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(Review Article)

A methodological framework for developing AI-enabled health information interoperability solutions to improve secure health information exchange across medicaid ecosystems

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Abstract

Medicaid continues to face fragmented HIE despite federal initiatives. This study develops a methodological framework for AI-enabled interoperability through a synthesis of literature, standards, and policy documents. Guided by STS, TOE, and DSR, the framework integrates readiness, standardization, governance, AI development, security, equity, and evaluation. The findings show that existing frameworks provide limited guidance for AI integration and governance, highlighting the need for a structured sociotechnical approach to achieve secure and equitable interoperability across Medicaid.

Keywords: Health Information Exchange; Interoperability; Artificial Intelligence; Medicaid; Federated Learning; Governance, Privacy; Equity; Methodological Framework; Machine Learning

1. Introduction

Medicaid, the largest U.S. public health insurer, serves tens of millions of low-income beneficiaries who interact with multiple providers and agencies, making health information exchange (HIE) essential for coordinated care (CMS, 2023). Despite federal incentives from CMS and ONC over the past decade (Adler-Milstein & Jha, 2017), interoperability remains fragmented due to data silos, inconsistent standards, and uneven policy implementation (Vest & Kash, 2016). Data are often incomplete, poorly formatted, or unavailable at the point of care (Adler-Milstein et al., 2014), and state-level variation in HIT maturity, funding, and organizational capacity further limits data reuse for analytics and population health (Gold et al., 2018; Ong et al., 2017).

Artificial intelligence offers transformative potential for diagnostics, predictive modeling, and efficiency (Esteva et al., 2019), but AI systems require large volumes of high-quality, standardized longitudinal data (Beam & Kohane, 2018). Fragmented Medicaid environments constrain the development of robust, fair, and generalizable models (Singh et al., 2025). While frameworks like MITA guide Medicaid modernization toward modular, standards-based architectures (CMS, 2015), they predate widespread AI and lack guidance for integrating workflows such as federated learning, explainability, and algorithm governance (Chiang & Friedman, 2019). Emerging research shows machine learning can optimize record matching and data routing, yet calls for stronger privacy, bias mitigation, and transparent governance, particularly critical for Medicaid's vulnerable populations (Denecke & Deng, 2022).

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Privacy-preserving techniques like federated learning and differential privacy enable collaborative analytics without centralizing sensitive data (Rieke et al., 2020; Kaissis et al., 2020), but ad-hoc approaches remain inadequate for complex public systems like Medicaid (Danks & London, 2017). Methodological frameworks are needed to guide stakeholders from design through evaluation while embedding security, privacy, equity, and accountability (Denecke & Deng, 2022). The literature reveals a critical gap: few studies integrate HIE, Medicaid modernization, and AI into a comprehensive framework addressing operational, ethical, and governance challenges (Gold et al., 2018). This study addresses that void by developing a methodological framework that synthesizes health informatics, AI, governance, and Medicaid architecture to guide secure, equitable, AI-enabled interoperability across Medicaid ecosystems (CMS, 2015; Friedman & Wyatt, 2017).

1.1. Objectives of the Study

The following are the objectives of this study:

- To assess HIE interoperability maturity across Medicaid
- To synthesize existing architectural and governance frameworks
- To examine AI applications for HIE
- To develop a methodological framework for AI-enabled interoperability
- To establish security, privacy, equity, and governance requirements; and
- To propose evaluation metrics and implementation guidelines.

1.2. Problem Statement

Medicaid, the largest U.S. public health insurer, continues to face fragmented and uneven HIE despite federal initiatives (Adler-Milstein & Jha, 2017; Vest & Kash, 2016). Incomplete and inconsistent data limit clinical decision making and constrain AI development, which depends on high-quality datasets (Adler-Milstein et al., 2014; Rudin et al., 2014; Beam & Kohane, 2018; Singh et al., 2025). Existing frameworks, including MITA, provide limited guidance for AI integration, while privacy-preserving approaches remain underutilized (Chiang & Friedman, 2019). As a result, no widely adopted methodological framework supports secure, equitable, and AI-enabled interoperability across Medicaid, leaving fragmented implementations vulnerable to security, governance, and equity challenges (Gold et al., 2018). This study addresses this gap by developing a methodological framework to support trustworthy AI-enabled interoperability and improve care coordination across Medicaid (Adler-Milstein & Jha, 2017).

1.3. Context and Motivation

Medicaid serves millions of low-income Americans, yet HIE remains uneven across states and providers due to persistent challenges such as incomplete data, patient matching, workflow disruption, and privacy concerns (ONC, 2018; Vest, 2010; Everson & Patel, 2016; Vest & Gamm, 2010). These barriers continue to limit coordinated care, particularly in hospitals with large Medicaid populations (Li et al., 2023). Although AI relies on interoperable, high-quality data, existing frameworks emphasize technical standards and policy while providing limited support for AI workflows, privacy-preserving analytics, and algorithm governance (Friedman & Parrish, 2013). This study addresses these gaps by proposing an evidence-informed methodological framework for secure, AI-enabled interoperability to improve equitable and trustworthy care across Medicaid (Adler-Milstein & Jha, 2017).

1.4. Research Questions

- RQ1: What is the maturity of Medicaid HIE interoperability, and how does it enable or constrain secure exchange?
- RQ2: Which frameworks support Medicaid HIE, and to what extent do they accommodate AI workflows?
- RQ3: How are AI techniques applied to enhance interoperability in Medicaid and public health contexts?
- RQ4: What components and phases constitute a methodological framework for AI-enabled interoperability?
- RQ5: What security, privacy, equity, and governance requirements must be embedded?
- RQ6: What evaluation metrics and guidelines assess effectiveness, scalability, and ethical soundness?

1.5. Scope and Delimitations

1.5.1. Scope

This framework supports secure data exchange among providers, Medicaid agencies, public health organizations, pharmacies, laboratories, and payers, while using interoperability standards such as HL7 FHIR, SMART on FHIR, USCDI, and APIs. It also incorporates AI/ML methods, privacy and cybersecurity controls, data integration and semantic interoperability, and robust system architecture design for implementation and performance evaluation.

1.5.2. Delimitations

This study focuses on U.S. Medicaid ecosystems and develops a conceptual framework through literature synthesis rather than operational implementation or empirical validation in live systems. It excludes economic evaluation, large-scale deployment, and broader clinical or patient-centered outcomes, concentrating instead on the technical, security, governance, and interoperability issues relevant to AI-enabled secure exchange.

2. Literature Review

2.1. Conceptual Foundations: Interoperability, Health Information Interoperability, and Medicaid

Health information exchange (HIE) refers to the electronic sharing of clinical data among authorized organizations to support care coordination and quality improvement, giving providers secure access to longitudinal patient information (Walker et al., 2005). Interoperability is a broader concept that describes systems' ability to communicate, exchange, and use data (HIMSS, 2013), with syntactic, semantic, and organizational interoperability working together to support consistent message parsing, clinical interpretation, and workflow support (Mandl et al., 2024).

AI-enabled systems build on these foundations by using machine learning for data standardization, record matching, risk prediction, and privacy-preserving sharing (Borna et al., 2023). Because AI depends on interoperable, high-quality data, inconsistent formats and weak agreements can create bias and safety risks (Mandl et al., 2024), making Medicaid a critical setting for secure, equitable, and trustworthy AI-enabled interoperability solutions (Sommers & Maylone, 2017; ONC, 2013). To provide a simple conceptual lens for summarizing interoperability in the literature, you can introduce an **interoperability index** defined as:

$$I = \frac{S + D + G}{3}$$

where I is an interoperability score, S represents standardization, D represents data accessibility, and G represents governance maturity.

2.2. State of Health Information Exchange and Interoperability in Medicaid

2.2.1. Adoption and Participation Trends

Empirical studies show HIE participation has increased over time but remains uneven across provider types. In South Carolina hospitals, participation rose from 43% in 2014 to 82% in 2020, with teaching, system-affiliated, and rural referral hospitals, as well as those with higher Medicare/Medicaid inpatient shares, more likely to participate (Li et al., 2023). National evidence indicates hospital use of exchange tools increased between 2014 and 2016, though no single tool consistently provided usable external information (Adler-Milstein et al., 2020).

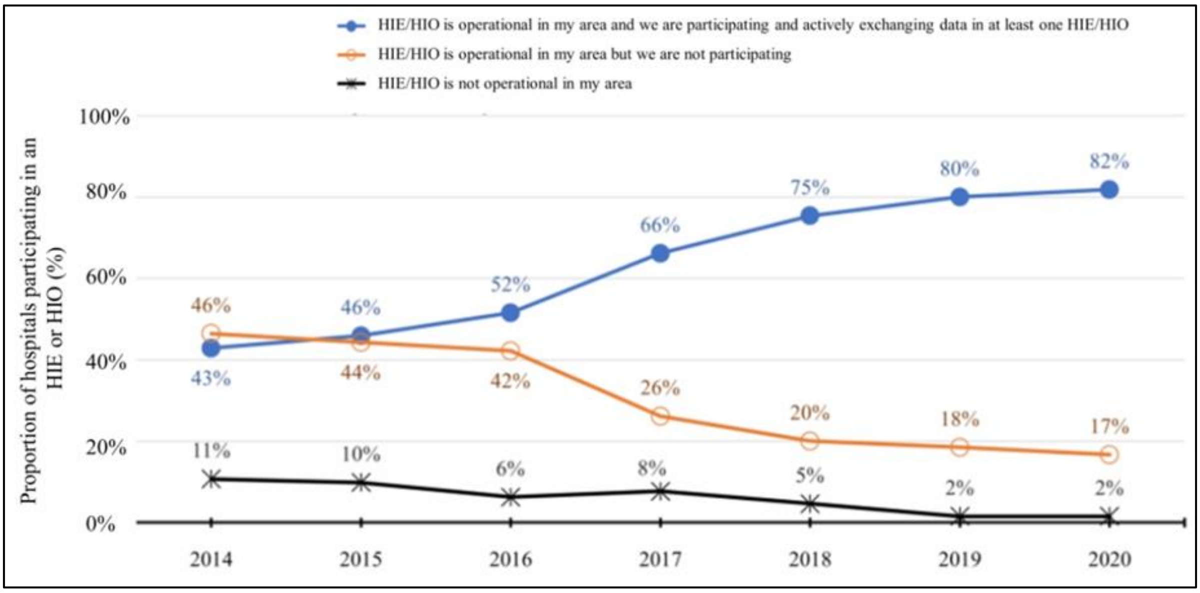

Figure 1 Proportion of hospitals with health information exchange technologies from 2014 to 2020. [Li et al, 2023]

Participation is higher in larger, better-resourced organizations and lower in smaller, resource-constrained facilities (Hung et al., 2023). This suggests HIE adoption depends on organizational capacity and network support, not just technology availability (McCullough et al., 2014).

2.2.2. Barriers and Facilitators to Interoperability

Li et al. (2023) found that despite increased HIE participation in South Carolina, substantial barriers persisted. In 2020, the most common barriers were difficulty locating provider contact information and relevant patient data (68% each), exchanging across vendor platforms (65%), patient matching (58%), and providers not exchanging data (58%); privacy laws were cited by 33%. The pattern showed similar issues: providers with EHRs unable to receive information (70%), providers lacking EHRs (67%), difficulty locating addresses (59%), finding relevant data (59%), and workflow burden (26%). This pattern confirms interoperability challenges encompass data availability, patient matching, platform incompatibility, and workflow design, not a single technical limitation.

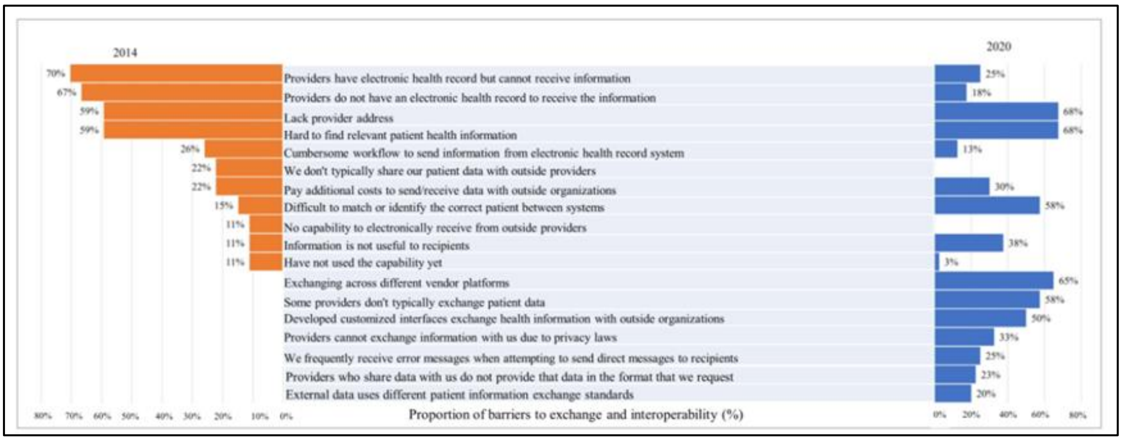

Figure 2 Barriers to exchange and interoperability across South Carolina hospitals in 2014 (n=27) and 2020 (n=40) [Li et al, 2023]

2.2.3. Facilitators to interoperability

The literature identifies several facilitators of interoperability: vendor collaboration and tighter EHR-HIE integration (Walker et al., 2023); shared data standards including SNOMED, LOINC, RxNorm, and CVX (Walker et al., 2023); senior leadership support and workflow resourcing (Walker et al., 2023); and strategic alignment with value-based payment models such as CPC, CPC+, and Primary Care First, which incentivize exchange investment (Walker et al., 2023; Li et al., 2023). Collectively, the evidence demonstrates that interoperability depends on both technical readiness and organizational commitment, improving when systems are connectable and institutions are incentivized to share usable data (Li et al., 2023).

2.3. Artificial Intelligence and Advanced Analytics in Health Information Exchange

AI improves data sharing speed, accuracy, and usability across fragmented Medicaid systems through data normalization, semantic mapping, and NLP that transform unstructured data into standardized formats (CMS, n.d.; Szarfman et al., 2022). AI also addresses patient matching via probabilistic and machine-learning approaches that improve record linkage despite incomplete identifiers (GAO, 2019), while decision support and workflow optimization prioritize incoming data, summarize documents, and alert providers to care gaps, reducing burden and encouraging HIE adoption (Szarfman et al., 2022).

Advanced analytics supports population-level interoperability by turning exchange data into operational intelligence for monitoring referral completion, tracking follow-up, identifying network bottlenecks, and anticipating exchange failures (CMS, n.d.). However, AI-enabled interoperability must remain secure, explainable, and policy-compliant, with scholars emphasizing governed, human-in-the-loop AI rather than fully automated exchange decisions in public-sector health systems (GAO, 2019).

2.4. Existing Frameworks and Standards for Interoperable, AI-Ready Health Data

Established frameworks underpinning interoperable, AI-ready health data environments include FHIR, openEHR, USCDI, and OpenHIE, which address different interoperability layers and are increasingly understood as complementary components of an AI-ready ecosystem (Kapitan et al., 2025).

FHIR as the Exchange Layer: FHIR is the practical exchange standard for interoperable health data, using a modular, API-oriented resource architecture that supports AI applications and connects EHRs, registries, and external systems (Kapitan et al., 2025), with effectiveness assessed using the Exchange Success Rate (HIMSS, 2020), expressed as:

$$\text{ESR} = \frac{\textit{Successful Data Exchanges}}{\textit{Total Exchange Requests}} \text{ x } 100$$

openEHR for Structured Clinical Recording: openEHR provides a semantically rich architecture for persistent clinical information management through reusable archetypes and templates, preserving semantic consistency and supporting AI systems that need structured, longitudinal clinical data (Kapitan et al., 2025). The quality of structured clinical documentation is commonly evaluated using record completeness (Weiskopf & Weng, 2013) measures:

$$\text{Completeness} = \frac{\textit{Observed Required Elements}}{\textit{Expected Required Elements}}\ x\ 100$$

USCDI for Minimum Exchange Content: USCDI establishes the minimum standardized data elements for nationwide health information exchange, and in Medicaid ecosystems these shared elements improve interoperability and AI readiness (ONC, 2020). Compliance with USCDI requirements is commonly evaluated using the Data Element Completeness Rate (DHIS, 2024):

$$\text{DECR} = \frac{\textit{Available Required Data Elements}}{\textit{Total Required Data Elements}}\ x\ 100$$

OpenHIE for Networked Exchange: OpenHIE is a governance-oriented architectural framework that coordinates shared health records, registries, and terminology services across fragmented health systems, making it well suited to Medicaid ecosystems with many stakeholders (Kapitan et al., 2025). The operational performance of OpenHIE implementations is commonly evaluated using the system reliability metric (ISO/IEC 25010, 2011):

$$\text{Reliability} = \frac{\textit{Successful Transactions}}{\textit{Total Transactions}}\ x\ 100$$

2.5. Technical Standards and Architectures (HL7, FHIR, MITA)

HL7, FHIR, and MITA provide the structural basis for interoperable health information exchange at different levels of abstraction, with HL7 and FHIR supporting data exchange and FHIR offering an API-oriented, web-based specification (Mahmoud, 2017; Bender & Sartipi, 2013). MITA complements these standards by organizing Medicaid business, information, and technical requirements to support governance, modularity, and integration across system domains (CMS, 2005).

FHIR is particularly relevant for AI integration because its modular, web-based design provides structured, machine-readable data that can be directly used by analytic and machine learning pipelines (Mandel et al., 2016; Saripalle et al., 2019). Its resource-based architecture, profiles, RESTful APIs, and adapters create consistent data models and access patterns that support prediction, classification, summarization, and patient matching across Medicaid stakeholders (Shreyas, 2024).

MITA provides an enterprise architecture for interoperability within Medicaid ecosystems by aligning business, information, and technical layers across policy, governance, data, and technology (CMS, 2003). For AI-enabled interoperability, it offers a governance framework that supports secure, scalable, and policy-compliant health information exchange tailored to Medicaid workflows.

2.6. Governance, Security, and Ethical Frameworks

The adoption of AI in HIE has heightened the need for comprehensive governance, security, and ethical frameworks to ensure interoperable health systems remain trustworthy and compliant, particularly in Medicaid (WHO, 2021). Health data governance addresses secure lifecycle management, while TEFCA, MITA, HIPAA, and the NIST Cybersecurity Framework provide national, Medicaid-specific, legal, and technical safeguards for secure exchange (ONC, 2023).

Privacy-preserving approaches such as federated learning support distributed model training without exchanging identifiable records, making them well suited to Medicaid's environment (McMahan et al., 2017). Ethical guidance from the WHO also helps address bias and discrimination, and interoperability standards strengthen trustworthy AI by improving data quality, reducing bias, and enhancing reproducibility (WHO, 2021; Arora et al., 2023).

2.7. Gaps in Methodological Guidance for Medicaid Contexts

Current methodological guidance falls short for Medicaid in three key areas: limited attention to governance realities, policy constraints, and accountability demands shaping data sharing (McGraw et al., 2009; Adler-Milstein & Jha, 2017); insufficient treatment of security and privacy in AI data pipelines, particularly given Medicaid's highly sensitive data (Abouelmehdi et al., 2018); and inadequate focus on equity, despite recognition that low-income populations can be harmed by biased data (Obermeyer et al., 2019). These gaps point to the absence of a comprehensive, Medicaid-tailored framework, directly motivating this study's objective to develop one explicitly grounded in Medicaid governance, security, privacy, and equity requirements.

2.8. Theoretical and Conceptual Framework

This study is grounded in three complementary theories: Sociotechnical Systems (STS), which emphasizes the integration of technology, organizations, and governance (Trist & Bamforth, 1951); the Technology-Organization-Environment (TOE) Framework, which explains technological, organizational, and environmental influences on Medicaid interoperability (Tornatzky & Fleischer, 1990); and Design Science Research (DSR), which guides the development and evaluation of the proposed methodological framework (Hevner et al., 2004). The conceptual framework synthesizes insights from the literature and guiding theories, proposing that successful AI-enabled interoperability within Medicaid is influenced by the interaction of interoperability standards (FHIR, openEHR, OMOP, USCDI, TEFCA, MITA), AI capabilities (machine learning, federated learning, advanced analytics), governance mechanisms, security and privacy safeguards, and equity considerations.

3. Methodology

3.1. Research Design and Theoretical Framework

This study adopts a meta-analytic and qualitative synthesis design to develop a methodological framework for AI-enabled health information interoperability in Medicaid, systematically examining existing literature, technical standards, and policy documents to identify recurring phases, processes, and decision points in secure HIE. Guided by STS Theory, the TOE Framework, and DSR Theory, the research interprets interoperability as a sociotechnical system where technology, people, governance, and institutional arrangements are interdependent, examines how technological capability, organizational readiness, and environmental pressures influence adoption, and applies DSR logic to translate synthesized evidence into a practical framework. The theoretical framework shapes study selection, coding, and synthesis, with the final framework emerging from structured synthesis of prior studies on sociotechnical alignment, governance, interoperability standards, AI integration, and security requirements.

3.2. System Architecture and Technical Specifications

3.2.1. Layer 1: Data source layer

The data source layer aggregates diverse Medicaid health data inputs and emphasizes capture, provenance, and source identification as the raw substrate for interoperability, governance, and AI processes. To assess the adequacy of this layer, data completeness may be measured using the formula:

$$\text{Completeness} = \frac{non-missing\ required\ elements}{total\ required\ elements}\ x\ 100$$

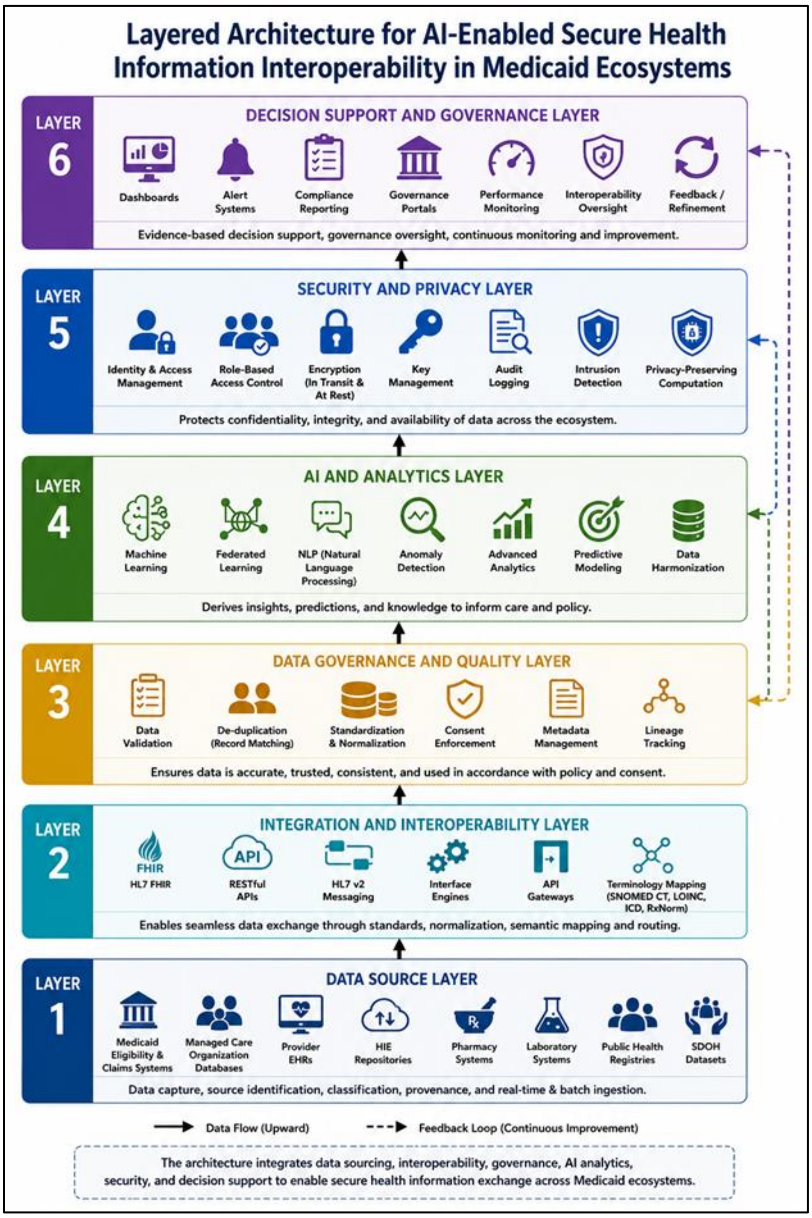

Figure 3 Layered Framework for AI-Enabled Secure Health Information Interoperability in Medicaid Ecosystems

3.2.2. Layer 2: Integration and interoperability layer

The integration and interoperability layer standardizes and exchanges data across heterogeneous systems using HL7 FHIR, RESTful APIs, and standard terminologies such as SNOMED CT, LOINC, ICD, and RxNorm through semantic mapping, message transformation, and API-based routing. A relevant measure of performance is semantic coverage, expressed as Semantic

$$\text{Coverage} = \frac{\textit{mapped codes}}{\textit{total distinct codes encountered}}\ x\ 100$$

which indicates the extent to which incoming data are successfully harmonized for cross-system interpretation.

3.2.3. Layer 3: Data governance and quality layer

The data governance and quality layer ensures exchanged information is accurate, consistent, traceable, and compliant through validation, de-duplication, standardization, consent enforcement, metadata management, and lineage tracking. Data completeness may be assessed using the formula:

$$\text{Completeness} = \frac{\textit{non-missing values}}{\textit{expected values}}\ x\ 100$$

while data validation failure may be summarized through the error rate, expressed as:

$$\text{Error Rate} = \frac{\textit{records failing validation}}{\textit{total records}}\ x\ 100$$

3.2.4. Layer 4: AI and analytics layer

The AI and analytics layer converts standardized, governed data into predictive and decision-support outputs using machine learning, federated learning, NLP, and anomaly detection, with performance evaluated by metrics such as precision, recall, and F1 score. The F1 score, a widely recognized metric in the machine learning literature, is expressed as:

$$\text{F1} = 2\ \text{x}\ \frac{\textit{Precision x Recall}}{\textit{Precision + Recall}}$$

3.2.5. Layer 5: Security and privacy layer

The security and privacy layer protects data integrity, confidentiality, and availability across exchange and analysis stages through access control, encryption, audit logging, intrusion detection, and privacy-preserving methods such as differential privacy and federated learning. A commonly used operational indicator is encryption coverage, which may be calculated as Encryption

$$\text{Coverage} = \frac{\textit{encrypted sensitive fields}}{\textit{total sensitive fields}}\ x\ 100.$$

3.2.6. Layer 6: Decision support and governance layer

The decision support and governance layer converts technical outputs into oversight and policy actions through dashboards, compliance reporting, governance portals, alerts, and performance monitoring, promoting accountable decision making across the Medicaid ecosystem. Key indicators include interoperability success rate, defined as Success

Rate = $\frac{\textit{successful exchanges}}{\textit{attempted exchanges}}\ x\ 100$, and adoption rate, defined as Adoption Rate = $\frac{\textit{active users}}{\textit{target users}}\ x\ 100$.

3.3. Algorithm Flowchart and Process Design

The algorithm flowchart reflects the operational sequence of the proposed framework, beginning with identification and selection of relevant literature, standards, and policy documents, followed by extraction and coding of evidence on interoperability maturity, governance, AI applications, security, and evaluation criteria. Synthesized evidence is organized into the layered framework, mapping relationships to show data movement from source systems through integration, governance, AI analysis, security enforcement, and decision support.

3.4. Data Processing and Privacy Preservation

Data processing involved organizing, screening, coding, and synthesizing publicly available literature, policy documents, and technical sources. Materials were classified into themes including interoperability, AI applications, governance, security, and evaluation. Privacy was preserved by excluding identifiable patient data and analyzing only summarized findings, coded themes, and conceptual frameworks.

4. Results and discussion

4.1. Presentation of Key Findings

This section presents the key findings derived from the systematic synthesis and analysis of the literature on AI-enabled health information interoperability in Medicaid ecosystems. The findings are organized according to the research questions that guided this study.

The findings indicate that health information interoperability across Medicaid remains at a partial level of maturity, with persistent technical, organizational, and governance challenges limiting secure HIE. Although hospital participation in South Carolina increased from 43% in 2014 to 82% in 2020, significant barriers, including provider contact identification, patient data access, cross-vendor exchange, and patient matching, continue to constrain interoperability (Li et al., 2023). Similar platform integration and workflow challenges were reported in Ohio (Walker et al., 2023), reinforcing Adler-Milstein and Jha's (2017) conclusion that HIE maturity remains uneven across states and provider settings. The review further shows that existing frameworks, including MITA, FHIR, OMOP, USCDI, TEFCA, and openEHR, provide a strong technical foundation for interoperability but offer limited support for AI workflows, privacy-preserving analytics, federated learning, explainability, and algorithm governance (Chiang & Friedman, 2019; Kapitan et al., 2025; ONC, 2020, 2023; Singh et al., 2025). These limitations justify the need for an AI-enabled methodological framework tailored to Medicaid. Finally, the evidence demonstrates that AI techniques, including natural language processing, machine learning, patient matching, knowledge graphs, and federated learning, enhance interoperability through data extraction, schema mapping, semantic interoperability, and privacy-preserving collaboration while improving workflow efficiency through data prioritization, record summarization, and care gap identification (Szarfman et al., 2022; Mirzaei et al., 2022; GAO, 2019; Kapitan et al., 2025; Rieke et al., 2020; Kaissis et al., 2020). Despite these advances, AI adoption within Medicaid remains constrained by fragmented data environments and insufficient governance across agencies and providers (CMS, n.d.).

4.2. Interpretation and Analysis

AI-enabled health information interoperability in Medicaid is a sociotechnical challenge requiring alignment of technology, governance, security, and organizational capacity. Persistent barriers, including information retrieval, cross-vendor exchange, and workflow integration, show that interoperability depends as much on organizational readiness as technical infrastructure (Li et al., 2023; Walker et al., 2023). Although frameworks such as FHIR, OMOP, USCDI, TEFCA, and MITA provide a technical foundation, they offer limited guidance for AI workflows, federated learning, explainability, and algorithm governance (Chiang & Friedman, 2019). Consequently, AI adoption in Medicaid remains constrained by fragmented data and limited governance despite advances in NLP, machine learning, and federated learning (Beam & Kohane, 2018). Achieving equitable AI-enabled interoperability therefore requires stronger data infrastructure, governance, workforce capacity, and ethical oversight, particularly for Medicaid's vulnerable populations (WHO, 2021).

4.3. Policy and Implementation Implications

4.3.1. For Policymakers and Regulators

Technical standards alone are insufficient for meaningful interoperability; regulatory frameworks must be complemented by resources and support mechanisms, particularly for safety-net and rural providers serving disproportionate Medicaid populations. Effective implementation requires technical assistance, staggered timelines for smaller organizations, and patient data use review boards to ensure accountability and transparency in how beneficiary data are used for AI development.

4.4. Limitations and Future Work

This study is limited by its reliance on literature synthesis rather than empirical validation and by the exclusion of patient records, large-scale implementations, economic analyses, and international comparisons. It focuses on technical and governance issues, and rapid advances in AI may affect the relevance of some findings. Future research should validate the framework through pilot studies, develop standardized evaluation metrics, examine governance for federated learning, compare implementation across states, and assess long-term health and equity outcomes.

5. Conclusion

Summary of Findings

Interoperability in Medicaid has advanced but remains fragmented due to persistent barriers, including patient information retrieval, cross-vendor exchange, patient matching, and workflow constraints (Li et al., 2023; Walker et al., 2023). Existing frameworks provide a technical foundation but offer limited guidance for AI workflows, federated learning, and algorithm governance (Chiang & Friedman, 2019). Although AI techniques show promise, their adoption remains limited and insufficiently governed (Szarfman et al., 2022; Rieke et al., 2020). The findings support the need for a structured sociotechnical framework that integrates standards, AI, security, privacy, equity, and continuous evaluation to achieve secure and trustworthy interoperability across Medicaid (Hevner et al., 2004).

Recommendations: For various authorities and institutions

- **For State Medicaid Agencies**

Establish dedicated interoperability governance bodies with diverse stakeholder representation to develop phased roadmaps prioritizing readiness assessment, standards adoption, AI capability building, and continuous evaluation, while allocating funding for workforce development in interoperability standards, AI tools, and privacy-preserving techniques.

- **For Healthcare Providers and Hospitals**

Adopt interoperability standards (FHIR, USCDI, standardized terminologies) and invest in data quality improvement programs to ensure exchange-ready data, while participating in collaborative initiatives including HIEs and federated learning networks for privacy-preserving AI development.

- **For Health Information Exchanges and Networks**

Expand technical infrastructure to support AI-enabled data processing, patient matching, and secure API-based exchange, while developing governance frameworks for AI use cases, data access policies, model validation, and transparency reporting, and facilitating stakeholder engagement to align priorities.

- **For Academic and Research Institutions**

Conduct implementation research on AI-enabled interoperability in Medicaid to generate evidence on effectiveness, scalability, and equity, develop and validate evaluation metrics, and engage beneficiaries through community-based participatory research to ensure their perspectives inform AI governance and interoperability design.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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