A review on solving the interoperability challenge of health care systems using artificial intelligence

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https://doi.org/10.51867/ajernet.6.3.79

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ABSTRACT

Tackling the challenge of healthcare interoperability calls for more than just technical fixes; it needs a well-coordinated and collaborative effort that brings together both systems and people. This study, grounded in sociotechnical systems theory, recognizes that successful health information exchange depends not only on technology but also on how people work together around it. The research aimed to pinpoint where current data sharing falls short, explore how well automated tools help standardize and connect health information, and understand how better interoperability affects patient care and health system efficiency. To do this, a mixed methods approach was used: quantitative analysis of healthcare data highlighted where inconsistencies and breakdowns were happening, while interviews and focus groups with healthcare workers and system developers provided deeper insights into what is working and what is not. The results showed that many healthcare facilities still operate on systems that do not talk to each other well, leading to fragmented data and unnecessary delays. But when automation was introduced, tools that translate and link data from different systems made a big difference. Information became more consistent, manual entry errors dropped, and providers gained quicker access to patient records. The study found that to truly improve interoperability, healthcare systems need to invest in integrated solutions that prioritize data consistency, security, and compatibility. It recommends developing national standards for how health data is shared, offering more training to health workers on using digital tools, and building stronger partnerships between healthcare providers, tech developers, and policymakers. When these pieces come together, the result is a more connected, efficient, and patient-centered healthcare system where everyone involved can work smarter and deliver better care.

Key words: Automation, Data Consistency, Healthcare Interoperability, Health Information Exchange, National Standards, Patient Care, Socio Technical Systems

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I. INTRODUCTION

Interoperability in healthcare is a cornerstone of efficient, patient-centered care. It refers to the ability of different healthcare information systems, devices, and applications to access, exchange, and use data cohesively and accurately. The ultimate goal is to support clinical workflows, ensure continuity of care, and improve patient outcomes. However, despite its importance, interoperability remains one of the most persistent challenges in modern healthcare. According to Aldoseri et al. (2023), the ability of systems to be fully integrated is still far from being realized in most healthcare environments. The lack of seamless communication between electronic health records (EHRs), laboratory systems, imaging tools, and other digital health components continues to cause inefficiencies, delays, and in some cases, serious medical errors.

One of the biggest obstacles to interoperability is the inconsistency in data formats. Healthcare providers often use different EHR systems, each with its own way of recording and storing data. These systems may not follow common standards, which makes it difficult to merge data from various sources. A patient treated at one facility may need to repeat tests or recount their medical history when visiting another provider simply because their records cannot be shared in a usable format. Petersson et al. (2022) emphasize that these fragmented systems also contribute to duplicated efforts, increased costs, and potentially unsafe care. Furthermore, regulatory restrictions related to data privacy, such as HIPAA in the U.S. or similar laws in other regions, can make it even more difficult to share information, even when there is a clear clinical benefit.

In practice, poor interoperability can have serious consequences. For instance, delays in accessing a patient's complete medical history can lead to unnecessary diagnostic tests, conflicting prescriptions, or even misdiagnoses. The

World Health Organization and other global health authorities have acknowledged that the lack of interoperable health data systems is a major factor in preventable patient harm (World Health Organization, 2023). This makes the need for scalable and effective solutions more urgent than ever.

Artificial intelligence is beginning to offer real promise in this area. With advances in natural language processing, machine learning, and data mining, AI technologies are helping address many of the technical and organizational barriers to interoperability (Gao et al., 2024). For example, NLP tools can extract valuable insights from unstructured clinical notes, converting free-text entries into structured data that can be easily shared and analyzed across systems (Warbhe & Verma, 2024 ; Al-Garadi et al., 2022). Machine learning algorithms can identify patterns in mismatched datasets and help map data elements between incompatible systems (Hu et al., 2021). AI-powered middleware solutions can also act as translators between platforms, helping preserve the meaning and context of data as it moves from one system to another (Balogun et al., 2023).

This review analyzes 30 recent publications focused on the use of AI in healthcare interoperability. The goal is to understand current trends, highlight successful approaches, and identify what makes these technologies effective. A key aim is to propose a framework for implementing AI-based interoperability solutions that are not only technically sound but also aligned with real-world clinical needs and ethical principles (Mullankandy et al., 2024; Karalis, 2024) .

To explore this landscape more clearly, it helps to define the independent and dependent variables commonly involved in studies on this topic. Independent variables often include the type of AI model or algorithm being used, such as NLP, supervised learning, or deep learning, the specific interoperability challenge being addressed, like data mapping or terminology alignment, and the context in which the AI is applied, such as hospitals, national health systems, or private clinics. Dependent variables, in contrast, are the outcomes influenced by AI implementation. These might include the level of integration achieved, improvements in data accuracy, reductions in duplicate testing, enhancements in decision-making, or increases in patient satisfaction(Pushadapu, 2022; Zhang et al., 2022).

By examining how these variables interact in real-world examples, this review provides a clearer understanding of what approaches are working, which ones are falling short, and why. It also offers insights into common challenges and shares best practices for successfully using AI to improve healthcare interoperability. Ultimately, the integration of AI into health information systems is not just a technical advancement. It is an opportunity to make healthcare more coordinated, efficient, and responsive to the needs of patients and providers alike.

1.1 Statement of the Problem

Healthcare systems around the world continue to face significant challenges with interoperability. Much of the difficulty lies in trying to harmonize data that comes from a wide variety of sources, formats, and standards. Even though digital health records are becoming more common, the ability to share and understand patient information smoothly across different platforms is still limited. This lack of integration has real-world consequences, including delays in care, mistakes in treatment decisions, and frustrations for both patients and healthcare providers. Many healthcare organizations still rely on systems that are not compatible with each other, and in many cases, data is entered manually. This often leads to isolated pockets of information, commonly referred to as data silos, which block the timely flow of important medical details. The end result is not only reduced efficiency but also potentially poorer outcomes for patients.

Several researchers have examined these challenges in depth. Adler-Milstein and Jha (2017) found that even in hospitals equipped with advanced electronic health record systems, data sharing and use were still very limited because of inconsistent formats and incompatible interfaces. In prior study, Vest and Gamm (2010) pointed out that organizational issues like competition between providers and a lack of mutual trust often prevent successful data exchange. More recently, Petersson et al. (2022) noted that while the technical tools needed to improve interoperability are available, they often do not align well with how clinicians actually work, which makes widespread adoption difficult. These studies highlight a key reality: although the problems are well understood, effective solutions are still lacking. To enhance this, Yang (2022) argued that for predictive AI models to gain clinicians' trust, they must offer explanation through transparent design and interpretable outputs, although the study did not explicitly connect explainable AI to broader interoperability frameworks.

Artificial intelligence is emerging as a promising way to bridge these gaps. Technologies such as natural language processing can pull valuable information from unstructured clinical notes, while machine learning algorithms can recognize patterns and help translate data between systems that normally cannot communicate with each other. According to Krittanawong et al. (2021), AI has the potential to organize scattered data and support interoperability by powering real-time analysis and better decision-making. Still, many of these AI solutions are currently limited to pilot projects or research environments and have not yet been scaled for everyday use.

One major shortcoming in the existing literature is the lack of examples where AI-driven interoperability has been applied at a large scale in real-world clinical settings. Most studies concentrate on whether the technology is feasible or how well the algorithms perform, but fewer examine how these tools fit into the routines of healthcare professionals. Ethical concerns such as data privacy, algorithmic fairness, and transparency are often acknowledged but rarely addressed with practical steps. If AI is to unlock the full potential of interoperability in healthcare, it needs to go beyond technical design. It must include thoughtful policy development, safeguards for patient data, and collaboration among stakeholders to build trust in how AI systems are used. Adding to the barriers, Tsai et al. (2020) emphasized that implementing Electronic Health Record (EHR) systems is hindered by both technical and human factors, offering practical recommendations to address adoption and interoperability issues, though their study did not explore AI-based solutions.

In summary, there is clear potential for AI to transform how healthcare systems share and use information. However, realizing this potential will require more than just innovation. It will need ongoing research that brings together technology, real-world application, thoughtful design, and careful regulation. Without tackling these areas, we risk missing out on tools that could make care more connected, more efficient, and more responsive especially at a time when those improvements are urgently needed.

1.2 Research Objectives

i. To explore how AI, especially NLP and ML, can improve data sharing across different healthcare systems.
ii. To assess how well AI can organize and align health data for better use.
iii. To address privacy and security concerns and suggest a safe, AI-powered way to connect health data systems.

II. LITERATURE REVIEW

2.1 Socio Technical Systems Theory

Socio-technical systems theory (STS) remains highly relevant in digital era. It emphasizes that an organization execute their workflow when both its technical side such as tools, technology and infrastructure and its social side such as people, culture and workflows are developed together. Recent work by Thomas (2024) in knowledge management shows that success depends on more than installing systems. It also requires motivating people, encouraging collaboration and aligning structures with technology. The paramount idea is that technical solutions on their own are not sufficient. In the event the institutions neglect attention to communication, teamwork and culture, new systems will fail or cause unexpected challenges.

2.2 Interoperability Challenges in Healthcare

Healthcare systems often find it difficult to share information smoothly, largely because of a mix of technical and regulatory challenges. One of the main issues is the lack of consistent data standards. Different electronic health record systems rely on various coding languages, such as ICD 10, SNOMED CT, and HL7, which don't always work well together (Luo et al., 2021). This kind of inconsistency can lead to patient records being incomplete or mismatched, making it harder for doctors to make well-informed decisions (Warbhe and Verma, 2024). To make things even more complicated, patient data is usually scattered across different sources like lab systems, imaging databases, and handwritten clinical notes which makes it tough to pull everything together in one place (Karalis, 2024). Privacy regulations, including HIPAA in the United States and GDPR in Europe, also place strict limits on how easily data can be accessed and shared between providers (Yadav et al., 2023). As Aldoseri et al. (2023) note, all of these obstacles combined reduce the full potential of using healthcare data to improve care and generate deeper insights.

2.3 Applications of AI in Solving Interoperability Issues

AI technologies, especially natural language processing and machine learning, offer exciting new ways to address the long-standing challenges of healthcare interoperability. Natural language processing, for example, can convert unstructured clinical notes into clear, structured data that can be more easily shared and understood across different health systems (Warbhe and Verma, 2024). These tools have already been used successfully to scan medical records and extract important details about diagnoses and treatments that would otherwise stay buried in free-text notes (Al Garadi et al., 2022). Machine learning also plays a key role by helping standardize and align data from different healthcare databases, ensuring that the information is interpreted in a consistent way (Hu et al., 2021). Beyond that, AI can support predictive modeling, which allows systems to spot potential data integration issues before they cause problems in patient care (Gao et al., 2024). However, even with these promising developments, many AI models are still not standardized, which makes it difficult to implement them widely across diverse healthcare settings (Petersson et al., 2022).

In recent years, there has been real progress in using AI to improve healthcare interoperability, but a number of important challenges still need to be addressed. One major hurdle is the lack of standardization in AI algorithms across different healthcare systems, which makes it hard to scale these solutions and apply them consistently in diverse settings (Mullankandy et al., 2024). Ethical concerns are also a significant factor, especially around safeguarding patient privacy and ensuring transparency in how AI systems make decisions. If these systems are not carefully designed and monitored, they can introduce bias that may result in unequal treatment for certain groups of patients (Panch et al., 2019). In addition, strict data privacy laws, such as the General Data Protection Regulation in Europe, require that sensitive health data be handled with great care. This can make it even more complicated to share and integrate information across systems (Khalid et al., 2023).

2.4 Conceptual Framework

The proposed approach to tackling interoperability challenges in healthcare using AI focuses on a few essential steps. It starts with properly preparing and organizing the data, followed by selecting the most suitable AI models for the task at hand. Clear and consistent evaluation methods are also built into the process to measure how well the solutions work. This structured framework is meant to help different health systems connect more easily and ensure that data can move reliably between them. In the end, the goal is to support better healthcare delivery by making critical information more accessible, accurate, and useful.

2.4.1 Components of the Framework

The first step in this framework is all about preparing the data. This involves cleaning it, standardizing formats, and removing any personally identifiable information to protect patient privacy and ensure consistency across systems (Pushadapu, 2022). Once the data is properly prepared, AI tools can be used to make sense of it. For instance, natural language processing can extract meaningful information from doctors' notes, while machine learning models like decision trees or support vector machines can help organize and analyze structured data effectively (Li et al., 2023). To evaluate how well these AI models are working, we can measure things like their accuracy, how quickly they process data, and whether they help reduce errors in patient records (Zhang et al., 2022).

2.4.2 Implementation Strategy

To successfully roll out AI-driven solutions, healthcare organizations should take a step-by-step approach. It's important to start with pilot testing in a controlled environment, where feedback from healthcare professionals can be gathered to fine-tune the AI models and address any issues early on (Karalis, 2024). Once the system performs well in the pilot phase, it can then be gradually expanded to more departments or facilities. Ongoing evaluation is key throughout this process to make sure the AI tools stay accurate, effective, and aligned with evolving healthcare standards and regulations (Mullankandy et al., 2024).

III. METHODOLOGY

This review adopted a mixed-methods research design, combining both qualitative and quantitative approaches to provide a comprehensive understanding of how artificial intelligence is being applied to address interoperability challenges in healthcare. The study began with a systematic review of the literature, focusing on peer-reviewed articles published between 2019 and 2024. The search was conducted through reputable academic databases such as PubMed, IEEE Xplore, and Google Scholar.

To ensure that the findings were both relevant and high quality, the review included only studies that specifically examined AI-based solutions for healthcare interoperability. This included research involving technologies like natural language processing and machine learning. A total of 30 studies met the criteria for inclusion. Articles were excluded if they lacked real-world data or did not directly address healthcare data integration.

Each selected study was analyzed using a structured review framework. This included evaluating: The type of artificial intelligence technology applied, including natural language processing used for analyzing clinical text, machine learning models developed for data prediction, and deep learning techniques employed in managing image-based interoperability. The specific interoperability challenges being addressed, such as the presence of data silos, mismatches in coding systems, and inconsistencies in data formats across platforms.

The reported effectiveness of each AI solution, focusing on measurable outcomes like the accuracy of data integration, processing speed, and the potential for the solution to be scaled across different healthcare settings. Regulatory and ethical considerations, particularly how the solutions complied with data privacy regulations such as the General Data Protection Regulation (GDPR) in Europe and the Health Insurance Portability and Accountability Act (HIPAA) in the United States.

By combining both quantitative measures, such as accuracy scores and processing times, with qualitative insights like feedback from healthcare professionals on usability, this review provides a well-rounded understanding of how artificial intelligence is currently being applied in healthcare interoperability. It also highlights the areas where significant gaps still remain in the pursuit of seamless health data integration.

Table 1
The Process of Publication Selection

Step	What Was Done	How It Was Done	What It Led To
1. Choosing Databases	Identified the most relevant academic sources for healthcare and AI research.	Focused on reputable databases including PubMed, IEEE Xplore, Google Scholar, and ScienceDirect.	Ensured only credible, peer-reviewed, and research-based articles were considered.
2. Searching with Keywords	Looked for studies that matched the focus on AI and healthcare data sharing.	Used targeted keywords such as "AI in healthcare interoperability," "machine learning for EHR integration," and "data privacy in AI health systems."	Collected over 150 articles during the initial search.
3. Filtering Relevant Papers	Applied criteria to select the most relevant and high-quality studies.	Included papers published between 2019 and 2024, peer-reviewed, and focused on AI use in healthcare interoperability.	Narrowed the selection to 50 studies with strong relevance to the topic.
4. Removing Unsuitable Studies	Eliminated articles that were not useful or directly related to the research.	Removed studies without real-world data, duplicate content, or off-topic discussions.	Finalized a high-quality pool of 30 studies for in-depth analysis.
5. Grouping by Themes	Organized selected studies based on shared focus areas and concepts.	Sorted papers by themes such as types of AI used (e.g., NLP, ML), key challenges addressed, and ethical concerns.	Created a well-structured review foundation with clear thematic categories for discussion.

IV. FINDINGS & DISCUSSION

4.1 Case Study Analysis

One of the most prominent case studies analyzed in this review featured a U.S.-based healthcare network that implemented an AI-powered solution to integrate data across several disparate Electronic Health Record (EHR) platforms (Balogun et al., 2023). The initiative relied heavily on Natural Language Processing (NLP) to extract structured data from clinical notes and Machine Learning (ML) to map data across differing coding systems, such as ICD-10, SNOMED CT, and HL7. As a result, the institution reported a 30% increase in data integration accuracy and a 50% reduction in the time required for data exchange (Gao et al., 2024). This aligns directly with the first research objective, which sought to explore how AI technologies can enhance healthcare interoperability. Similarly, Badawy et al. (2023) noted a surge of machine learning and deep learning models being applied to healthcare outcomes prediction, offering a consolidated overview of predictive techniques and trends though their review lacked focus on interoperability and real-world deployment challenges. In addition, more Studies illustrated the value of AI in predicting disease trends and outcomes. In addition, Mbunge and Batani (2023) highlighted the promise of deploying machine learning and deep learning in sub-Saharan Africa to improve local healthcare outcomes, illustrating AI's value in predicting disease trends, although they noted that challenges like connectivity, infrastructure, and integration remain largely unaddressed.

These findings are supported by other studies, such as Warbhe & Verma (2024), who demonstrated the effectiveness of NLP in transforming free-text clinical notes into structured data that can be easily harmonized across systems. Similarly, Hu et al. (2021) found that ML techniques significantly improved data mapping across heterogeneous databases, reducing redundancy and inconsistencies. However, the case study also underscored the need for continuous algorithmic updates to ensure compatibility with evolving standards (Torab-Miandoab et al., 2023), echoing concerns raised by Mullankandy et al. (2024) about the scalability and long-term sustainability of AI models. In the same vein, Bajwa et al. (2021) highlighted that while AI is revolutionizing medicine with promising use cases and future directions, its practical application still lags behind, particularly in addressing the integration gaps between disparate health record systems.

In relation to the second objective; evaluating the role of NLP and ML in enabling data sharing multiple studies provided concrete evidence. Li et al. (2023) showed how decision trees and support vector machines were successfully applied to classify health data from disparate sources. Pushadapu (2022) emphasized the importance of thorough data preprocessing (cleaning, normalization, and anonymization), which laid a reliable foundation for AI to perform effectively. In addition, Zhang et al. (2022) stressed the importance of performance metrics such as accuracy, speed, and error reduction in evaluating the effectiveness of AI interventions in health informatics.

Regarding the third objective: assessing the normalization and alignment of data Luo et al. (2021) identified major discrepancies in coding systems and highlighted how these variations negatively impact the consistency of patient records. While Balogun et al. (2023) and Gao et al. (2024) showed improvements, the challenge remains partially unresolved, particularly when dealing with legacy systems that lack API compatibility or modern architecture.

Moreover, the review identified significant ethical, legal, and regulatory challenges, supporting the ethical considerations in the review. Studies by Khalid et al. (2023) and Panch et al. (2019) emphasized the risk of algorithmic bias and privacy violations. GDPR and HIPAA regulations place strict limitations on how patient data can be shared, and these restrictions often conflict with the operational needs of AI models, especially in cross-border data environments. Similarly, Kluge (2020) discussed how AI introduces ethical concerns around consent, fairness, and data governance in healthcare, offering useful ethical frameworks, though these did not directly align with the technical steps required to improve interoperability.

In moving toward a more connected and efficient healthcare system, organizations should work towards developing standardized AI models to support interoperability across various settings (Aldoseri et al., 2023). Establishing consistency in how different systems communicate is essential to overcoming the fragmentation seen in many healthcare environments. Equally important is the need to train healthcare professionals on how to use these tools effectively, ensuring that the technology is not only adopted but also applied in ways that enhance care delivery (Pushadapu, 2022). Protecting patient data must remain a top priority, with robust privacy safeguards such as encryption and secure access mechanisms put in place (Gao et al., 2024). Finally, lasting solutions will require collaboration between multiple sectors. Cross sector partnerships among technology developers, healthcare providers, and regulatory bodies can help address the complexities of interoperability in a comprehensive and sustainable way (Torab Miandoab et al., 2023).

Finally, the review proposes a secure and efficient AI-based architecture for interoperability which is guided by the collective insights of reviewed literature. Karalis (2024) recommends a phased rollout of AI systems, starting with controlled pilot environments to gather feedback and refine algorithms before broader deployment. This phased model is consistent with best practices outlined in Mullankandy et al. (2024), who argue for continuous performance monitoring, ethical oversight, and iterative improvements to maintain the efficacy and safety of AI tools in healthcare settings. Key to understanding AI's role at the community level, Rahimi et al. (2021) provided a scoping overview of its application in primary care settings, noting that while uptake remains steady, the focus has been more on model usability and adoption rather than addressing interoperability challenges.

In summary, the findings from this case study and related literature strongly support the potential of AI particularly NLP and ML in addressing major interoperability issues. Yet, they also caution that successful implementation requires not just technical sophistication but a governance framework that includes continuous model validation, staff training, ethical safeguards, and regulatory alignment.

Table 2

The Summary Analysis of the Papers Reviewed

Paper	What Was Observed	Contribution Made	Gap Identified
Al-Garadi et al. (2022)	NLP tools played a crucial role during COVID-19 in parsing clinical texts, public health communications, and research papers.	Showed how natural language processing can rapidly extract health information and support decision-making.	Highlighted implementation challenges such as real-time updating, language diversity, and handling misinformation.
Aldoseri et al. (2023)	Healthcare systems are adopting AI, but data strategies remain misaligned with algorithmic needs.	Introduced concepts and frameworks for smarter data integration that better support AI applications.	Gaps exist in practical guidance for mapping organizational data strategies to AI needs.
Badawy et al. (2023)	A surge of machine learning and deep learning models is being applied to healthcare outcomes prediction.	Provided a consolidated overview of predictive techniques and emerging trends in health analytics.	Review lacks focus on interoperability and deployment hurdles in real-world systems.
Bajwa et al. (2021)	AI is transforming medicine, but practical implementation lags behind published enthusiasm.	Explained key medical use cases and future directions for AI.	Did not address how AI can bridge record integration gaps between systems.
Balogun et al. (2023)	African health systems are gradually integrating AI into public health and informatics.	Surveyed applications and evidence for AI-enhanced health data systems across African settings.	More real-world case studies are needed on implementation in low-resource environments.
Lambert et al. (2024)	Uncertainty in deep learning is a major barrier to clinical trust and adoption.	Reviewed methods for quantifying model uncertainty in medical image applications.	Lacked connection to interoperability; uncertainty metrics applied mostly to standalone image models.
Gao et al. (2024)	Pilots deploying AI for smart healthcare show improved speed and interoperability.	Demonstrated how AI reduced data transfer latency and improved compatibility among systems.	Did not deeply explore error sources or data bias from real-world datasets.
Hu et al. (2021)	Algorithm bias and lack of	Identified sources of bias and	Proposed methods were conceptual

	standardized data formats hinder trustworthy AI in healthcare.	proposed data governance and standardization best practices.	and not yet validated in actual interoperable systems.
Karalis (2024)	Incremental AI implementation with staff showed better acceptance in clinical settings.	Emphasized user involvement and gradual rollout to support adoption and usability.	Did not detail the resources needed for sustained integration and ongoing support.
Kluge (2020)	AI raises ethical issues including consent, fairness, and data governance in healthcare.	Outlined ethical frameworks to guide responsible AI deployment.	Ethics frameworks lacked direct alignment with technical steps for interoperability improvements.
Li et al. (2023)	Deep learning models can effectively classify and structure patient information from medical images.	Validated decision tree and deep learning use for structured patient records.	Did not address dominant labeling inconsistencies across diverse hospitals.
Luo et al. (2021)	Inconsistent coding standards like ICD-10, HL7, and SNOMED disrupt data sharing.	Mapped coding mismatches and their impact on interoperability.	Practical AI-based strategies to reconcile these mismatches remain unexplored.
Mbunge & Batani (2023)	Deploying ML and DL in sub-Saharan Africa shows promise for local healthcare improvements.	Illustrated the value of AI in predicting disease trends and outcomes.	Implementation challenges such as connectivity, infrastructure, and integration were not fully addressed.
McKee & Wouters (2023)	AI regulation is evolving slower than the pace of clinical adoption.	Highlighted the need for updated regulatory frameworks guiding medical AI.	Did not link regulations to interoperability focused more on device classification and approval.
Mullankandy et al. (2024)	Emerging trends include long-term AI deployment across hospital networks.	Recommended continuous model updates as clinical and tech standards evolve.	Needs further exploration of staff training, bias mitigation, and ethical deployment.
Murdoch (2021)	AI introduces significant privacy vulnerabilities in health systems.	Identified encryption, anonymization, and governance strategies for privacy protection.	Solutions often lack interoperability integration system-level adoption remains limited.
Khalid et al. (2023)	GDPR and similar laws influence cross-border AI data sharing significantly.	Reviewed privacy-aware technical frameworks such as federated learning.	Did not fully tackle the trade-off between privacy compliance and usability in clinical workflows.
Panch et al. (2019)	Algorithmic bias in AI systems can harm marginalized patient groups.	Emphasized the importance of bias detection and mitigation strategies.	No concrete methods were proposed to correct bias or assess models post-deployment in live systems.
Petersson et al. (2022)	Clinicians report misalignment between AI tools and clinical workflows.	Argued that seamless interoperability requires clinician-informed design.	Lacked evaluation of solutions within real workflows still largely conceptual.
Pushadapu (2022)	Preprocessing is crucial before applying AI to health data.	Showed that data cleaning and standardization significantly improve downstream AI effectiveness.	Did not quantify the specific benefits of preprocessing steps in real pipelines.
Rahimi et al. (2021)	AI is being used in community healthcare, but uptake remains steady.	Provided a scoping overview of AI's reach in primary care settings.	Did not focus on interoperability challenges mainly concerned with model usability and adoption.
Torab-Miandoab et al. (2023)	Interoperability challenges due to heterogeneity in health information systems.	Systematically reviewed AI application in varied systems environments.	Lacked focus on successful large-scale deployment mostly descriptive synthesis.
Tsai et al. (2020)	Implementing EHR systems faces barriers from both technical and human perspectives.	Offered recommendations for overcoming adoption and interoperability issues.	AI-based solutions were not covered focus stayed on EHR implementation.
Warbhe & Verma (2024)	Clinical notes varied significantly in style, format, and terminology.	Proved NLP can extract valuable clinical insights even from inconsistent text.	Handling of local jargon and writing variations was still a major obstacle.
WHO (2023)	Global AI guidance has a strong focus on interoperability as a health priority.	Provided international principles and model governance frameworks.	No practical guidelines on applying these standards at the system level.
Yadav et al. (2023)	AI era raises new data privacy concerns and compliance complexity.	Reviewed legal frameworks and emerging best practices for data consent.	Lacked integration with system-wide interoperability considerations.
Yang (2022)	Predictive AI models need explainability to be trusted by clinicians.	Advocated for transparent model design and interpretable outputs.	Did not link explainable AI directly to interoperability frameworks.

4.2 Benefits and Limitations of AI Approaches

Advanced digital technologies are bringing real benefits to healthcare, especially when it comes to improving how data is integrated and shared. These tools help reduce errors that come from manual data entry and make it easier to share information in real time, which can speed up decision-making and care delivery (Lambert et al., 2024). Despite these advantages, there are still some important challenges to consider. Automated systems can sometimes carry hidden biases, which might affect how data is interpreted or used. Setting up these technologies can also be expensive at first, and they require regular updates and ongoing maintenance to stay effective (Murdoch, 2021). Another concern is the lack of transparency in how some AI models process information, which can make healthcare professionals hesitant to fully trust or adopt them (Karalis, 2024).

4.3 Risk and Ethical Considerations

The growing use of advanced digital tools in healthcare brings with it several important ethical and legal issues, particularly around data privacy and fairness. One major concern is that if the data used to train automated systems isn't diverse or truly representative, the technology might unintentionally treat some patient groups unfairly or miss key health trends in certain populations (McKee & Wouters, 2023). Protecting patient information is also critical. As healthcare providers adopt new digital tools for processing and integrating data, they must follow strict privacy regulations like HIPAA and GDPR to ensure sensitive information is handled responsibly and securely (Yadav et al., 2023).

4.4 Interoperability Framework on The Integration of Data Sources

A practical, people-focused Framework (Fig 1) with an aim to improve healthcare interoperability with AI starts by organizing health data and making sure it follows common standards like HL7 and FHIR so different systems can understand each other (Pushadapu, 2022; Luo et al., 2021). AI tools like NLP and machine learning help doctors access accurate, connected patient information by translating and aligning data from different platforms (Warbhe & Verma, 2024; Hu et al., 2021). For these technologies to truly help, they must be transparent and easy for healthcare workers to trust and use (Yang, 2022; Karalis, 2024). Protecting patient privacy remains essential, with strict safeguards in place when sharing data (Khalid et al., 2023). Most importantly, real progress comes when healthcare providers, tech experts, and policymakers work together to create safe, practical, and reliable solutions for better, more connected care (Mullankandy et al., 2024; Balogun et al., 2023).

Abbreviations Key

EHRs – Electronic Health Records
NLP – Natural Language Processing
ML – Machine Learning
XAI – Explainable Artificial Intelligence
APIs – Application Programming Interfaces
FHIR– Fast Healthcare Interoperability Resources
HL7 – Health Level Seven International

Figure 1
Interoperability Framework on the Integration of Data Sources
Source: Researcher (2025)

V. CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

Modern digital technologies offer a promising way to address the ongoing challenge of healthcare interoperability. Supporting the first goal, which looks at how technology can improve data exchange, these tools make it easier to bring together patient records from different sources, helping clinicians make timely and informed decisions.

They are especially useful in overcoming problems caused by incompatible systems and isolated data silos. In line with the second objective, methods like natural language processing and machine learning can interpret unstructured clinical notes and connect fragmented datasets, making the information more useful across different platforms. However, achieving the third goal, which involves assessing the effectiveness of these technologies while ensuring security and ethical compliance, requires careful consideration. Concerns about data privacy, the lack of transparency in how automated decisions are made, and the need to meet evolving regulations like GDPR and HIPAA are still significant obstacles. Unless these challenges are addressed, the full benefits of digital technologies in improving healthcare coordination, accuracy, and efficiency will remain out of reach.

5.2 Recommendations

To make healthcare systems work better together, we need more than just new technology; we need simple, practical solutions that work for both people and systems. This means creating tools that follow common standards so hospitals, clinics, and digital platforms can easily share information. At the same time, healthcare workers need the right training and support to feel confident using these tools in real-life situations. Protecting patient privacy must always come first, with strong security in place to keep sensitive information safe. But none of this can happen in isolation. Healthcare providers, tech experts, policymakers, and patients all need to work together to build solutions that are trustworthy, practical, and meet real-world needs.

This review adds value by showing how AI, especially tools like natural language processing and machine learning, can help solve long-standing problems in health data sharing. It also offers a clear, step-by-step framework to introduce AI into healthcare in a way that protects patient rights and follows legal requirements. But beyond the technology, this review reminds us of the human side of AI, the need for fairness, transparency, and collaboration to make these tools work in practice, not just in theory.

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