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AI

MDPI

Systematic Review

Digital Technologies Impact on Healthcare Delivery: A Systematic Review of Artificial Intelligence (AI) and Machine-Learning (ML) Adoption, Challenges, and Opportunities

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Abstract: Recent significant advances in the healthcare industry due to artificial intelligence (AI) and machine learning (ML) have been shown to revolutionize healthcare delivery by improving efficiency, accuracy, and patient outcomes. However, these technologies can face significant challenges and ethical considerations. This systematic review aimed to gather and synthesize the current knowledge on the impact of AI and ML adoption in healthcare delivery, with its associated challenges and opportunities. This study adhered to the PRISMA guidelines. Articles from 2014 to 2024 were selected from various databases using specific keywords. Eligible studies were included after rigorous screening and quality assessment using checklist tools. Themes were identified through data analysis and thematic analysis. From 4981 articles screened, a data synthesis of nine eligible studies revealed themes, including productivity enhancement, improved patient care through decision support and precision medicine, legal and policy challenges, technological considerations, organizational and managerial aspects, ethical concerns, data challenges, and socioeconomic implications. There exist significant opportunities, as well as substantial challenges and ethical concerns, associated with integrating AI and ML into healthcare delivery. Implementation strategies must be carefully designed, considering technical, ethical, and social factors.

Keywords: artificial intelligence; machine learning; adoption; challenges and opportunities; healthcare delivery

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1. Introduction

Advances in digital technologies have revolutionized various industries, and healthcare is no exception. Digital technologies, such as artificial intelligence (AI) and machine learning (ML) have the potential to bolster healthcare-delivery efficiency, quality, and access by automating routine tasks, personalizing care, predicting outcomes, and supporting clinical decision-making [1]. AI refers to the ability of machines to perform cognitive tasks, like thinking, perceiving, learning, problem-solving, and decision-making, that are usually associated with humans. ML is an important subset of AI, referring to the ability of computer systems to learn from data without being explicitly programmed [2]. Other subsets of AI include deep learning, natural processing, and robotics.

A study by Thrall et al. [3] highlighted the positive impact of AI and ML adoption in healthcare delivery. One key area of impact is improved diagnostic accuracy. AI and ML algorithms can analyze substantial amounts of patient data, including medical images, test results, and patient records, to assist in the diagnosis of diseases. These algorithms can identify patterns, anomalies, and correlations that may be difficult for clinicians to detect [3]. Gulshan et al. [4] developed a deep-learning algorithm for detecting diabetic retinopathy in retinal fundus photographs. In a test set of images, the algorithm achieved 90.3% sensitivity and 98.1% specificity, outperforming ophthalmologists. Natural language processing (NLP) virtual assistants and chatbots are other areas of AI and ML that hold great opportunities. NLP techniques can extract and analyze information from unstructured clinical notes, research papers, and patient records [5].

AI and ML have also shown promise in research and population health management. These technologies can identify disease patterns, risk factors, and treatment outcomes on a population level, contributing to evidence-based decision-making, public health interventions, and developing preventive strategies [6]. Drug discovery and development are another area where AI and ML hold great promise. AI and ML algorithms can analyze large datasets, including molecular structures, genetic data, and clinical trial results, to accelerate the drug discovery and development process [7].

Through administrative automation, intelligent triage and routing, workflow optimization, supply-chain optimization, and intelligent monitoring, alert AI and ML can contribute to streamlining healthcare workflows [8]. AI-powered virtual assistants and chatbots can interact with patients, answer their questions, and provide basic healthcare information [9]. This can lead to increased efficiency, reduced administrative burden, enhanced patient care, and improved overall healthcare delivery.

Despite the acknowledged impacts and potentials of AI and ML in healthcare, the adoption of these technologies poses significant challenges. Ensuring data privacy, security, and ethical considerations are crucial in the era of digital healthcare. Char et al. [10] stated that the ethical implications of AI and ML algorithms, such as bias, fairness, and transparency, need to be carefully addressed to ensure equitable and responsible use of these technologies. The use of AI and ML in healthcare also raises liability and legal concerns, as noted by Naik et al. [11]. In particular, the issue of accountability in cases of errors or adverse outcomes resulting from AI and ML algorithms remains a complex challenge. While Ali et al.'s [12] systematic review thoroughly explores the healthcare benefits, challenges, methodologies, and functionalities of AI, it overlooks the specific concerns of healthcare professionals regarding the adoption of these technologies.

A literature review by Kuwaiti Al et al. [13] discusses the wider applications and implications of AI in various sectors of healthcare but fails to address the concerns of healthcare professionals about the potential limitations of AI in replacing human interaction in patient care. Similarly, the review by Udegbe et al. [14] addresses the broader applications and limitations of AI technologies in healthcare. However, it lacks the inclusion of specific concerns of healthcare professionals regarding the adoption of these technologies.

The lack of standardized approaches and interoperability among AI and ML systems and existing healthcare infrastructure according to He et al. [15] also pose challenges to adoption. The complexity and ever-changing nature of medical data, as noted by Esteva et al. [16], pose significant technical challenges to developing robust ML models. Another challenge is the need for algorithm training and validation, as healthcare data can be complex, unstructured, and distributed across various systems. Obtaining and curating datasets for the training and validation of AI and ML can be time-consuming and resource-intensive [17].

Additionally, the integration of AI and ML into existing healthcare systems requires organizational and cultural changes. Resistance to change, skepticism, and lack of awareness among healthcare professionals can hinder adoption efforts [18]. The black-box nature of some AI and ML algorithms, as noted by Saraswat et al. [19], can also be a limitation in healthcare.

Rationale of Research

The impact of digital technologies, particularly AI and ML in healthcare delivery, has gained significant attention due to their potential to revolutionize healthcare outcomes, efficiency, and patient experiences. While there is a growing body of literature on the applications of AI and ML in healthcare, much of the existing research is fragmented and lacks a comprehensive evaluation of the collective impact of these technologies. Individual studies often focus on specific applications or are limited to single institutions or regions, resulting in a lack of synthesized evidence.

By conducting a systematic review, this research aims to bridge these gaps and provide a comprehensive understanding of the benefits, opportunities, and challenges associated with the integration of AI and ML technologies in real-world healthcare settings and the overall impact of AI and ML adoption on healthcare delivery. In particular, the gaps addressed in our study include exploring the in-depth perspectives of healthcare professionals, healthcare leaders and experts in informatics, industry experts, and public and patients' perspectives regarding the use of AI and ML technologies in healthcare settings. The cultural differences and regional barriers in disease profiles and treatments associated with the integration of AI and ML technologies, as perceived by the participants in the published literature, are also explored in our study. Healthcare providers, policymakers, and researchers require evidence-based insights to make informed decisions regarding the adoption and implementation of AI and ML technologies in healthcare. By synthesizing the existing evidence, this research will provide a robust foundation for decision-making, policy development, and future research endeavors. The findings will enable stakeholders to understand the benefits, limitations, and potential risks associated with AI and ML adoption, thereby facilitating evidence-based decision-making in healthcare organizations.

2. Materials and Methods

2.1. Study Protocol

The Preferred Reporting Items for Systematic Review and Meta-analysis protocol (PRISMA) were followed for this systematic review [20].

The study's search was conducted by 3 researchers. The articles were screened using the inclusion criteria by two researchers who screened the articles to determine the consistency of article selection and inclusion of articles in English independently to reduce any subjective bias.

2.2. The Objectives of the Study Were To

- evaluate the impact and potential of AI and ML adoption in healthcare delivery;
- examine the challenges and ethical dilemmas presented by AI and ML adoption and implementation in healthcare settings;
- explore the opportunities and prospects presented by AI and ML adoption for optimizing healthcare delivery.

2.3. Method of Data Collection

The data collection for this study involved conducting a comprehensive literature search on identified relevant databases and screening and selecting relevant articles.

2.4. Search Strategy

The relevant electronic databases (PubMed, IEEE Xplore, ACM Digital Library, and Google Scholar) were searched for peer-reviewed studies. A combination of keywords, including "artificial intelligence (AI)", "Machine Learning (ML)", "Healthcare Delivery", "Adoption", "Implementation", "Challenges", and "Opportunities" was employed. The Boolean operators "And", "Or", and "Not" and proper parentheses were used to fine-tune the search to ensure that the relevant articles were efficiently retrieved from the databases. A hand search of the relevant references was also carried out.

2.5. Framing of Search Query

Table 1 informs the search query that was framed using the SPIDER (sample, phenomenon of interest, design, evaluation, research type) tool to ensure a structured and focused review.

Table 1. SPIDER framed search query.

Spider	Search Terms
Sample	Healthcare Organizations, Healthcare Systems, Healthcare Professionals, Administrators, Patients
Phenomenon of Interest	Artificial Intelligence, Machine Learning, Deep Learning, Neural Network
Design	Qualitative, Quantitative, or Mixed-Methods Studies
Evaluation	Adoption, Challenges, Opportunities
Research type	Primary research

2.6. Database Search Procedure and Search Strategy

The selected databases (PubMed, IEEE Xplore, ACM Digital Library, and Google Scholar) were searched by limiting the search to peer-reviewed articles published between January 2014 and April 2024 in the English language, using MeSH (medical subject headings) terms, as shown in Table 2. A hand search was also carried out.

Table 2. Search strategies and keywords used for database searches.

Database	Search Query/Format	Search Dates	Inclusion Year	Search Results
PubMed	("Healthcare Delivery" OR "Patient Care" OR "Healthcare Services") AND ("Artificial Intelligence" OR "Machine Learning") AND ("Impact" OR "Challenges" OR "Obstacles" OR "Opportunities")	25 April 2024	2014–2024	393
IEEE Xplore	("Healthcare Delivery" OR "Patient Care" OR "Healthcare Services") AND ("Artificial Intelligence" OR "Machine Learning") AND ("Impact" OR "Challenges" OR "Obstacles" OR "Opportunities")	25 April 2024	2014–2024	62
ACM Digital Library	("Healthcare Delivery" OR "Patient Care" OR "Healthcare Services") AND ("Artificial Intelligence" OR "Machine Learning") AND ("Impact" OR "Challenges" OR "Obstacles" OR "Opportunities")	25 April 2024	2014–2024	209
Google Scholar	(Artificial Intelligence" OR "Machine Learning") AND ("Impact" OR "Challenges" OR "Opportunities") AND ("Healthcare Delivery")	25 April 2024	2014–2024	4310
Hand Search		25 April 2024	2014–2024	7
Total Articles		25 April 2024	2014–2024	4981

2.7. Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were framed using the SPIDER (sample, phenomenon of interest, design, evaluation, research type), as presented in Table 3. The inclusion and exclusion criteria were used to ensure the selection of relevant studies that provided valuable insights into the impact of digital technologies in healthcare delivery, specifically focusing on AI and ML adoption, challenges, and opportunities.

Table 3. Inclusion and exclusion criteria.

Spider	Inclusion Criteria	Exclusion Criteria
Sample	Studies involving healthcare professionals, patients, or healthcare organizations implementing digital technologies, specifically focusing on AI/ML adoption in healthcare delivery.	Studies that did not focus on the impact of digital technologies in healthcare delivery, specifically AI and ML adoption.
Phenomenon of Interest	Studies examining the impact of AI and ML adoption on patient outcomes, healthcare efficiency, diagnostic accuracy, and workflow management.	Studies not focused on AI/ML adoption in the healthcare-delivery context.
Design	Qualitative, quantitative, or mixed-methods study designs.	Commentaries, Editorials.
Evaluation	Studies reporting on adoption, challenges, and opportunities regarding AI/ML in healthcare settings	Studies that did not address the adoption, challenges, or opportunities associated with these technologies.
Research type	Primary research	Research published in non-peer-reviewed sources.
Year Range	January 2014–April 2024	Articles before January 2014 and after April 2024.

The search results were then reviewed based on the predefined inclusion and exclusion criteria (Table 3). Articles relevant to the research question and objectives were included, and articles that did not meet the inclusion criteria were excluded, as presented in Table 4.

Table 4. Eligible articles.

Database	Search Dates	Inclusion Year	Search Results	Excluded	Included
PubMed	25 April 2024	2014–2024	393	380	13
IEEE Xplore	25 April 2024	2014–2024	62	44	18
ACM Digital Library	25 April 2024	2014–2024	209	197	12
Google Scholar	25 April 2024	2014–2024	4310	4281	29
Hand search	25 April 2024	2014–2024	7	3	4
Total Articles	25 April 2024	2014–2024	4981	4905	76

2.8. Titles and Abstracts Screening

Initial screening of titles and abstracts of the identified studies was conducted to exclude irrelevant articles that did not focus on the AI and ML adoptions, challenges, and opportunities in healthcare settings (Table 4). The screening process aimed to select studies that provided relevant insights into the adoption, challenges, and opportunities associated with AI and ML in healthcare delivery and contributed to the systematic review. After the titles and abstracts screening, 22 articles were identified.

2.9. Studies Selection

After evaluating the eligibility of each article based on title and abstract screening, the full text of the remaining 22 studies that passed the initial screening were then reviewed by 3 reviewers. The selection process aimed to identify studies that contributed valuable insights into the research aims and objectives and were suitable for inclusion in the systematic review. The selection process followed a rigorous scientific method to ensure the inclusion of relevant and high-quality studies. The full texts of the 22 remaining articles were carefully reviewed to determine if they provided substantial information on AI and ML adoption in healthcare delivery and addressed the challenges and opportunities associated with these technologies. Studies that did not provide sufficient data on the outcomes of interest were excluded from the final selection by 2 reviewers. The excluded papers were commentaries, editorials, review articles, conference papers, non-primary studies, and studies not focused on AI/ML adoption in the healthcare-delivery context that did not meet the inclusion criteria. Nine qualitative studies met the inclusion criteria after the full article review for quality assessment and were reviewed.

2.10. Quality Assessment of Included Studies

The quality and risk of bias of the nine eligible qualitative studies were assessed using the Critical Appraisal Skills Programme (CASP) checklists [21]. The quality assessment aimed to ensure that the included studies met rigorous methodological standards and minimized the risk of bias, thereby enhancing the reliability and validity of the systematic review findings. The CASP tools provide a structured approach to critically appraise the methodological rigor, validity, and reliability of the studies included in the systematic review [22]. The assessment of study quality contributed to the overall evaluation of the strength and robustness of the evidence related to the impact of digital technologies, specifically AI and ML adoption, challenges, and opportunities in healthcare delivery. The nine selected studies passed the quality assessment with all scoring seven and above out of the ten CASP qualitative studies checklist items and the ACcurate COnsensus Reporting Document (ACCORD) [23] checklist tool for the Delphi study and were included in the final review, as presented in Tables S1 and S2 and submitted as Files Materials in Supplementary Materials.

2.11. Data Synthesis

The selected studies were read and reviewed to understand the key concepts, findings, and perspectives presented in the study. This involved systematically highlighting relevant segments of the study results, such as quotes, excerpts, or summary statements, related to AI and ML adoption, challenges, and opportunities in healthcare delivery. The highlighted points were extracted, organized, and grouped into potential themes and subthemes according to Braun and Clarke's [24] thematic analysis, in alignment with the study's objectives. This process involved a careful examination of similarities and differences between the highlighted extracted points/concepts and the creation of meaningful clusters. The themes developed were based on the objectives of this study and the content of the included studies. The identified themes and subthemes were then reviewed, refined, and defined to ensure internal consistency and coherence and were presented comprehensively. The final step involved interpreting the themes and their implications within the context of the research topic and objectives.

3. Results

3.1. PRISMA Flow Chart

The PRISMA flowchart (Figure 1) was employed to ensure consistency and transparency throughout the literature search process. The PRISMA flow diagram visually represents the number of articles identified from various databases and the subsequent steps involved in screening, reviewing, and selecting relevant articles for inclusion in the study [20]. Following the PRISMA guidelines, this flow diagram provided a clear and structured overview of the literature search methodology, promoting transparency and reproducibility in the systematic review process.

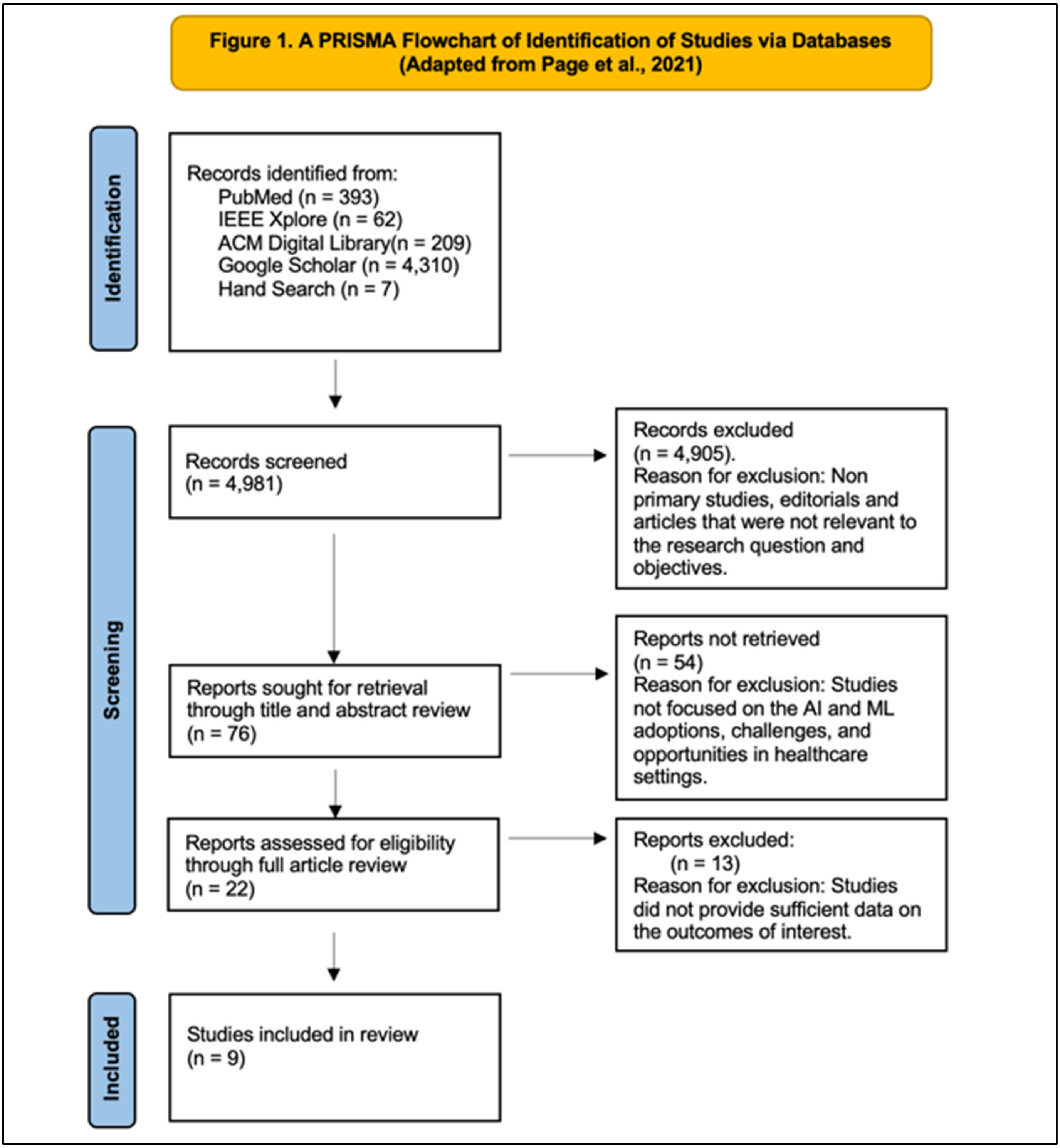

Figure 1. A PRISMA flowchart showing the literature search of the articles [20].

3.2. Data Extraction of Included Studies

Data extracted from the relevant studies were based upon the study's objectives, which included the evaluation of the impact and potential of AI and ML adoption on healthcare delivery; examination of the challenges and ethical dilemmas presented by AI and ML adoption and implementation in healthcare settings; and exploring the opportunities and prospects presented by AI and ML adoption for optimizing healthcare delivery, as shown in Table 5. The data-extraction process involved systematically reviewing each included study and extracting pertinent information using a standardized data-extraction form.

The extracted data included the title and author information for proper citation and identification. The publication year and date of data extraction were recorded to contextualize the study timeline. The study country was noted to understand the geographical context of the research. Information regarding the purpose of the study, study design, population characteristics, and sample size were extracted to gain insights into the study's focus, methodology, and target participants. The setting information provided details about the healthcare environment where the study was conducted. The extracted data served as the foundation for the subsequent analysis, synthesis, and interpretation of findings related to the impact of AI and ML in healthcare delivery.

3.3. Study Characteristics

The nine selected studies included in the final review are described below.

Petersson et al. [25] conducted a qualitative interview study with healthcare leaders in Sweden to investigate the challenges associated with implementing artificial intelligence (AI) in healthcare. The study focused on a regional healthcare setting in Sweden and aimed to gain insights into the perceived challenges faced by healthcare leaders about the integration of AI in healthcare. The research involved interviews with 26 healthcare leaders, providing a valuable qualitative perspective on the topic.

Pumplun et al. [26] conducted a qualitative interview study to examine the factors that influence the adoption of machine-learning systems for medical diagnostics in clinics. The research aimed to gain insights into the adoption process and understand the current state of adoption in clinics. The study involved interviews with 22 medical experts from clinics and their suppliers in Germany who had extensive knowledge in the field of machine learning.

Liyanage et al. [27] conducted a three-round Delphi qualitative study to establish a consensus on the perceptions, issues, and challenges surrounding the use of artificial intelligence (AI) in primary health care. The study involved experts in primary health care informatics and clinicians from multiple countries, including Australia, Belgium, Canada, Croatia, Italy, New Zealand, Spain, the United Kingdom, and the United States. In the first round, 20 participants were involved, followed by 12 participants in the second round, and 8 participants in the final round. The study's aim was to gather expert opinions and insights to identify and address the key issues and challenges related to integrating AI into primary healthcare settings.

Sun and Medaglia's study [28] aimed to map the challenges to implementing artificial intelligence (AI) in the public healthcare sector in China, as perceived by key stakeholders. The research adopted a qualitative case-study approach and involved interviews with government policymakers, hospital managers and doctors, and information technology (IT) firm managers. There were 20 participants included in the study.

In Alanazi's study [29], the author sought to investigate clinicians' perspectives on the current and potential applications of artificial intelligence (AI) in healthcare, as well as the challenges related to its implementation. The study used a qualitative approach, specifically focus group interviews, to gather insights from 26 clinicians. The research was conducted in Riyadh, Saudi Arabia, with a focus on healthcare delivery and the integration of AI with electronic health record (EHR) systems.

Blease et al. [30] conducted an exploratory qualitative study to investigate the perspectives of UK General Practitioners (GPs) on the potential impact of future technology on key tasks in primary care. The study involved 720 GPs practicing in various primary care settings across the United Kingdom. By exploring the views of GPs, the research aimed to gain insights into their opinions and expectations regarding the role of artificial intelligence (AI) and other emerging technologies in shaping the future of primary care.

Dumbach et al. [31] conducted a cross-national comparison to analyze the adoption of artificial intelligence (AI) in small and medium-sized enterprises (SMEs) in the healthcare sector in Germany and China. The study employed a qualitative multiple case study design and focused on examining the status of AI development and adoption, and the perceived advantages and challenges associated with AI in healthcare. Additionally, the researchers investigated the expected future development and implementation of AI in healthcare over the next five years. The study involved expert interviews with 14 SMEs in the healthcare sector.

In their 2023 study, Lammons et al. [32] conducted a qualitative research study to center the perceptions of patients and the public on the translation of artificial intelligence (AI) into clinical practice. The study aimed to understand the perceived benefits and challenges of AI from the perspectives of patients and the public, as well as to explore how patient and public involvement and engagement (PPIE) can be effectively conducted in projects related to translating AI into clinical practice, considering the public perceptions of AI. The research utilized a PPIE focus group consultation methodology involving public collaborators representing seven National Institute of Health and Care Research Applied Collaborations across England. Seventeen public collaborators participated in the study.

Katirai et al. [33] conducted an exploratory qualitative study to examine the perspectives of a Patient and Public Involvement Panel in Japan on the use of artificial intelligence (AI) in healthcare. The research employed a qualitative research design and involved 11 members of the Patient and Public Involvement Panel in Japan. The study was conducted online through the Apisnote platform. The research's aim was to gain insights into the views, opinions, and concerns of the panel members regarding the application of AI in healthcare.

3.4. Data Extraction and Synthesis

The themes and subthemes identified and extracted across the nine selected studies are presented in Table 5.

Table 5. Study characteristics of the included articles.

Author	Petersson et al. [25]	Pumplun et al. [26]	Liyanage et al. [27]	Sun and Medaglia, [28]	Alanazi [29]	Blease et al. [30]	Dumbach et al. [31]	Lammons et al. [32]	Katirai et al. [33]
Title:	Challenges to Implementing Artificial Intelligence in Healthcare: A Qualitative Interview Study with Healthcare Leaders in Sweden	Adoption of Machine Learning Systems for Medical Diagnostics in Clinics: Qualitative Interview Study	Artificial Intelligence in Primary Health Care: Perceptions, Issues, and Challenges	Mapping the Challenges of Artificial Intelligence in the Public Sector: Evidence from Public Healthcare	Clinicians' Views on Using Artificial Intelligence in Healthcare: Opportunities, Challenges, and Beyond	Artificial Intelligence and the Future of Primary Care: Exploratory Qualitative Study of UK General Practitioners' Views	The Adoption of Artificial Intelligence in SMEs—A Cross-National Comparison in German and Chinese Healthcare	Centring Public Perceptions on Translating AI Into Clinical Practice: Patient and Public Involvement and Engagement Consultation Focus Group Study	Perspectives on Artificial Intelligence in Healthcare From a Patient and Public Involvement Panel in Japan: An Exploratory Study
Publication Year	2022	2021	2019	2019	2023	2019	2021	2023	2023
Extraction Date	30 March 2024	30 March 2024	30 March 2024	30 March 2024	30 March 2024	30 March 2024	30 March 2024	30 March 2024	30 March 2024
Study Country	Sweden	Germany	Australia, Belgium, Canada, Croatia, Italy, New Zealand, Spain, United Kingdom, and USA	China	Saudi Arabia (Riyadh)	United Kingdom (UK)	Germany and China.	United Kingdom (UK)	Japan
Article Source	*BMC Health Services Research*	*Journal of Medical Internet Research*	*Yearbook of Medical Informatics*	*Government Information Quarterly*	*Cureus journal*	*Journal of Medical Internet Research*	*CEUR-WS*	*Journal of Medical Internet Research*	*Frontiers in Digital Health*
Study Purpose	The study aimed to explore the challenges perceived by healthcare leaders in a regional Swedish healthcare setting regarding the implementation of artificial intelligence (AI) in healthcare.	To explore the factors influencing the adoption process of machine-learning systems for medical diagnostics in clinics and to provide insights into measuring the clinic status quo in the adoption process.	To form consensus about perceptions, issues, and challenges of AI in primary care.	To map the challenges in the adoption of artificial intelligence (AI) in the public healthcare sector as perceived by key stakeholders.	The study aimed to explore the current and potential uses of artificial intelligence (AI) in healthcare from the perspective of clinicians, as well as to examine the challenges associated with its implementation.	The study aimed to explore the views of UK General Practitioners (GPs) regarding the potential impact of future technology on key tasks in primary care.	The study aimed to examine the current status of AI development and adoption, perceived advantages and challenges of AI, and the expected future development and implementation of AI in healthcare over the next five years.	To understand patients' and the public's perceived benefits and challenges for AI and to clarify how to best conduct patient and public involvement and engagement (PPIE) in projects on translating AI into clinical practice, given public perceptions of AI.	To explore the perspectives of a Patient and Public Involvement Panel in Japan regarding the use of artificial intelligence (AI) in healthcare.
Study Design	Qualitative interview study	Qualitative interview study	Three-round Delphi qualitative study	Qualitative case study	Qualitative study using focus group interviews	Exploratory qualitative study	Qualitative multiple-case expert interviews	Qualitative focus group study	Qualitative research design.

Table 5. *Cont.*

Author	Petersson et al. [25]	Pumplun et al. [26]	Liyanage et al. [27]	Sun and Medaglia, [28]	Alanazi [29]	Blease et al. [30]	Dumbach et al. [31]	Lammons et al. [32]	Katirai et al. [33]
Study Population and Participant Selection Criteria	Healthcare leaders in Sweden	Medical experts from clinics and their suppliers with profound knowledge in the field of machine learning.	Experts in primary health care informatics and clinicians	Government policymakers, hospital managers/doctors, and information technology (IT) firm managers.	Clinicians with interest in AI-enabled health technology	UK general practitioners (GPs) according to gender and age.	Industry experts from small and medium-sized enterprises (SMEs) in the healthcare sector in Germany and China.	Public collaborators representing 7 National Institute of Health and Care Research Applied Collaborations across England participated in the study and were those who had special interest in AI	Members of a Patient and Public Involvement Panel in Japan ensuring diverse perspectives and knowledge
Sample Size	26	22	Round 1 (n = 20), Round 2 (n = 12), Round 3 (n = 8)	20	26	720	14	17	11
Setting	Regional Swedish healthcare setting.	The study was conducted in clinics.	Primary healthcare setting	Public healthcare sector in China	Healthcare-delivery context and the integration of AI with electronic health record (EHR) systems.	GPs practicing in various primary care settings in the UK	Healthcare sector, specifically focusing on SMEs in Germany and China	National Institute of Health and Care Research Applied Research across England	Online setting using the Apisnote platform
Validity and reliability of findings	The study is rigorous in that it adhered to the Consolidated Criteria for Reporting Qualitative Research (COREQ) checklist, ensuring methodological rigor and quality standards. The snowball recruitment to select participants from a diverse sample. Semi-structured interviews conducted by trained researchers are clearly outlined and, therefore, contribute to data reliability. Qualitative content enhances reliability and consistency. The healthcare leaders' perceptions viewed qualitatively enhanced the study's validity, transparency, and reflexivity, along with professional translation of quotations, enhancing the credibility and trustworthiness of the study.	In-depth interviews using a qualitative approach, and the interviews with experts added to the rigor of the study. Data collection and analysis included theoretical sampling, iterative coding, and multi-researcher triangulation, adding further to the rigor and reliability of the study. The theoretical framework (NASSS) for analysis, model development, and triangulation of data sources ensured internal validity.	The structured three-round Delphi study, which provided clear guidelines and objectives, ensured rigor, credibility and consistency. Reliability is achieved through a panel of 20 experts participating in multiple rounds. Internal validity is demonstrated through a systematic approach in each Delphi round of appropriateness of the method used for data collection.	The study's use of multiple data sources and rigorous analysis techniques enhanced the reliability of the findings. However, there is no measure for inter-coder reliability or member checking; the internal validity is ensured via use of multiple data sources and triangulation. However, external validity is limited, as the focus is solely on the Chinese case study and cannot be generalized to the findings in other healthcare contexts	Purposive sampling ensured inclusion of participants with relevant perspectives and experiences, enhancing rigor and reliability of the study. An appropriate sample size was employed, ethical considerations were ensured, and the data collection method using semi-structured discussions and open-ended questions ensured further rigor. Participant demographics were transparent, and therefore, reproducibility and reliability of the study were further ensured. The study's validity was ensured by addressing ethical considerations. Triangulation minimized bias and enhanced validity, especially due to the consistency in perspectives across participants, allowing broader representativeness.	A broad representation was ensured using a web-based survey of UK General Practitioners. Anonymity ensured or encouraged possible honest responses and response validity. There was a respectable response rate of 48.84%, which enhanced sample representativeness. The survey instrument and consultations ensured face validity. Overall methodology can be replicated, as detail is described. External validity enhanced via the widely accessed Doctors.net.uk platform, enhancing internal validity by clear communication and comprehension.	Yin's guidelines were followed, ensuring a structured research procedure and data-collection procedures via interviews with diverse participants. Detailed methodologies, accurate transcription and translation processes, and data triangulation ensured data reliability, study rigor, and internal validity. Detailed descriptions allow assessment of findings' transferability. Interviews and analysis across different countries enhance external validity.	The use of Consolidated Criteria for Reporting Qualitative Research (COREQ) ensures transparency and validity of the research. Analysis reliability enhanced via iterative coding processes. Public collaborators who participated in focus groups contributed as coauthors and co-analysts adding credibility to the analysis. Closed-captioned recordings and pseudonymization of transcripts ensured transparent and reliable data analysis. Internal validity is demonstrated through authors' review, discussion of discrepancies, and clarifying edits, enhancing analysis credibility.	The methodologies are rigorous, as a balanced representation of patients, caregivers, and the public is included in participant selection. Detailed information about workshop sessions enhanced transparency and reproducibility, adding to reliability of the study.

Table 5. *Cont.*

Author	Petersson et al. [25]	Pumplun et al. [26]	Liyanage et al. [27]	Sun and Medaglia, [28]	Alanazi [29]	Blease et al. [30]	Dumbach et al. [31]	Lammons et al. [32]	Katirai et al. [33]
Main outcomes of the study	The study identified several challenges to implementing AI systems in healthcare that are categorized into three main areas: external conditions, capacity for change management, and transformation of professions and practices.	The study provided an integrated overview of factors specific to the adoption of machine-learning (ML) systems in clinics, utilizing the NASSS framework. It emphasizes the importance of deep integration while highlighting common challenges faced by clinics.	The study highlights the potential of AI to enhance both managerial and clinical decisions in primary care, particularly through predictive modeling and decision-making capabilities.	The study reveals biases among stakeholder groups in framing challenges related to AI adoption. These biases lead to distinct viewpoints across seven dimensions, with no shared issues identified.	AI offers various opportunities in healthcare, including decision-support systems, predictive analytics, natural language processing (NLP), patient monitoring, and mobile technology, which can enhance clinical procedures, patient engagement, continuity of care, and population health management. However, challenges and concerns surround the implementation of AI in healthcare, such as data quality, patient privacy, technical limitations, regulations, and cybersecurity threats. Integrating AI into existing systems poses operational challenges, and concerns exist about accuracy, reliability, and ethical implications.	The study provides foundational insights into GPs' views but acknowledges limitations in comment brevity and probing responses, suggesting further research to explore attitudes among other healthcare professionals and patients. Overall, the study underscores the importance of medical education to prepare physicians for potential technological changes in clinical practice.	The study highlighted the importance of addressing challenges in data quality, transparency, and legal guidelines for successful AI adoption. Limitations include sample-size constraints, prompting the need for further research in diverse contexts.	The study findings highlighted common concerns, such as data security and bias. Public involvement is deemed crucial for successful AI implementation. Benefits include system improvements and enhanced patient care quality, while concerns revolve around security, bias, and potential loss of human touch in decision-making.	The themes highlighted consistent concerns such as patient autonomy and data, security. Notably, concerns about bias, regulatory frameworks, and commercial involvement were absent among Japanese participants.

The summary of the findings of the nine selected studies is presented below under the themes identified and is also shown in Table 6.

Table 6. Subthemes and themes identified.

Theme 1: Impact and Potentials of AI and ML Adoption in Healthcare Delivery **Subtheme 1: Advantages of integrating AI and ML into healthcare** According to the studies by Blease et al. [30] and Katirai et al. [33], the use of AI as a personal assistant was highlighted by many GPs, as shown below: *"Be useful to develop AI to do analyses of pathology returns, and read all the letters, to provide another presence in the consulting room, and to write the referral letters, organize investigations and the like, i.e., act like a personal assistant might do"* [Participant 135] [30] (p. 4). *"I think technology's place is more about informing patients about conditions and management booking appointments, ordering prescriptions, contacting the surgery* via *the internet rather than the phone"* [Participant 683] [30] (p. 4). *"Please hurry up with the technological advances to take away some of the crap that I still have to sort out—then I will be able to get back to proper diagnosing and doctoring"* [Participant 693] [30] (p. 4). *"The possibility that healthcare professionals will be able to concentrate on the work that they should be able to focus on"* [Extract 1, Group 2] [33] (p. 03).
Subtheme 2: AI's Contribution to Medical Performance and Efficiency Participants' perspectives from studies by Dumbach et al. [31] and Blease et al. [30] served to highlight the efficiency of AI in the healthcare sector, as shown below: *"AI is seen as a technology that leads to better performance compared to humans or traditional algorithms. Higher accuracy (C4–5, C7), better data processing (G3–4), path planning for medical robots (C2), or the ability to find solutions for existing problems (G1) are linked to this benefit category."* [Several Participants] [31] (p. 91). *"Medicine will be unrecognizable compared to its present form in 25 years"* [Participant 312] [30] (p. 5). *"All twelve AI adopters highlighted 'efficiency improvement' as a benefit, that manifests in* e.g., *speeding up data and image processing (G1–5, C1, C5–7) or improving management efficiency (C2–4)."* [Several Participants] [31] (p. 91).
Subtheme 3: AI Replacing Routine or Simple Tasks The advantages and disadvantages of AI in carrying out mundane tasks were also observed as a positive outcome of the use of AI in the healthcare sector, as shown in the studies by Sun and Medaglia [28], below: *"Some simple and boring work may be replaced by AI. But not all jobs."* [1GOV01] [28] (p. 376). *"Doctors may feel they will be replaced [by Watson]. Because they [i.e., the doctors] made many efforts to achieve their status."* [3IT04] [28] (p. 376). *"Hospital managers/doctors report to experiencing frustration when facing the real technology after the societal hype."* [3IT01] [28] (p. 373).
Subtheme 4: AI Assisting in Data Interpretation and Automation and Enhanced Diagnostic and Imaging Capabilities The use of AI in data interpretation was also mentioned in two studies [30,33]: *"AI may make it easier to interpret a blood result or follow a protocol, but AI will always struggle when the same human can score 1/10 for a symptom today and 10/10 tomorrow"* [Participant 201] [30] (p. 4). *"AI can assist with routine tasks, such as analyzing pathology results or organizing patient records, acting like a personal assistant."* [Participant 135] [30] (p. 4). *"AI was expected to facilitate better communication in clinical settings, and overall, there was the expectation that AI would become a familiar entity in patients' lives, with hopes for personalized interactions"* [Extract 3, Group 2] [33] (p. 4).
Subtheme 5: Patient and Public Adaptation to AI Integration According to participants in patient and public involvement (PPI), in a study by Katirai et al. [33], the PPI groups raised concerns about acceptability by patients. *"The question is whether they will be acceptable to patients although they may be very accessible compared to the current system"* [Participant 88] [30] (p. 5).
Subtheme 6: Improved Access and Communication and Potential For Enhanced Data Utilisation According to participants in patient and public involvement (PPI) in a study by Katirai et al. [33], the PPI groups felt that AI would be useful for improving patient communications and reducing disparities in healthcare. *"Standardization of the level of healthcare, elimination of the concentration of patients at large hospitals"* [Extract 6, Group 2] [33] (p. 4). *"Possibility of clinical examinations and treatment from home for people in remote areas, the elderly, and people with disabilities"* [Extract 2, Group 2] [33] (p. 4). Another study by Petersson et al. [25] highlighted ways in which AI could be used to improve communications with patients: *"If the legislation is changed so that the management information can be automated. . .but they're not allowed to do that yet. It could, however, be so that you open an app in a few years' time, then you furnish the app with the information that it needs about your health status. Then the app can write a prescription for medication for you."* [Leader 2] [25] (p. 5–6).

Table 6. *Cont.*

Subtheme 7: Enhancing Diagnosis, Therapeutics, and Patient Care Alanazi's study [29] focuses on the use of AI in facilitating personalized treatment recommendations, improving patient outcomes, and for the use of precision medicine, which are direct components of personalized medicine. The study by Lammon et al. [32] extended insights into the perspective of public collaborators on the perceived benefits and challenges of adopting AI in clinical practice. The study by Katirai et al. [33] identified the expectation of improved quality of care and personalized interactions as one of the benefits of AI in healthcare. This implies the use of AI to provide individualized care experiences to patients, aligning with the principles of personalized medicine. These are supported by quotes from participants from some of the above studies: *"The integration of AI technology has significantly improved healthcare. It has made patient record management more efficient, boosted diagnostic accuracy, and allowed physicians to devote more time to patient care."* [29] (p. 3). *"The integration of AI into EHRs has streamlined the extraction and analysis of detailed data, thereby facilitating the development of personalized treatment recommendations and ultimately leading to improved patient outcomes."* [29] (p. 3). *"The healthcare organization has been transformed by incorporating AI technologies into their process, clinically and administratively. AI technology has enhanced the efficiency of patient data extraction, analysis, and treatment recommendations by aiding decision-making processes."* [29] (p. 3). *"With emerging applications of AI in medical imaging technology and diagnostic screenings, there has been an unprecedented enhancement in patient care."* [29] (p. 3). *"Excited about the future of healthcare because AI will be something the children will be familiar with going forward"* [Extract 3, Group 1] [33] (p. 4). *"In the future, the researchers, when they have large data, AI will help to accurately analyze them."* [FG1] [32] (p. 5). *"AI can even detect things before […] a human can."* [FG3] [32] (p. 5). *"AI can be used for detection…monitoring…management…decision making…as a carer, I think there is a lot of elements to AI, which I don't think healthcare providers are using enough."* [FG2] [32] (pp. 5–6). Blease et al.'s study [30] focuses on participant skepticism about AI's ability to replicate the human aspects of care, such as empathy and non-verbal communication, which are ethically important in patient care: *"Technology will never attain a personal relationship with patients. We are essentially a people business. It's personal relationships that count"* [Participant 45] [30] (p. 3). *"Technology cannot replace doctors. There is definitely a 6th sense"* [Participant 635] [30] (p. 3). *"Technology won't replace GPs as patient management is about negotiation and managing risks and different patients have different views"* [Participant 703] [30] (p. 4). The study [30] also discussed the patient acceptance of AI accountability and trust: *"The somewhat blunt tool of technology as it stands will need to evolve some way before the culture of clinicians and patients will accept it"* [Participant 453] [30] (p. 5). *"Technology will be supporting clinicians in the very near future—the issue is responsibility and liability in legal terms for such tools"* [Participant 453] [30] (p. 5). Lammons et al.'s study [32] discusses the data security and bias associated with data security, emphasizing the need for ethical data management: *"AI picking up more Black people than the white population…we have to consider those kinds of ethical questions."* [FG2] [32] (p. 6). *"We have to be careful…when we code the programming for AI, that [it] isn't just the white population."* [FG2] [32] (p.6). *"Some contributors warned that AI, through challenges like access and bias, could increase inequality. We need to think about how it's going to affect everyone. I think we are running in terms of artificial intelligence and some people are going to get left behind.* [FG1] [32] (p. 6). *"You must involve patients and families and carers in that development and the design […]. Without that […] systems will be meaningless or less effective."* [FG2] [32] (p. 7). Patient Involvement in AI design was at the heart of Lammon et al.'s study [32]. Participants in this study focused on inclusivity: *"You must involve patients and families and carers in that development and the design. Without that, systems will be meaningless or less effective."* [FG2] [32] (p. 7). *"Certain Black minority ethnic people feel that this is yet another white exercise for white people. If you've got clinicians, leaders, researchers who have got their same background, they will appeal to a certain group."* [FG3] [32] (p. 8). Katirai et al. [33] found that members of the Patient and Public Involvement Panel (PPIP) had high expectations for AI's impact, anticipating improvements in hospital administration, better quality of care, resource optimization, enhanced diagnosis and treatment, personalized interactions, cost savings, and reduced healthcare disparities. One patient participant expressed hopes for AI to simplify hospital procedures, shorten waiting times, and improve accessibility: *"I expect that procedures at the hospital will be simplified… I hope that hospital visits will no longer exhaust patients and lead to a breakdown in their health"* [Extract 5, Group 3] [33] (p. 4).

Table 6. *Cont.*

Theme 2: Challenges, Limitations, Concerns, and Risks Alanazi [29] outlined several challenges associated with AI adoption in healthcare, including concerns about data quality, privacy, and cybersecurity, as well as ethical and philosophical questions. Workforce displacement, transparency issues, cost allocation, and unintended consequences of AI also emerged as key barriers. One participant voiced concerns about AI governance: *"Biased data can lead to unfair outcomes, while a lack of transparency and regulation can result in AI misuse. Proper governance is crucial for ethical and responsible AI use that does not harm society"* [29] (p. 4). Katirai et al. [33] revealed additional concerns from the public, such as the potential for AI to alter healthcare dynamics and limit human autonomy, as well as issues with accuracy, accountability, and ethical implications. One group member raised concerns about AI's tendency toward absolutes: *"I think that in healthcare, the language of 'absolutes' is avoided, but AI healthcare may come with such absolutes" Psychological anxiety over the lack of human interaction was also noted, with one participant expressing worry about "no longer being able to meet the real thing"* [Extract 7, Group 1] [33] (p. 5). Dumbach et al.'s [31] and Katirai et al.'s [33] findings all showed participants' concerns regarding reliability and technological limitations: *"Ten interviewees showed a consistent opinion regarding 'reliability and technological limitations,' concerning the current AI accuracy and needed supervision (G3, C1, C5–7) or existing issues of non-reproducibility and robustness in heterogeneous environments (G2–3)."* [G3, C1, C5–7, G2–3] [31] (p. 2). *"Issues of backups when online platforms are unavailable due to natural disasters, etc."* [Extract 10, Group 2] [33] (p. 5).
Theme 3: Opportunities and Prospects Presented by AI and ML **Subtheme 1: AI's Role in Enhancing Patient Care and Reducing Healthcare Disparities** The potential for AI to reduce healthcare disparities and improve patient experience was a significant opportunity highlighted by Katirai et al. [33]. In particular, AI's ability to optimize resources, enhance diagnosis and treatment, and provide personalized care were seen as key factors in improving healthcare outcomes: *"It will become easier to accumulate and search (personal) information"* [Extract 4, Group 3] [33] (p. 4). Petersson et al. [25] noted that AI can support patients, which can lead to more effective self-care and management of chronic conditions. *"The complexity in terms of for example apps is very, very, very much greater, we see that now. Besides there being this app, so perhaps the procurement department must be involved, the systems administration must definitely be involved, the knowledge department must be involved and the digitalization department, there are so many and the finance department of course and the communication department, the system is thus so complex"* [Leader 9] [25] (p. 9). Similarly, Pumplun et al. [26] suggest that AI can enhance the interpretation of large datasets, which is crucial for personalized treatment plans, since many physicians feel that they have fewer numbers of years of experience when compared to ML datasets: *As a doctor who may have ten or 20 years of experience [. . .], would I like to be taught by a machine [. . .]?* [S-03] [26] (10). *"Nowadays, in the feel of health inequality and so on, I feel sometimes AI perhaps can be a fairer instrument"* [FG3] [26] (p. 6). *"It's like with the police force, the facial recognition and AI [. . .] picking up more Black people than the white population. . . we have to consider those kind of ethical questions"* [FG2] [26] (p. 6). *"I feel sometimes, patient safety could be endangered if you have, a very rigid, algorithm, that overlook [sic] some sometime very vital clue"* [FG3] [26] (p. 7).
Subtheme 2: Risks Associated with Use Of AI and ML In Healthcare Liyanage et al. [27] highlighted the risks associated with AI in primary care, such as the limited competence of current AI technology in replacing human decision-making in clinical scenarios, risks of medical errors, biases, and secondary effects of AI use. The study also emphasized the need for regular scrutiny by clinicians due to uncertainties regarding AI accuracy and relevance. Sun and Medaglia [25] emphasized several challenges, including societal misunderstandings of AI's capabilities and a lack of innovation spirit, especially in comparison to Western countries. An IBM China director noted: *"We have to say the innovation spirit in the U.S. should be admired by us [Chinese]. [. . .] We need to learn from them"* [2IBM01] [25] (p. 373). The ethical and social challenges highlighted in Sun and Medaglia's study involved issues related to racial differences and disease profiles. For instance *"Western countries have more vascular-related diseases, while China has more hepatic diseases"* [5GOV01] [25] (p. 373). Differences in treatment attitudes, such as cancer management, also present a challenge: *"In the West. . . there is a greater emphasis on managing cancer as a chronic disease. [In China] patients do not see it this way"* [1HP01] [25] (p. 373). Pumplun et al. [26] identified the lack of transparency and adaptability in ML systems as significant barriers to their adoption. The fragmented nature of proprietary clinic systems and legal concerns, such as liability for incorrect ML model results, were cited as critical challenges: *"Who is responsible for the interpretation and possibly wrong results of the ML model?"* [C-14] [26] (p. 10). Liyanage et al. [27] acknowledged the potential of AI to improve healthcare delivery but recommended further scrutiny of AI systems and mechanisms to detect biases in unsupervised algorithms. This suggests a future where AI systems could become more refined and trusted in primary care settings. Sun and Medaglia [28] noted that AI systems like Watson could offer solutions to healthcare challenges, but these opportunities are hampered by societal and technological limitations, including the need for more country-specific data and standards.

Several subthemes were highlighted by the participants in our systemic review under the three main themes of (1) impact and potentials of AI and ML adoption in healthcare delivery, (2) challenges, limitations, concerns, and risks, and (3) opportunities and prospects presented by AI and ML, which are presented here accordingly under the three themes and subthemes with applicable quotes from the studies, as shown below in Table 6 and further depicted with key points in Table S3 in Supplementary Materials.

The overall common themes identified (Table 6) cover a wide range of aspects related to the impact, challenges, and opportunities of AI and ML adoption in healthcare delivery. These themes cover areas such as productivity enhancement, improved patient care, legal and policy challenges, technological considerations, organizational and managerial aspects, ethical concerns, data challenges, social and economic implications, and specific applications of AI and ML in healthcare. The themes identified do share commonalities in terms of the impact, challenges, and opportunities associated with the adoption and implementation of AI and ML in healthcare settings. Some prevalent trends include the potential for productivity and workflow improvements, enhanced quality of patient care through decision support and precision medicine, concerns related to legal and policy frameworks, challenges in data management and ethics, and the need for addressing technological and organizational considerations. The data does not necessarily point in one direction only. Instead, it highlights a range of perspectives, opportunities, challenges, and risks associated with the adoption and implementation of AI and ML in healthcare settings. These themes identified reflect a diverse set of considerations and viewpoints, indicating the multifaceted nature of this topic.

4. Discussion

The adoption of artificial intelligence (AI) and machine learning (ML) in healthcare settings has gained significant attention due to its potential to revolutionize healthcare delivery. This study aimed to systematically review the impact of digital technologies, specifically AI and ML, in healthcare delivery, focusing on the adoption, challenges, and opportunities. This discussion is structured into three themes based on the objectives of the study, namely the impact and potential of AI and ML adoption, the challenges and limitations associated with adoption and implementation, and the opportunities and prospects presented by AI and ML adoption for optimizing healthcare delivery.

4.1. Theme 1—Impact and Potentials of AI and ML Adoption in Healthcare Delivery

The reviewed studies highlighted several benefits and potentials of adopting AI and ML in healthcare delivery. These include enhancing productivity and efficiencies, better performance compared to traditional algorithms, talent attraction, cost reduction, workload reduction for physicians, system improvements, improved quality of patient care, improved hospital administration, and reduced healthcare disparities.

Enhancing productivity and workflow efficiencies is a frequently cited advantage, as these technologies can assist with administrative tasks and paperwork [30–34]. This aligns with findings from another study that showed a significant reduction in documentation time using AI documentation assistants [34]. However, as noted by Liu et al. [32] realizing productivity gains involves changing clinician workflows and responsibilities, which can pose adoption challenges. While the review suggested AI can improve clinician productivity and reduce workload, it is unclear if these benefits persist long-term [34]. Productivity gains from technology adoption often decrease over time as users find ways to fill up the recovered time [33]. To sustain benefits, workflow redesign and continued user engagement are needed.

The studies also highlighted the potential for AI and ML algorithms to outperform humans or traditional statistical methods in certain clinical tasks, like diagnostic accuracy and treatment planning [32–34]. For instance, the ability of AI algorithms has been demonstrated to outperform human experts in diagnosing certain medical conditions [34]. This supports the notion that AI and ML technologies can improve the accuracy and efficiency of healthcare delivery. The diagnostic superiority of AI algorithms over healthcare professionals for conditions like skin cancer, ophthalmic diseases, and neurological disorders has also been demonstrated [32,35]. However, it should be noted that performance varies across algorithms and medical specialties [33]. More research is needed to establish the reliability of AI diagnosis across diverse patient populations, as there may be limited data for training AI models for different patient populations and rare diseases [33].

Several studies mentioned talent attraction, cost reduction, and workload reduction for clinicians as the benefits of adopting AI and ML in healthcare [32–34]. However, realizing these benefits may require significant upfront investments in technology infrastructure. Cost and resource allocation are key challenges associated with AI adoption [29]. Healthcare systems must strategically evaluate costs versus expected benefits when adopting AI solutions. The review also highlighted talent attraction as a benefit of adopting AI, but this could also increase disparities. There are risks of exacerbating inequities, as more privileged health systems gain early access to scarce AI talent [36].

These findings are consistent with previous studies that have highlighted the transformative potential of AI and ML technologies in healthcare. However, evidence of actual realized benefits is still limited. Most published studies are proofs-of-concept or prototypes, with few rigorously designed trials evaluating impacts on patient outcomes or system performance [37]. More research is needed on the tangible impacts of AI and ML technologies after implementation in real-world clinical settings, such as an implementation study across diverse care settings to evaluate the real-world effectiveness, as well as the unintended consequences of specific AI solutions designed to improve care quality, coordination, and accessibility.

In summary, while promising, current evidence on the impacts of AI and ML in healthcare remains limited. More pragmatic research is needed on tangible system-level outcomes over long time horizons. To actualize the full benefits, careful implementation and change management will be essential. International collaborations and public sector participation will be important to ensure balanced AI skill development globally.

4.2. Theme 2—Challenges, Limitations, Concerns, and Risks

The systematic review identifies various challenges and concerns related to the adoption and implementation of AI and ML in healthcare settings. These include government regulations and policy challenges, technological challenges, organizational challenges, acceptance by physicians and patients, data challenges, social challenges, economic challenges, and ethical challenges. These findings are consistent with the literature on AI and ML adoption in healthcare, which has highlighted the need for addressing legal and policy frameworks, ensuring data quality and privacy, managing workforce displacement, building trust in AI systems, and addressing ethical concerns [38,39]. The identification of these challenges underscores the complexity of integrating AI and ML technologies into healthcare systems and the need for comprehensive strategies to address them.

The reviewed studies highlighted concerns around integrating AI and ML into healthcare, including ethical issues, legal and regulatory uncertainties, lack of transparency, and limitations in accuracy and accountability [29,32]. Another study has shown that key challenges include unclear legal liability, the validity of real-world evaluation metrics, opaque development processes, and integrating AI safely into clinical workflows [40]. It has also been highlighted that regulatory gaps around privacy, safety validation, and liability present barriers to translating AI innovations into clinical practice [10]. The legal, regulatory, and policy issues raised are critical to address, as healthcare AI and ML systems must comply with data protection, privacy, and other regulations [41]. Collaborating with policymakers to develop appropriate frameworks will be key.

Several studies emphasized technological challenges, like developing systematic implementation approaches, building trust in AI systems, and addressing technical limitations and biases [26,28,29]. These technological barriers are common issues with any modern technology adoption [42]. The concerns about trust, limitations, and biases are well-founded given AI's and ML's nascency in healthcare [43]. A major concern is medical errors and patient harm from the "black box" nature of AI systems. It is argued that poor model interpretability could lead to inappropriate and unsafe uses of AI in clinical practice [44]. Strategies like developing explainable AI models, auditing algorithms, and integrating human oversight during deployment are critical to mitigate risks of errors. More research and design focused on building transparent, interpretable, and unbiased AI will be needed [45]. However, the availability of Biobanks globally, initiated to capture and store large-scale biomedical, clinical, imaging, and genomic data, which provide a rich research resource, will go a long way in addressing some of these challenges [46].

Other prominent concerns included limitations in AI's capability to replicate human clinical reasoning and empathy [30], threats of workforce displacement, and risks related to cybersecurity and data privacy [29]. Variations in clinical practice patterns will challenge broad AI adoption. Standardized protocols and a judicious adaptation of care patterns to align with algorithm design will be needed [47]. This highlights the socio-technical factors involved in successfully embedding AI and ML within healthcare. Organizational challenges around strategy alignment, workflows, and workforce are expected transition pains with any disruptive technology [48]. As highlighted in the review, workforce impacts from AI remain unclear but concerning. Analyses predict automation could affect a substantial number of jobs within 20 years [49]. Proactive policies around training, job transitioning, and social support will be important to mitigate displacement. Proactive change management and training will be vital to the human–AI collaboration [50].

The potential for AI systems to embed and propagate biases was a common concern [29–33]. Biased datasets and algorithms can lead to inequitable patient care. The data challenges highlighted, including quality, standardization, ethics, and accessibility, represent significant hurdles for healthcare AI and ML adoption [51]. The sector's data is complex, siloed, and regulated. Developing the tools and standards for responsible data sharing and AI training will enable advances [52]. Multiple studies have shown issues with algorithmic bias, disfavoring marginalized groups, including racial/ethnic minorities and women [10,36]. Biases can arise from limitations in training data composition and labeling. Most of the evidence comes from high-income country contexts utilizing curated clinical datasets, thus limiting transferability, and the understanding of opportunities and barriers faced under resource constraints that are common in many low- and middle-income settings [53]. Providers must consciously evaluate algorithms for fairness before deployment in care settings. Rigorous testing and ongoing monitoring of AI systems using diverse patient data is essential to evaluate and mitigate the risks of bias [10]. Dixon et al. [54] noted that health agencies face unique barriers to integrating these digital tools due to budget constraints, workforce capacity issues, and meeting diverse community health needs.

Concerns around the acceptance of AI systems by clinicians and patients were a prevalent theme [29,30]. Physician and patient buy-in will make or break adoption success [55]. Physicians may resist disruptions to traditional clinical practice, while patients may be skeptical of being diagnosed or treated by an algorithm. The social, economic, and ethical concerns noted should caution against hasty AI and ML development and implementation in healthcare settings [10]. AI could widen disparities, and oversight is required to ensure it improves access [56]. Costs and benefits to various stakeholders need equitable analysis to ensure the realization of the gains of AI/ML deployment [57]. Fostering trust through stakeholder engagement and transparency around AI capabilities and limitations is critical [34]. In summary, while AI offers opportunities, implementing it safely in healthcare will require addressing complex challenges around ethics, law, human–AI collaboration, and social impacts. Several of these pose risks of direct harm if not addressed proactively. This will necessitate developing appropriate regulatory regimes, technical strategies, and organizational policies.

4.3. Theme 3—Opportunities and Prospects Presented by AI and ML

The systematic review identifies several opportunities and prospects presented by AI and ML adoption for optimizing healthcare delivery. These include decision-support tools and systems, pattern recognition in imaging results, predictive modeling of health data, business analytics for providers, precision medicine, robotic surgeries, drug discovery and development, and population health management. These findings align with previous research that has highlighted the opportunities and benefits of AI and ML technologies in the various aspects of healthcare delivery. Key prospects include AI-enabled diagnostic tools, intelligent clinical decision-support systems, personalized treatment planning, and population health analytics [56].

The reviewed studies highlighted the opportunities presented by AI for enhancing clinical decision-making, pattern recognition in medical images, predictive analytics, and business analytics [29]). Several reviews have evaluated the potential of AI for improving cancer screening and diagnosis through the automated analysis of medical imaging [34,57]. AI imaging algorithms can rapidly analyze large datasets of CT scans, X-rays, and tissue slides to detect lesions and abnormalities that are difficult for humans to consistently identify. Another study demonstrated the effectiveness of AI-based decision-support systems in the improvement of clinical decision-making and patient outcomes [58]. By optimizing the speed and accuracy of diagnosis, AI can improve cancer outcomes through earlier intervention. In predictive analytics, AI techniques using deep learning for electronic health records analysis show promise for identifying patients at risk of hospital readmission or mortality and prompting early intervention [34]. However, realizing these opportunities requires a careful evaluation of algorithmic performance, integration with clinician workflows, and ongoing updates as new data emerges. User-centered design, clinician training, and iteration will be critical for successfully translating AI prototypes into clinical practice. Other promising applications include precision medicine, robotic surgery, drug discovery, population health management, natural language processing for clinical notes, and virtual health assistants [29]. In drug discovery, AI methods can rapidly screen thousands of molecular candidates, predict interactions, and design optimized compounds to accelerate the development of new therapies [59]. However, realizing these will require building integrated AI ecosystems within provider organizations. Realizing the benefits of AI and ML in healthcare requires addressing key challenges around transparency, ethics, and building trust through robust evaluation using heterogeneous real-world data [10,34]. Thoughtful integration of AI tools that augment clinician capabilities while centering human oversight and shared decision-making is key for patient and provider adoption. Siloed AI deployment will limit value [34]. Health systems must invest in enterprise data integration, interoperable algorithms, and user-centered design. Workflows and interfaces enabling seamless clinician–AI interaction will be critical. Significant technical barriers also remain, including handling diverse, messy real-world data and rare diseases [60]. Alleviating these requires accumulating large volumes of high-quality annotated data over time. Initiatives like data-sharing consortiums can accelerate this. In order to provide improved patient outcomes, enhanced efficiency, and more equitable access to care, healthcare providers and policymakers must use resource optimization and training, which means developing AI and clinically interfacing training programs and educating staff on how to interpret AI-generated insights and use these tools to complement their expertise, empowering them with AI knowledge and potentially leading to better resource optimization, improved diagnostic accuracy, and enhanced patient care [61,62]. Furthermore, solutions need to be sought to support patients with long-term chronic conditions by developing AI-powered apps and wearable devices that monitor patients' health metrics and provide real-time feedback, enabling patients to manage their conditions more effectively. These strategies would hopefully improve patient adherence to treatment plans and better self-management of chronic diseases, leading to improved health outcomes. Another useful strategy would be to use big data on patient demographics, socioeconomic status, and healthcare outcomes to identify areas with disparities globally [63,64]. This would enable policymakers and healthcare providers to tailor interventions to address these gaps, such as providing targeted care or resources to underserved populations, potentially leading to a decrease in healthcare disparities and more equitable access to high-quality care. This can only be achieved by a seamless integration of AI tools with the existing healthcare systems, an area for further collaborative research, including the collaborative development of ethical and regulatory frameworks. This would also be a progression towards building trust in AI-led healthcare technologies among healthcare providers and patients, leading to the safe and ethical use of patient data, better-personalized treatment, and fostering national and global collaboration in the striving for continual improvement in healthcare.

5. Limitations

One notable limitation of the systematic review is the limited representation of studies from low- and middle-income countries (LMICs). Most of the included studies were from high-income countries (HICs), potentially creating a geographical imbalance and limiting the generalizability of the findings to a global context. There is also a limited representation of patient perspectives, which is concerning given that they are most impacted by AI adoption in healthcare. Additionally, to minimize individual bias regarding the selection of studies, a standardized protocol was followed to ensure rigor and accuracy in the review process. The systematic review may be subject to publication bias, as it relies on published studies. Unpublished or negative studies might not have been included, leading to a potential overrepresentation of positive findings.

While the review draws insights from diverse global settings, provides balance in discussing both opportunities and challenges and covers multiple real-world aspects of implementing AI in healthcare, the subjective and heterogeneous nature of the synthesized data, along with gaps in patient perspectives, limit the robustness and generalizability of the conclusions. For example, in terms of context-specific insights, such as AI's role in reducing healthcare disparities, enhancing patient care, and supporting chronic condition management, these are often derived from specific studies or healthcare settings. This specificity can limit the extent to which these findings can be applied to other contexts, such as different healthcare systems, regions, or populations. Again, due to diverse healthcare systems in terms of infrastructure, patient demographics, regulatory environments, and resource availability, the applicability of AI-driven solutions might be limited if these themes were developed based on studies conducted in well-resourced or technologically advanced settings. Hence, the generalizability to under-resourced or different healthcare environments might be limited. Due to variability in AI implementation, its effectiveness, including the quality of data, the integration with existing systems, and the training of healthcare professionals, may vary significantly across different settings, impacting its generalizability. Additionally, the ethical implications and acceptance of AI in healthcare can differ across cultures and patient populations, as discussed in our study, and would limit its generalizability across different cultural or societal contexts. As highlighted in our study, the adoption of AI in healthcare is also shaped by the regulatory environment and the availability of technological infrastructure. Differences in data privacy laws, patient consent norms, and technological readiness would also limit the generalizability of the results across different regions or countries. Finally, AI technology is evolving rapidly, and findings or themes derived from current studies may become outdated as newer, more advanced AI applications are developed. This evolution could also impact the generalizability of current results to future AI developments in healthcare.

As with all emerging technology debates, discourse and projections tend to outpace evidence.

6. Conclusions

The findings of the systematic review on the adoption of AI and ML in healthcare delivery have significant implications for healthcare practitioners, policymakers, researchers, healthcare administrators, clinicians, patients, and AI developers.

The identified benefits highlight the transformative potential of AI to enhance clinical workflows, decision-making, access to care, and patient outcomes. Realizing these benefits requires significant investments in technology infrastructure and redesigned organizational policies and care-delivery models to effectively integrate AI and ML in healthcare delivery. Leaders must proactively address ethical concerns regarding patient privacy, clinician displacement, and equitable access to AI and ML innovations across communities. The limitations and risks highlighted in the review emphasize the need for cautious, evidence-based adoption of AI technologies. Rigorous pre-deployment testing using heterogeneous datasets reflective of diverse patient populations is essential to evaluate predictive accuracy, risk of bias, and generalizability across settings. Continuous monitoring of performance metrics and unintended consequences should remain a priority following implementation. Active clinician oversight and shared decision-making must be centrally embedded in AI solutions for critical tasks, like diagnosis and treatment planning, to uphold patient safety and trust.

7. Future Research Needs

Studies need to be implemented across diverse care settings to evaluate the real-world effectiveness and unintended consequences of specific AI solutions designed to improve care quality, coordination, and accessibility should be conducted. Participatory research designs that actively engage all stakeholders, especially patients from marginalized communities, in co-designing patient-centered AI tools should be employed. Additionally, frameworks to assess AI quality, safety, equity, and effects on clinician workflows across healthcare-delivery models should be developed and validated. The impacts of AI implementation on patient trust in health systems, clinician job satisfaction, and the economic sustainability of care organizations should be evaluated using robust mixed-methods designs. Addressing these evidence gaps through stakeholder-engaged scholarship focused on patient-centered outcomes will provide vital insights to guide the translation of AI innovations into equitable clinical practice and optimize benefits while proactively mitigating risks.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/ai5040095/s1. Table S1. Quality assessment of the eligible studies using the CASP Qualitative Studies Checklist; adapted from the critical appraisal skills program [19]. Table S2. Quality assessment of the Delphi study using the ACCORD checklist tool [20]. Table S3. Overall common themes and subthemes.

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References

1. Topol, E. The topol review. In *Preparing the Healthcare Workforce to Deliver the Digital Future*; Health Education England: Leeds, UK, 2019; pp. 1–48.
2. Jiang, F.; Jiang, Y.; Zhi, H.; Dong, Y.; Li, H.; Ma, S.; Wang, Y.; Dong, Q.; Shen, H.; Wang, Y. Artificial intelligence in healthcare: Past, present and future. *Stroke Vasc. Neurol.* **2017**, *2*, 230–243. [CrossRef] [PubMed]
3. Thrall, J.H.; Li, X.; Li, Q.; Cruz, C.; Do, S.; Dreyer, K.; Brink, J. Artificial intelligence and machine learning in radiology: Opportunities, challenges, pitfalls, and criteria for success. *J. Am. Coll. Radiol.* **2018**, *15*, 504–508. [CrossRef] [PubMed]

4. Gulshan, V.; Peng, L.; Coram, M.; Stumpe, M.C.; Wu, D.; Narayanaswamy, A.; Venugopalan, S.; Widner, K.; Madams, T.; Cuadros, J.; et al. Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs. *JAMA* **2016**, *316*, 2402–2410. [CrossRef]
5. Kreimeyer, K.; Foster, M.; Pandey, A.; Arya, N.; Halford, G.; Jones, S.F.; Forshee, R.; Walderhaug, M.; Botsis, T. Natural language processing systems for capturing and standardizing unstructured clinical information: A systematic review. *J. Biomed. Inform.* **2017**, *73*, 14–29. [CrossRef]
6. Noorbakhsh-Sabet, N.; Zand, R.; Zhang, Y.; Abedi, V. Artificial intelligence transforms the future of health care. *Am. J. Med.* **2019**, *132*, 795–801. [CrossRef] [PubMed]
7. Paul, D.; Sanap, G.; Shenoy, S.; Kalyane, D.; Kalia, K.; Tekade, R.K. Artificial intelligence in drug discovery and development. *Drug Discov. Today* **2021**, *26*, 80. [CrossRef]
8. Xu, L.; Sanders, L.; Li, K.; Chow, J.C. Chatbot for health care and oncology applications using artificial intelligence and machine learning: Systematic review. *JMIR Cancer* **2021**, *7*, e27850. [CrossRef] [PubMed]
9. Pulimamidi, R.; Buddha, G.P. The Future of Healthcare: Artificial Intelligence's Role in Smart Hospitals and Wearable Health Devices. *Tuijin Jishu/J. Propuls. Technol.* **2023**, *4*, 2498–2504.
10. Char, D.S.; Shah, N.H.; Magnus, D. Implementing machine learning in health care—Addressing ethical challenges. *NEJM* **2018**, *378*, 981. [CrossRef]
11. He, J.; Baxter, S.L.; Xu, J.; Xu, J.; Zhou, X.; Zhang, K. The practical implementation of artificial intelligence technologies in medicine. *Nat. Med.* **2019**, *25*, 30–36. [CrossRef]
12. Naik, N.; Hameed, B.M.; Shetty, D.K.; Swain, D.; Shah, M.; Paul, R.; Aggarwal, K.; Ibrahim, S.; Patil, V.; Smriti, K.; et al. Legal and ethical consideration in artificial intelligence in healthcare: Who takes responsibility? *Front. Surg.* **2022**, *9*, 266. [CrossRef] [PubMed]
13. Ali, O.; Abdelbaki, W.; Shrestha, A.; Elbasi, E.; Ali Alryalat, M.A.; Dwivedi, Y.K. A systematic literature review of artificial intelligence in the healthcare sector: Benefits, challenges, methodologies, and functionalities. *J. Innov. Knowl.* **2023**, *8*, 100333. [CrossRef]
14. Al Kuwaiti, A.; Nazer, K.; Al-Reedy, A.; Al-Shehri, S.; Al-Muhanna, A.; Subbarayalu, A.V.; Al Muhanna, D.; Al-Muhanna, F.A. A review of the role of artificial intelligence in healthcare. *J. Pers. Med.* **2023**, *13*, 951. [CrossRef] [PubMed]
15. Udegbe, F.E.; Ebulue, Ogochukwu Roseline; Ebulue, Charles Chukwudalu; Ekesiobi, Chukwunonso. The role of artificial intelligence in healthcare: A systematic review of applications and challenges. *Int. Med. Sci. Res. J.* **2024**, *4*, 500–508. [CrossRef]
16. Esteva, A.; Robicquet, A.; Ramsundar, B.; Kuleshov, V.; DePristo, M.; Chou, K.; Cui, C.; Corrado, G.; Thrun, S.; Dean, J. A guide to deep learning in healthcare. *Nat. Med.* **2019**, *25*, 24–29. [CrossRef]
17. Ngiam, K.Y.; Khor, W. Big data and machine learning algorithms for health-care delivery. *Lancet Oncol.* **2019**, *20*, e262–e273. [CrossRef]
18. Shinners, L.; Aggar, C.; Grace, S.; Smith, S. Exploring healthcare professionals' understanding and experiences of artificial intelligence technology use in the delivery of healthcare: An integrative review. *Health Inform. J.* **2020**, *26*, 1225–1236. [CrossRef]
19. Saraswat, D.; Bhattacharya, P.; Verma, A.; Prasad, V.K.; Tanwar, S.; Sharma, G.; Sharma, R. Explainable AI for healthcare 5.0: Opportunities and challenges. *IEEE Access* **2022**, *10*, 84486–84517. [CrossRef]
20. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *134*, 178–189. [CrossRef]
21. Critical Appraisal Skills Programme. CASP Checklist. 2018. Available online: https://casp-uk.net/casp-tools-checklists/ (accessed on 31 May 2024).
22. Critical Appraisal Skills Programme. CASP Qualitative Checklist. 2018. Available online: https://casp-uk.net/casp-tools-checklists/ (accessed on 31 May 2024).
23. Gattrell, W.T.; Logullo, P.; van Zuuren, E.J.; Price, A.; Hughes, E.L.; Blazey, P.; Winchester, C.C.; Tovey, D.; Goldman, K.; Hungin, A.P.; et al. ACCORD (ACcurate COnsensus Reporting Document): A reporting guideline for consensus methods in biomedicine developed via a modified Delphi. *PLoS Med.* **2024**, *21*, e1004326. [CrossRef]
24. Braun, V.; Clarke, V. Using thematic analysis in psychology. *Qual. Res. Psychol.* **2006**, *3*, 77–101. [CrossRef]
25. Petersson, L.; Larsson, I.; Nygren, J.M.; Nilsen, P.; Neher, M.; Reed, J.E.; Tyskbo, D.; Svedberg, P. Challenges to implementing artificial intelligence in healthcare: A qualitative interview study with healthcare leaders in Sweden. *BMC Health Serv. Res.* **2022**, *22*, 850. [CrossRef] [PubMed]
26. Pumplun, L.; Fecho, M.; Wahl, N.; Peters, F.; Buxmann, P. Adoption of machine learning systems for medical diagnostics in clinics: Qualitative interview study. *J. Med. Internet Res.* **2021**, *23*, e29301. [CrossRef] [PubMed]
27. Liyanage, H.; Liaw, S.T.; Jonnagaddala, J.; Schreiber, R.; Kuziemsky, C.; Terry, A.L.; de Lusignan, S. Artificial intelligence in primary health care: Perceptions, issues, and challenges. *Yearb. Med. Inform.* **2019**, *28*, 041–046. [CrossRef]
28. Sun, T.Q.; Medaglia, R. Mapping the challenges of Artificial Intelligence in the public sector: Evidence from public healthcare. *Gov. Inf. Q.* **2019**, *36*, 368–383. [CrossRef]
29. Alanazi, A. Clinicians' Views on Using Artificial Intelligence in Healthcare: Opportunities, Challenges, and Beyond. *Cureus* **2023**, *15*, 1–11. [CrossRef]

30. Blease, C.; Kaptchuk, T.J.; Bernstein, M.H.; Mandl, K.D.; Halamka, J.D.; DesRoches, C.M. Artificial intelligence and the future of primary care: Exploratory qualitative study of UK general practitioners' views. *J. Med. Internet Res.* **2019**, *21*, e12802. [CrossRef]
31. Dumbach, P.; Liu, R.; Jalowski, M.; Eskofier, B.M. The Adoption of Artificial Intelligence in SMEs-A Cross-National Comparison in German and Chinese Healthcare. *Joint Proceedings of the BIR 2021 Workshops and Doctoral Consortium Co-Located with 20th International Conference on Perspectives in Business Informatics Research (BIR 2021) (2991)*. 2021, pp. 84–98. Available online: https://ceur-ws.org/Vol-2991/paper08.pdf (accessed on 31 May 2024).
32. Lammons, W.; Silkens, M.; Hunter, J.; Shah, S.; Stavropoulou, C. Centering Public Perceptions on Translating AI Into Clinical Practice: Patient and Public Involvement and Engagement Consultation Focus Group Study. *J. Med. Internet Res.* **2023**, *25*, e49303. [CrossRef]
33. Katirai, A.; Yamamoto, B.A.; Kogetsu, A.; Kato, K. Perspectives on artificial intelligence in healthcare from a Patient and Public Involvement Panel in Japan: An exploratory study. *Front. Digit. Health* **2023**, *5*, 1229308. [CrossRef]
34. Tran, B.D.; Chen, Y.; Liu, S.; Zheng, K. How does medical scribes' work inform development of speech-based clinical documentation technologies? A systematic review. *JAMIA Open* **2020**, *27*, 808–817. [CrossRef]
35. Liu, X.; Faes, L.; Kale, A.U.; Wagner, S.K.; Fu, D.J.; Bruynseels, A.; Mahendiran, T.; Moraes, G.; Shamdas, M.; Kern, C.; et al. A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging: A systematic review and meta-analysis. *Lancet Digit. Health* **2019**, *1*, e271–e297. [CrossRef] [PubMed]
36. Brynjolfsson, E.; Rock, D.; Syverson, C. Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In *The Economics of Artificial Intelligence: An Agenda*; University of Chicago Press: Chicago, IL, USA, 2019; pp. 23–57. ISBNs: 978-0-226-61333-8 (cloth); 978-0-226-61347-5 (electronic). Available online: http://www.nber.org/books/agra-1 (accessed on 31 May 2024).
37. Shen, J.; Zhang, C.J.; Jiang, B.; Chen, J.; Song, J.; Liu, Z.; He, Z.; Wong, S.Y.; Fang, P.H.; Ming, W.K. Artificial intelligence versus clinicians in disease diagnosis: Systematic review. *JMIR Med. Inform.* **2019**, *7*, e10010. [CrossRef] [PubMed]
38. Nagendran, M.; Chen, Y.; Lovejoy, C.A.; Gordon, A.C.; Komorowski, M.; Harvey, H.; Topol, E.J.; Ioannidis, J.P.; Collins, G.S.; Maruthappu, M. Artificial intelligence versus clinicians: Systematic review of design, reporting standards, and claims of deep learning studies. *BMJ* **2020**, *368*. [CrossRef]
39. Lainjo, B. The Global Social Dynamics and Inequalities of Artificial Intelligence. *Int. J. Innov. Sci. Res. Rev.* **2020**, *5*, 4966–4974.
40. Liu, X.; Rivera, S.C.; Moher, D.; Calvert, M.J.; Denniston, A.K.; Ashrafian, H.; Beam, A.L.; Chan, A.W.; Collins, G.S.; Deeks, A.D.J.; et al. Reporting guidelines for clinical trial reports for interventions involving artificial intelligence: The CONSORT-AI extension. *Lancet Digit Health* **2020**, *2*, e537–e548. [CrossRef]
41. Miotto, R.; Wang, F.; Wang, S.; Jiang, X.; Dudley, J.T. Deep learning for healthcare: Review, opportunities, and challenges. *Brief Bioinform.* **2018**, *19*, 1236–1246. [CrossRef] [PubMed]
42. Karimian, G.; Petelos, E.; Evers, S.M. The ethical issues of the application of artificial intelligence in healthcare: A systematic scoping review. *AI Ethics* **2022**, *2*, 539–551. [CrossRef]
43. Morley, J.; Machado, C.C.; Burr, C.; Cowls, J.; Joshi, I.; Taddeo, M.; Floridi, L. The Ethics of AI in Health Care: A Mapping. *Ethics Gov. Policies Artif. Intell.* **2021**, *144*, 313.
44. Gerke, S.; Minssen, T.; Cohen, G. Ethical and legal challenges of artificial intelligence-driven healthcare. In *Artificial Intelligence in Healthcare*; Academic Press: Cambridge, MA, USA, 2020; pp. 295–336.
45. Wang, Y.; Kung, L.; Byrd, T.A. Big data analytics: Understanding its capabilities and potential benefits for healthcare organizations. *Technol Forecast. Soc Change* **2018**, *126*, 3–13. [CrossRef]
46. Zhang, J.; Zhang, Z.M. Ethics and governance of trustworthy medical artificial intelligence. *BMC Med Inform Decis Mak.* **2023**, *23*, 7. [CrossRef]
47. Wiens, J.; Saria, S.; Sendak, M.; Ghassemi, M.; Liu, V.X.; Doshi-Velez, F.; Jung, K.; Heller, K.; Kale, D.; Saeed, M.; et al. Do no harm: A roadmap for responsible machine learning for health care. *Nat Med.* **2019**, *25*, 1337–1340. [CrossRef] [PubMed]
48. Rajkomar, A.; Dean, J.; Kohane, I. Machine learning in medicine. *NEJM* **2019**, *380*, 1347–1358. [CrossRef] [PubMed]
49. Kabir, R.; Sivasubramanian, M.; Hitch, G.; Hakkim, S.; Kainesie, J.; Vinnakota, D.; Mahmud, I.; Apu, E.H.; Syed, H.Z.; Parsa, A.D. "Deep learning" for Healthcare: Opportunities, Threats, and Challenges. In *Deep Learning in Personalized Healthcare and Decision Support*; Academic Press: Cambridge, MA, USA, 2023; pp. 225–244.
50. Sverdlov, O.; Ryeznik, Y.; Wong, W.K. Opportunity for efficiency in clinical development: An overview of adaptive clinical trial designs and innovative machine learning tools, with examples from the cardiovascular field. *Contemp Clin Trials.* **2021**, *105*, 106397. [CrossRef] [PubMed]
51. Davenport, T.; Kalakota, R. The potential for artificial intelligence in healthcare. *Future Healthc. J.* **2019**, *6*, 94. [CrossRef]
52. Howard, J. Artificial intelligence: Implications for the future of work. *Am. J. Ind. Med.* **2019**, *62*, 917–926. [CrossRef]
53. Jarrahi, M.H.; Askay, D.; Eshraghi, A.; Smith, P. Artificial intelligence and knowledge management: A partnership between humans and AI. *Bus Horiz.* **2023**, *66*, 87–99. [CrossRef]
54. Deardorff, A. Assessing the impact of introductory programming workshops on the computational reproducibility of biomedical workflows. *PLoS ONE* **2020**, *15*, e0230697. [CrossRef]
55. Hlávka, J.P. Security, privacy, and information-sharing aspects of healthcare artificial intelligence. In *Artificial Intelligence in Healthcare*; Academic Press: Cambridge, MA, USA, 2020; pp. 235–270.

56. McCool, J.; Dobson, R.; Whittaker, R.; Paton, C. Mobile health (mHealth) in low-and middle-income countries. *Annu. Rev. Public Health* **2020**, *43*, 525–539. [CrossRef] [PubMed]
57. Dixon, B.E.; Kharrazi, H.; Lehmann, H.P. Public health and epidemiology informatics: Recent research and trends in the United States. *Yearb. Med. Inform.* **2015**, *24*, 199–206. [CrossRef]
58. Nundy, S.; Montgomery, T.; Wachter, R.M. Promoting trust between patients and physicians in the era of artificial intelligence. *JAMA* **2019**, *322*, 497–498. [CrossRef]
59. Panch, T.; Mattie, H.; Celi, L.A. The "inconvenient truth" about AI in healthcare. *NPJ Digit Med.* **2019**, *2*, 77. [CrossRef] [PubMed]
60. Tuomi, I. The Impact of Artificial Intelligence on Learning, Teaching, and Education: Policies for the Future. JRC Science for Policy Report. *Eur. Comm.* **2019**, *9*, 70–78. [CrossRef]
61. Alowais, S.A.; Alghamdi, S.S.; Alsuhebany, N.; Alqahtani, T.; Alshaya, A.I.; Almohareb, S.N.; Aldairem, A.; Alrashed, M.; Bin Saleh, K.; Badreldin, H.A.; et al. Revolutionizing healthcare: The role of artificial intelligence in clinical practice. *BMC Med. Educ.* **2023**, *23*, 689. [CrossRef] [PubMed]
62. McKinney, S.M.; Sieniek, M.; Godbole, V.; Godwin, J.; Antropova, N.; Ashrafian, H.; Back, T.; Chesus, M.; Corrado, G.S.; Darzi, A.; et al. International evaluation of an AI system for breast cancer screening. *Nature* **2020**, *577*, 89–94. [CrossRef] [PubMed]
63. Kim, J.T. Application of machine and deep learning algorithms in intelligent clinical decision support systems in healthcare. *J. Health Med. Inform.* **2018**, *9*, 321. [CrossRef]
64. Kolluri, S.; Lin, J.; Liu, R.; Zhang, Y.; Zhang, W. Machine learning and artificial intelligence in pharmaceutical research and development: A review. *AAPS J.* **2022**, *24*, 1–10. [CrossRef]