shortcomings by introducing the unified theory of acceptance and use of technology (UTAUT). UTAUT underscores the main individual factors affecting technology acceptance but also identifies contingencies that amplify or constrain their effects [26]. Venkatesh and Zhang [26] identify three factors impacting the behavioral intention to use technology: performance expectancy, effort expectancy, and social influence. Contingencies include age, gender, experience, and voluntariness. Longitudinal studies in the United States prove that the UTAUT explains 77 % of the variance in behavioral intention to use technology and 52 % of that in technology use [27]. In addition, it is assumed that culture, defined as the belief systems that shape individuals' schemata about the world around them, affects the adoption of technologies [1,26,28,29].

On the organizational level, the technological-organizational-environmental (TOE) model is the leading model for explaining adoption [30,31]. Technological factors incorporate external and internal resources required for adoption, reliability, security capability, and relative cost advantages. Organizational factors include firm scope and size, the level of formalization and centralization of the organization, the quality of the human resource department and availability as well as utilization of resources, organizational readiness, and top-management support. Finally, the environmental factors encompass competition, governmental policies, and regulations. As the TOE model aims at explaining predominantly organizational adoption, scholars recommend integrating it with other adoption models seeking to explain (readiness for) adoption on the individual level [32–34]. Following this advice, we consider the TOE model in combination with the UTAUT model as the theoretical background for our review.

Finally, contingency theory shows that innovations behave different in different contexts and that firms with a similar resource set-up achieve different levels of success. Consequently, exogenous factors such as organizational and environmental contingencies seem to contribute to success [35,36]. In terms of our research, we will consider that different environments foster different levels of success regarding the adoption of AI in healthcare due to organizational or environmental contingency factors.

2.2. Related literature

Related literature, on the adoption of AI in health institutions can be clustered in five distinct areas of research: clinical applications, technical papers, ethical considerations, health economic studies, and research examining the adoption of AI by users working in health institutions.

Most publications focus on clinical applications aiming at personalization of healthcare delivery and efficiency [e. g. Ref. [37]]. Specifically, the research explores applications in the fields of wearables, optimized drug usage, prediction tools, triaging, and workflow-optimization tools. AI-powered wearables utilize patient-level sensors to identify potential at-risk incidents (e. g., falls or strokes), enhance patient outcomes by increasing the level of information available for clinical decision making, and can minimize treatment casts as a result [e. g. Refs. [38–40]]. The research on tools to optimize drug usage comprises investigations into mechanisms supporting clinicians in providing the optimal administration of medication [e. g. Refs. [41,42]]. AI-based prediction tools focus on charting the potential course of disease, such as the metastasis of cancers, and the likely responses to treatments [e. g. Ref. [43]]. Triaging tools assist physicians in prioritizing patients, based on, for example, survival probabilities [44,45]. Finally, workflow-optimization applications seek to optimize the efficiency of the health institution, for instance, by providing smart algorithms helping to reduce waiting times for patients [37,46]. Besides research on clinical applications, a considerable number of scholars focus on enhancing technical solutions and developing algorithms to further mitigate existing barriers of adoption. This stream further aims at exploring how higher levels of cyber security can be achieved, for example through blockchain technology, and the possibilities that cloud, edge, and fog deployments offer [e. g. Refs. [47,48]]. In addition, researchers investigate the ethical challenges emerging from the implementation of AI in clinical settings. These challenges include the lack of explicability resulting from the complex and opaque architecture of the AI systems and concerns about fairness due to insufficient data to consider minority groups [e. g. Refs. [17–19]]. Few studies examine the health-economic impact of AI covering the hospital and societal perspectives. On the hospital level, the cost-effective analysis of AI in sepsis care revealed enhanced clinical outcomes and less severe infections, resulting in 49 % cost savings compared to standard care. Meanwhile, research on the societal perspectives on cost effectiveness is close to non-existent [49]. Finally, researchers have begun to investigate the drivers of users' acceptance of AI in healthcare [e. g. Refs. [13,50,51]]. Key contributions explore individual factors such as a person's beliefs regarding usefulness, ease of use, and behavioral control.

Although these five pillars touch on the topic of adoption, insights into how AI can be adopted in healthcare remain very scattered, and a holistic overview is lacking. Four literature reviews attempt to shed light on the adoption of AI in the healthcare industry. As demonstrated in Table 1, these reviews provide valuable inputs, but they have either different focus areas compared to our review's objectives or focus exclusively on individual aspects of AI adoption in the healthcare industry.

To our knowledge, to date no theoretically grounded paper integrates both organizational- and individual-level factors that may influence the adoption of AI in healthcare, although several clinical and technical papers call for studies on implementation and adoption [20, 22]. To fill this research gap and add to the academic literature on adoption, we formulate our research objective as follows:

To integrate the literature on the factors influencing the adoption of AI in the healthcare industry into a comprehensive framework.

3. Methodology

3.1. Research approach

To explore our phenomenon of interest and integrate the existing relevant literature, we followed an inductive approach and conducted a systematic literature review [55–58]. A systematic literature review seems to be a promising approach to investigate our objective as various disciplines have already touched upon the topic and the relevant literature is fragmented [59]. Further, our goal is to enrich the current understanding of factors influencing the adoption of AI in healthcare [60] by using a systematic and transparent methodology, yielding reproducible results [55].

3.2. Data collection

To perform the systematic literature review, we followed the process proposed by leading scholars [e. g., 57,60], as illustrated in Fig. 1.

First, we conducted a scoping review to identify both the need for this structured review and relevant search terms. In this step, we also consulted literature reviews in our field of interest to validate our anticipated keywords. Second, we carried out the systematic literature review by searching in EBSCOhost Integrated Search and ScienceDirect. We decided for EBSCOhost in its Business Source Complete version as our main data base for several reasons: (1) It is one of the most comprehensive databases in the business research domain covering more than 2500 journals in the field of management research. (2) We adhere to recommendations of leading recent guidelines for conducting systematic literature reviews in the management research domain to use EBSCOhost [e. g. Refs. [56,57]]. (3) We follow recently published studies in the field of technology and healthcare in high-ranked management journals with using EBSCOhost as the primary database [e. g. Ref. [37]]. Building on EBSCOhost as the primary database we decided to add ScienceDirect as a second database for complementing the sample once again, following recent publications in the field [e. g. Ref. [37]].

Within these data bases we searched for "(adoption OR implementation OR usage) AND (AI OR ML OR machine learning OR artificial intelligence) AND (health care OR medical technology OR health)" in the titles and abstracts of English-language peer-reviewed papers between August and October 2022. By extending our search terms to machine learning (ML) we also capture articles which not explicitly mention AI. This search yielded 1107 articles in total. Third, we applied a quality gate and only included articles with an impact factor greater than 1.5. Fourth, we removed all duplicates from our sample. Fifth, we checked the titles and abstracts of the remaining 796 papers for topic fit and carefully excluded all papers that did not address our research objective. Sixth, we analyzed the remaining papers for topic fit in greater depth by reviewing the full paper. Finally, we investigated the references of our final sample and Google Scholar, ensuring we included all relevant papers, resulting in the inclusion of further relevant publications.

3.3. Data processing

To analyze our final sample, we followed a four-step approach [58]. First, we processed the data in Microsoft Excel and extracted all factors influencing adoption on both the organizational and the individual levels to grasp the actual intention of the respective authors. In the next step, we clustered codes related to the same factor and identified a common overarching terms as first-order influencing factors. Such terms include, for example, "clear value-add", "user-friendliness", "data privacy", "interoperability", and "customization". Then, we applied axial

Table 1
Overview of relevant literature reviews; Source: authors' own work.

Authors/Date	Title	Journal	Key contributions	Limitations of SLRs' focus
Khanijahani et al., 2022 [9]	Organi-zational, professional, and patient character-istics associated with artificial intelligence adoption in healthcare: A systematic review	Health Policy and Tech-nology	Organizational (including organization size, workflow, training, security), professional, and patient characteristics (including perceived usefulness, performance, effort expectancy, social influence) influencing the adoption of AI in healthcare were derived and grounded in the TAM	1. TAM focuses solely on the factors impacting individual adoption of AI in healthcare and does not shed light on e. g., macro-economic, technological, and regulatory factors 2. Research on relationships among the different factors is not part of the review's focus
Hashiguchi et al., 2022 [52]	Fulfilling the Promise of Artificial Intelligence in the Health Sector: Let's Get Real	Value in Health	Description of the potential of AI and key concerns	1. Review solely focuses on technology. Analysis of physicians' and patients' acceptance of the adoption of AI in healthcare are not part of review's focus. 2. Grounding findings in prior theory such as technology acceptance theory is out of focus within this review.
Sunarti et al., 2021 [53]	Artificial intelligence in healthcare: opportunities and risk for future	Gaceta sanitaria	Outline of opportunities and risks associated with the use of AI in health services (11 studies)	1. Grounding findings in prior theory such as technology acceptance theory is out of focus within this review.
Becker, 2019 [54]	Artificial intelligence in medicine: What is it doing for us today?	Health Policy and Tech-nology	Review of early work regarding AI in medicine, including an outline of key applications, drawbacks, and how to prepare healthcare for adoption	1. Review solely focuses on technology. Analysis of physicians' and patients' acceptance of the adoption of AI in healthcare are not part of review's focus. 2 Grounding findings in prior theory such as technology acceptance theory is out of focus within this review.

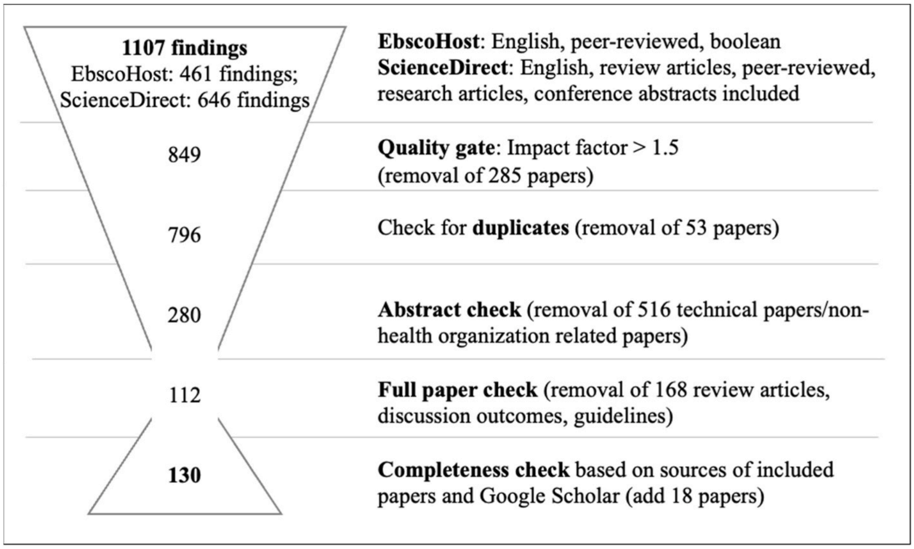

Fig. 1. Sampling procedure. The figure visualizes the data collection methodology, source: authors' own work.

coding to pinpoint second-order influencing factors. For example, the first-order influencing factors listed above were clustered to "multi-faceted value proposition" during the axial coding process. Further, we derived in this step the relationships among these different clusters based on the information provided in our sample. Finally, we performed selective coding to identify higher-level influencing dimensions and to understand how the different dimensions relate to each other [58]. In this step, we clustered, for example, the second-order influencing factors "overcome algorithmic challenges", "multi-faceted value proposition", and "evidence based applications" to technological readiness. Technological readiness is grounded in technology acceptance theory, in particular in the TOE model. Following the clustering, we derived from our data how the different dimensions relate to each other. The complete coding scheme can be found in Appendix A.

4. Results

4.1. Descriptive insights

In total, we identified 130 relevant publications covering our topic of interest, 57.6 % of which were published within the past two years, reflecting the recent growing academic interest. Most of the included studies were published in journals related to information technology (IT) and medicine, such as *Artificial Intelligence in Medicine*, *Digital Medicine*, and the *International Journal of Medical Informatics*. Only a few publications are available in business management journals, such as *Health Policy & Technology*, *Technovation*, *Technology Forecasting and Social Change, and Technology in Society*, confirming the scarcity of much-needed business research on this topic. From a regional perspective, most studies (60 %) do not focus on specific regions but elaborate generally on the factors influencing AI adoption in the healthcare industry, in contrast to the suggestion of contingency theory. However, 13.8 % of the identified studies are specifically tied to the United States, indicating above-average interest in the topic in this country. Most publications addressing the adoption of AI in health settings refer to explainable AI, mostly based on pattern-recognition functionality. AI seems to be most widely adopted in cardiology and radiology and rather at an early stage in dermatology and psychiatry. The details of the descriptive statistics can be found in Appendix B.

4.2. Adoption of AI in the Healthcare Industry Model

Based on technology acceptance theory, factors influencing the adoption of technologies to leverage societal value exist at both the individual and the organizational levels [32,33]. This theoretical claim was confirmed by our analysis. Four factors—*macro-economic readiness*, *technological readiness*, *regulatory readiness*, and *organizational readiness*—were identified on the organizational level and one factor—*user readiness*—on the individual level. Once readiness is achieved within all five dimensions, AI seems to be able to be successfully adopted, while overcoming previously outlined concerns and leveraging sustainable benefits. We summarized the macro-economic, technological, and regulatory readiness as *external antecedents* and the organizational and user readiness as *internal antecedents* as well as integrated these factors in the *Adoption of AI in the Healthcare Industry Model* as portrayed in Fig. 2.

Macro-economic readiness. Macro-economic readiness is mainly driven by governments and captures the existence of adequate IT infrastructure and communities so that societal value can be leveraged by the adoption of AI. Adequate IT infrastructure encompasses access to smart devices for the population and energy adequacy. Especially for the adoption of applications in the AI-based remote health surveillance field, it is crucial for the target population to have access to smart devices [61,62]. Energy adequacy describes access to energy sources to cope with network failures resulting from irregular power supplies and limited battery capacities.

The establishment of communities refers to the creation of partnerships, collaborations to exchange data, and communities for sharing best practices. According to survey research in the Chinese context [63], interdisciplinary partnerships across regions and clinical specialties seem to have the potential to promote policies and attract funding from investors as well as governments to support much-needed research. Further, research illustrates the benefits to multi-stakeholder collaborations between medical institutions, clinicians, and researchers to facilitate the collection of high-quality data as well as the sharing and merging of data sets [64]. Lastly, the literature calls for effective knowledge management and sharing best practices to raise awareness and create trust [cf [65,66]]. In the United Kingdom, for example, a qualitative study revealed the impactful signaling effect of the decisions made by the National Health Service. Evidence shows that private health institutions in the United Kingdom are willing to adopt AI once National Health Service adopts it and shares this best practice [67].

Technological readiness. Besides macro-economic readiness, technological readiness is crucial to the adoption of AI in the healthcare industry. Literature indicates that AI providers are the key responsible in terms of ensuring technological readiness. We identify three factors influencing the level of technological readiness, namely, the needs to

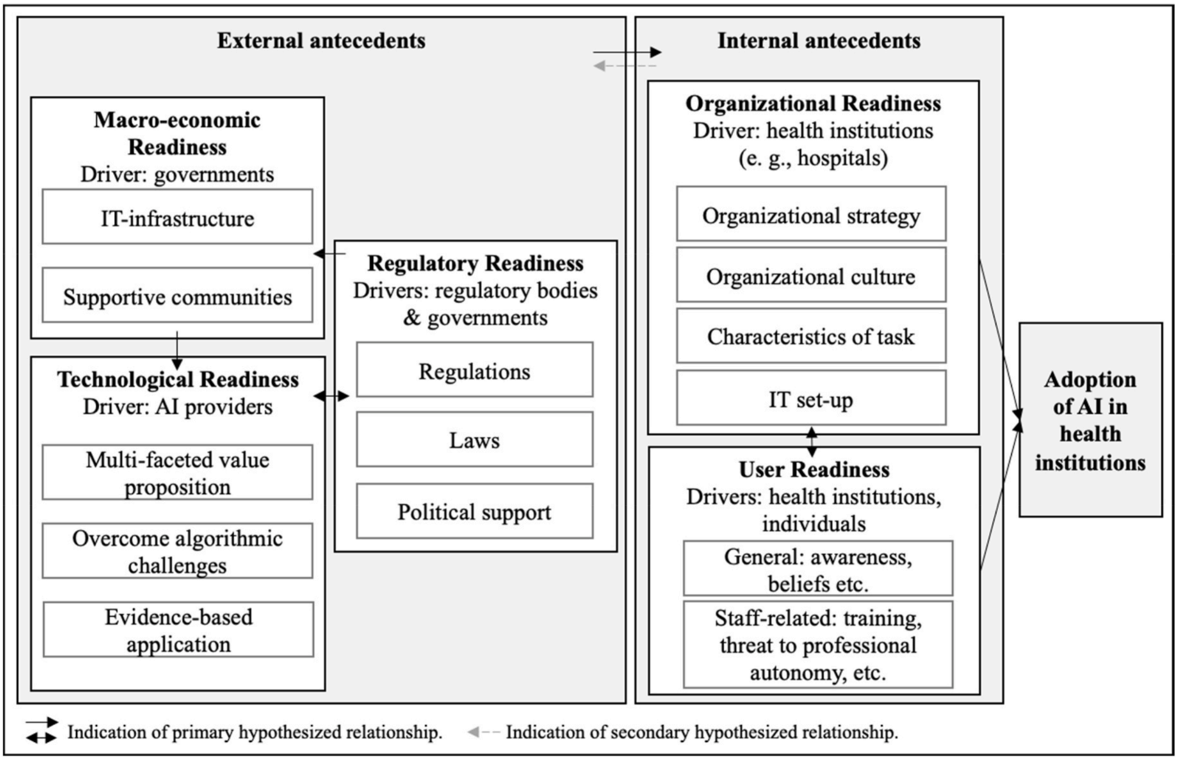

Fig. 2. Adoption of AI in the Healthcare Industry Model. The figure contextualizes the factors influencing adoption of AI in the healthcare industry, source: authors' own work.

overcome algorithmic challenges, provide a compelling, multi-faceted value proposition, and ground the AI application on real-world evidence. Addressing these factors is crucial to overcome previously outlined ethical concerns of the adoption of AI in health setting [e. g. Refs. [17–19]].

To overcome algorithmic challenges, tackling the lack of data and its often-insufficient quality is key [68]. Missing or incomplete data in training and testing data sets entail risks of biases, misleading predictions, and large-scale discrimination [69]. Due to the associated ethical concerns, lacking access to data and incomplete training or testing data sets hinder the adoption of AI in healthcare [70]. Further, AI in healthcare is often unexplainable, meaning that experts cannot retrace how an AI application arrived at a certain decision despite its far-reaching consequences [e. g. Refs. [68,71,72]]. This insufficient explicability further restricts AI adoption [73]. In addition, scholars point out that it is important to understand the level of certainty with which an algorithm determines an outcome, as low-probability but high-consequence scenarios are often not covered due to a lack of access to such rare data [74].

Apart from tackling algorithmic challenges, providing a compelling, multi-faceted solution through the AI application is essential to foster adoption. This includes a clearly added value, user-friendliness, adherence to data-privacy regulations, interoperability, and the ability to tailor the application to individual needs. The added value can include enhanced efficiency through a reduction in paperwork and diagnostic time, improved time to patient care, increased safety, and a higher degree of patient satisfaction [14,67]. Besides offering a compelling value proposition, the user friendliness of the application is key [e. g. Refs. [71,75]]. Furthermore, AI vendors must adhere throughout the product's entire lifecycle to general data-privacy and cybersecurity regulations such as the General Data Protection Regulation established by the European Union [62,76,77]. A scoping review outlines exemplary that blockchain technology appears to be promising to overcome prevailing data-privacy concerns regarding cloud applications [78]. Moreover, the AI application must be interoperable with existing IT systems at the customers' sites—such as the hospital information system or the electronic health records—and integrated into existing clinical information systems in primary and secondary care [68,75]. Finally, it is essential for the AI application to be adaptable to the health institution's individual needs, preferences, and contexts of use [79]. For example, it is not clear whether AI applications that were trained on US data perform equally reliably in Asian contexts since the population's anatomy is different [80].

In addition to addressing algorithmic challenges and providing a compelling value proposition, the added value must be proven by evidence from internal and external validations [75]. When performing internal validations, the testing data set should differ from the training data set, but both should originate from the same population [76]. Before using AI in routine clinical settings, scholars recommend validating the performance of the solution externally in large cohort studies, multi-center studies, randomized controlled trials, or prospective studies and applying a variety of testing strategies to ensure generalizability and prove effectiveness [e. g. Refs. [14,61,71,76]]. This importance is also highlighted by a retrospective study [16] showing that although an AI model in the clinical field of diabetes can be transferred to a different context, its performance reduces substantially.

Regulatory readiness. Once the macro-economic and technical prerequisites are established, regulatory readiness becomes crucial. Regulatory readiness can be achieved through joint efforts of regulatory bodies and governments. We extract three regulatory-related needs from our analysis: political support, the clarification of legal questions, and the establishment of regulations. Political support is essential with regards to funding clinical studies which aim at assessing the efficiency of AI applications [72]. Additionally, we observe the need to resolve legal uncertainties, as the accountability for decision-making when using AI remains unclear. Scholars raise ethical concerns and point out that machines must not be responsible for human life, calling for collaborations between different stakeholders, including AI vendors, and collective responsibility [e. g. Refs. [53,81,82]]. Lastly, introducing new regulations may also foster the adoption of AI in healthcare. Guidelines defining the ownership and custodianship of data are valuable to ensure appropriate access to high volumes of data to train and test algorithms ethically [83].

Organizational readiness. Apart from regulatory readiness, organizational readiness is required and needs to be institutionalized by respective health institutions such as hospitals prior to adopting AI. We identify four core influencing factors: an organizational strategy, a supportive organizational culture, the characteristics of the task, and an adequate IT setup.

First, a top-down strategy of the health institution outlining an overall plan regarding goals and resource distribution is essential to implementing AI successfully [80]. This strategy must consider the allocation of dedicated resources since staff skilled in IT and statistics is needed so that data can be gathered locally, and algorithm performance can be evaluated on-site [80,82]. Furthermore, scholars point out that health organizations need to transform their workflows and business models to exploit AI to leverage health economic benefits [69]. The institution needs to define policies regarding the use of AI, adapt processes, and innovate workflows to unleash the added value of AI and to ensure proper human-AI collaboration [84,85]. In this vein, the role of the IT department must be redefined as radiologists need to work closely with IT specialists [86].

Second, a supportive organizational culture and the beliefs of an organization are crucial to the successful implementation of AI. In particular, social pressure—understood as beliefs regarding what others think about an organization using such an application—influences adoption [87,88]. Moreover, a workforce that is resistant to change because of, for example, fear of losing their professional competence and becoming deskilled, may hinder the successful introduction of AI [54, 89]. To overcome cultural barriers, the establishment of dedicated change ambassadors who provide support for bridging the knowledge-action gap seems promising [90].

Third, the characteristics of the task that may be facilitated by AI influences adoption on the organizational level. Specifically, task complexity and perceived difficulty, including the load required to accomplish a certain task, influence adoption [87,88].

Last, the status of an organization's IT setup and infrastructure is decisive. Our analyses reveal prevalent challenges, including inflexible IT infrastructures that are unable to incorporate external software, outdated hardware that cannot handle the required computing power and is not energy efficient, and organizations' data privacy concerns [82]. Consequently, research points out that big-data capabilities are essential and edge computing provides the opportunity to reduce latency and energy consumption by moving processes closer to data sources [3].

User readiness. At the individual level we identified factors influencing the adoption of AI covering general factors valid for all end users and staff-related factors that only apply to the professionals of health institutions.

Regarding the general factors, we observe four distinct pillars influencing adoption: awareness, beliefs, personal innovativeness, and the financial situation of the individual. Scholars revealed that awareness of both the consequences of certain diseases and AI applications positively impacts the intention to use AI solutions [63]. Beliefs affecting the adoption of AI include perceived risk, trust, societal norms such as lacking individual innovation spirit in China, subjective norms including awareness of health disparities that may be addressed through the implementation of AI, perceived behavioral control, and perceived usefulness [80,87,91,92]. Further, personal innovativeness—understood as the willingness of an individual to try something out and its respective skills —significantly impacts adoption [87,88,93]. Independent personalities that are keen on overcoming technical anxieties and have an understanding of AI as well as IT skills are most likely to use AI solutions in healthcare [87,88,92]. The personal innovativeness can be unleashed by transformational leadership [94]. Lastly, the financial situation of users influences the adoption of AI in healthcare. Studies report that AI-powered solutions are often not affordable, and it is financially challenging to adopt such solutions [95].

Regarding staff-related factors, our review reveals that both the threat to professional autonomy and training affect the adoption of AI. Research shows that the threat to professional autonomy has a negative influence on the perceived usefulness of IT and the intention to use it [72,96]. Evidence suggests that employees tend to hide knowledge once they perceive their roles as threatened by the adoption of AI [97]. For this reason, scholars recommend engaging with key users, such as clinicians, early in the development and implementation process to overcome their potential concern that AI can reduce their professional autonomy [72]. In terms of training, it is crucial to teach users the benefits and limitations as well as how AI can be used in patient care to avoid misinterpretations consciously [62,76,83,86,98]. Consequently, IT and AI specific knowledge should be built up for the respective user groups – in addition to their medical expertise. In the long term, the transfer of these skills may be even incorporated into the formal training of medical experts and in their continuous education paths [[86,99, 100], cf [101]].

Adoption of AI in the Healthcare Industry Model. Having introduced the organizational and individual factors influencing AI adoption in the healthcare industry, we shed light on their interdependencies. Our analysis indicates that macro-economic, regulatory, and technological readiness resemble an external antecedent for adoption. Once these are in place to a certain extent, the organizational and user-specific influencing factors (internal antecedents) become relevant and reinforce each other. Nevertheless, organizational readiness can also impact technological, regulatory, and macro-economic readiness once AI is implemented in organizations. For instance, through the implementation and adoption of AI, further data can be collected to contribute to technological readiness, best practices can be gathered, and thus motivate regulatory bodies to clarify open topics such as accountability.

5. Conclusion

5.1. Discussion

Throughout our systematic literature review, aiming to integrate and contextualize the factors influencing the adoption of AI, we identified five such factors: *macro-economic readiness, technological readiness, organizational readiness, regulatory readiness*, and *user readiness*. Theory suggests that technology acceptance happens on the organizational and individual levels [32,33]. On the organizational level, the leading model is the TOE framework, while on the individual level, the predominant framework is the UTAUT model [26]. Whereas theory states that adoption on the organizational level depends on technological, organizational, and environmental factors, our findings suggest further differentiating environmental factors into regulatory and macro-economic readiness, taking the highly regulated nature of the healthcare industry into consideration [30,31]. On the individual level, the UTAUT model identifies three determinants of adoption: performance expectancy, effort expectancy, and social influence [26,29]. Our research also reveals these three influencing factors but adds additional factors such as awareness, personal innovativeness, and the respective financial situation of the user. With respect to medical professionals, we also identify the threat to professional autonomy, training, and perceived job loss as crucial influencing factors, thus going beyond the hypotheses of the UTAUT model.

Prior research proposes that contextual factors such as culture impact technology acceptance [1,26,29]. This hypothesis is supported by our review as we found that independent personalities, which are tied to cultural contexts, seem to have a higher probability to adopt AI in healthcare. Moreover, we observe differences in adoption related to clinical fields in line with hypotheses from contingency theory. For well-established specialties such as cardiology and radiology, the research focuses on how to adopt AI in healthcare successfully based on regulatory, advanced technical, and user-readiness considerations [e. g. Ref. [99]]. However, for specialties such as dermatology, the research is still in its infancy and concentrates on fostering technological readiness through e. g., the development of solutions [e. g. Ref. [102]], in line with our hypothesis that technological readiness constitutes an antecedent for the organizational adoption of AI.

5.2. Theoretical contribution

In this review, we conducted exploratory research to investigate, integrate, and contextualize the factors influencing the adoption of AI in healthcare. Research on AI adoption in the healthcare industry was fragmented across various areas of research and hardly present in business research. To address the academic and societal relevance of our research, we close this gap by introducing the *Adoption of AI in the Healthcare Industry Model*, which summarizes and connects relevant influencing factors. We are the first authors to provide a holistic overview and theoretically well-grounded conceptualization of the factors influencing the adoption of AI in the healthcare industry, answering several calls for research [e. g. Refs. [20,22]] and contributing to tackle prevalent challenges of health systems. We extend existing technology acceptance models such as the TOE and UTAUT models with additional factors that are specific to the much-regulated healthcare industry. Beyond extending and detailing the existing technology acceptance models for the healthcare context, we put the different factors influencing adoption into context by differentiating between external and internal antecedents. In particular, we argue that (1) macro-economic readiness, regulatory readiness, and technological readiness are external antecedents for the adoption of AI, (2) organizational readiness and user readiness serve as internal antecedents, and (3) a special focus on regulatory, legal, as well as political requirements and needs is essential to foster the adoption of AI by this industry. We shed light on the sequence of the readiness-dimensions to reach adoption of AI in healthcare.

Apart from contributing to technology acceptance theory, we extend research on adoption of AI in healthcare. Prior research focused predominantly on the effectiveness of clinical applications [e. g. Ref. [37]], progressing technically [e. g. Refs. [47,48]], ethical considerations [e. g. Refs. [17–19]], health economic studies [49] and research examining the willingness to adopt AI by end-users [e. g. Refs. [13,50,51]]. Building on this prior research, we provide a holistic framework contextualizing the factors influencing adoption of AI in healthcare and their interdependencies. To-date research focused solely on individual aspects of that framework and lacks an integrated, holistic framework contextualizing factors influencing adoption of AI in healthcare.

We conclude that our findings are generalizable to other industries. In particular, we believe in the transferability of the findings as they are in line well-established technology acceptance models such as the UTAUT and TOE describing organizational, technological, environmental and individual dimensions relevant for adopting technological innovations. However, following contingency theory we expect environmental contingencies across different industries [e. g. Refs. [35,36]]. The healthcare industry constitutes a highly regulated industry in which AI can directly impact patient health and thus may have severe impacts. For this reason, environmental factors such as regulatory readiness (e. g., regulations on accountability) and macro-economic readiness (e. g., consistent energy supply to ensure continuous AI support) are especially pronounced in this industry.

5.3. Limitations & avenues for future research

Despite fruitful contributions to the current body of research, our review is subject to limitations, which open windows of opportunities for further research. The analysis reviews the current literature and adds value by integrating and connecting it. However, as the established model rests exclusively on a structured literature review, the identified relationships between first-, second order constructs and the aggregate dimensions have not been verified. To overcome this shortcoming, we call for a subsequent quantitative study to validate the derived relationships and further investigate the factors' influence on adoption, also comparing different contexts such as cultures and clinical sub-areas. We propose the application of a survey-based research methodology to assess the potential influence of the identified factors via structural equation modelling and analyze variances to capture deviations among the distinct factors regarding groups such as cultures and clinical subfields. We perceive such research as valuable as it has the potential to guide managers of diverse cultural backgrounds and clinical sub-fields even more precisely, considering specific antecedents of different contexts [cf [35,36]].

Following this strain of thought we also recommend investigating the individual first-, and second order constructs in more detail. Within our research we integrate and contextualize relevant factors driving the adoption of AI in the healthcare industry. For some first-order influencing factors, as for example, user readiness and technological readiness, specific in-depth qualitative and mixed-method studies exist examining their influence on adoption of AI in healthcare [cf [88,89]]. However, other's factors influence on the adoption of AI in healthcare was rather stated as a side product of studies examining, for example, the clinical effectiveness of an AI solution. To further underpin the importance of such factors and provide concise guidance for managers (e. g., first-order influencing factors of macro-economic, regulatory, and organizational readiness), we recommend conducting specific studies exploring a) the relevance and b) the impact of these factors on successful adoption.

Further, this review is predominantly based on literature stemming from non-country specific contexts or developed markets such as the United States. Given the relevance of AI in healthcare in emerging and developing nations we call for additional qualitative research to explore which factors trigger adoption of AI in healthcare in emerging markets. Once initial insights got established, they may be further examined using quantitative research methodologies. In this vein, academia will be able to support emerging countries leveraging societal value from the adoption of AI in healthcare.

Our review builds on the hypothesis that the adoption of technologies such as AI contributes to addressing societal challenges such as having an increase in patients while facing challenges to attract qualified staff. However, prior research also outlines societal challenges which are associated with the adoption of technology [12]. Therefore, we recommend exploring the concrete societal challenges associated with the adoption of AI in healthcare contexts to derive potential further factors relevant to adopt AI in healthcare successfully. Such an exploratory study may be conducted by means of e. g., qualitative in-depth expert interviews or a multiple case study. The resulting insights will be vital to complement our model with additionally relevant factors to leverage the promises of AI related to societal benefit in healthcare.

Finally, the focus of this review rests upon integrating and contextualizing factors influencing adoption of AI in healthcare. However, we did not explore and integrate the steps following AI adoption. Also, prior research – to our knowledge – does not go beyond examining adoption of technologies. However, from a holistic, sustainable implementation and adoption perspective, we consider it as crucial to also explore the post AI adoption steps initiated by health organizations. This will allow an understanding on how health institutions cope with their volatile business environments and consequences following the adoption of AI while striving for long-term success and competitiveness.

5.4. Practical implications

Our review has practical implications for AI providers, health institutions, and official bodies. To foster adoption and leverage value, we advise AI providers to focus on the technological readiness of their solutions and push internal and real-world validations to prove the generalizability and efficiency of the solution. In addition, our research reveals desirable functionalities which AI providers shall incorporate into their solutions to provide a compelling, multi-faceted value proposition to the end users. We recommend AI vendors to focus on a clear value add, an intuitive user interface, adherence to data privacy regulations, interoperability, and customizable offerings.

Through our research, health institutions can become aware that the adoption of AI requires both external and internal antecedents. Depending on the level of adoption of AI in the clinical field of interest, health instiutions may focus on shaping internal and/or external antecedents. Externally, health institutions shall engage with AI providers or governments to further shape technological solutions and regulations fostering the adoption of AI in this respective clinical field. Internally, our research outlines that – besides ensuring user readiness - a dedicated organizational strategy showing commitment of the organization towards adopting AI, an organizational culture fostering openness for (technological) innovations, specific tasks which can be automated, and a respective IT set-up is vital. More mature clinical fields in terms of adopting AI in healthcare, such as radiology, focus, for example, on shaping internal antecedents such as organizational readiness and user readiness. Burgeoning clinical fields related to adopting AI in healthcare, such as dermatology, focus rather on technological readiness to set the foundation for clinical routine adoption. It is of utmost importance that the health institutions manage change strategically, adopt existing processes, educate staff, and facilitate the integration of AI through support from the IT department.

In addition, our review highlights the pressing need for support from governments and regulatory bodies to further promote the adoption of AI. On a macroeconomic level, we outline the need for continuous energy supplies allowing the use of AI in routine practice in healthcare also in emerging and developing markets. In this vein, the challenge of having staff shortage while facing an increase in patients may be effectively addressed in both developed and emerging/developing countries. In addition, our findings call for governmental support to e. g., co-finance much needed external evidence such as costly, prospective clinical studies and to clarify accountability of decisions proposed by AI solutions. Further, we highlight the importance of introducing uniformed data-collection regulations that allow companies to access training and testing data more easily and ethically. Finally, we call for governmental awareness campaigns and interests groups fostering the acceptance of AI by clinical users and the population to further facilitate the sustainable development of health systems and, thus, of societies.

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CRediT authorship contribution statement

Julia Stefanie Roppelt: Conceptualization, Data curation, Resources, Writing - original draft, Writing - review & editing. **Dominik K. Kanbach:** Supervision, Writing - original draft, Writing - review & editing. **Sascha Kraus:** Methodology, Writing - original draft, Writing - review & editing.

Declaration of competing interest

None.

Data availability

No data was used for the research described in the article.

Appendices.

Appendix A. Coding Scheme Extract

Table A.1
Coding Scheme Extract; Source: authors' own work.

Influencing dimensions	2nd order influencing factors	1st order influencing factors
Macro-economic readiness	IT infrastructure	Access to smart devices required
		Energy adequacy
	Supportive communities	Creation of research partnerships
		Collaborations (for exchanging data)
		Sharing of best practices
Technological readiness	Overcome algorithmic challenges	Overcome lacking data availability
		Foster explicability of algorithm
		Understanding of uncertainty
	Multi-faceted value proposition	Clear value-add
		User-friendliness
		Data privacy
		Interoperability
		Customizability to individual needs
	Evidence based application	Internal validation
		External validation
Regulatory readiness	Political support	Funding of studies
	Laws	Clarification of accountability
	Regulations	Ownership of data
Organizational readiness	Organizational strategy	Commitment of organization
		Business transformation
	Organizational culture	Social pressure
		Resistance to change
	Characteristics of task	Perceived difficulty
		Task complexity
	IT set-up	Need: Big data capability
		Need: energy efficiency
		Need: edge computing

(*continued on next page*)

Table A.1 (*continued*)

Influencing dimensions	2nd order influencing factors	1st order influencing factors
		Challenge: Inflexible infrastructure
		Challenge: hardware limitations
		Challenge: data privacy threats
User readiness	General factors	Awareness
		Beliefs
		Personal innovativeness
		Financial situation
	Staff-related factors	Threat to professional autonomy
		Training

Appendix B. Sample characteristics

Table B.1
Sample Characteristics; Source: authors' own work.

Dimensions	Number of publications
Methodology	
Systematic literature review	28
Survey research	25
Other literature reviews	18
Clinical study	13
Technical paper	10
Qualitative study	10
Others	7
Case study	6
Mixed method study	5
Quantitative study	5
Experiment	3
Year	
2022	45
2021	30
2020	17
2019	24
<2019	14
Journal	
Others	74
Artificial Intelligence in Medicine	7
npj Digital Medicine	6
International Journal of Medical Informatics	5
Scientific Reports	4
Digital Health	3
Health Policy and Technology	3
Information Systems Frontiers	3
Journal of Medical Systems	3
lancet digital health	3
Value in Health	3
Academic Radiology	2
Decision Support Systems	2
Government Information Quarterly	2
Journal of Medical Internet Research	2
Physica Medica	2
Technological Forecasting and Social Change	2
Technology in Society	2
Technovation	2
Regional focus	
General	78
United States	18
Others	13
China	10
Africa	3
Australia	3
Germany	3
United Kingdom	3
Clinical field	
General	51
Others	39
Cardiology	10
Radiology	7
Pulmonary	6
Oncology	4
Surgery	4
Dermatology	3
Diabetes	3
Ophthalmology	3

(*continued on next page*)

Table B.1 (*continued*)

Dimensions	Number of publications
Level of analysis	
Organizational level	92
Individual level	21
Both	17
Total	**130**

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