Received Date: 12 November 2025 I Accepted Date: 5 February 2025

OPUS
Journal of Society Research

RESEARCH ARTICLE

Challenges for the Integration of Artificial Intelligence in Healthcare Services: A Decision-Making Approach

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January 2025
Volume:22
Issue:1
DOI: 10.26466/opusjsr.1583315

Citation:
Gedikli, E. (2025). Challenges for the integration of artificial intelligence in healthcare services: A decision-making approach. *OPUS– Journal of Society Research*, *22*(1), 23-32.

Abstract

This study aims to elucidate the interdependent effects of the challenges and risks of using artificial intelligence in the healthcare sector. The ten challenges and risks obtained by literature were assessed by five professionals involved in managing health. Participants were selected based on having at least ten years of academic or professional experience in health. The participants made their judgments on the topic of structured forms. DEMATEL (The Decision-Making Trial and Evaluation Laboratory) technique investigated the cause-effect relationships between the identified integration challenges. According to DEMATEL analysis results in terms of the degree of importance, safety and security risk (SSR) is ranked in the first place, and inadequate patient risk assessments (IPRA), data quality risks (DQR), verifiability risks (VR), stakeholders perceived mistrust (SPM), integration challenges (IC), ethical considerations (EC), algorithm/decision-making bias (AMB) and job displacement risks (JDR) are ranked in the following places. In addition, DQR, AMB, SSR, VR, IPRA, and DPR are causal variables; EC, IC, JDR, and SPM are regarded as effects. These factors highlight the need for robust mechanisms to ensure the integrity of data, the accuracy of risk assessments, and the transparency of the decision-making processes of AI. Negative impacts on ethics, inclusion, employment, and trust between stakeholders will likely be reduced by addressing the root causes, such as data quality, risk assessment, and algorithmic bias, and developing policies to address them.

Keywords: *Decision-making, digital health technology, health services administration*

Öz

Bu çalışma, sağlık sektöründe yapay zekânın kullanımına özgü zorlukların ve risklerin birbirine bağlı etkilerini ortaya koymayı amaçlamaktadır. Literatürden elde edilen on farklı zorluk ve risk, sağlık yönetiminde yer alan beş uzman tarafından değerlendirilmiştir. Katılımcılar, sağlık alanında en az on yıllık akademik veya profesyonel deneyime sahip olmalarına göre seçilmiştir. Katılımcılar konuyla ilgili değerlendirmelerini yapılandırılmış formlar üzerinden yapmıştır. Belirlenen entegrasyon zorlukları arasındaki neden-sonuç ilişkilerini araştırmak için DEMATEL tekniği kullanılmıştır. DEMATEL analizi sonuçlarına göre önem derecesi açısından emniyet ve güvenlik riski (SSR) ilk sırada yer alırken, yetersiz hasta risk değerlendirmeleri (IPRA), veri kalitesi riskleri (DQR), doğrulanabilirlik riskleri (VR), paydaşların algıladığı güvensizlikler (SPM), entegrasyon zorlukları (IC), etik hususlar (EC), algoritma/karar verme yanlılığı (AMB) ve iş değiştirme riskleri (JDR) sonraki sıralarda yer almaktadır. Ek olarak, DQR, AMB, SSR, VR, IPRA, DPR nedensel değişken olarak; EC, IC, JDR ve SPM ise etki olarak değerlendirilmiştir. Bu faktörler, verilerin bütünlüğünü, risk değerlendirmelerinin doğruluğunu ve yapay zekanın karar alma süreçlerinin şeffaflığını sağlamak için güçlü argümanlara olan ihtiyacı vurgulamaktadır. Etik, kapsayıcılık, istihdam ve paydaşlar arasındaki güven üzerindeki olumsuz etkiler, veri kalitesi, risk değerlendirmesi ve algoritmalardaki yanlılıklar gibi temel nedenlerin ele alınması ve bunlara yönelik politikaların geliştirilmesi ile azaltılabilir.

Anahtar Kelimeler: *Dijital sağlık teknolojisi, karar verme, sağlık hizmetleri yönetimi*

Introduction

Artificial Intelligence (AI) continues to grow in its potential to be involved in various healthcare-related tasks. These roles enable the automation of routine medical practices, robotics, simple transcription, resource management, and decision support mechanisms. However, there is still a long way to go regarding the digitization of healthcare (due to technical and other challenges) and effective stakeholder engagement to increase the reliability of these use cases, ensure their validation, and link or hierarchically structure the components. Meanwhile, several risks and challenges arise, including patient injury due to system errors, patient privacy in obtaining data and drawing conclusions from AI, and more (Sunarti et al., 2021).

Implementing AI in healthcare opens the door to a set of benefits. There are clear benefits to applying the technology to healthcare diagnosis and treatment processes, such as improving and clarifying patient management options and outcomes, as well as potential secondary benefits, such as reduced referrals, reduced costs, and time savings. It can also support rural health facilities and encourage recruitment and retention in rural areas. Ultimately, this can contribute to a more equitable global health system (Tobore et al., 2019; Jawaid, 2023). Finally, while there are benefits, the future of AI in healthcare is not entirely optimistic. Many issues surround AI, including how AI will meet physicians' rights and responsibilities, how AI will protect privacy, and how current laws will cope with these developments. It has been demonstrated that technology and rules can be developed and applied to healthcare product development (Peterson et al., 2022).

Despite the benefits and opportunities of implementing AI in healthcare, several studies have explored the implications, risks, and challenges of integrating AI into the healthcare sector. Some researchers enlarged challenges perceived by healthcare leaders in Sweden regarding AI implementation, including external conditions, internal capacity building, and professional role transformations (Peterson et al., 2022). Also, from the perspective of ethical and legal risks, other researchers investigated a series of considerations (Chikhaoui et al., 2022; Wang & Liu, 2023). Finally, with their study, the scientists aimed to guide principles for the responsible development of AI tools in healthcare (Badal et al., 2023).

Artificial Intelligence Integration Challenges and Risks in Healthcare

As mentioned above superficially, the literature highlights diverse critical risk factors associated with AI implementation (Table 1). These factors include algorithm/decision-making bias, integration challenges, practical implementation, variability, safety, security, ethical considerations, data quality, inadequate patient risk assessment, job displacement, and stakeholders' perceived mistrust. Authors have all contributed insights into these risk factors, emphasizing the importance of mitigating biases, ensuring data quality, and addressing ethical concerns to build trust and enhance the effectiveness of AI tools.

Table 1. Artificial Intelligence Integration Challenges and Risks in Healthcare

	Challenges	References
DPR	**Data privacy risks** Potential threats and vulnerabilities associated with the use of AI in the processing of sensitive/critical patient information.	Kelly et al., 2019 Ma, 2022 Velev et al., 2023 Abid et al., 2023 Matheny et al., 2020 Zhou & Liu, 2022 Dwiedi et al., 2021 Yılmaz, 2024
AMB	**Algorithm/decision-making bias** It covers a multitude of factors that may hinder the effective use of AI technologies in health systems, such as data integrity, data ownership, data sharing across organizational silos, medical ethics issues, liability for medical errors, and system failure.	Kelly et al., 2019 Ma, 2022 Abid et al., 2023 Matheny et al., 2020 Zhou & Liu, 2022 Esmaeilzadeh, 2020
IC	**Integration challenges** It addresses numerous factors that may hinder the effective use of AI technologies in health systems, such as data integrity, data ownership, data sharing across organizational silos, medical ethics issues, liability for medical errors, and system failure.	Kelly et al., 2019 Matheny et al., 2020 Zhou & Liu, 2022
VR	**Verifiability risks** This refers to the potential for inconsistency or variation in the performance and outcomes of AI algorithms and systems.	Dwiedi et al., 2021
SSR	**Safety and security risks** It addresses potential vulnerabilities and threats to the confidentiality, integrity, and availability of critical health data and AI systems.	Ma, 2022 Zhou & Liu, 2022 Dwiedi et al., 2021
EC	**Ethical considerations**	Ma, 2022

	It addresses the potential ethical implications and challenges associated with the development, deployment, and use of AI technologies in the delivery of healthcare services.	Velev et al., 2023 Abid et al., 2023 Matheny et al., 2020 Zhou & Liu, 2022 Esmaeilzadeh, 2020
DQR	**Data quality risks** It addresses potential challenges and vulnerabilities related to the accuracy, completeness, and reliability of the data used to develop and deploy AI algorithms.	Velev et al., 2023
IPRA	**Inadequate patient risk assessment** The potential for AI systems to incorrectly assess or evaluate patient health risks leads to inappropriate or incorrect treatment decisions.	Nizam et al., 2021
JDR	**Job displacement risks** This refers to the potential impact of AI technologies on the roles and responsibilities of healthcare workers. With the integration of AI, certain tasks traditionally performed by healthcare workers have the potential to be automated, leading to concerns about job displacement in the healthcare sector.	Matheny et al., 2020 Zhou & Liu, 2022 Sevim et al., 2024
SPM	**Stakeholders perceived mistrusts** It refers to the concerns and reservations of various individuals and groups involved in health service delivery regarding the adoption and use of AI technologies. These stakeholders include healthcare professionals, patients, policymakers, and the public.	Esmaeilzadeh, 2020

his study aims to identify the interdependent effects of the challenges and risks inherent in using artificial intelligence in the healthcare sector.

This study is divided into five sections. The first section provides an overview of the role of AI in the healthcare sector. The second section identifies the challenges and risks of implementing AI in healthcare. The third section presents detailed information about the methods employed in the study. The fourth section presents the study's results in a step-by-step format. The fifth section discusses the results and offers a conclusion.

Material and Methods

Data for this cross-sectional study was collected between 19th and 23rd August 2024. It is a study designed according to the DEMATEL approach, one of the techniques used in Operations Research. XXX University Ethics Committee approved this study for Non-Interventional Clinical Research (Number: E-10840098-202.3.02-4783, Decision Number: 753, Date: 01.08.2024). Written informed consent was provided by all participants using the tenets of the Declaration of Helsinki.

Participants

As a result of the literature review, artificial intelligence and its risks in the provision of health services have been revealed and categorized. Five different health and health management professionals, living and working in Türkiye, assessed the risks that were obtained. In the selection of the participants, it was determined that they had at least ten years of academic or professional experience in health management. Participants performed their judgments about the topic on DEMATEL forms.

Table 2. Detailed Information of Participants

Participants (Part.)	**Specialization**	**Education**	**Position**	**Experience**
Part. 1	Health Management	PhD	Prof.	20 years
Part. 2	Health Management	PhD	Asst. Prof.	10 years
Part. 3	Health Management	Master	Lecturer	18 years
Part. 4	Nurse	Master	Lecturer	15 years
Part. 5	Physician	PhD	Deputy Chief Physician	13 years

DEMATEL Method

DEMATEL is a methodology for constructing and analysing a structural model that includes the causal relationships between complex factors such as (Wu, 2008; Wu & Lee, 2007). Apart from the other multicriteria decision-making techniques, DEMATEL assumes that there is a causal relationship between criteria. DEMATEL is based on graph theory and solves problems with directed graphs, known as digraphs. They visualize factors into cause group and effect group and represent a communication network (Wu & Lee, 2007; Lin & Tzeng, 2009). In DEMATEL analysis, the factors are compared to each other with the numbers between 0 and 4, and their influence levels are obtained. Table 3 shows the linguistic expressions and numerical equivalents of DEMATEL analysis (Wu & Lee, 2007).

Table 3: DEMATEL Linguistic Expressions

Linguistic terms	Abbreviated Notation	Influence Scores
No Influence	NO	0
Very Low Influence	VL	1
Low Influence	L	2
High Influence	H	3
Very High Influence	VH	4

The steps of the DEMATEL method are briefly as follows;

Step 1: Determination of the relationships between the criteria with the pairwise comparison forms

For the identified risks in the effective use of AI in health services, the direct-relation matrix (A) was determined with the numbers corresponding to the linguistic expressions (Table 3) in line with the expert opinions by creating a pairwise comparison matrix.

Step 2: Normalization of the direct-relation matrix

Based on the direct-relationship matrix (A), the normalized direct-relationship matrix (M) is obtained using equations (1) and (2) below (Hung et al., 2006; Tsai & Chou, 2009).

$$M = k \times A \tag{1}$$

$$k = Min\left(\frac{1}{\max\limits_{1\le i\le n}\sum_{j=1}^{n}|a_{ij}|}, \frac{1}{\max\limits_{1\le i\le n}\sum_{j=1}^{n}|a_{ij}|}\right) \tag{2}$$

$i, j \in \{1,2,3, \dots, n\}$

Step 3: Calculation of the total relation matrix

After a normalized direct-relationship matrix is obtained, the total relationship matrix (S) is constructed using equation 3 (Hung et al., 2006; Tsai & Chou, 2009).

$$S = M + M^2 + \cdots = \sum_{i=1}^{\infty\leftarrow} M^i = M\,(I - M)^{-1} \tag{3}$$

Step 4: Calculation of the dispatcher and receiver group

The sum of the columns in the S matrix is (R) and the sum of the rows is (D), and the degree of influence of each criterion on the others and the relationship with the others is determined by using D-R and D+R values by calculating equations 5 and 6 after calculating equation 4 (Wu & Lee, 2007; Tsai & Chou, 2009)

$$S = \left\lfloor S_{i,j} \right\rfloor_{nxn},\ \mathrm{i,j} \in \{1,2,3 \dots, n\} \tag{4}$$

$$D = \sum_{j=1}^{n} S_{i,j} \tag{5}$$

$$R = \sum_{i=1}^{n} S_{i,j} \tag{6}$$

Step 5: Setting the threshold value and obtaining the influence-directional graph diagram

With the DEMATEL method, the 'four degrees' values of each factor, including 'R_i', 'D_i', 'D_i+R_i' and 'D_i-R_i', can be calculated to determine the criteria (Lin & Tzeng, 2009). Where 'R_i' represents the degree of influence exerted on other factors and 'D_i' represents the degree of influenced from other factors. 'D_i + R_i' indicates the degree of relationship with other factors, and 'D_i - R_i' means the strength of influence that can be divided into dispatchers or receivers (Chen et al., 2020).

Results

After literature review AI integration challenges in healthcare were determined. The determined challenges were then evaluated by employing DEMATEL as mentioned material and method section. As a result of the data collected from experts in the field, the opinions of each different expert were integrated into a direct-relation matrix table (Table 4).

Table 4. The Initial direct-relation matrix (Integrated)

	DPR	AMB	IC	VR	SSR	EC	DQR	IPRA	JDR	SPM
DPR	0,00	2,40	3,00	2,80	3,40	2,60	1,40	1,80	1,20	3,20
AMB	2,00	0,00	2,80	3,00	2,40	3,60	2,20	3,20	0,80	3,20
IC	1,80	2,60	0,00	1,80	2,40	2,40	2,40	2,40	2,00	2,20
VR	2,00	2,20	3,00	0,00	3,00	3,00	3,00	3,40	0,80	2,80
SSR	3,60	2,20	2,60	3,20	0,00	2,80	2,80	2,80	1,60	4,00
EC	3,60	2,60	2,00	2,40	2,00	0,00	1,60	2,20	1,20	2,80
DQR	2,40	3,60	2,60	3,60	2,80	3,20	0,00	3,80	1,60	2,40
IPRA	2,00	2,60	2,80	3,20	2,40	2,40	3,20	0,00	1,60	3,40
JDR	0,80	0,40	1,80	0,60	1,20	0,80	1,20	0,40	0,00	2,00
SPM	2,60	1,00	3,20	1,40	2,20	2,20	1,60	2,60	3,00	0,00

The normalized direct-relation matrix is calculated from Eq. (1) and Eq. (2) as demonstrated in Table 5.

The normalized direct-relation matrix switch to the Total Relation Matrix by employing Eq. (3) as demonstrated in Table 6.

Table 5. The normalized direct-relation matrix

	DPR	AMB	IC	VR	SSR	EC	DQR	IPRA	JDR	SPM
DPR	0,00	0,09	0,12	0,11	0,13	0,10	0,05	0,07	0,05	0,12
AMB	0,08	0,00	0,11	0,12	0,09	0,14	0,08	0,12	0,03	0,12
IC	0,07	0,10	0,00	0,07	0,09	0,09	0,09	0,09	0,08	0,08
VR	0,08	0,08	0,12	0,00	0,12	0,12	0,12	0,13	0,03	0,11
SSR	0,14	0,08	0,10	0,12	0,00	0,11	0,11	0,11	0,06	0,15
EC	0,14	0,10	0,08	0,09	0,08	0,00	0,06	0,08	0,05	0,11
DQR	0,09	0,14	0,10	0,14	0,11	0,12	0,00	0,15	0,06	0,09
IPRA	0,08	0,10	0,11	0,12	0,09	0,09	0,12	0,00	0,06	0,13
JDR	0,03	0,02	0,07	0,02	0,05	0,03	0,05	0,02	0,00	0,08
SPM	0,10	0,04	0,12	0,05	0,08	0,08	0,06	0,10	0,12	0,00

Table 6. The total relation matrix

	DPR	AMB	IC	VR	SSR	EC	DQR	IPRA	JDR	SPM
DPR	0,4190	0,4740	**0,5697**	**0,5289**	**0,5464**	**0,5434**	0,4386	**0,5137**	0,3283	**0,6136**
AMB	**0,5199**	0,4200	**0,5956**	**0,5679**	**0,5444**	**0,6082**	**0,4929**	**0,5921**	0,3341	**0,6482**
IC	0,4457	0,4484	0,4247	0,4608	0,4760	**0,4977**	0,4376	**0,4940**	0,3297	**0,5374**
VR	**0,5238**	**0,5035**	**0,6063**	0,4702	**0,5681**	**0,5936**	**0,5234**	**0,6036**	0,3372	**0,6406**
SSR	**0,6057**	**0,5297**	**0,6304**	**0,6101**	**0,4982**	**0,6201**	**0,5432**	**0,6159**	0,3863	**0,7165**
EC	**0,5156**	0,4579	**0,5103**	**0,4914**	0,4770	0,4257	0,4202	**0,4987**	0,3098	**0,5707**
DQR	**0,5792**	**0,5892**	**0,6434**	**0,6394**	**0,6076**	**0,6490**	0,4613	**0,6638**	0,3909	**0,6822**
IPRA	**0,5202**	**0,5128**	**0,5993**	**0,5766**	**0,5476**	**0,5727**	**0,5275**	0,4856	0,3634	**0,6568**
JDR	0,2079	0,1817	0,2626	0,2052	0,2262	0,2214	0,2072	0,2068	0,1240	0,2835
SPM	0,4515	0,3764	**0,5142**	0,4245	0,4501	0,4668	0,3930	0,4750	0,3534	0,4362

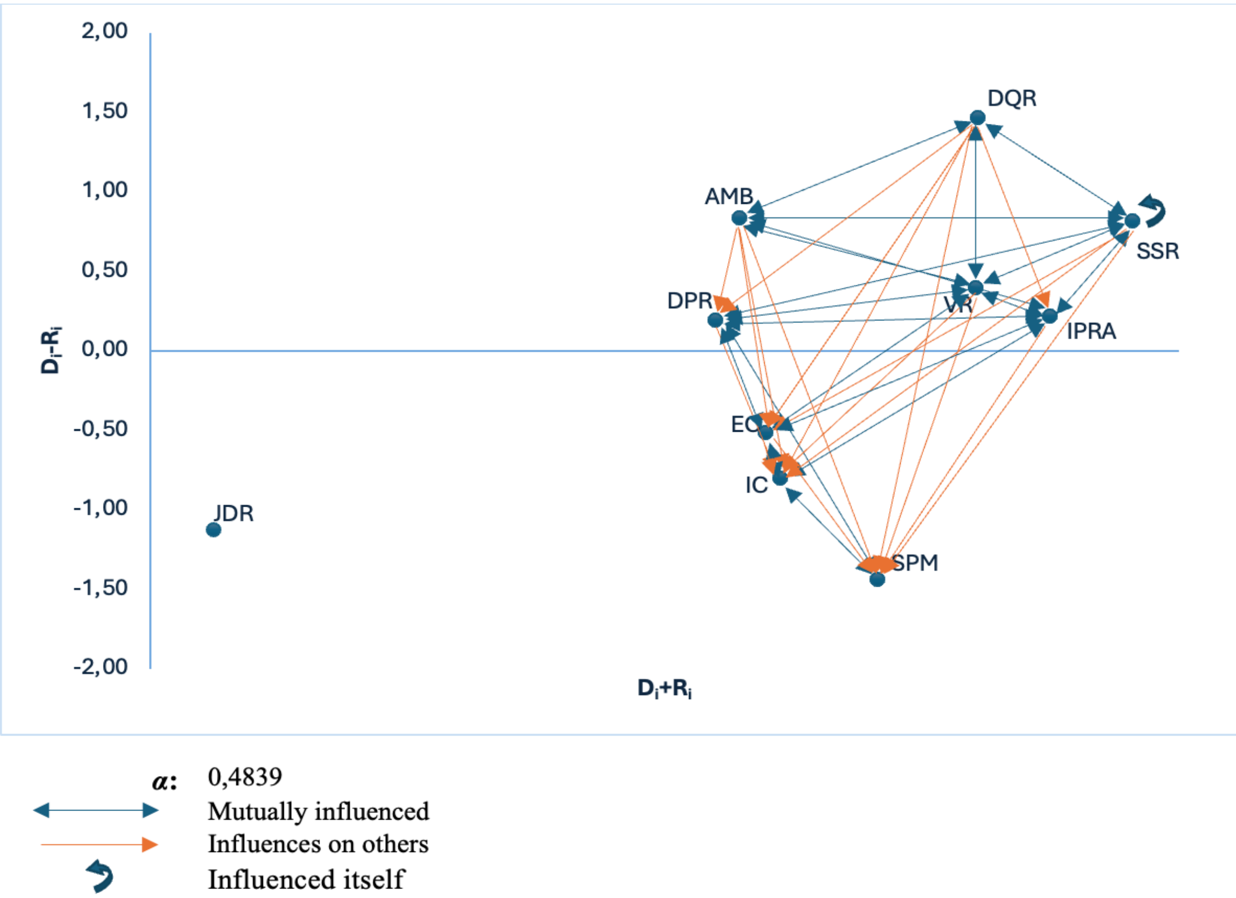

Figure 1. The cause-and-effect values

According to the computed total relation matrix, the threshold value is computed as 0,4839. To compute the threshold value for relations, it is sufficient to calculate the average values of Table 6. In order to obtain an appropriate impact-relationship map, such a threshold value is used to obtain sufficient information for further analysis and decision-making. A graph is created using the threshold data in Figure 1. The model of significant relations is presented in bold letters in Table 7.

Table 7. The cause-and-effect values

	D_i	R_i	D_i+R_i	D_i-R_i
DPR	4,9756	4,7884	9,7639	**0,1872**
AMB	5,3233	4,4935	9,8168	**0,8298**
IC	4,5520	5,3565	9,9085	-0,8045
VR	5,3702	4,9751	10,3453	**0,3951**
SSR	5,7561	4,9417	10,6978	**0,8144**
EC	4,6774	5,1985	9,8758	-0,5211
DQR	5,9060	4,4449	10,3509	**1,4611**
IPRA	5,3624	5,1492	10,5116	**0,2133**
JDR	2,1265	3,2572	5,3837	-1,1307
SPM	4,3411	5,7857	10,1268	-1,4446

Figure 1 shows the model of significant relations. This model can be represented as a diagram in which the values of (D_i+R_i) are placed on the horizontal axis and the values of (D_i-R_i) on the vertical axis. The position and interaction of each factor with a point in the coordinates (D_i+R_i, D_i-R_i) are determined by the coordinate system.

(D_i+R_i) represents the degree of importance each factor plays in the entire system. In other words, (D_i+R_i) indicates both factor's impact on the whole system and other system factors' impact on the factor. In terms of the degree of importance, SSR is ranked in the first place, and IPRA, DQR, VR, SPM, IC, EC, AMB, DPR, and JDR are ranked in the next place.

The positive value of (D_i-R_i) represents a causal variable, and the negative value of (D_i-R_i) represents an effect. In this study, DQR, AMB, SSR, VR, IPRA, and DPR are considered to be a causal variable; EC, IC, JDR, and SPM are regarded as an effect.

These results carry both theoretical and practical implications. Theoretically, the study extends the application of DEMATEL in healthcare by demonstrating its capacity to dissect complex interrelations among integration challenges. Practically, the insights offer a roadmap for healthcare organizations to prioritize interventions. For example, enhancing DQR and SSR as foundational elements could create a ripple effect, positively influencing dependent factors like JDR and SPM.

Discussion

A few challenges and risks need to be considered for the effective and ethical use of AI technologies in health care. These include factors that may make it difficult for healthcare systems to smoothly orient themselves to and utilise the use of AI tools. These challenges have been identified in various academic papers as DPR, AMB, IC, VR, SSR, EC, DQR, IPRA and JDR and were the argument for this study. The associated challenges relate to the complexities associated with the use of AI to process vital patient information and to deliver services in an efficient and responsible manner.

Unfortunately, it is not possible for decision-makers to solve various problems at the same time or in a limited period with fixed resources. For this reason, it is necessary to allocate scarce resources in the most optimal way for the purpose. The interplay of challenges and risks in the use of artificial intelligence in health services has been the subject of analysis by the DEMATEL method. By this method, among the barriers to the use of AI in health services and those that affect other barriers were identified. In this context, it would be appropriate for decision-makers to focus on DQR, AMB, SSR, VR, IPRA, and DPR barriers. As a matter of fact, there are findings and inferences in the literature regarding these barriers.

DPR is cited as a key risk and includes threats and vulnerabilities when managing critical patient data (Shahriar et al., 2023). Indeed, this risk is further exacerbated by the presence of AMB, which includes data integrity, ownership, data retention, and various ethical issues that can complicate the use of AI tools in healthcare service delivery (Mosaiyebzadeh et al., 2023). Furthermore, immature procedures regarding data ownership, data sharing and data processing, medical ethics, and liability with IC pose significant barriers and make the integration of AI in healthcare even more complex and challenging (Nia et al., 2023). In addition, trust in AI applications can be increased by reducing concerns about data privacy at the stage of service delivery using AI applications (Kar et al., 2021). In addition, trust in AI applications can be enhanced through the reduction of data privacy concerns at the service delivery stage of AI applications (Kar et al., 2021). Ensuring that AI is seamlessly integrated into clinical workflows while prioritizing patient safety can provide insights into key issues such as data sharing, algorithm transparency, data standardization, and interoperability (Temsah, 2024).

The risk of verifiability is an important factor in the application of AI to ensure that the performance and outcomes are verifiable (Massella et al., 2022). Furthermore, the risks associated with the use and processing of health data in AI applications can be explained by SSR. At this point, Sreenivasan (2024) highlighted that the importance of preventing and protecting against potential vulnerabilities and threats.

EC explains some ethical implications and challenges associated with the active use of AI applications in delivering healthcare. In this regard, Amedior (2024) notes that there are aspects of AI technologies that require ethical development. Furthermore, research on the ethical implications of AI in healthcare emphasizes that important issues such as confidentiality, trust, accountability, and bias should be taken into account in order for AI applications to be more involved in-service delivery (Dhar et al., 2023).

DQR also includes factors that can lead to vulnerabilities and biased results in data analysis, i.e., data quality risks. In fact, Arigbabu (2024) also highlighted the possibility of data quality as a source of security vulnerabilities and emphasized the creation and processing of data in a quality manner.

Among other factors, deficiencies and biases in patient risk assessment processes (IPRA) are fundamental factors in wrong treatment decisions and jeopardize patient outcomes (Li et al., 2023). The digital transformation of healthcare and its further development of AI practices may have an impact on the roles and responsibilities of the existing healthcare workforce. Indeed, Williamson (2024) interprets this transformation through automation and decision support systems, arguing that it will increase concerns about the displacement of personnel.

Moreover, Douglas et al. (2022) have put forth the proposition that the deployment of AI in healthcare applications can serve to mitigate negative bias and facilitate the effective integration of AI through the engagement of relevant stakeholders.

By systematically addressing the identified causal factors and their interrelations, healthcare organizations can achieve more sustainable and effective AI integration, ultimately enhancing patient outcomes and system efficiency.

Conclusion

The effective navigation of challenges and risks by healthcare stakeholders can be achieved through the utilization of insights derived from current research. This enables the responsible and ethical deployment of AI technologies to enhance the delivery of healthcare and the outcomes for patients. The performed analysis revealed that ethical considerations, integration challenges, and stakeholder perceived mistrust are effect variables influenced by the aforementioned causal factors. This implies that addressing the root causes, such as data quality, risk assessments, and algorithmic biases, will likely mitigate the negative impacts on ethics, integration, employment, and trust among stakeholders. Decision makers should adopt rigorous data management practices to ensure the reliability of AI systems, implement advanced AI-driven risk assessment tools, and promote algorithm transparency through explainable AI techniques to build trust between healthcare providers and patients. Continuing training programs are essential to stay abreast of AI developments and improve their application in healthcare. Adhering to ethical guidelines and actively reducing bias in AI algorithms will ensure fair and equitable healthcare delivery. Collaboration with IT specialists, data scientists, and other healthcare professionals is also important for successful AI integration into clinical workflows.

Literature-based challenges can be the limitations of this study. Future research should focus on exploring sector-specific nuances to validate the findings across different healthcare domains. Longitudinal studies assessing the impact of targeted interventions on these challenges would provide valuable insights into the evolving dynamics of AI integration in healthcare. With various and comprehensive data collection methods like face-to-face interviews, the Delphi technique, etc., deep investigation can be performed.

Conflict of Interest

No conflict of interest.

Financial Support

No financial support was provided.

Ethical Consideration

This study was approved by the Istanbul Medipol University Ethics Committee for Non-Interventional Clinical Researches (Number: E-10840098-202.3.02-4783, Decision Number: 753, Date: 01.08.2024).

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