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Fatores que influenciam a aceitação de Tecnologias de Inteligência Artificial na Saúde

Factors that influence the acceptance of Artificial Intelligence Technologies in Healthcare

Factores que influyen en la aceptación de las Tecnologías de Inteligencia Artificial en Salud

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RESUMO
Desde 2010, a utilização de tecnologias de Inteligência Artificial na saúde e promoção da qualidade de vida apresenta um progresso significativo na área de saúde. Entretanto, há muitas barreiras e resistência quanto a sua implementação seja por parte da gestão do hospital, paciente, profissional de saúde, conselho e sociedade de forma geral. O objetivo desta pesquisa é identificar os fatores que influenciam a aceitação da Inteligência Artificial na área da saúde por meio de uma revisão sistemática dos estudos que avaliaram empiricamente o uso dessa tecnologia. Para composição do arcabouço literário, foi realizada uma revisão sistemática da literatura na base de periódicos Web of Science com amostra final de 50 artigos. Como principais resultados, foram identificados 11 fatores: aspectos clínicos, aspectos humanos, aspectos organizacionais, aspectos regulatórios, experiência do usuário, grau de instrução para

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desenvolvimento de tecnologia, grau de instrução para uso da tecnologia, infraestrutura tecnológica, implantação tecnológica, percepção de potencial e resistência à inovação.
Palavras chave: Inteligência Artificial; Aplicações da Informática Médica; Sistemas de Apoio a Decisões Clínicas; Revisão Sistemática.

ABSTRACT
Since 2010, the use of Artificial Intelligence technologies in health and promotion of quality of life has shown significant progress in healthcare. However, there are many barriers and resistance to its implementation, whether by hospital management, patients, health professionals, professional boards and society in general. The objective of this research is to identify the factors that influence the acceptance of Artificial Intelligence in healthcare through a systematic review of studies that empirically evaluated the use of this technology. For this purpose, a systematic literature review was carried out on the bibliographic database Web of Science, with a final sample of 50 articles. As main results, 11 factors were identified: clinical aspects, human aspects, organizational aspects, regulatory aspects, user experience, level of education for technology development, level of education for the use of technology, technology infrastructure, technology implementation, perception of potential and resistance to innovation.

Keywords: Artificial Intelligence. Medical Informatics Applications. Clinical Decision Support Systems. Systematic Review.

RESUMEN
Desde 2010, el uso de tecnologías de Inteligencia Artificial en salud y promoción de la calidad de vida ha mostrado un avance significativo en el cuidado de la salud. Sin embargo, existen muchas barreras y resistencias para su implementación, ya sea por parte de la dirección hospitalaria, de los pacientes, de los profesionales de la salud, de los colegios profesionales y de la sociedad en general. El objetivo de esta investigación es identificar los factores que influyen en la aceptación de la Inteligencia Artificial en el cuidado de la salud a través de una revisión sistemática de los estudios que evaluaron empíricamente el uso de esta tecnología. Para componer el marco literario se realizó una revisión sistemática de la literatura basada en revistas Web of Science, con una muestra final de 50 artículos. Como principales resultados se identificaron 11 factores: aspectos clínicos, aspectos humanos, aspectos organizacionales, aspectos regulatorios, experiencia del usuario, nivel de educación para el desarrollo tecnológico, nivel de educación para el uso de la tecnología, infraestructura tecnológica, implementación tecnológica, percepción de potencial y resistencia a la innovación.

Palabras clave: Inteligencia Artificial; Aplicaciones de la Informática Médica; Sistemas de Apoyo a Decisiones Clínicas; Revisión Sistemática.

1. Introduction

It is unquestionable that the use of information technology has expanded in the health sector, notably motivated by the Covid-19 pandemic. These technologies are important for quality improvement of health services and to raise patients' satisfaction. Furthermore, health teams may benefit from significant increase in efficiency and effectiveness in their work when using technology appropriately.

2. Theoretical Framework

Artificial Intelligence (AI) is a technology that mimics human cognitive functioning on the computer [(1)]. The use of AI in health and in the promotion of quality of life is still incipient [(2)]. However, since 2010 there has been substantial progress in AI and its application in medicine [(3)]. Presently, there are studies suggesting that AI has the possibility of performing essential tasks in health, as diseases diagnoses [(4)], better than or as well as humans.

According to an article published on The Lancet Digital Health in 2021 [(5)], Covid-19 pandemic led health services providers and governments worldwide to accelerate the development of AI tools and expand their use in medicine even before proving, in some cases, that they are ready for use. Besides, the ambiguous regulatory panorama related to AI algorithms raised substantial concern among researchers in the health area.

In this context, the World Health Organization (WHO) published in 2021 a report that identifies the ethical challenges and risks of the use of AI in health and lists six principles of consensus to ensure that AI functions in the public benefit of all countries. In the report there is also a set of recommendations to ensure that AI governance in healthcare maximizes the promise of technology and maintains all interested parts – in the public and private sectors – responsible and attentive to health professionals who will trust these technologies and to communities and individuals whose health will be affected by their use [(6)].

For this reason, it is important to understand how individuals, especially healthcare workers, react to the emergence of new technologies and specifically to the use of AI as support technology. Low levels of acceptance of a certain technology may lead to failures or delays in the implementation and increase costs, among other negative effects [(7)]. Thus, user acceptance is often a crucial factor for the success or failure of a new technology.

Along the years, the acceptance of different information technologies in healthcare has been studied in various perspectives, contexts and applications [(8) (9) (10) (11) (12)]. These technologies include, for example, websites with health contents, medical image archives, communication systems, mobile applications, chatbots, telemedicine and patients electronic records. They were examined using different technology acceptance models in an attempt to better understand users behavior in relation to technology by means of the factors that support them [(13)].

The scholarly discussion on the factors that influence the use, or at least the intention of use, of a given technology is broad and has been occurring for decades. Since the 1990s, several theoretical models, with adaptations and extensions, were proposed with the purpose of understanding the levels of acceptance and the behavior of individuals in relation to various fields of application. Several studies have been dedicated to describing, comparing or criticizing the existing models [14] [15] [16].

The Technology Acceptance Model (TAM) has become the dominant model of investigation of factors that influence user acceptance of new technical systems. TAM is based on principles of Ajzen and Fishbein's Theory of Reasoned Action. The model proposes the hypothesis that the Perceived Usefulness (PU) and the Perceived Ease of Use (PEU) have primary relevance for technology acceptance. Perceived Usefulness is the user expectation that the system will be useful for the work. The Perceived Ease of Use is the expectation that the system is friendly and easy to use. In a review of the use of TAM in healthcare, Holden and Karsh [17] verified that this model was capable of predicting 30 to 70 percentage points in the variation of Behavioral Intention of Use, which can be considered reasonably high. The objective of TAM is to describe the factors that lead users to accept or reject a given technology [18].

It is believed that the identification of these factors may potentiate AI adoption and effectiveness in healthcare, by enabling those concerned (scholars and practitioners) to investigate technical, social and cultural aspects and to understand the correlation between these factors and users readiness to utilize the technology in healthcare services.

The objective of this research was to identify the factors that influence the acceptance of Artificial Intelligence in healthcare by means of a systematic review of studies that empirically evaluated the use of this technology.

3. Methodology

This chapter presents the procedures used in the methodology for the identification of factors that influence the acceptance of Artificial Intelligence (AI) Technologies in Healthcare. The Systematic Literature Review (SLR) was the chosen methodological framing.

The systematic literature review was performed using the bibliographic database Web of Science for the composition of the literature framework. Table 1 shows the three pillars used for the composition of the search string: artificial intelligence, adoption, acceptance, diffusion, resistance or barriers, and physician or physicians.

Table 2 shows the criteria adopted for the research sources. In the first stage, named first filter, the evaluation considered only the title and the abstract of 455 studies, according to the criteria of inclusion and exclusion and selection of studies that would be in the scope of the research question: "What are the factors that influence the acceptance of Artificial Intelligence Technologies in Healthcare?"

Table 1 – Results of the sample of the literature review

Search	Terms	Data base	Result	Sample
Artificial Intelligence – Research with Physicians	(Artificial intelligence) AND (adoption OR acceptance OR diffusion OR resistance OR barriers) AND (physician OR physicians).	Web of Science	455	50

Source: Authors (2022).

Table 2 – Criteria for the research sources

#	Criteria
1	Consultation of articles in digital libraries.
2	Availability of consultation of articles through the web.
3	Occurrence of search mechanisms through keywords that support the search string.
4	Having the studies available in English.

Source: Authors (2022).

In the second stage (or second filter), a full reading was performed of the 198 studies selected in the first filter. The articles were included/excluded according to the criteria of inclusion and exclusion, presented on Tables 3 and 4, resulting in 50 articles about the issue under study. For the organization and analysis of articles drawing on the SLR criteria of inclusion and exclusion, this study used the StArt tool of the Laboratory of Research on Software Engineering of the Federal University of São Carlos [(19)].

Table 3 – Criteria of Inclusion

#	Criteria of Inclusion
CI1	Studies with research on acceptance, adoption, resistance, barriers and challenges regarding AI technologies in healthcare.
CI2	Studies on AI technologies in healthcare.

Source: Authors (2022).

Table 4 – Criteria of Exclusion

#	Criteria of Exclusion
CE1	Studies based on analysis of patients' electronic records.
CE2	Scientific publications that are not in English.
CE3	Scientific publications that are not available.

Source: Authors (2022).

Following the analysis, the base structure used for the organization of the factors found in the SLR was the one proposed by Palma *et al.* [20], which analysed the factors that influence the acceptance of telemedicine by physicians in Brazil. The categories of this structure served as starting point for others to be added as they emerged from the analysed literature. The results of these stages are systematized in the next section.

4. Discussion and Analysis of the Results

In the literature review, various panoramas were identified in healthcare that directly influence the acceptance of the use of Artificial Intelligence technologies, generate resistance in their implementation or are barriers for their applicability. The analysis considers the perspectives of hospital organization, healthcare professionals, patients and society, regulatory agencies, professional boards and implementation team. For the organization of the different perspectives listed, categories of factors were created for correlated contexts.

Regarding the factor clinical aspects, Mendelson [21] points that an error on the computer by an algorithmic failure may result in an erroneous evaluation of the patient's condition. In this context, there is the questioning of what will prevail: the diagnosis or the clinical decision. Another point mentioned is diagnostic uncertainty, because false positives cause a lack of interpretative confidence. Gu *et al.* [28] mention that the results indicated by decision support systems through machine learning, used in disease management, are usually not recognized by the medical community due to the low diagnosis precision.

According to Xu *et al.* [24], the evaluation of the precision of AI results is crucial to ensure diagnosis basis. An example is cancer genomics, whose classification of variants, clinical relevance, literature validation and summarization are traditionally made by human specialists. In order to avoid the limitation of AI use in this area, it is fundamental to evaluate the results drawing on specialists instead of only comparing with AI solutions. However, this comparison is jeopardized by the absence of publicly available databases with clinical data closer to reality. Yamada and Mori [22] point out that absolute truth in medical conditions is a meaningful barrier in the use of Artificial General Intelligence (AGI).

For Gomolin *et al.* [25], the decisions made by AI are not based on existing clinical evidences, which would be a physician's traditional procedure. The lack of this base influences society and the regulatory agencies in the acceptance of AI in medicine. This statement is corroborated in evidences used to support clinical decision making in machine learning (AI subarea). This decision, in many cases, is empirically guided by clinical essays, without physiopathological base of the treatment [27]. Thus, physicians would have to trust results without fully understanding each essential component used in the composition of the final result. According to the study "Exploring healthcare professionals' understanding and experiences of artificial intelligence technology use in the delivery of healthcare: An integrative review", health professionals tended to a lesser degree of AI use in healthcare services if they did not feel confident about the technology or did not understand its applicability in patients results [23].

Table 5 - Factors that influence the acceptance of AI technologies – literature review

Factor	Definition	Level of analysis	References
Clinical aspects	This factor is related to diagnosis decisions originating from AI algorithms and the non-reliability on the results.	Society, organization, regulatory agencies, professional boards and health professional.	21,22,23,24,25, 26,27,28,29,30
Human aspects	This factor is related to the probability of decision-making by AI technologies with minimum human interference. Besides the concern about not making medical processes become more automatized.	Health professional and patient.	22, 31, 32, 33
Organizational aspects	This factor is related to the managerial capacity, organizational structure and leadership in the adoption of AI solutions by the organization.	Organization	34, 35
Regulatory aspects	This factor is related to the lack of clarity or inadequacy of legislation that regulates responsibilities and directives of the relation medical negligence versus AI.	Organization, health professional and patient.	21,36,37,25,38, 33,39,40,29
User experience	This factor is related to the interaction of users (patients) with AI technology in the ambit of healthcare.	Patient	41, 42
Level of education for technology development	This factor is related to the capacity of health professionals to collaborate with IT teams in the development of AI technologies.	Health professional	21, 43, 44
Level of education for the use of technology	This factor is related to the capacity of health professionals and patients to use AI technologies.	Health professional and patient	45, 46, 47, 48, 49, 50, 51
Technology infrastructure	This factor is related to the phases of training, testing and processing algorithms used in AI, besides the usability of technologies, data security and privacy.	Health professional, patient and organization	52, 21, 53, 54, 25, 55, 56, 57, 58, 46, 35, 29, 59, 60, 61
Technology implementation	This factor is related to the adaptation and application of IT technologies in the organizations.	Implementation team, individual and organization	35
Perception of potentiality	This factor is related to the non-perception of the potentiality of AI technologies.	Health professional and patient	62, 63, 60
Resistance to innovation	This factor is related to the preference for traditional approach in health management. Besides having resistance due to fear of change and believing that the use of this technology is meant only for highly specialized professionals.	Patient and health professional	1, 41, 25, 64, 33

Source: Authors (2022).

According to Esmaeilzadeh *et al.* [(29)], the results of the study “Patients’ Perceptions Toward Human–Artificial Intelligence Interaction in Health Care: Experimental Study” imply that the incompatibility with ethical values may be a reason for the rejection of AI applications in healthcare. The definition of ethical functioning of an AI system is a subjective practice and requires field experience and perception of the use of AI technologies [26].

It is a fact that AI has been facilitating the analysis, integration and interpretation of large data sets. An example of this positive effect occurs with the processing of data on intestinal inflammatory diseases. However, the heterogeneity in AI methods, the data sets and especially the clinical results are barriers for the incorporation of AI in the clinical practice. There is also the need of studies to validate impartial prospectives [30].

Regarding the factor human aspects, Briganti and Le Moine [31] mention that for physicians, a great barrier for the adoption of intelligent medical technologies is the fear that medicine becomes dehumanized, even though AI would reduce the burden of physicians' work. For Prakash [33], health professionals perceive a threat regarding their professional performance. An example would be a radiologist who resists in using AI for believing that her/his role in clinical decision making may be reduced.

Kasperbauer [32] brings up another perspective about the conflict of AI with health systems regarding human role and learning process. For this author, there are gaps in the decisions made by health professionals, in the transparency of decision making by AI technology, and in the involvement of patients in the care with their health. Yamada e Mori [22] also point that the processes of decision-making cannot be performed by the computer in the same way that humans have thoughts, perceptions, intuitions and insights.

Regarding the factor organizational aspects, Zhai *et al.* [35] state that the organization's leaders should consider a top-down management process in relation to technology-assisted AI. Hospital directors and department heads must present the functionalities, advocate the implementation of the new technology and engage subordinate physicians in its use. Mohammadzadeh *et al.* [34] point that the implementation of multi-agents systems to improve cancer treatment faces organizational challenges, such as the organizational culture and high-level management support. The factor organizational aspects was identified in the study "Factors that influence the acceptance of telemedicine among doctors in Brazil" [20]. The main difference in the use of AI technologies in healthcare is the advocacy by organizational leaders of the implementation of the technological solutions in hospital organizations. This is different than what is seen in telemedicine, which is a technology already adapted.

Regarding the factor regulatory aspects, Mendelson [21] points that ethical and regulatory concerns were put on the agenda due to algorithmic failures of an AI. Gomolin *et al.* [25] point that there is the issue of accountability. If the AI outcome is adverse, there is doubt whether the physician will be made accountable. For Schwartz *et al.* (37), as high-risk decisions augment and are delegated to AI systems, the legal issues must be answered, since it is not yet well defined who is responsible for AI predictive errors and algorithms.

Humanity is at a moment of technological turning point, because the trustability of diagnoses is in the hands of the system developer and of the computer’s processing capacity. Therefore, the replication and interpretation of AI algorithms reverberates, both in health professionals and patients, ethical issues and medical-legal challenges (36).

Prakash and Das (33) points that there is resistance from hospital systems users, including health professionals, in relation to the perception of medical-legal risk, since the current legal norms are not sufficient to establish the directives of the relation medical negligence versus AI.

Regarding the regulation for the use of digital technologies in healthcare, the inexistence of effective regulation for devices (AI, chatbots, applications etc.) applied in medicine is a fact and there the need of new regulatory approaches (39). Thus, there are several limitations in the logistical, ethical, administrative, legal and technical ambits to achieve consistent and reproductive analyses of radiological data in oncology from distributed learning (AI) (65). Bergier *et al.* (40) mention that Big Data and AI applications open discussions on legal and healthcare policies considerations, especially regarding rare diseases that refer to privacy, confidentiality and informed consent.

Tarakji *et al.* (38) report that the daily use of intelligent devices for the evaluation of patients’ health problems, at any place and time, brings up questionings on who should or could regulate the reach of use and the influence that impacts daily life. According to Esmaeilzadeh *et al.* (29), the results of the study “Patients’ Perceptions Toward Human–Artificial Intelligence Interaction in Health Care: Experimental Study” imply that the incompatibility with regulatory values may be a reason to reject AI application in healthcare.

The factor regulatory aspects was also identified in the study “Factors that influence the acceptance of telemedicine among doctors in Brazil” (20). The approaches are similar regarding regulatory milestones and clinical responsibilities.

Considering the factor user experience, Ye *et al.* (41) mention that patients might reject ophthalmic devices that use AI due to previous experiences with new technological products. This understanding is comprised in the study “Psychosocial Factors Affecting Artificial Intelligence Adoption in Health Care in China: Cross-Sectional Study”.

Cao *et al.* (42) conducted the study “Barriers and Enablers to the Implementation of Intelligent Guidance Systems for Patients in Chinese Tertiary Transfer Hospitals: Usability Evaluation”. In this study, the authors identified that the degree of users' satisfaction with the systems of intelligent guidance to patients was low and that they were not fully accepted due to problems pointed in the application.

In relation to the factor level of education for technology development, Mendelson [(21)] points that health professionals need AI education to be able to collaborate with computer scientists in more accurate technology development. Cheng *et al.* [(43)] point that uncertainty in the incorporation of AI technology in healthcare creates a situation of caution to avoid undesirable consequences in the implementation of AI. It is recommended to use algorithms that can process imprecise data, common in healthcare, in the development of healthcare systems specialized in prediction and diagnosis [(44)].

In relation to the factor level of education for the use of technology, Tran *et al.* [(49] mention that the knowledge of the technology characteristics and the ability to use it are also absent in the adoption of AI in healthcare, based on a study involving undergraduate medicine students in Vietnam. In this context, it is necessary to have specialists trained in the use of AI, because the lack of professionals with this knowledge is a barrier for the use of AI in healthcare [(46)]. According to Xu *et al.* [(24)], health professionals (physicians) must learn to use AI technologies in the delivery of healthcare services, since it is health professionals' limitations regarding this knowledge that affects the acceptance to use AI technologies in healthcare [(51)].

These statements corroborate the conclusion of Poon and Sung [(48)] about the hesitation of health professionals to trust and adopt technology because they do not fully understand how it works and consider it similar to a black box.

It is important to unveil the nature of the "black box" to improve the clinical acceptance of machine learning systems, a subarea of AI [(45)]. It is also necessary to increase the efficiency of physicians so that they are more efficacious in their work with technologies [(50)]. Having knowledge and ability with AI technology helps patients in the acceptance of its use [(47)].

The level of education for the use of technology was also identified in the study "Factors that influence the acceptance of telemedicine among doctors in Brazil" [(20)]. The approaches are similar in relation to knowledge, capacities and abilities in the use of both technologies.

Regarding the factor technology infrastructure, Mendelson [(21)] states that the outcomes of algorithm failure are a factor of resistance. This failure could result from insufficient data entry for the recognition of an ideal pattern of a neural network (AI) in breast imaging or from the low amount of training data of the algorithm model. Furthermore, the lack of integration of the systems used in a hospital setting is a limitation predicted for AI. It is difficult to predict when

AI will enter in ample clinical application in the capsule endoscopy and what will be its exact role, since there still is mistrust in algorithms processing of these technologies [61].

According to Hu *et al.* [57], AI depends on infrastructure to support urgent clinical needs in diagnosis and prognosis of diseases. Foreman [58] mentions that Big Data applicability for clinical use in healthcare can occur in description, prediction and prescription. However, the barriers for its use at the bedside are the lack of infrastructure development in the health sector, the lack of standardization in data entry, and AI outputs from the scientific viewpoint.

Gomolin *et al.* [25] mention that entry data used for system training affect AI decision-making. This means that if the application is trained on a population and tested on another population, the outcomes tend to be distorted. This problem of generalization directly affects dermatology, because the area works with data of various demographic factors (age, gender, race, ethnic group, etc.) that affect the diagnosis. The main barrier for the use of AI in healthcare is the large quantity of training data, because without high quality data AI will not function with optimal accuracy [46].

Following the same line, in the perception of patients interviewed in the study “Artificial Intelligence in Skin Cancer Diagnostics: The Patients’ Perspective”, if a system based on AI could distinguish well the images of nevi and melanoma, they would be willing to use AI in the early detection of skin cancer [56]. The fast adoption of AI in gynecologic oncology will depend on overcoming challenges related to transparency, quality and interpretation of data [60].

An algorithm trained with distorted data (e.g., cardiac imaging from a specific section), might not make a holistic diagnosis approach [55]. Following the biasing tendency, there is potential inherent selection bias in gastroenterology regarding diagnosis, prognosis and image analysis through deep learning (AI). In sum, there is the chance of overestimating the accuracy of the outcome. Thus, external validation of the analysis is recommended [53].

Another perspective in relation to AI algorithms is the process of construction. According to Chen *et al.* [66], the process is considered a “black box” and the results are based on various studies. This avoids that physicians make clinical application of technologies that use machine learning (AI). Following another line of study, Zhai *et al.* [35] point that the interface of the user of the AI-assisted system must be as similar as possible to the interfaces normally used in the hospital. In this way, there is a reduction of time for the adaptation of the new technology. According to Spänig *et al.* [54], presently the available AI systems do not interact with the patient in the anamnesis performance. The interaction occurs with physicians for diagnosis or prognosis predictions.

Another topic studied is data protection. For Gopal *et al.* [52], data security and the concern with privacy hinder the efficiency of the use of health data to ensure satisfactory outcomes of all parties interested in healthcare. Therefore, the barriers to data sharing using integrated and universal protocols should be overcome to enable that the use of AI and machine learning become widely applicable [59].

According to Esmaeilzadeh *et al.* [29], the results of the study "Patients' Perceptions Toward Human–Artificial Intelligence Interaction in Health Care: Experimental Study" imply that the incompatibility with instrumental and technical values may be a reason to reject AI applications in healthcare.

The factor technology infrastructure was also identified in the study "Factors that influence the acceptance of telemedicine among doctors in Brazil" [20]. The main difference in the use of AI technologies in healthcare is the concern about algorithms processing, data input and output, treatment and results accuracy. Differently from what occurs in telemedicine, which is more focused on equipment infrastructure.

In relation to the factor technology implementation, Zhai *et al.* [35] mention that the process of adaptation from perceptual intelligence to cognitive intelligence needs to be gradual. An example is the project of consultant oncologist specialist of IBM Corporation: instead of placing an AI doctor, Chinese hospitals first created an AI technology to perform as an assistant tool for medical imaging, exempting doctors from this routine. However, the most evident scenario of application was the implementation of medical AI. Amid the technology implementation, it was identified that training was pointed as an important barrier for the implementation of clinical decision support systems [67].

Regarding the perception of potential, Hughes *et al.* [62] point that although Natural Language Processing (NLP), an area of AI, has an important application in industries and businesses in general, health professionals (largely physicians) do not see the huge potential of this technology in medicine. This has entailed a limited implementation of NLP in research and treatment of breast cancer, for instance. Many physicians do not know that this technology is being used in medicine and that it can generate a better understanding of statistics and computer science behind diagnoses algorithms [60].

Juravle *et al.* [63], drawing on the outcomes of the study "Trust in artificial intelligence for medical diagnoses", concluded that people have performance patterns comparable to AI and physicians. It also concluded that trust on AI does not increase when people are informed that AI can present better performance than the physician.

Regarding resistance to innovation, Ye *et al.* [41] point that there is a natural preference from patients for the use of traditional approaches in healthcare management. This observation is in the aforementioned study on “Psychosocial Factors Affecting Artificial Intelligence Adoption in Health Care in China: Cross-Sectional Study”. According to Prakash and Das [33], the inertia of health professionals is considered a strong element of resistance. These professionals feel insecure with AI. Thus, they prefer to maintain the status quo and resist to the use of a new system that assists in diagnostic decision-making. People’s acceptance and the real adoption of AI solutions in hospitals are barriers for the use of these technologies in healthcare. The resistance in relation to automatized tools that provide assistance in various healthcare services is a great obstacle to be overcome [64].

For Gomolin *et al.* [25], there are many questions about the need of using advanced AI in the face of more primitive technologies, since the performance of tasks is the same. Padmanabhan *et al.* [1] state that there still is a perception from health professionals that machine learning (AI variation) is only accessible to trained specialists. Hence, physicians and biologists show resistance to the use of tools, especially in their researches.

Comparatively, in similar studies on the acceptance of medical technologies in Brazil, it was verified that the factor resistance to innovation was identified by Palma *et al.* [20], but named “resistance to change”. In this sense, the main difference in the use of AI technologies in healthcare is the wish that traditional approaches in healthcare are not changed for automatized approaches. It is important to stress that in relation to the new factors listed in the study by Palma *et al.* [20], this systematic literature review did not identify the following aspects: financial availability, perception of value, and social influence among professionals and physicians.

In relation to the factors listed in this study, six were not cited by Palma *et al.* [20], namely: clinical aspects, human aspects, user experience, level of education for technology development, technology implementation, and perception of potential. This reinforces that the acceptance of distinct technologies, though applied in the same context, present various factors that require the attention of theorists and practitioners.

5. Conclusion

The objective of this research was to identify the factors that influence the acceptance of Artificial Intelligence (AI) in healthcare, by means of a systematic review of studies that empirically evaluated the use of this technology. Finally, the findings of the research were confronted with the reviewed literature.

As main results, 11 factors were identified that influence the acceptance of Artificial Intelligence in healthcare. The following factors were found: clinical aspects, human aspects, organizational aspects, regulatory aspects, user experience, level of education for technology development, level of education for the use of technology, technology infrastructure, technology implementation, perception of potential, and resistance to innovation. Thus, this article contributes to deepening the knowledge on factors of Artificial Intelligence acceptance in both theoretical and practical dimensions.

In the theoretical dimension, the factors identified corroborate previous researches and show new factors that emerged from the data, which enable the formulation of theoretical models better adjusted to the problem of AI acceptance in healthcare. A factor to be mentioned is resistance to innovation, which points that one of the barriers for the use of AI technologies is the wish that traditional approaches in healthcare are not changed for automatized approaches.

In the practical dimension, this article provides specific factors for managers (organizational aspects) and developers (user experience, technology infrastructure and implementation) who seek to implement or develop AI applications in their organizations, and for public policy makers (regulatory aspects) on the theme. Therefore, the mapping of these factors can guide public managers' actions and, consequently, contribute to AI acceptance and adoption, with the use of the benefits by health professionals, who will trust these technologies, and by the society, whose health will be affected by their use.

As suggestions for future studies and deepening of the research, it is suggested to investigate the factors that emerged from this systematic review: clinical aspects, human aspects, user experience, level of education for technology development, technology implementation, and perception of potential, because based on this SLR, these were not identified in previous studies on the acceptance of technologies in healthcare in Brazil.

Additionally, institutional factors, such as resolutions of professional boards, legislation, and organizational influences of managers or users (patients), can be explored in future studies.

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