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Efforts To Adopt Artificial Intelligence As Support For Primary Healthcare

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Abstract:
Background*: Artificial Intelligence (AI) and data analysis in healthcare enhance patient outcomes through improvements in diagnosis and treatment planning. This research aims to identify barriers to the adoption of AI as support for primary healthcare. Healthcare systems are deliberate social responses to the needs of populations expressed in their health situations. Consequently, there must be a fine-tuning between these needs and the way in which health systems are organized to respond to them socially.*
Materials and Methods*: To achieve the prescribed objectives of the article, the following method was employed: literature review and critical and qualitative content analysis of relevant scientific articles seeking a theoretical overview of the topic.*
Results*: The results showed that the inclusion of data analysis offers new answers to the challenges of healthcare management, providing greater safety and well-being for the public served.*
Conclusion:*Research on the topic is still in its beginning, highlighting the urgency of systematizing patient data using AI, but there is a growing appreciation of data analysis in the context of health care management.*
Key Word*:Primary healthcare; Artificial intelligence; Decision-making; Innovation; Business intelligence.*

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I. Introduction

Healthcare is one of the most impactful sectors, affecting strongly all aspects of society ranging from medical services to social, governmental, business, and economic implications[1]. To achieve effective and equitable care delivery, it is vital that healthcare systems' decision makers appropriately allocate the expenditures between diverse care activities (e.g. preventive and curative care) or care providers (e.g. hospitals or ambulatory centers)[2].

Primary healthcare (PHC) plays a fundamental role as a gateway to health services, coordinating care and guiding the actions and services available in the health network. It operates according to several guidelines, including the territorialization and management of a registered population, covering a set of health actions that encompass health promotion, prevention, protection and surveillance at the individual, family and community levels, considering the context of the community and the territory[3].

Considering that PHC is understood as the first access to health services, it is understood that this access should be simple and fast[4]. However, many users face obstacles when trying to access PHC. Studies indicate that the expansion of PHC coverage faces challenges related to factors such as shortage of health professionals, budget constraints, lack of adequate infrastructure, lack of medicines and equipment, remote locations, and lack of information about available health services[5]. These challenges particularly affect vulnerable populations, such as residents of rural areas, indigenous communities, immigrants, refugees, and people living in poverty. This can result in unequal opportunities based on everyone's social position, which characterizes situations of social injustice, often called inequities[6]. These aspects are even more crucial when moving from higher to lower levels of analysis. Business Intelligence (BI) stands out as a system that encompasses data collection, storage, analysis, and reporting and has significant potential to provide timely and quality data to research unjustified variations[7,8]. Additionally, BI can incorporate new advanced analytics to better separate unwarranted variances from total observed variances[9].

Artificial Intelligence (AI) is defined as "the theory and development of computer systems capable of performing tasks that normally require human intelligence, such as visual perception, speech recognition, decision making, and translation between languages"[10]. AI has the potential to revolutionize the healthcare industry. Analysing patient data can improve disease diagnosis[11], and AI can also help create personalized treatment plans by analysing a patient's genetic and electronic medical record (EMR) data, which is a key goal of personalized medicine[12-13]. Additionally, AI can support population health management by analysing data from electronic health records and other sources to identify health trends in specific populations[14]. While data growth enables the use of AI, implementing innovation in healthcare is challenging, and effective acquisition strategies are vital[15]. Change and adoption of AI in healthcare has been reduced, but the potential benefits make it an important area to pursue. Implementing AI into clinical workflows can help improve processes and can lead to better patient outcomes[16], more efficient and accurate diagnoses[17], reduced healthcare costs[18], and improved disease prevention and management[19].

Additionally, the adoption of AI in healthcare also presents a variety of ethical and patient-related issues, such as those around error liability[18], patient privacy[20], and transparency[21]. These barriers arise due to the potential risk and unintended consequences of using AI in health care settings. Similarly, AI requires a lot of data, including patient data, and this opens the possibility of, for example, a data leak. Rubin[22]identifies that a lack of trust in AI technology and insufficient training for healthcare professionals can be obstacles to the widespread implementation of AI. This lack of trust may stem from the fact that AI is often seen as a "black box" that is not well understood. In addition to ethical difficulties, the adoption of AI in healthcare faces practical obstacles, such as the need for regulatory authorization for rapidly evolving models[23], the high cost of implementation[24], and the lack of experienced experts to build and manage AI systems[25]. Therefore, the aim of this study is to identify the main barriers to implementing AI in healthcare and explore the specific role that AI can play in primary healthcare. The key problem that this study aims to address is: "What are the main barriers to adopting AI in healthcare from a primary healthcare perspective?"

Theoretical framework in the context of Primary Healthcare to explore the adoption of Artificial Intelligence in medical assistance

In this section, AI is used as an umbrella term for machine learning, natural language processing, deep learning, and other AI-enabled tools that are intended to aid in the discussion of patient care, treatment, and outcomes.

AI has been present in healthcare since it was first described in 1950. AI began as a simple set of "if, then" rules and has evolved over several decades to incorporate increasingly complicated algorithms that function similarly to the human brain. However, the limitations of early models hindered their general adoption and medical use[26]. The history of AI in healthcare might be divided into three time periods: 1950 to 1970, 1970 to 2000, and the current period from the 2000s. In the first period, from 1950 to 1970, the focus of early AI was on producing robots with the ability to make judgements previously made only by humans. One early example is the computer program Eliza, introduced by Joseph Weizenbaum in 1964, which is one of the earliest algorithms capable of mimicking human conversation using natural language processing[27]. During this first period, the adoption of AI in medicine was slow but it sparked the digitalization in healthcare that was necessary for the future growth of AI in medicine[26].

The second period in the history of AI in healthcare, from 1970 to 2000, is called the "AI Winter" by Greenhill and Edmunds[28]. During this period, initial interest in AI had waned, and it was assumed that it would take decades for AI to increase in productivity. The high costs of AI research and the pessimistic outlook on the future capabilities of AI were some of the factors that led to this decline in interest[27], which was accompanied by a decline in funding for AI research. However, in 1972, MYCIN was developed, an expert system that uses expert clinical decision criteria to advise physicians on treatment selection for bacterial infections[29]. It was not implemented in use.

By the 2000s, the increase in data in the field helped AI in medicine overcome one of its main obstacles, data scarcity. In addition to the increase in data, AI's success is enabled by the exponential growth in computing power and the widespread adoption of cloud computing[28]. In 2015, AlphaGo, a Google-made program using deep neural networks, demonstrated the ability to manage large data sets and make complicated judgments. IBM later used its Watson AI model to recommend personalized cancer treatments to patients[30]. This attempt to improve cancer treatment has been heavily criticized, as some have argued that it provided ineffective and sometimes even harmful recommendations. While cancer therapy may not be the best application for Watson, there are successful cases where Watson has appeared to add value. It can be a source of medical information for clinicians when deciding on a treatment plan, which is one way it can add value[30].

Types of AI used in healthcare

There is a growing need for healthcare services, which makes it crucial that medical professionals' time is spent on areas where they contribute most, caring for patients[31]. Interest in implementing AI in healthcare to improve patient care and outcomes is growing[32]. Several types of AI are already used in healthcare today, such as machine learning, natural language processing, and cognitive systems. To understand the potential of AI in health care, it is necessary to examine the types of AI already used in the field.

Machine learning (ML) can identify patterns in data that can be used to understand the current world or make predictions[33]. The goal is to build a model that describes the data as best as possible, and therefore requires a large data set. There is a large amount of data in healthcare due to the use of electronic health records (EHRs). This data is useful for a wide range of clinical tasks. It can be used in the intensive care unit to predict ICU mortality rate and length of stay[34]. It can also be used to detect high-risk, high-cost patients. This is crucial to creating value because the reduced income that healthcare has can be used more effectively where they are needed most[35]. However, ML has some drawbacks, including the need for large datasets to train the model, the need for data preparation, and the possibility of bias in the algorithm's predictions[36]. Recently, the application of deep learning in healthcare has made AI more effective and overcome some of the limitations of ML[37]. Deep learning is a process involving deep-layered neural networks[36], where neural networks analyse problems in terms of inputs, outputs, and variable weights that relate the input to the output[38]. Deep learning combines data at multiple levels, which makes it a more adaptable algorithm with greater precision and accuracy than traditional machine learning algorithms. Deep learning could further improve AI applications in healthcare and is a powerful approach for complex problems involving large amounts of data[39].

Another type of AI used in healthcare is natural language processing (NLP) which is used to analyse data, such as speech and text[40]. EHRs include a large amount of unstructured speech and text data that could be used for NLP in the future[41]. Aramaki et al.[42] identified applications of NLP in healthcare, some examples are information extraction, information retrieval, user interfaces, and document categorization. According to Bakken[43] the healthcare industry faces high error rates by extracting relevant information from EHRs, NLP can help minimize error rates providing significant support for decision-making, consequently reducing costs and increasing healthcare processes. Another example is the usage of speech recognition-based user interfaces, which may enable people to speak with computer systems to aid with simple manual tasks in an effective manner[44]. Patients can interact with a computer to take control of their health or, because of their situation, obtain information about future treatments.

Computer vision directs on discerning videos and images and involves problems such as object recognition image and categorization[41]. The use of computer vision in healthcare has the potential to increase diagnostic accuracy and patient care[45]. One example is in the radiology field in which computer vision can be used to pre-screen images and identify features, effectively reducing the input needed by trained radiologists[46]. Computer vision also has shown enormous potential in surgery, where it has been used to enhance certain features and skills such as suturing and knot-tying[47].

Expert systems are rule-based systems that turn the knowledge of experts into a set of rules[48]. They are algorithms that simulate the decision-making skills of humans and are therefore considered AI[49]. Expert systems are a convenient and easy-to-use way to get professional expertise and can relieve human experts from some workload[49]. While expert systems can help physicians in the decision-making process, they have several problems and limitations, two important limitations are knowledge bottleneck and performance brittleness[50]. An expert system is only as good as the knowledge it is based on, and its scope is also limited by this knowledge. They are slowly being replaced by approaches that are based on data and machine learning algorithms[32].

Barriers to the Implementation of AI in Healthcare

The implementation of AI in healthcare raises several legal and ethical concerns. One of these concerns is data sharing, as AI requires a large amount of data to work properly; data are abundant in healthcare, but much of this data is patient data. Patients must consent to the use of their data, and the data must be anonymized and deidentified, to protect their privacy[21]. Furthermore, the transparency of AI algorithms is also a significant problem. AI systems that are based on for example neural networks have a "black box" design, that is nearly impossible for humans to analyse and verify. This leaves a significant accountability hole because if physicians cannot check the output of AI, the question of who is accountable for errors arises[52]. Another transparency issue is the potential for bias. This is possible that the data it is trained on has an unequal representation of certain populations, which can lead to unequal healthcare outcomes[52].

For optimal performance, AI needs constant development, necessitating continual maintenance and updates to software algorithms. Without the assurance that AI will provide value to healthcare, this is a costly endeavour, and it is unclear how AI will be reimbursed[21]. This is illustrated by IBM's artificial intelligence Watson, which has been used in public healthcare in China. Patients thought a visit with Watson was too expensive, and the hospital also found Watson to be costly because they did not realize any revenues from utilizing Watson[26]. Making sure that patients' sensitive data is handled securely introduces another economic challenge because, on average, a breached health record costs $355, and because AI must be trained on a large dataset, this expense will be substantial[53].

Furthermore, medical personnel must be trained to handle the digital shift and to educate patients and colleagues[54]. The workforce should be aware of both the benefits and drawbacks of AI; ideally, they should also understand how algorithms are designed. This knowledge is essential for healthcare practitioners to maximize their role in human-machine teams[21]. While the benefits are apparent, healthcare professionals must be able to observe their value; otherwise, they will be unwilling to drive adoption ahead[22]. Thus, AI's value must be assessed before it can be utilized in the healthcare industry. The general public's lack of confidence in AI-based decisions presents doctors with a second adoption barrier. Due to the historical importance of face-to-face communication between patients and physicians, the necessity for physicians to interact with a machine for important decision-making raises trust issues[25].

Government policymakers and healthcare professionals point to a lack of regulation as a barrier; there is no accepted definition of AI, no official standards for how AI can be used, and no official standards to evaluate its performance. Finally, there is the issue of countries with differing regulations. AI may, for example, produce a treatment that is legal in one country but illegal in another[25].

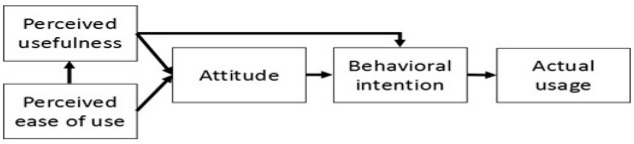
Support to AI implementation

Technology Acceptance Model (TAM)

To acquire a comprehensive image of the adoption of AI in healthcare, both the Technology Acceptance Model (TAM) and the Theory of Planned Behaviour (TPB) are used as theoretical frameworks.

The TAM is a framework designed to explain how and why individuals or organizations accept and employ innovative technologies[55]. According to Figure 1, the actual usage of technology is primarily influenced by the user's overall attitude toward using it. This attitude shapes behavioural intention and is driven by two key beliefs: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which an individual believes that using a particular system will enhance their work performance. On the other hand, perceived ease of use is the degree to which an individual perceives that using the system will require minimal physical or mental effort. These two factors are closely interconnected, as a system that is easy to use often directly enhances its perceived usefulness. This is because users who find simple technology to operate are likely to use it more efficiently, leading to improved productivity in their tasks.

Figure 1. Technology Acceptance Model (TAM) [55]



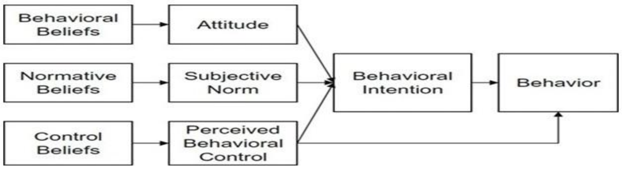
In the paper by Hu et al.[56], they used TAM to examine physicians' acceptance of telemedicine technology. They found that the perceived usefulness of telemedicine has a significant influence on physicians' intent to use the technology, but apparent ease of use was found to have no significant impact on behavioural objective and supposed utility. One plausible argument they give is the possibility that the perceived ease of use component of the TAM might not apply to individuals with above-average intelligence, such as physicians. The model had a weaker utility for explaining physician's attitude formation and intention development, PU and PEOU explained 37% of the variance, in comparison to other studies that reported between 65% and 73%[56].

Theory of Planned Behaviour (TPB)

TPB is a theory that aims to explain and predict human behaviour[57]. It is considered an extension of the Theory of Reasoned Action (TRA) which was proposed by Ajzen and Fishbein[58]. The theory of planned behaviour is focused on an individual's intention to perform a given behaviour. Intentions capture the reasons why someone does something and show how hard people are willing to try and how much effort they plan to put in to do the behaviour. Generally, the more convincingly somebody wants to do something, the more likely they are to do it. The theory identifies attitude, subjective norm, and perceived behavioural control as significant determinants of the behavioural intention and, therefore, the behaviour.

The theory argues that perceived behavioural control influences the intention and the behaviour and refers to the degree to which an individual believes they have control over performing a particular behaviour (Figure 2). Perceived behavioural control is based on experience, available resources, and situational factors. If a person believes that they have control over their behaviour because, for example, they have done it in the past and that it is easy to perform they are more likely to intend to engage in that behaviour. For example, a person can believe that their behaviour determines their outcomes but at the same time, they can still believe that their chances of curing cancer are very slim. Attitude relates to an individual's overall assessment of behaviour. It is the extent to which a person feels favourable or unfavourable feelings about performing the behaviour. These feelings are influenced by a person's experiences, prejudice and cultural factors. For instance, a person who grew up in an environment where data privacy was a priority is likely to have negative feelings about adopting AI, given that AI requires a large amount of data, which is frequently gathered through data sharing. Subjective norms relate to the perceived social pressure to perform or not perform a behaviour. This social pressure can come from friends, family, or colleagues. Subjective norms are influenced by normative norms, which are based on an individual's perception of social norms.

Figure 2. Theory of Planned Behaviour Model (TPB)[57]



II. Discussion

This study aims to discuss the barriers that influence the adoption of AI in medical assistance. The study by Kaul et al.[26] presented a brief historical overview of AI in healthcare and the limitations that hindered the general adoption of earlier models in healthcare. Although these model limitations are no longer an issue, widespread acceptance, and utilization of AI for medical applications have not yet occurred. Literature has identified several barriers to the adoption of AI in healthcare. The study by He et al.[21] stated that for widespread implementation of AI, data privacy would be a significant barrier. Because data would need to be anonymized and therefore, patient confidentiality and patient privacy may need to be reimagined entirely. Another study mentioned that biased outcomes are a barrier[52].

Accountability is an important subject in healthcare organizations[59]. In the study by Hashimoto et al.[51], they identified a significant accountability issue due to a lack of clarity of error responsibility when working with AI. This issue is a particularity of healthcare and AI because AI is often not transparent[21], and physicians are therefore not able to verify the decision-making of AI. This is in line with the study by Reddy et al.[18] in which the authors state that the determination of liability regarding the use of the system is an area that legal and regulatory authorities must consult with a wide variety of stakeholders. Healthcare organizations would be one of those stakeholders and therefore are involved in this barrier, but they are not responsible for making the regulations.

In the paper by Arkorful et al.[60], the intention to use technology among medical students has been evaluated using an extended model of the theory of planned behaviour. They supervised a field study with 322 medical students from various medical institutions who were completing obligatory clinical rotations in Ghana. The core constructs of TPB were able to explain 26% of the variance in technology adoption, and including the extension construct, and descriptive norm, the model was able to explain 33% of the variance. It is stated that TPB is a promising paradigm with a higher probability of accurately predicting intention. The fact that they did not define the type of technology was a limitation of their study, as they claim that doing so would have made the research more robust, distinct, precise, and effective.

III. Conclusion

The reorganization of the health system guided by comprehensive primary healthcare, leading the care process with good integration of the service network, is a perspective for reducing social and regional inequalities in access to and use of health services that contributes to realizing the right to health.

The stakeholders' attitudes in the process can influence the adoption of AI medical diagnosis. A positive attitude is the extent to which a person feels favourable about performing the behaviour. Organizational culture likely influences the attitude towards AI. Organizations that foster innovation and research have employees who are more fascinated by innovations, such as AI and are therefore more likely to have a positive attitude towards AI. Furthermore, only the key stakeholders must have a positive attitude because they have more influence on the implementation process.

What is acceptable reliability for AI is an ethical consideration. Furthermore, the business case for AI is still unclear because the potential benefits of AI are not directly measurable, whereas the costs are. Physicians' resistance to change is a barrier because the implementation process will fail if they are unwilling to adopt and use AI, the implementation process will fail. This resistance to change may come from concerns about the AI's reliability or from feeling threatened by the AI taking over some of its work.

A limitation of this research is the fact that the research topic is still in its rudimentary steps. AI is still being actively developed and evolving rapidly. Healthcare organizations have only recently started to implement AI in medical assistance, and most have not even started yet. It is recommended to investigate if the barriers to AI adoption in primary healthcare change over time. What could be a significant barrier at this moment does not have to be a significant barrier in the future.

Conflict of Interest

None.

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