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Adoption of Artificial Intelligence and Robotics in Healthcare: A Systematic Literature Review

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Abstract

Even though the acceptance of AI-based technologies among healthcare professionals is significant, little is known about the factors that influence their acceptance. This study aims to examine the theories and models used to study the adoption of AIR in healthcare and to identify the significant factors that affect the adoption of AIR in healthcare across countries. A systematic literature review with the PRISMA framework was conducted. The results reveal an increase in the number of studies concentrating on AIR adoption in healthcare sector in recent years. In addition, this study revealed that the UTAUT model is the most frequently used one. The AIR adoption among countries is primarily due to three main factors: perceived usefulness, perceived ease of use, and behavioural intention. Thirteen factors in developed countries and seventeen factors in developing countries have been identified due to their impact on AIR adoption. The findings of this study constitute a valuable contribution to the current body of knowledge by enhancing the understanding of AIR adoption in healthcare. Moreover, the results offer assistance to policymakers when making decisions and developing strategies related to the adoption of AIR in healthcare.

1. Introduction

The healthcare industry is currently experiencing a paradigm shift, where change has become the prevailing norm. The digitalisation of health and patient data has a significant transformation in clinical, operational, and business models, as well as in the broader economic landscape, with implications that are expected to persist in the near future [1]. Artificial Intelligence (AI) encompasses several technologies aimed at the creation and development of computers that can simulate human intelligence. This technology facilitates the development of systems that possess human-like skills, including the capacity to understand, perceive, and respond appropriately. The field of AI has seen significant advancements over decades, and it is currently experiencing a period of rapid growth. This can be attributed to various causes, including the widespread adoption of digitalisation, the development of novel technologies such as neural networks, deep learning, and machine learning, as well as the increased availability of high-performance computing power, and many more [2]. AI possesses the potential to significantly transform existing healthcare practices across several domains, encompassing prevention, diagnosis, screening, treatment, and care [3]–[5]. AI provides more precise predictions of behavioural patterns and comprehension of existing conditions using machine learning and deep learning approaches [5]. These advantages would enhance the clinical decision-making process, increase the efficacy and accuracy of diagnosis, and reduce physician workload [3]. Hence, the lack of understanding about the factors influencing the reluctance of healthcare professionals to accept AI-driven technologies can yield significant negative impacts. This includes hindering advancements in healthcare service, as well as causing wasteful expenditures on research and design [6]. Therefore, it is important to investigate the factors that affect healthcare professionals' acceptance of AIR.

1.1. Knowledge Gap

According to Scopus database analysis, scientific research on AI first appeared in indexed journals in 1878. There are 29,828 English journal articles published between 1878 and August 15, 2023, containing the keywords artificial intelligence or AI in the publication titles indexed in the Scopus database. Since 2015, 23,780 articles have been published, representing a rise in the number of articles published over the past five years, see Figure 1. The bibliometric network analysis results with the VOSviewer software showed that the most common keywords in the selected databases were artificial intelligence (f = 14,283), robotics (f = 228), adoption (f = 91), technology adoption (f = 99), healthcare (f = 495), and systematic review (f = 211). Figure 2 shows the existing research focus of AI studies. Accordingly, this study includes two research gaps. First, AI is expanding in several fields but is still in its infancy in healthcare, and much research is needed on adopting this technology. Second, theories and models about this technology are not equally applicable in all scenarios and contexts [7]. Therefore, there is a dearth of studies that categorize the factors influencing AI adoption in healthcare across both developed and developing countries.

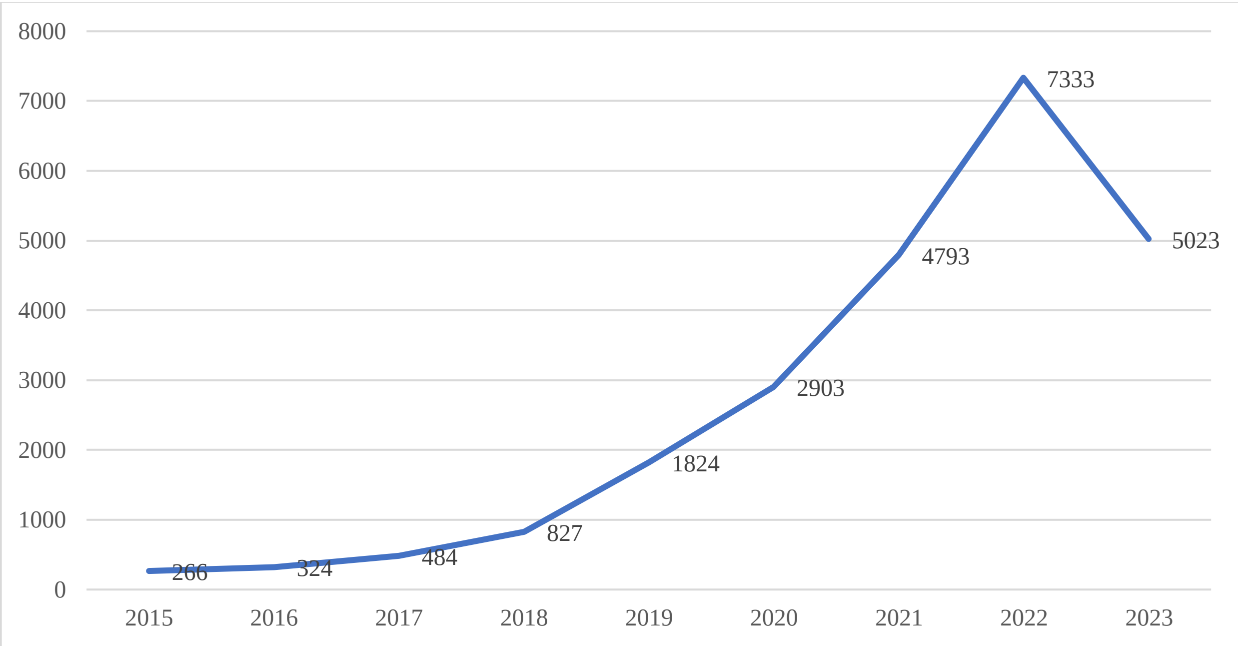

Figure 1: Number of AI articles published from 2015 to 2023

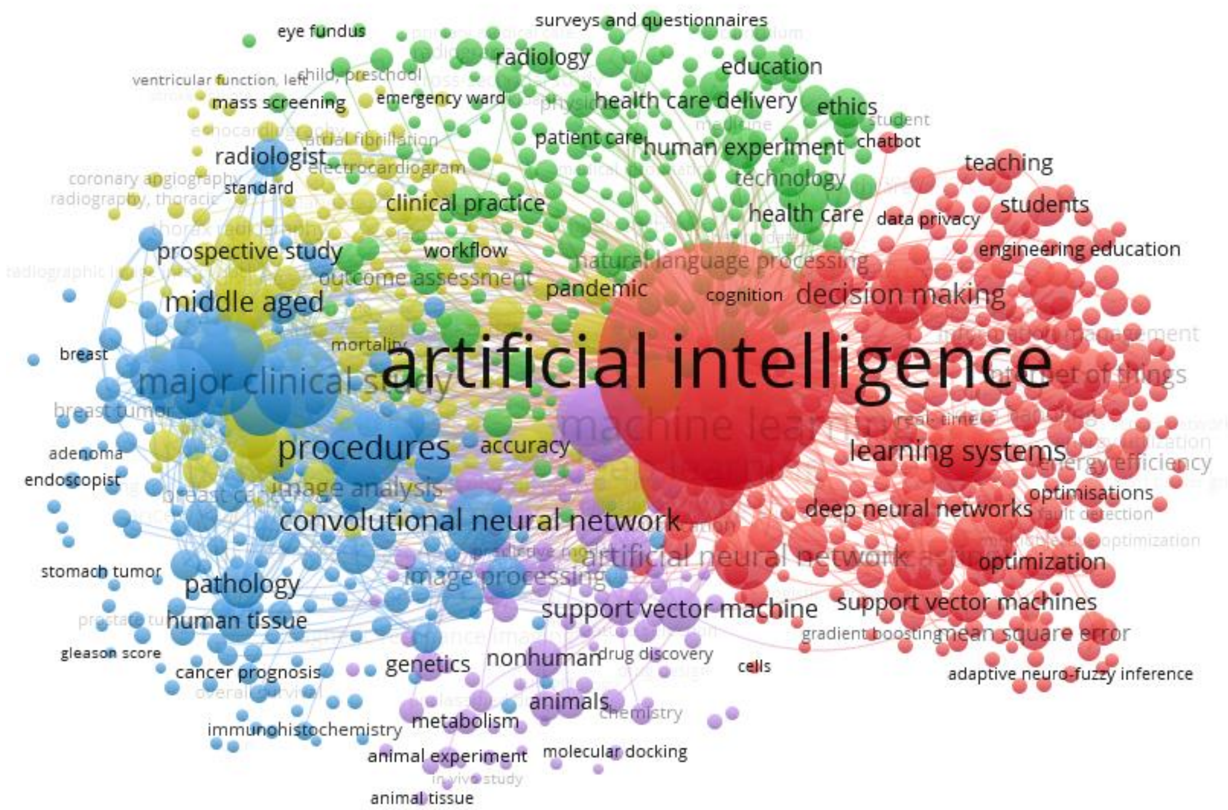

Figure 2: The most used keywords

1.2. Aim and Contribution

This SLR aims to provide academics and practitioners with a current review of AIR adoption in healthcare. Therefore, this study assesses prior studies to review their contributions, identify gaps, and offer future insights. Additionally, this study examines several frameworks and adoption models of technology to identify the primary factors impacting the adoption of AIR in healthcare. The originality of this SLR, to the best of the researcher's knowledge, is in performing an SLR to identify the technological adoption models that are used in AIR within the context of healthcare. Furthermore, it is critical to identify the most important factors that have a substantial impact on the acceptance of AIR in healthcare across different countries. This was not previously addressed in SLRs on AIR adoption in healthcare. Accordingly, this SLR has six contributions:

RO1. To find out the key contributions of previous studies done in the field of AIR adoption in healthcare.

RO2. To identify the theoretical and conceptual models used in the field of AIR adoption in healthcare.

RO3. To specify the key factors that affect the adoption of AIR in healthcare across different countries.

RO4. To identify the common factors among countries that affect AIR adoption in healthcare.

RO5. To specify the key factors that affect the adoption of AIR across developed and developing countries.

RO6. To determine the relationship between the most used adoption model and the use of AIR in healthcare.

1.3. Theories of Adoption

Within the healthcare field, the technology acceptance model and the unified theory of acceptance and use of technology are the most common theories used in the field of technology adoption in the healthcare sector [8]. These models have been employed to understand and explain the factors contributing to an individual's adoption and acceptance of innovative technology in healthcare. The Technology Acceptance Model (TAM) was developed by [9] to better understand the patterns of computer usage behaviour. TAM aimed to predict how consumers feel towards different types of technology and identify the factors that exert an impact on their adoption of these technologies [10]. Furthermore, the Unified Theory of Acceptance and Use of Technology (UTAUT) was established by [11] by integrating eight significant models and their respective modifications. The UTAUT model was developed to discover the main factors that can precisely predict an individual's intentions and behaviour about the adoption and utilisation of technology.

1.4. Related Work

Multiple SLRs have been conducted in the domain of AI in healthcare, examining the topic from multiple perspectives. To understand factors influencing medical AI and end-user trust in AI technology, a comprehensive literature review was performed by Tucci *et al.* [12]. A systematic review of barriers to AI implementation in healthcare management has been done as well by Assadullah [13]. In addition, Donins and Behmane [14] provide an SLR on the challenges and solutions for AI adoption in healthcare. Karimian et al [15] offered a systematic scoping review on the ethical issues surrounding the use of AI in healthcare. An SLR was used to address the challenges, benefits, methodologies, and functions of AI in the healthcare industry by Ali *et al.* [16]. Furthermore, Gunasekeran *et al.* [17] conducted a systematic review of applications of AI and other digital solutions for public health in the hospital operational environment, during the COVID-19 pandemic. Similarly, Mahdi *et al.* [18] conducted a review of the applications of AI in dental healthcare to determine how AI impacts digital healthcare initiatives. Gerich *et al.* [19] also conducted a scoping literature review on AI-based technologies in nursing. Moreover, Mustapha *et al.* [20] performed an SLR on the effects of Industry 4.0 on the healthcare industry. IoT and AI in healthcare have also been investigated using SLR by Alanazi [21]. In addition, Albahri *et al.* [22] introduced an SLR on trustworthy and explicable AI in healthcare. Loh *et al.* [23] provided a systematic review of the past ten years (2011–2022) regarding the explainable AI applications in healthcare. The impact of AI on patient safety outcomes was the subject of an SLR by Choudhury and Asan [24]. Moreover, Wolff *et al.* [25] conducted an SR on the economic impact of AI in the healthcare industry. Additionally, a systematic review of health economic evaluations for AI applications in healthcare was conducted by Voets *et al.* [26] to investigate relevant methods, quality of reporting, and challenges for future AI applications in healthcare. In low and middle-income countries, Ciecierski-Holmes *et al.* [27] conducted a systematic scoping review on the use of AI to strengthen healthcare systems in these countries. Moreover, to increase the adoption of AI in healthcare, Chew and Achananuparp [28] conducted a scoping review on the perceptions and needs of AI in healthcare. In addition, Young *et al.* [29] conducted a systematic review of the literature regarding patient and general public attitudes toward adopting clinical AI. Moreover, Mehta *et al.* [30] introduced a systematic mapping research on how big data analytics and AI are transforming healthcare. In addition, Nazar *et al.* [31] provided an SLR of human-computer interaction (HCI) and explainable AI in healthcare with AI techniques. Khanijahani *et al.* [32] published a systematic review of the professional, organisational, and patient characteristics associated with the adoption of AI in healthcare. Alhashmi *et al.* [33] presented an SLR on the factors influencing the AI Implementation in Healthcare. Finally, an SLR on AI and business models in the sustainable development objectives was conducted by Vaio *et al.* [34].

2. Research Methodology

In this study, SLR is used since it is very important to determine the main factors that affect the use of AIR in healthcare. The procedures outlined in the PRISMA Statement Flow Diagram [35] were used to make this SLR. To ensure that the result is beneficial, this study used the stages suggested by [36], [37] to construct the process of this SLR using the PRISMA framework [35]. The process includes five stages: formulating questions, locating studies, selecting and evaluating the articles, analysing and synthesising, and finally, reporting and using the results. Prior to initiating the first phase, the SLR was planned using research methodology and the formulation of research questions. Consequently, the first phase consisted of database queries to identify relevant studies. Scopus, published by Elsevier, and the Web of Science, published by Thomson Reuters Institute for Scientific Information, were searched for relevant studies. The advantages and disadvantages of the medical research databases Scopus, Web of Science, PubMed, and Google Scholar were analysed in [38]. PubMed was excluded from the analysis of this SLR due to its emphasis on medical and life sciences [38]. According to [38], Scopus incorporates a broader spectrum of academic journals than Web of Science, but with a restriction on more recent articles (those published after 1995). Similar to the Web in general, Google Scholar can facilitate access to highly specialised information. However, its efficacy is hampered by outdated and insufficient citation information. The research conducted by Harzing and Alakangas [39] was an interdisciplinary and longitudinal study into the scope of coverage provided by Scopus, Google Scholar, and the Web of Science. The results revealed a consistent and relatively quarterly increase in the number of articles and citations across all three databases. Consequently, the researcher selected two datasets of impeccable quality. Both the Web of Science Core Collection and Scopus databases were queried.

2.1. Question Formulation

Formulating the research questions is the initial step in conducting an SLR. Therefore, it is essential to begin a literature review by formulating specific research questions. This study's principal objective is to answer the following research questions:

RQ1. What are the key contributions of previous studies done in the field of AIR adoption in healthcare?

RQ2. What are the different theoretical and conceptual models used in the field of AIR adoption in healthcare?

RQ3. What are the factors that influence AIR adoption in healthcare across different countries?

RQ4. What are the common factors among countries that affect the AIR adoption in healthcare?

RQ5. What factors influence AIR adoption in healthcare across developed and developing countries?

RQ6. What is the relationship between the most used model and the use of AIR in healthcare?

2.2. Locating Studies

To ensure the transparency and quality of the SLR, the "Web of Science Core Collection" and "Scopus" were utilised, two well-known and reliable databases. These databases were used to identify relevant articles that contained research terms associated with the study's research questions. Despite its limitations, the "title search" method is beneficial when an SLR requires the evaluation of a large number of references in a short period of time [40], [41]. On June 1, 2023, the researcher conducted a search using the article title search method. The groups of keywords are as follows:

Group A Keywords: Artificial Intelligence, Deep Learning, Robo*, AIR, Expert System, Machine Learning, ANN, Cognitive Learning, Neural Networking, Recomm* system, Fuzzy Logic, Unsupervised learning, Intelligent Systems, Supervised learning, Service Automation, Reinforcement learning.

Group B Keywords: Acceptance, Theories, Frameworks, adop*, Adoption models, Acceptance models, Adoption frameworks, Acceptance frameworks, Success factors, Readiness, Challenges, Determinants.

2.3. Selection and Evaluation of the Articles

Table 1 presents the Protocol for the current research. Articles were selected and evaluated following the inclusion and exclusion criteria established. Utilising a three-step screening procedure, articles were excluded from the study. This methodology examines paper titles, abstracts, and then full-text articles. The Rayyan tool, designed to assist researchers in implementing the SLR technique, supports the approach depicted in Figure 3. The accepted papers were stored in Mendeley and organised systematically and statistically using an Excel spreadsheet.

2.4. Analysis and Synthesis

The papers included in this study were analysed and synthesised thoroughly. Multiple criteria were used to classify them, including the country type, the publication year, the research setting, and the statistical tool(s) employed. After analysing the literature, this study also carefully organised the factors that affect AIR adoption in the healthcare sector.

2.5. Reporting and Using the Results

This SLR examines the existing literature on the adoption of AIR in healthcare. The subsequent sections provide answers to the study's research questions.

Table 1: Adopted Protocol for The Systematic Literature Review

1.	Objectives	1) To find out the key contributions of previous studies done in the field of AIR adoption in healthcare. 2) To identify the theoretical and conceptual frameworks used in the field of AIR adoption in healthcare. 3) To specify the key factors that affect the adoption of AIR in healthcare across different countries. 4) To identify the common factors among countries that affect AIR adoption in healthcare. 5) To specify the key factors that affect the adoption of AIR across developed and developing countries. 6) To determine the relationship between the most used adoption model and the use of AIR in healthcare.	
2.	Research questions	1) What are the key contributions of previous studies done in the field of AIR adoption in healthcare? 2) What are the different theoretical and conceptual frameworks used in the field of AIR adoption in healthcare? 3) What are the factors that influence AIR adoption in healthcare across different countries? 4) What are the common factors among countries that affect the AIR adoption in healthcare? 5) What factors influence AIR adoption in healthcare across developed and developing countries? 6) What is the relationship between the most used model and the use of AIR in healthcare?	
3.	Keywords and synonyms	Group A Keywords: Artificial Intelligence, Deep Learning, Robo*, AIR, Expert System, Machine Learning, ANN, Cognitive Learning, Neural Networking, Recomm* system, Fuzzy Logic, Unsupervised learning, Intelligent Systems, Supervised learning, Service Automation, Reinforcement learning. Group B Keywords: Acceptance, Theories, Frameworks, adop*, Adoption models, Acceptance models, Adoption frameworks, Acceptance frameworks, Success factors, Readiness, Challenges, Determinants.	
4.	Source selection	Criteria: The sources should be available and globally recognized as high-quality sources.	
	A- Criteria definition	Studies Language: English. Source Search Methods: The sources should be available and globally recognized as high-quality sources. Source List: Web of Sciences; Scopus.	
	B- Study selection criteria	Inclusion Criteria IC1: The paper addresses the adoption of AIR by applying one or more theories or models of technology adoption in healthcare sector. IC2: The paper should be peer-reviewed. IC3: The paper should be with a digital object identifier (DOI).	Exclusion Criteria EC1: The paper does not identify the sector in which it addresses AIR adoption. EC2: The paper is not available in full text. EC3: It is a conference paper/book chapter/ review/ book/ note/conference review/ Editorial. EC4: The paper is not in English.
5.	Study type definition	Papers published in journals.	
6.	Study initial selection	Initial search executed on 1st June, 2023.	

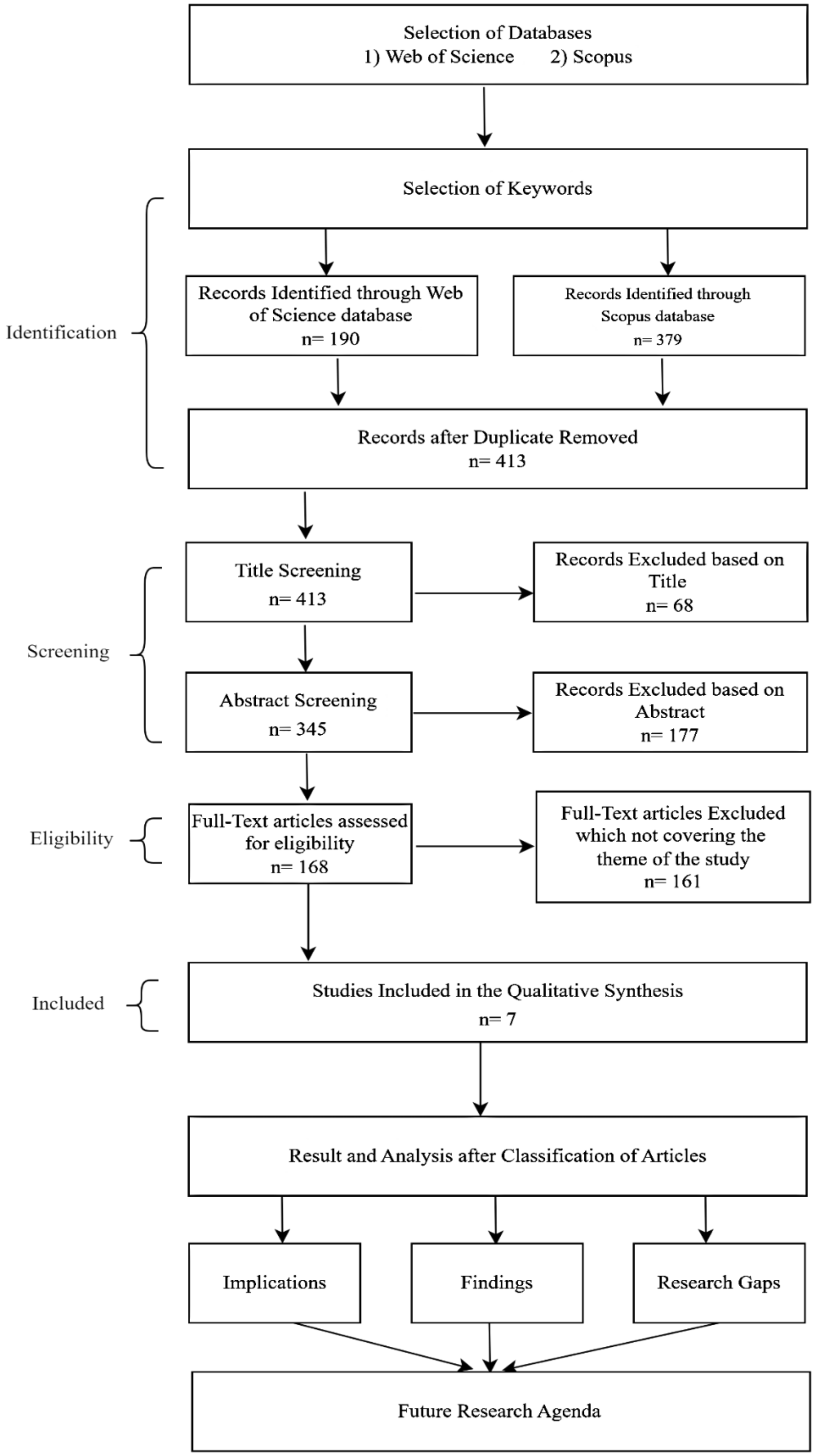

Figure 3: PRISMA flowchart of the study

3. Results

This section contains exhaustive answers to all research questions addressed in this SLR. A total of seven publications satisfied the inclusion and exclusion criteria of this SLR. Table 2 lists the articles included in the SLR to offer an exhaustive summary of the existing body of literature.

Table 2: Factors Affecting AIR Adoption in healthcare (N=5)

Authors	Objectives	Theory	Statistical tool	Factors
1. [42]	To understand the factors affecting the intention of medical professionals to adopt AI-assisted treatment and diagnosis	UTAUT and Human–Computer Trust Theory	AMOS	1. Performance Expectancy 2. Effort Expectancy 3. Social Influence 4. Human-Computer Trust 5. Behavioural Intention
2. [2]	To determine the key factors influencing the adoption of AI among Medical Specialists	TAM2 and UTAUT2	SmartPLS	1. Performance Expectancy 2. Effort Expectancy 3. Facilitating Conditions 4. Price Value 5. Results Demonstrability 6. Behavioural Intention
3. [6]	To investigate factors Influencing medical professional's acceptance of A I-based technologies	UTAUT	SPSS	1. Medical Performance Expectancy 2. Non-medical Performance Expectancy 3. Effort Expectancy 4. Social Influence Patients 5. Facilitating Conditions 6. Social Influence Medical Experts 7. Perceived Trust 8. Anxiety 9. Professional Identity 10. Innovativeness 11. Behavioural Intention
4. [43]	To investigate the factors that influence consumer adoption of SWH devices	TAM	PLS-SEM and Artificial Neural Network (ANN)	1. Perceived Ease of Use 2. Perceived Usefulness 3. Functional Congruence 4. Health Belief 5. Health Information Accuracy 6. Compatibility 7. Behavioural Intention
5. [44]	To investigate the factors that influence the acceptance of AI contouring technology in China	UTAUT	AMOS	1. Performance Expectancy 2. Effort Expectancy 3. Social Influence 4. Facilitating Conditions 5. Perceived Risk 6. Resistance Bias 7. Behavioural Intention 8. Usage Behaviour

6. [45]	To investigate the acceptance and intention to adopt artificial intelligence-based medical diagnosis support system	UTAUT and Trust Theory	SmartPLS	1. Effort Expectancy 2. Task Complexity 3. Performance Expectancy 4. Social Influence 5. Initial Trust 6. Propensity to Trust 7. Personal Innovativeness in IT 8. Technology Characteristics 9. Perceived Substitution Crisis 10. Behavioural Intention
7. [3]	To identify the primary factors that influence the adoption of AI for medical jobs	UTAUT	SmartPLS	1. Performance Expectancy 2. Effort Expectancy 3. Social Influence 4. Perceived Substitution Crisis 5. Task Complexity 6. Personal Innovativeness in IT 7. Technology Characteristics 8. Initial Trust 9. Behavioural Intention

RQ1. What are the key contributions of previous studies done in the field of AIR adoption in healthcare?

First, the researcher presented the number of articles published in developing as well as developed countries. The results are depicted in Figure 4. This SLR included two studies in developed countries and five studies in developing countries. Therefore, the researcher can conclude that developing countries drive the adoption of AIR in healthcare.

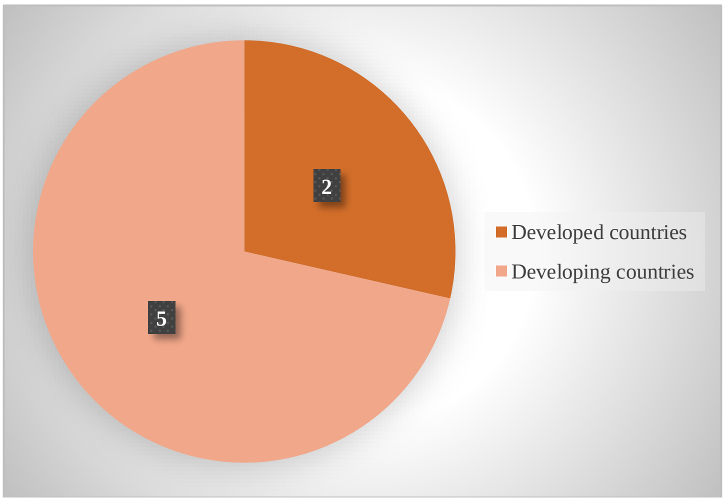

Figure 4: The distribution of articles by developed and developing countries

Second, Figure 5 depicts the publishing distribution over time. In 2020 one article satisfied the research criteria, whereas two publications did in 2021. Furthermore, three publications in 2022 and one article in 2023 were deemed to match the criteria indicating a notable inclination for AIR adoption in healthcare.

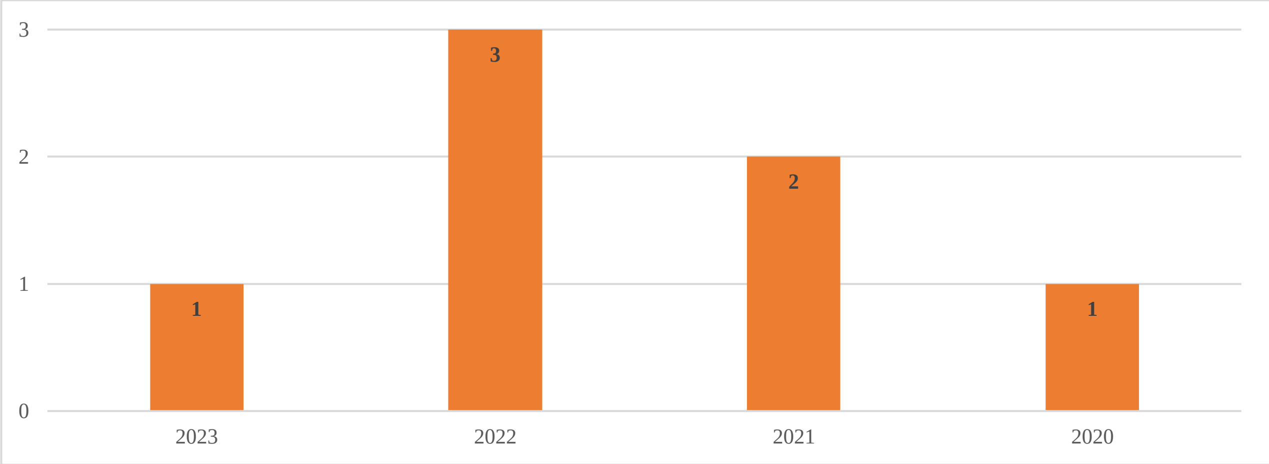

Figure 5: The distribution of articles by year

Thirdly, Figure 6 illustrates the distribution of papers across various countries. Notably, China provided three publications on AIR adoption in healthcare, whereas the other countries each contributed one.

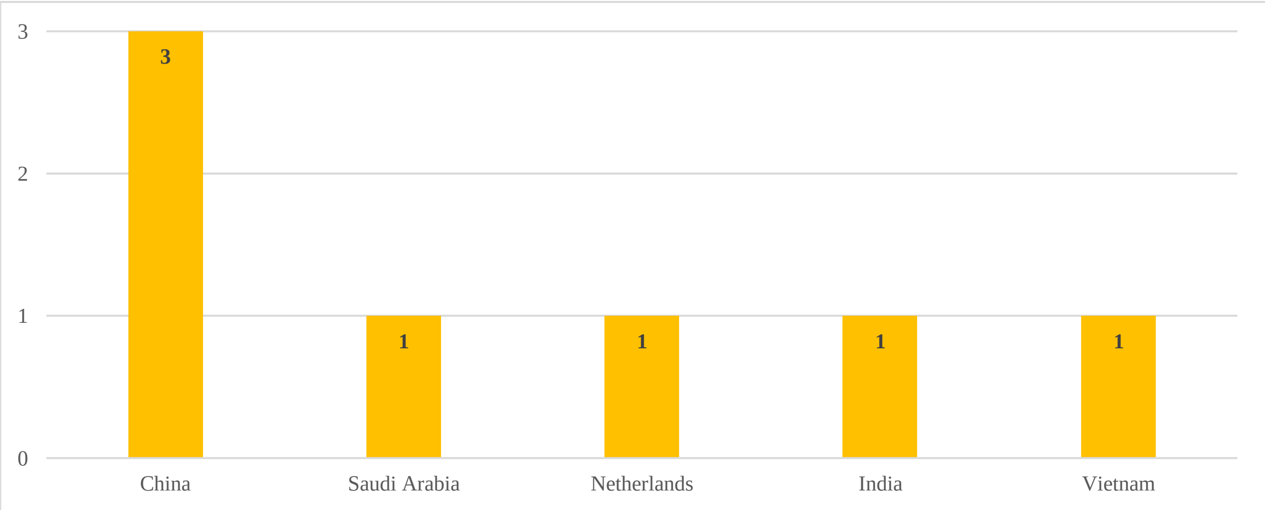

Figure 6: Distribution of articles by country

Fourth, Figure 7 represents the statistical approaches used to validate the conceptual framework of research in this SLR. Prior research used approaches such as Partial Least Squares-Structural Equation Modelling (PLS-SEM), Analysis of Moment Structure-Structural Equation Modelling (AMOS-SEM), Statistical Package for the Social Sciences (SPSS), and dual-stage SEM-ANN analysis based on deep learning. According to Figure 7, three studies employed the PLS-SEM method, whereas two publications used the AMOS-SEM, in addition, one article used PLS-SEM and ANN. Finally, SPSS was also used in one article.

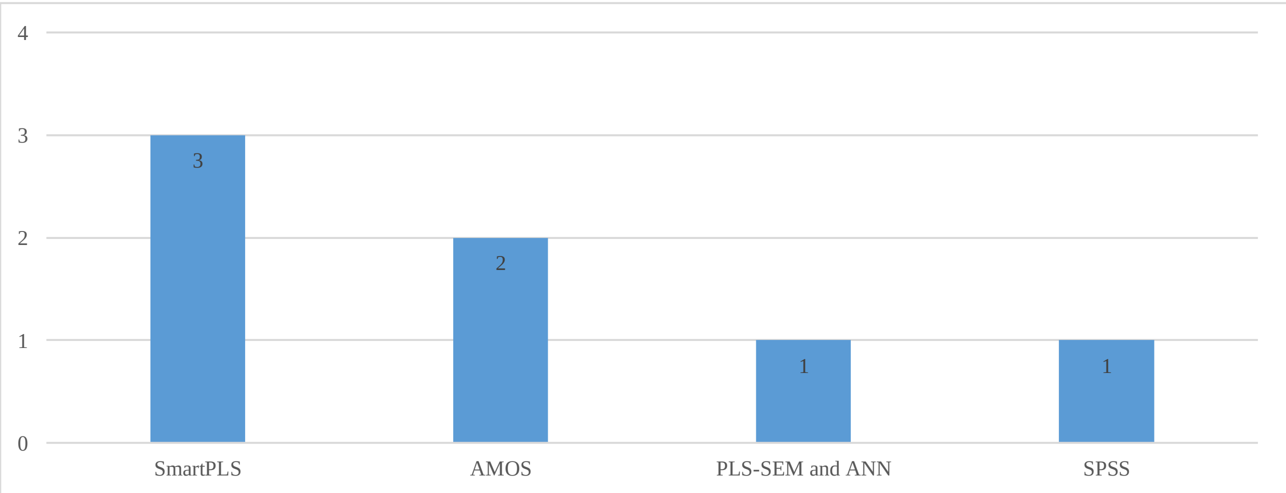

Figure 7: Statistical technique applied in prior studies

Finally, according to Table 3, performance expectancy or perceived usefulness was found as a factor influencing AIR adoption in healthcare in 8 articles, behavioral intention, and effort expectancy or perceived ease of use were each used in 7 articles. Furthermore, social influence was observed in 6 articles.

Table 3: Factors presentation with number of studies quoting these factors (n=23)

Factor	No. of articles	Factor	No. of articles
1. Performance Expectancy or Perceived Usefulness	8	13. Functional Congruence	1
2. Behavioural Intention	7	14. Health Belief	1
3. Effort Expectancy or Perceived Ease of Use	7	15. Health Information Accuracy	1
4. Social Influence	6	16. Human-Computer Trust	1
5. Facilitating Conditions	3	17. Perceived Risk	1
6. Trust	3	18. Price Value	1
7. Innovativeness	3	19. Professional Identity	1
8. Perceived Substitution Crisis	2	20. Propensity to Trust	1
9. Task Complexity	2	21. Resistance Bias	1
10. Technology Characteristics	2	22. Results Demonstrability	1
11. Anxiety	1	23. Usage Behaviour	1
12. Compatibility	1		

RQ2. What are the different theoretical and conceptual frameworks used in the field of AIR adoption in healthcare?

Several previous studies employed various theoretical frameworks to understand AIR adoption in the healthcare sector. Figure 8 depicts the models/frameworks used in prior studies. According to the statistics in the figure, the UTAUT model was the most frequently used model, found in three publications. TAM, TAM2, UTAUT2, UTAUT and trust theory, and UTAUT and human-computer trust theory, have been each used in one article.

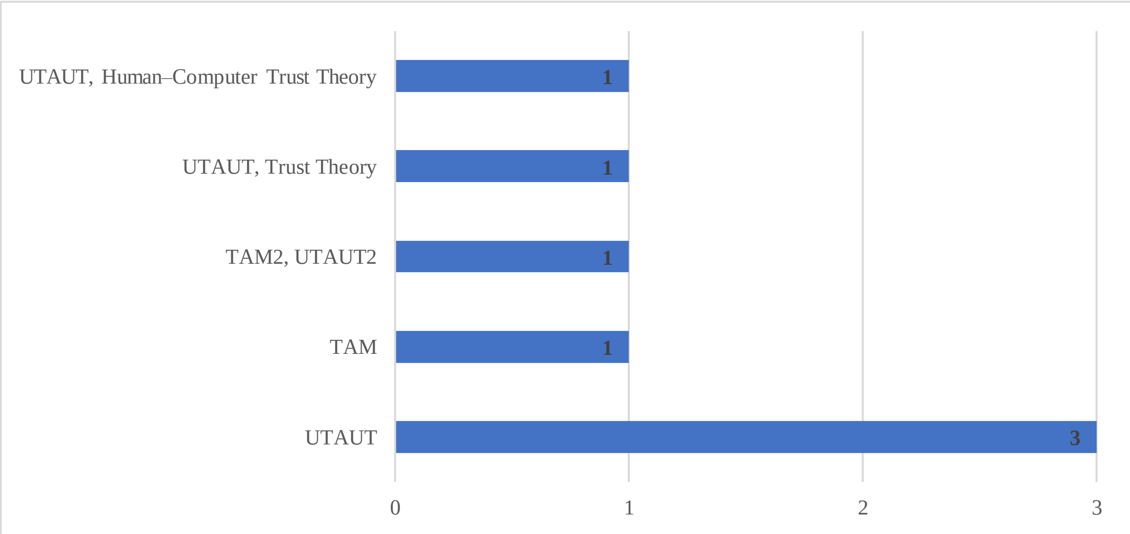

Figure 8. Theories applied in prior studies

RQ3. What are the factors that influence AIR adoption in healthcare across different countries?

The SLR comprehensively analyses factors influencing AIR in healthcare across different countries. The key factors include perceived ease of use/effort expectancy, perceived usefulness/performance expectancy, and behavioural intention observed in most countries: Saudi Arabia, the Netherlands, India, China, and Vietnam. In addition, trust appeared in countries such as the Netherlands, China, and Vietnam. Lastly, countries such as China and Vietnam highlight the influence of technology characteristics as factors in AIR adoption in healthcare. The common factors among countries are in Table 4.

Table 4: Factors influencing AIR adoption in healthcare across countries

Country	Factors
Saudi Arabia	1. Perceived Ease of Use, 2. Perceived Usefulness, 3. Functional Congruence, 4. Health Belief, 5. Health Information Accuracy, 6. Compatibility, 7. Behavioural Intention
Netherlands	1. Medical Performance Expectancy, 2. Non-medical Performance Expectancy, 3. Effort Expectancy, 4. Social Influence Patients, 5. Facilitating Conditions, 6. Social Influence Medical Experts, 7. Perceived Trust, 8. Anxiety, 9. Professional Identity, 10. Innovativeness, 11. Behavioural Intention
China	1. Performance Expectancy, 2. Effort Expectancy, 3. Social Influence, 4. Human-Computer Trust, 5. Behavioural Intention, 6. Task Complexity, 7. Initial Trust, 8. Propensity to Trust, 9. Personal Innovativeness, 10. Technology Characteristics, 11. Perceived Substitution Crisis, 12. Perceived Risk, 13. Resistance Bias, 14. Usage Behaviour
India	1. Performance Expectancy, 2. Effort Expectancy, 3. Facilitating Conditions, 4. Price Value, 5. Results Demonstrability, 6. Behavioural Intention
Vietnam	1. Performance Expectancy, 2. Effort Expectancy, 3. Social Influence, 4. Perceived Substitution Crisis, 5. Task Complexity, 6. Personal Innovativeness in IT, 7. Technology Characteristics, 8. Initial Trust, 9. Behavioural Intention

RQ4. What are the common factors among countries that affect the AIR adoption in healthcare?

Upon analysing the data, Table 5 represents the common factors for AIR adoption in the healthcare sector across countries. It is evident that several factors commonly influence AIR adoption across a range of countries. The most prevalent factors include perceived ease of use/effort expectancy, perceived usefulness/performance expectancy, and behavioural intention, which resonate with five countries, highlighting the importance of user perception, the utility of the technology, and individuals' intentions in facilitating the adoption of AIR in healthcare. Social influence also emerged as a notable factor across three countries, reflecting the crucial role of social factors toward technological adoption.

Table 5: Common factors influencing AIR adoption in healthcare across countries

Factor	Countries
Performance Expectancy/ Perceived Usefulness	Saudi Arabia, Netherlands, China, India, Vietnam
Effort Expectancy or Perceived Ease of Use	Saudi Arabia, Netherlands, China, India, Vietnam
Behavioural Intention	Saudi Arabia, Netherlands, China, India, Vietnam
Social Influence	Netherlands, China, Vietnam
Facilitating Conditions	Netherlands, India
Technology Characteristics	China, Vietnam
Perceived Substitution Crisis	China, Vietnam

RQ5. What factors influence AIR adoption in healthcare across developed and developing countries?

Table 6 represents the analysis of factors influencing AIR adoption in healthcare across developed and developing countries. 13 factors in developed countries and 17 factors in developing countries were identified as influencers of AIR adoption in healthcare. Anxiety, compatibility, and innovativeness are factors identified in developed countries. Trust, technology characteristics, and perceived risk were among the factors identified in developed countries.

Table 6: Factors influencing AIR adoption in healthcare across developed and developing countries

Country	Factors
Developed countries	1. Performance Expectancy/ Perceived Usefulness, 2. Effort Expectancy/ Perceived Ease of Use, 3. Social Influence, 4. Facilitating Conditions, 5. Perceived Trust, 6. Anxiety, 7. Professional Identity, 8. Innovativeness, 9. Behavioural Intention, 10. Functional Congruence, 11. Health Belief, 12. Health Information Accuracy, 13. Compatibility.
Developing countries	1. Performance Expectancy, 2. Effort Expectancy, 3. Social Influence, 4. Human-Computer Trust, 5. Behavioural Intention, 6. Task Complexity, 7. Initial Trust, 8. Propensity to Trust,

9. Personal Innovativeness in IT, 10. Technology Characteristics, 11. Perceived Substitution Crisis, 12. Facilitating Conditions, 13. Price Value, 14. Results Demonstrability, 15. Perceived Risk, 16. Resistance Bias, 17. Usage Behaviour.

RQ6. What is the relationship between the most used model and the use of AIR in healthcare?

As per the results of this SLR, UTAUT was used in six articles. Therefore, this section identifies the relationship between the UTAUT model and the use of AIR in healthcare. Tables 7 and 8 represent the results of the UTAUT model and the adoption of AIR in healthcare. 23 factors impacted the reasons for using AIR across the seven studies included in the SLR. Factors relevant to the UTAUT model in AIR adoption in healthcare include performance expectancy, effort expectancy, social influence, facilitating conditions, price value, and behavioural intention. In terms of external factors, 13 factors affected the adoption of AIR in healthcare, including perceived trust, anxiety, professional identity, innovativeness, human-computer trust, task complexity, personal innovativeness in IT, technology characteristics, initial trust, perceived substitution crisis, results demonstrability, perceived risk, and resistance bias. According to Table 7, almost all factors of UTAUT are identified as important influencers for behavioural intention which have been identified in many studies.

Table 7: The influence of UTAUT on air adoption in healthcare

Factors	Affected Factor	Total
1. Performance expectancy	Behavioural intention [2], [3], [6], [42], [44], [45], Social influence [42]	2
2. Effort expectancy	Behavioural intention [2], [3], [6], [42], [44], [45], Performance expectancy [3], [45], Social influence [42]	3
3. Social influence	Behavioural intention [3], [6], [42], [44], [45]	1
4. Facilitating conditions	Behavioural intention [2], [6], [44], Actual Behaviour [44]	2
5. Price value	Behavioural intention [2]	1
7. Behavioural intention	Actual Behaviour [44]	1

Furthermore, based on the data presented in Table 8, initial trust and perceived substitution crisis emerged as factors in two studies and have been shown to affect behavioural intention. Task complexity also emerged as an external factor in two studies that have been shown to affect performance expectancy. In addition, personal innovativeness in IT and technology characteristics were also observed in two studies that influence effort expectancy.

Table 8: The influence of the external factors on air adoption in healthcare

Factors	Affected Factor	Total
1. Perceived trust	Behavioural intention [6]	1
2. Anxiety	Behavioural intention [6]	1
3. Professional identity	Behavioural intention [6]	1
4. Innovativeness	Behavioural intention [6]	1
5. Human-computer trust	Behavioural intention [42]	1
6. Task complexity	Performance expectancy [3], [45]	2
7. Personal innovativeness in IT	Effort expectancy [3], [45]	2
8. Technology characteristics	Effort expectancy [3], [45]	2
9. Initial trust	Behavioural intention [3], [45]	2
10. Perceived substitution crisis	Behavioural intention [3], [45]	2
11. Results demonstrability	Behavioural intention [2]	1
12. Perceived risk	Behavioural intention [44]	1
13. Resistance bias	Behavioural intention [44]	1

Finally, among the studies that provided evidence on the UTAUT and the adoption of AIR in healthcare, most studies attempted to identify the factors influencing the behavioural intention to use AIR, see Figure 9. Among the 23 factors mentioned above, 10 factors were addressed as influencers of behavioural intentions: perceived trust, anxiety, professional identity, innovativeness, human-computer trust, initial trust, perceived substitution crisis, results demonstrability, perceived risk, and resistance bias. Furthermore, there were two influencers of effort expectancy: personal innovativeness and technology characteristics, and one influencer of performance expectancy, namely; task complexity. Finally, age, gender, experience, and profession were identified as moderators.

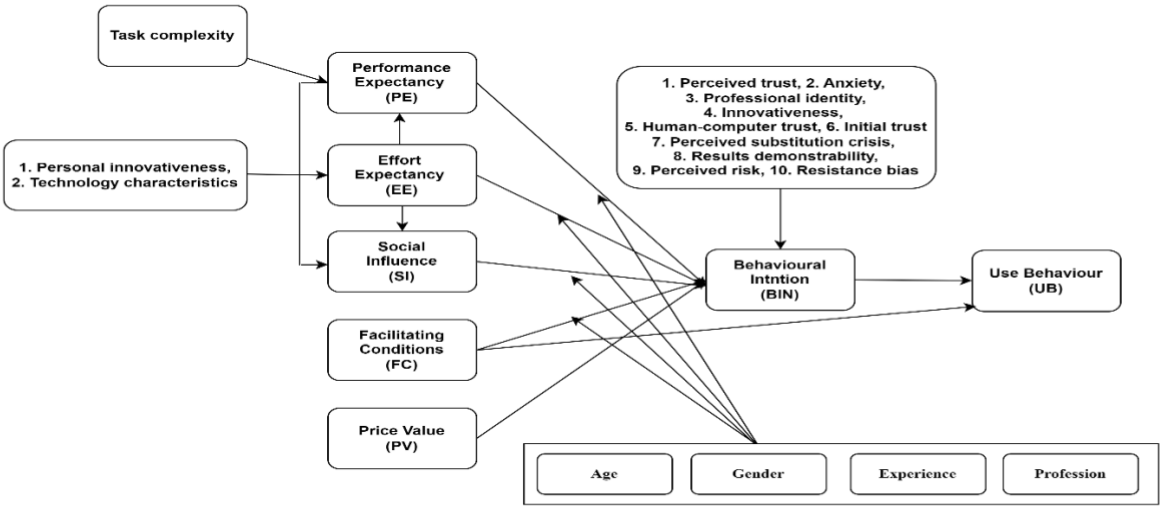

Figure 9: Different factors influencing the UTAUT when adopting AIR in healthcare

4. Discussion

The purpose of this study was to perform a systematic review to find papers addressing technological models/theories for AIR adoption in healthcare and the crucial factors influencing AIR adoption among countries. Hence, this study adds to previous knowledge on AIR adoption in healthcare in some ways. First, it acknowledged the contributions provided by previous studies and highlighted areas that require further investigation. AIR adoption by healthcare professionals in the healthcare sector is significant necessitating more research. Second, this study investigated factors influencing the adoption of AIR in healthcare across countries. These factors may potentially contribute to furthering research efforts in this area. The identification of different factors can significantly contribute to facilitating decision-making processes for AIR adoption in healthcare. Third, contrary to previous studies, this SLR conducted a comparative analysis of countries about the adoption of AIR in healthcare.

5. Gaps, limitations, and Future Work

The present study conducted a comprehensive systematic review and a rigorous analysis of the existing literature regarding the adoption of AIR in healthcare, which revealed several notable research gaps. First, policymakers and academics can identify more factors that influence users' AIR adoption in healthcare. Hence, further investigation of AIR implications in healthcare is required. Second, Saudi Arabia is the only country that has conducted research on AIR adoption in healthcare among Arab countries. Hence, it is imperative to do more research on the adoption of AIR in Arab countries. Finally, it is worth noting that there exists just one study that has verified data through the use of the SEM-ANN technique. Recently, several studies have employed the SEM-ANN technique as a methodological enhancement [46]–[48]. This kind of hybrid approach assists in decision-making [49], [50], validates the SEM findings [43], and offers a deeper understanding of the problem in the research [51]. Therefore, future studies on AIR adoption that apply dual-stage SEM-ANN analysis are required.

There are multiple opportunities for researchers and decision-makers to explore further this topic. It is crucial to recognise the limitations of this study to give an accurate overview for future research. There are two limitations to this research. First, it was limited to the widely used databases Scopus and Web of Science for this SLR. Future research may search databases including Scholar, EBSCO host, IEEE Explore, and Science Direct to identify and collect new papers. Second, the present study employed the research strategy known as article title. Future studies can use the research method known as article title, abstract, and keywords.

6. Conclusion

This study holds significance due to its novel approach in systematically investigating the adoption of AIR in healthcare, specifically focusing on technology adoption models and frameworks. Previous research in this area failed to comprehensively address this aspect. An SLR was conducted using the PRISMA technique [35]. Two databases, namely Web of Science and Scopus, were utilised to ensure a comprehensive examination of the literature. After reviewing the 7 selected studies from the literature, it was found that there are few studies available on the adoption of AIR in healthcare and that more research is needed. This study identified 23 factors influencing AIR adoption in healthcare. In China, fourteen factors were found and in the Netherlands 11 factors were discovered. The most critical factors for AIR adoption across countries were perceived usefulness, perceived ease of use, and behavioral intention. Furthermore, 13 factors affecting AIR adoption in healthcare were discovered in developed countries, while 17 factors in developing countries.

References

[1] K. Abouelmehdi, A. Beni-Hessane, and H. Khaloufi, "Big healthcare data: preserving security and privacy," *J. Big Data*, vol. 5, no. 1, pp. 1–19, 2018, doi: 10.1186/s40537-017-0110-7.

[2] B. Thakkar and S. V. Bharathi, "Medical Specialists' Perception About Adoption of Artificial Intelligence in the Healthcare Sector," *CARDIOMETRY*, no. 25, pp. 426–434, Feb. 2023, doi: 10.18137/cardiometry.2022.25.426434.

[3] A. Q. Tran *et al.*, "Determinants of Intention to Use Artificial Intelligence-Based Diagnosis Support System Among Prospective Physicians," *Front. Public Heal.*, vol. 9, no. November, pp. 1–9, Nov. 2021, doi: 10.3389/fpubh.2021.755644.

[4] A. Bohr and K. Memarzadeh, *The rise of artificial intelligence in healthcare applications*, no. January. 2020.

[5] C. Blease, C. Locher, M. Leon-Carlyle, and M. Doraiswamy, "Artificial intelligence and the future of psychiatry: Qualitative findings from a global physician survey," *Digit. Heal.*, vol. 6, p. 205520762096835, Jan. 2020, doi: 10.1177/2055207620968355.

[6] L. Cornelissen, C. Egher, V. van Beek, L. Williamson, and D. Hommes, "The Drivers of Acceptance of Artificial Intelligence–Powered Care Pathways Among Medical Professionals: Web-Based Survey Study," *JMIR Form. Res.*, vol. 6, no. 6, p. e33368, Jun. 2022, doi: 10.2196/33368.

[7] D. Straub, M. Keil, and W. Brenner, "Testing the technology acceptance model across cultures: A three country study," *Inf. Manag.*, vol. 33, no. 1, pp. 1–11, Nov. 1997, doi: 10.1016/S0378-7206(97)00026-8.

[8] A. Shachak, C. Kuziemsky, and C. Petersen, "Beyond TAM and UTAUT: Future directions for HIT implementation research," *J. Biomed. Inform.*, vol. 100, no. 103315, pp. 1–5, Dec. 2019, doi: 10.1016/j.jbi.2019.103315.

[9] F. D. Davis, "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Q.*, vol. 13, no. 3, p. 319, Sep. 1989, doi: 10.2307/249008.

[10] F. D. Davis, R. P. Bagozzi, and P. R. Warshaw, "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models," *Manage. Sci.*, vol. 35, no. 8, pp. 982–1003, Aug. 1989, doi: 10.1287/mnsc.35.8.982.

[11] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, "User acceptance of information technology: Toward a unified view," *MIS Q. Manag. Inf. Syst.*, vol. 27, no. 3, pp. 425–478, 2003, doi: 10.2307/30036540.

[12] V. Tucci, J. Saary, and T. E. Doyle, "Factors influencing trust in medical artificial intelligence for healthcare professionals: a narrative review," *J. Med. Artif. Intell.*, vol. 5, no. August 2021, pp. 4–4, Mar. 2022, doi: 10.21037/jmai-21-25.

[13] M. M. Assadullah, "Barriers to Artificial Intelligence Adoption in Healthcare Management: A Systematic Review," *Available SSRN 3530598*, 2019.

[14] U. Donins and D. Behmane, "Challenges and Solutions for Artificial Intelligence Adoption in Healthcare–A Literature Review," in *International KES Conference on Innovation in Medicine and Healthcare*, 2023, pp. 53–62.

[15] G. Karimian, E. Petelos, and S. M. A. A. Evers, "The ethical issues of the application of artificial intelligence in healthcare: a systematic scoping review," *AI Ethics*, vol. 2, no. 4, pp. 539–551, 2022, doi: 10.1007/s43681-021-00131-7.

[16] O. Ali, W. Abdelbaki, A. Shrestha, E. Elbasi, M. A. A. Alryalat, and Y. K. Dwivedi, "A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities," *J. Innov. Knowl.*, vol. 8, no. 1, 2023, doi: 10.1016/j.jik.2023.100333.

[17] D. V. Gunasekeran, R. M. W. W. Tseng, Y. C. Tham, and T. Y. Wong, "Applications of digital health for public health responses to COVID-19: a systematic scoping review of artificial intelligence, telehealth and related technologies," *npj Digit. Med.*, vol. 4, no. 1, pp. 1–7, 2021, doi: 10.1038/s41746-021-00412-9.

[18] S. S. Mahdi, G. Battineni, M. Khawaja, R. Allana, M. K. Siddiqui, and D. Agha, "How does artificial intelligence impact digital healthcare initiatives? A review of AI applications in dental healthcare," *Int. J. Inf. Manag. Data Insights*, vol. 3, no. 1, p. 100144, Apr. 2023, doi: 10.1016/j.jjimei.2022.100144.

[19] H. von Gerich *et al.*, "Artificial Intelligence -based technologies in nursing: A scoping literature review of the evidence," *Int. J. Nurs. Stud.*, vol. 127, p. 104153, 2022, doi: 10.1016/j.ijnurstu.2021.104153.

[20] I. Bin Mustapha, N. Khan, M. I. Qureshi, and A. Harasis, "Impact of Industry 4.0 on Healthcare: A Systematic Literature Review (SLR) from the Last Decade Sustainablity View project Sea freight for SME View project," *Int. J. Interact. Mob. Technol.*, vol. 1, pp. 116–128, 2021, [Online]. Available: https://doi.org/10.3991/ijim.v15i18.25531.

[21] A. Alanazi, "IoT and AI in Healthcare: A Systematic Literature Review," in *PLOMS Journal of Artificial Intelligence (PLOMS AI)*, 2021, pp. 319–343.

[22] A. S. Albahri *et al.*, "A systematic review of trustworthy and explainable artificial intelligence in healthcare: Assessment of quality, bias risk, and data fusion," *Inf. Fusion*, vol. 96, no. January, pp. 156–191, 2023, doi: 10.1016/j.inffus.2023.03.008.

[23] H. W. Loh, C. P. Ooi, S. Seoni, P. D. Barua, F. Molinari, and U. R. Acharya, "Application of explainable artificial intelligence for healthcare: A systematic review of the last decade (2011–2022)," *Comput. Methods Programs Biomed.*, vol. 226, p. 107161, Nov. 2022, doi: 10.1016/j.cmpb.2022.107161.

[24] A. Choudhury and O. Asan, "Role of Artificial Intelligence in Patient Safety Outcomes: Systematic Literature Review," *JMIR Med. Informatics*, vol. 8, no. 7, p. e18599, Jul. 2020, doi: 10.2196/18599.

[25] J. Wolff, J. Pauling, A. Keck, and J. Baumbach, "Systematic Review of Economic Impact Studies of Artificial Intelligence in Health Care," *J. Med. Internet Res.*, vol. 22, no. 2, p. e16866, Feb. 2020, doi: 10.2196/16866.

[26] M. M. Voets, J. Veltman, C. H. Slump, S. Siesling, and H. Koffijberg, "Systematic Review of Health Economic Evaluations Focused on Artificial Intelligence in Healthcare: The Tortoise and the Cheetah," *Value Heal.*, vol. 25, no. 3, pp. 340–349, Mar. 2022, doi: 10.1016/j.jval.2021.11.1362.

[27] T. Ciecierski-Holmes, R. Singh, M. Axt, S. Brenner, and S. Barteit, "Artificial intelligence for strengthening healthcare systems in low- and middle-income countries: a systematic scoping review," *npj Digit. Med.*, vol. 5, no. 1, p. 162, Oct. 2022, doi: 10.1038/s41746-022-00700-y.

[28] H. S. Jocelyn Chew and P. Achananuparp, "Perceptions and Needs of Artificial Intelligence in Health Care to Increase Adoption: Scoping Review," *J. Med. Internet Res.*, vol. 24, no. 1, pp. 1–19, 2022, doi: 10.2196/32939.

[29] A. T. Young, D. Amara, A. Bhattacharya, and M. L. Wei, "Patient and general public attitudes towards clinical artificial intelligence: a mixed methods systematic review," *Lancet Digit. Heal.*, vol. 3, no. 9, pp. e599–e611, 2021, doi: 10.1016/S2589-7500(21)00132-1.

[30] N. Mehta, A. Pandit, and S. Shukla, "Transforming healthcare with big data analytics and artificial intelligence: A systematic mapping study," *J. Biomed. Inform.*, vol. 100, no. October, p. 103311, 2019, doi: 10.1016/j.jbi.2019.103311.

[31] M. Nazar, M. M. Alam, E. Yafi, and M. M. Su'ud, "A Systematic Review of Human–Computer Interaction and Explainable Artificial Intelligence in Healthcare With Artificial Intelligence Techniques," *IEEE Access*, vol. 9, pp. 153316–153348, 2021, doi: 10.1109/ACCESS.2021.3127881.

[32] A. Khanijahani, S. Iezadi, S. Dudley, M. Goettler, P. Kroetsch, and J. Wise, "Organizational, professional, and patient characteristics associated with artificial intelligence adoption in healthcare: A systematic review," *Heal. Policy Technol.*, vol. 11, no. 1, p. 100602, 2022, doi: 10.1016/j.hlpt.2022.100602.

[33] S. F. S. Alhashmi, M. Alshurideh, B. Al Kurdi, and S. A. Salloum, "A systematic review of the factors affecting the artificial intelligence implementation in the health care sector," in *Proceedings of the International Conference on Artificial Intelligence and Computer Vision (AICV2020)*, 2020, pp. 37–49.

[34] A. Di Vaio, R. Palladino, R. Hassan, and O. Escobar, "Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review," *J. Bus. Res.*, vol. 121, no. January, pp. 283–314, 2020, doi: 10.1016/j.jbusres.2020.08.019.

[35] D. Moher, A. Liberati, J. Tetzlaff, and D. G. Altman, "Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement," *PLoS Med.*, vol. 6, no. 7, p. e1000097, Jul. 2009, doi: 10.1371/journal.pmed.1000097.

[36] D. Denyer and D. Tranfield, "Producing a systematic review.," 2009.

[37] R. B. Briner and D. Denyer, "Systematic review and evidence synthesis as a practice and scholarship tool," 2012.

[38] M. E. Falagas, E. I. Pitsouni, G. A. Malietzis, and G. Pappas, "Comparison of PubMed, Scopus, Web of Science, and Google Scholar: strengths and weaknesses," *FASEB J.*, vol. 22, no. 2, pp. 338–342, Feb. 2008, doi: 10.1096/fj.07-9492LSF.

[39] A. W. Harzing and S. Alakangas, "Google Scholar, Scopus and the Web of Science: a longitudinal and cross-

disciplinary comparison," *Scientometrics*, vol. 106, no. 2, pp. 787–804, Feb. 2016, doi: 10.1007/s11192-015-1798-9.

[40] M. Tian, P. Deng, Y. Zhang, and M. P. Salmador, "How does culture influence innovation? A systematic literature review," *Manag. Decis.*, vol. 56, no. 5, pp. 1088–1107, May 2018, doi: 10.1108/MD-05-2017-0462.

[41] L. Pittaway, M. Robertson, K. Munir, D. Denyer, and A. Neely, "Networking and innovation: a systematic review of the evidence," *Int. J. Manag. Rev.*, vol. 5–6, no. 3–4, pp. 137–168, Sep. 2004, doi: 10.1111/j.1460-8545.2004.00101.x.

[42] M. Cheng, X. Li, and J. Xu, "Promoting Healthcare Workers' Adoption Intention of Artificial-Intelligence-Assisted Diagnosis and Treatment: The Chain Mediation of Social Influence and Human–Computer Trust," *Int. J. Environ. Res. Public Health*, vol. 19, no. 20, p. 13311, Oct. 2022, doi: 10.3390/ijerph192013311.

[43] I. H. Rehman, A. Ahmad, F. Akhter, and A. Aljarallah, "A Dual-Stage SEM-ANN Analysis to Explore Consumer Adoption of Smart Wearable Healthcare Devices," *J. Glob. Inf. Manag.*, vol. 29, no. 6, pp. 1–30, Feb. 2022, doi: 10.4018/JGIM.294123.

[44] H. Zhai *et al.*, "Radiation oncologists⇔ perceptions of adopting an artificial intelligence⇓assisted contouring technology: Model development and questionnaire study," *J. Med. Internet Res.*, vol. 23, no. 9, 2021, doi: 10.2196/27122.

[45] W. Fan, J. Liu, S. Zhu, and P. M. Pardalos, "Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS)," *Ann. Oper. Res.*, vol. 294, no. 1–2, pp. 567–592, Nov. 2018, doi: 10.1007/s10479-018-2818-y.

[46] M. A. Al-Sharafi, M. Al-Emran, M. Iranmanesh, N. Al-Qaysi, N. A. Iahad, and I. Arpaci, "Understanding the impact of knowledge management factors on the sustainable use of AI-based chatbots for educational purposes using a hybrid SEM-ANN approach," *Interact. Learn. Environ.*, vol. 0, no. 0, pp. 1–20, May 2022, doi: 10.1080/10494820.2022.2075014.

[47] S. Parhi, K. Joshi, T. Wuest, and M. Akarte, "Factors affecting Industry 4.0 adoption – A hybrid SEM-ANN approach," *Comput. Ind. Eng.*, vol. 168, no. March, p. 108062, Jun. 2022, doi: 10.1016/j.cie.2022.108062.

[48] M. Elareshi, M. Habes, E. Youssef, S. A. Salloum, R. Alfaisal, and A. Ziani, "SEM-ANN-based approach to understanding students' academic-performance adoption of YouTube for learning during Covid," *Heliyon*, vol. 8, no. 4, p. e09236, Apr. 2022, doi: 10.1016/j.heliyon.2022.e09236.

[49] K. B. Ooi, J. J. Hew, and B. Lin, "Unfolding the privacy paradox among mobile social commerce users: a multi-mediation approach," *Behav. Inf. Technol.*, vol. 37, no. 6, pp. 575–595, Jun. 2018, doi: 10.1080/0144929X.2018.1465997.

[50] S. M. Wan, L. N. Cham, G. W. H. Tan, P.-S. Lo, K. B. Ooi, and R. S. Chatterjee, "What's Stopping You from Migrating to Mobile Tourism Shopping?," *J. Comput. Inf. Syst.*, vol. 62, no. 6, pp. 1223–1238, Nov. 2022, doi: 10.1080/08874417.2021.2004564.

[51] J. E. Scott and S. Walczak, "Cognitive engagement with a multimedia ERP training tool: Assessing computer self-efficacy and technology acceptance," *Inf. Manag.*, vol. 46, no. 4, pp. 221–232, May 2009, doi: 10.1016/j.im.2008.10.003.