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Interoperability as a dynamic capability for artificial intelligence-augmented and sustainable health systems

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ABSTRACT

Introduction: Healthcare systems face growing pressure to integrate artificial intelligence into clinical workflows, yet a fundamental governance gap constrains these tools' potential: a lack of interoperability across health information systems, institutions, and care levels.
Objectives: This study examines how interoperability functions as a dynamic capability that enables synergistic collaboration between artificial and human intelligence in healthcare systems, and identifies governance, workforce, and implementation implications for health administrators at the national, regional, and institutional levels.
Methodology: A systematic literature review guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 statement analyzed 40 peer-reviewed studies published between 2020 and 2025, retrieved from Scopus, Web of Science, PubMed, and IEEE Xplore. Quality assessment by two independent reviewers using the Mixed Methods Appraisal Tool achieved 89% inter-rater agreement; thematic synthesis inter-coder reliability reached a Cohen's kappa of 0.78.
Results: Three interconnected themes emerged: interoperability as a meta-governance mechanism, in which governance-first design is an empirical predictor of artificial intelligence implementation success; an artificial intelligence and human intelligence augmentation cycle, in which interoperable data foundations elevate clinical roles and generate new workforce competencies; and sustainable development goal pathways, with mental health data integration identified as a consequential and underexplored governance frontier. Complementary empirical evidence from a Brazilian reference hospital documents annual losses exceeding four million United States dollars attributable to interoperability failure.
Conclusion: Interoperability must be conceptualized as strategic dynamic capability-building, not information technology infrastructure. Governance-first implementation, legal clarity, workforce development, and multilevel coordination are preconditions for equitable, artificial intelligence-enabled health systems.

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RESUMO

Introdução: Os sistemas de saúde enfrentam uma pressão crescente para integrar inteligência artificial aos fluxos de trabalho clínicos, mas o potencial dessas ferramentas permanece limitado por uma lacuna fundamental de governança: a ausência de interoperabilidade entre sistemas de informação em saúde, instituições e níveis de cuidado.
Objetivos: Este estudo examina como a interoperabilidade funciona como uma capacidade dinâmica que possibilita a colaboração sinérgica entre inteligência artificial e inteligência humana em sistemas de saúde e identifica implicações de governança, força de trabalho e implementação para administradores de saúde nos níveis nacional, regional e institucional.
Metodologia: Uma revisão sistemática da literatura, guiada pela declaração Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020, analisou 40 estudos revisados por pares publicados entre 2020 e 2025, extraídos de Scopus, Web of Science, PubMed e IEEE Xplore. A avaliação de qualidade por dois revisores independentes, com a Ferramenta de Avaliação de Métodos Mistos, alcançou 89% de concordância entre os avaliadores; a confiabilidade entre os codificadores de síntese temática atingiu um coeficiente kappa de Cohen de 0,78.
Resultados: Surgiram três temas interconectados: interoperabilidade como um mecanismo meta-governança, no qual o design governança-prioritária é um preditor empírico do sucesso da implementação da inteligência artificial; um ciclo de aumento de inteligência artificial e inteligência humana, no qual fundações de dados interoperáveis elevam papéis clínicos e geram novas competências na força de trabalho; e caminhos para metas de desenvolvimento sustentável, com a integração de dados de saúde mental identificada como consequência e fronteira de governança pouco explorada. Evidências empíricas complementares de um hospital de referência brasileiro documentam perdas anuais superiores a quatro milhões de dólares americanos atribuídas à falha de interoperabilidade.
Conclusão: A interoperabilidade deve ser conceituada como a construção estratégica e dinâmica de capacidades, e não como infraestrutura de tecnologia da informação. A implementação centrada na governança, na clareza jurídica, no desenvolvimento da força de trabalho e na coordenação multinível é uma pré-condição para sistemas de saúde equitativos e habilitados por inteligência artificial.

Introduction

Healthcare systems worldwide face mounting pressures from aging populations, chronic disease burdens, and resource constraints, while simultaneously navigating the rapid integration of artificial intelligence into clinical workflows, diagnostic processes, and population health surveillance. Artificial intelligence (AI) has demonstrated potential to improve diagnostic accuracy, optimize resource allocation, and support epidemiological surveillance.[1,2] However, this potential remains unrealized in many health systems, constrained not by algorithmic limitations but by a more fundamental, pre-existing challenge: the absence of interoperability, defined here as the capacity for secure, standards-based data and process integration across diverse health information systems, institutions, and care levels.

The problem is systemic. Municipal health departments often lack the technical infrastructure to receive AI alerts generated nationally. Regional health authorities struggle to coordinate care pathways across primary care, specialist services, and mental health providers. National health information exchanges cannot deliver value without foundational investment in governance and semantic alignment. In each case, the constraint is not the absence of artificial intelligence tools but the absence of the institutional and technical capacity to connect them. This paper conceptualizes interoperability as the dynamic capability health administrations need to govern collaboration between artificial intelligence and human clinical intelligence.

The fragmentation between physical and mental health data systems represents a consequential interoperability gap in contemporary health informatics: artificial intelligence tools deployed for early detection of depression or burnout cannot access the same longitudinal patient data used for cardiovascular risk stratification, leading to systematic inequities in the quality of artificial intelligence-supported care across conditions. Addressing this gap is essential to progress toward the targets of Sustainable Development Goal 3 (SDG 3.4) on non-communicable diseases and mental health.

The central research question is: *How does interoperability function as a dynamic capability that enables synergistic collaboration between artificial and human intelligence in healthcare systems?* The primary objective is to synthesize current evidence on interoperability as a mediating capability in artificial intelligence-enabled health systems and to derive governance, workforce, and implementation implications for health system administrators at national, regional, and institutional levels.

Theoretical framework

The analysis integrates two complementary theoretical frameworks. First, the Dynamic Capabilities view[3,4] conceptualizes healthcare organizations as possessing resources, artificial intelligence tools, clinical data, and human expertise that must be continuously integrated, built, and reconfigured to address changing technological environments. Interoperability is positioned as a higher-order dynamic capability that enables this reconfiguration. Second, Socio-Technical Systems Theory[5,6] posits that health system performance emerges from the joint optimization of social (human, organizational) and technical (artificial intelligence, information technology infrastructure) subsystems, with interoperability as the critical interface structuring this interaction.

Interoperability as a dynamic capability

The Resource-Based View identifies data, artificial intelligence algorithms, and clinical expertise as valuable healthcare resources. In high-velocity technological environments, the ability to integrate and reconfigure these resources becomes more consequential than the resources themselves.[7] Interoperability functions as the orchestrating capability[4] that enables health systems to combine artificial intelligence computational power with the contextual and ethical reasoning of human clinical intelligence.[8] Without it, both artificial intelligence and human intelligence operate in informational silos, limiting innovation and health equity.

The socio-technical architecture of Artificial Intelligence and Human Intelligence (AI-HI) collaboration

Effective integration of artificial intelligence and human intelligence in healthcare is not only a technical challenge but a socio-technical endeavor. Socio-Technical Systems Theory posits that performance is maximized when social and technical subsystems are jointly optimized.[5] Lebovitz et al.[9] demonstrate that artificial intelligence clinical impact is determined not by standalone accuracy but by how its integration reconfigures collaborative routines and cognitive workflows of clinical teams. Co-production theory[10,11] extends this insight to patients: interoperable personal health record systems, such as those enabled by FHIR-based APIs, allow patients to contribute longitudinal health data and participate in preventive programs. Patient-generated data is consequential for mental health informatics, where self-reported well-being data and social indicators, integrated through interoperable channels, create the longitudinal datasets needed for AI-supported early detection of depression and burnout. Equitable co-production requires deliberate investment in accessible interfaces and digital literacy programs, as populations with limited access to devices or distrust of data sharing are systematically excluded.

Governance architecture: macro, meso, and micro levels

Responsible deployment of artificial intelligence in healthcare requires governance architectures that operate simultaneously at multiple levels. Macro-level governance encompasses national and international policy frameworks, including the European Union (EU) Artificial Intelligence Act, which classifies high-risk medical artificial intelligence and establishes mandatory transparency and safety requirements, as well as data governance legislation such as the General Data Protection Regulation (GDPR).[12] These frameworks set the legal and ethical terms within which regional and institutional health administrators must operate, but do not resolve the operational challenges that arise at lower levels of governance.

Meso-level governance encompasses organizational accountability structures: multidisciplinary artificial intelligence review boards, algorithmic audit processes, and continuous monitoring of deployed artificial intelligence systems. These structures require diverse human intelligence, including clinicians, data scientists, ethicists, and patient representatives, to exercise ongoing oversight of artificial intelligence tools integrated into clinical information systems. Micro-level governance encompasses technical interoperability standards (HL7, FHIR, SNOMED CT) that serve not only as data-exchange protocols but also as governance instruments that encode values, structure data access, and determine accountability.[13,14]

A technically important dimension of micro-level governance concerns privacy-preserving data collaboration modalities that enable artificial intelligence training and inference without centralizing sensitive health data. Federated learning architectures allow institutions to train AI models locally, sharing only model parameters, not patient data, across the network, preserving data sovereignty while enabling population-scale analytics.[15] Split learning and hybrid federated approaches extend this principle to resource-constrained settings by distributing model layers across participating sites.[16] Secure aggregation protocols and differential privacy mechanisms provide additional layers of protection against re-identification from shared model updates, addressing a governance gap that traditional interoperability standards alone cannot resolve.[13] For health system administrators, these modalities represent a governance instrument enabling artificial intelligence collaboration across institutions that cannot legally share patient-level data under GDPR or equivalent frameworks. Interoperability governance must therefore encompass not only data exchange standards but also federated infrastructure protocols, audit mechanisms, and contractual frameworks that govern distributed artificial intelligence training across institutional boundaries.[13]

Comparative evidence from national and regional governance initiatives reinforces the governance-first finding across diverse health system contexts. In the United States, the Trusted Exchange Framework and Common Agreement (TEFCA), established by the Office of the National Coordinator for Health Information Technology, operationalizes nationwide interoperability through a legally binding governance framework that defines the terms of data exchange before designating Qualified Health Information Networks as technical participants.[16] The governance architecture precedes and conditions the technical architecture, consistent with the governance-first pattern identified across the corpus. In the United Kingdom, the National Health Service data strategy has pursued a federated data platform model in which regional Integrated Care Systems negotiate data access agreements and algorithmic accountability structures within a national policy framework, providing a multi-level governance exemplar in which national standards and regional implementation autonomy are explicitly balanced.[17,18] In India, the Ayushman Bharat Digital Mission establishes a national health identifier and consent manager architecture that positions citizen-controlled data access as the governance mechanism mediating between artificial intelligence applications and health records, demonstrating that low- and middle-income countries (LMIC) health systems can design governance-first interoperability at national scale.[19] Estonia's cross-border digital health infrastructure, operating within the European Health Data Space framework, provides evidence that semantic and legal interoperability across national jurisdictions is achievable when governance agreements precede technical integration, with artificial intelligence diagnostic tools accessing unified longitudinal records across participating states.[13] Across these four contexts, varying in income level, health system structure, and regulatory environment, the governance-first pattern holds: the jurisdictions that have advanced furthest in artificial intelligence-enabled interoperability are those that resolved questions of data ownership, consent architecture, and institutional accountability before deploying technical standards at scale.

Municipal and regional governance levels remain an underexplored frontier for implementation. Health administrations at this level must translate national policy frameworks into locally adapted strategies, often working with fragmented legacy information technology systems and constrained budgets. Municipal departments with interoperable patient records can identify at-risk populations for preventive interventions; regional authorities with integrated mental health and primary care data can detect early epidemiological signals, enabling proactive governance. Moreira et al.[20] document this challenge empirically: at a Brazilian reference hospital, the absence of organizational and semantic interoperability resulted in annual losses exceeding US$4 million and cascading administrative failures. Interoperability investment must therefore be justified to institutional, municipal, and regional administrators who govern the implementation capacity that determines whether national standards produce clinical results.

Conceptual model: interoperability as the mediating dynamic capability

Building on this synthesis, the paper proposes a three-layer model: a Foundational Layer of clinical data, artificial intelligence systems, and human clinical intelligence aligned to SDG 3 and its interconnected targets; a Central Mediating Mechanism of interoperability across technical, semantic, and governance sub-capabilities; and a Synergistic Output Layer of governed artificial intelligence and human intelligence collaboration yielding sustainable health outcomes.

The SDG Nexus

The Sustainable Development Goals present an integrated framework in which progress on health (SDG 3) depends on advances across other sectors.[21-23] Within this nexus, interoperability serves as a foundational enabler of infrastructure that links technological innovation to sustainability pathways. Interoperability advances SDG 3.8 (Universal Health Coverage) by reducing care fragmentation, reducing redundant diagnostic costs[17], and enabling longitudinal continuity of care. Open interoperability standards democratize health innovation globally, enabling the development of artificial intelligence tools in low-resource settings (SDG 9). Nordic pandemic data infrastructures demonstrate the role of interoperability in equitable resource distribution (SDG 10).[24] Interoperable telehealth platforms reduce patient and staff travel, while climate-health data integration enables predictive models for climate-sensitive diseases (SDGs 12 and 13).[25]

Mental health data integration offers another, underexplored SDG pathway. SDG 3.4 targets a one-third reduction in premature mortality from non-communicable diseases and the promotion of mental health and well-being by 2030. However, in most health systems, mental health data remains a fragmented segment of health information ecosystems: psychiatric records are siloed from primary care, crisis episode data is not linked to outpatient follow-up, and community mental health services operate on separate platforms from hospital systems. This fragmentation prevents artificial intelligence-supported early detection and the coordinated care pathways that reduce preventable hospitalizations. For regional and municipal health administrations that govern preventive mental health programs, including depression screening, workplace burnout prevention, and adolescent well-being initiatives, interoperability investment in mental health information systems is a

precondition for evidence-based governance. Linking mental health data across education, housing, employment, and health services through interoperable platforms requires the intersectoral coordination SDG 3.4 calls for. However, most jurisdictions still face limited semantic and organizational interoperability in mental health information systems.

Methodology

This study employs a systematic literature review guided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 statement[24] to identify, synthesize, and appraise scholarly evidence at the intersection of healthcare interoperability, artificial intelligence governance, and sustainable health outcomes. The review protocol was designed before data collection and follows standard systematic literature review methodology for health informatics research.

Search strategy and database coverage

Systematic searches were conducted between December 2024 and January 2025 across four databases: Scopus, Web of Science, PubMed, and IEEE Xplore. The search strategy combined four thematic domains: (1) interoperability standards and health information exchange; (2) artificial intelligence technologies in clinical settings; (3) artificial intelligence and human intelligence governance, clinical workflow, and workforce dynamics; and (4) sustainability and SDG alignment. The 2020–2025 timeframe was selected to capture the rapid maturation of HL7 FHIR adoption, the accelerated deployment of artificial intelligence in clinical settings following the COVID-19 pandemic, and the growing regulatory focus on artificial intelligence governance and SDG alignment in health systems.

Table 1. Search strategy by thematic domain.

Domain	Search terms
1. Interoperability standards and health information exchange	interoperability AND (health information exchange OR HIE OR HL7 FHIR OR SNOMED CT OR electronic health record OR EHR)
2. Artificial intelligence in clinical settings	artificial intelligence AND (clinical decision support OR diagnostic AI OR machine learning OR deep learning OR natural language processing) AND healthcare
3. AI-HI governance, clinical workflow, and workforce dynamics	(AI governance OR algorithmic accountability OR human-in-the-loop OR AI oversight OR explainable AI) AND (health system OR clinical workflow OR workforce)
4. Sustainability and SDG alignment	(sustainable development goals OR SDG 3 OR universal health coverage OR health equity) AND (digital health OR health informatics OR interoperability)

Source: The authors (2026)

Boolean operator: AND across domains; OR within domain synonym clusters. Databases: Scopus, Web of Science, PubMed, IEEE Xplore. Search period: December 2024 — January 2025. Publication period: January 2020 — January 2025. Language restriction: English only.

Inclusion and exclusion criteria

Studies were included if they: (1) addressed interoperability in health information systems or artificial intelligence deployment in clinical or public health contexts; (2) were published in peer-reviewed venues; (3) were available in English; and (4) were published between 2020 and 2025. We excluded studies that addressed interoperability solely in non-health domains, were conference abstracts without full-text availability, or were grey literature without peer-reviewed documentation.

Study selection and quality assessment

The final corpus comprised 40 studies: 17 empirical case studies (42.5%), 14 conceptual or theoretical papers (35%), 6 mixed-methods evaluations (15%), and 3 systematic reviews (7.5%). Quality assessment was conducted independently by two reviewers using adapted criteria from the Mixed Methods Appraisal Tool; inter-rater agreement reached 89%. Thematic synthesis employed inductive coding followed by interpretive pattern analysis; inter-coder reliability was assessed using Cohen's kappa ($\kappa = 0.78$), indicating substantial agreement. Studies scoring 75% on the Mixed Methods Appraisal Tool (MMAT) met all applicable criteria for their study type (empirical, conceptual, or mixed-methods). Still, they had minor limitations in external validity or transferability. Studies scoring 100% were primarily theoretical or methodological papers where all criteria were fully satisfied. No included study fell below the 75% threshold; we applied the 50% minimum as an exclusion criterion at full-text assessment, excluding 86 studies. Quality ratings did not differentially weight studies in the narrative synthesis; however, empirical case studies and mixed-methods evaluations (n = 23) were treated as the primary evidentiary base for governance and implementation claims, while conceptual and theoretical papers (n = 17) anchored the dynamic capabilities and socio-technical frameworks.

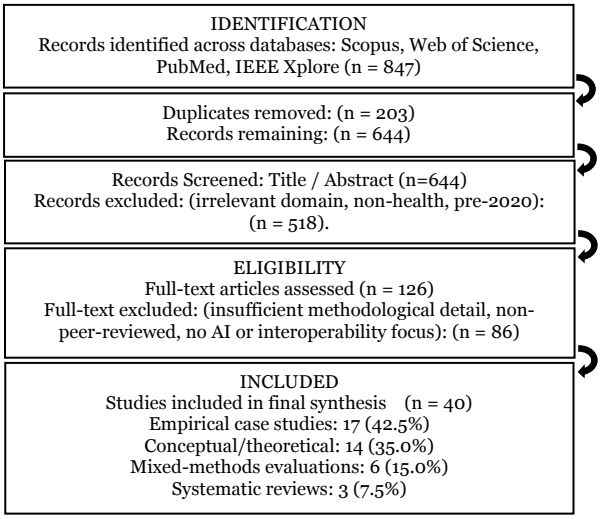

Figure 1. PRISMA 2020 flow diagram: study selection process.
Source: Adapted from Page et al.[26]

Table 2 presents a full list of included studies with study-level characteristics, country context, interoperability standard, thematic contribution, and MMAT quality rating. Not all included studies are cited in the narrative synthesis; those contributing to thematic patterns without direct quotation are listed in Table 2 and included in the reference list.

Results

Interoperability as a meta-governance mechanism

The reviewed literature converges on a consistent finding: successful interoperability initiatives are not merely technical projects but governance architectures that structure the relationship between artificial intelligence and human intelligence within health systems. Effective interoperability platforms are characterized by governance-first design, in which legal, ethical, and institutional frameworks precede and enable technical integration.[27,28,16] Gilboa's[27] analysis of Israel's National Health Information Exchange documents how data ownership rules, patient consent protocols, and inter-institutional accountability structures were negotiated and codified before technical standard deployment, establishing clear rules of engagement for how artificial intelligence applications could access and act upon the unified data ecosystem, preserving human clinical authority while enabling computational augmentation.

From a health system administration perspective, the Israel case illustrates the organizational capabilities required for governance-first implementation. The Ministry of Health developed new administrative competencies extending well beyond conventional information technology project management: the ability to negotiate binding data-sharing agreements with autonomous hospital systems and health maintenance organizations; the capacity to design and enforce patient consent mechanisms satisfying both clinical workflow requirements and data protection law; and the institutional authority to maintain interoperability standards across a politically fragmented health sector. The implementation produced governance capabilities that outlasted the initial technical deployment, enabling rapid integration of artificial intelligence diagnostic tools in subsequent years without the ad hoc governance negotiations characteristic of less-prepared systems.[24]

Contemporary scholarship recognizes technical standards, particularly HL7 FHIR, not only as data exchange protocols but also as governance instruments that encode values and structure power relations between institutions and artificial intelligence systems.[13,14] A central dimension of interoperability-as-governance is the enabling of accountability: Mökander et al.[19,29] demonstrate that audits of deployed artificial intelligence systems are feasible only in interoperable environments in which data lineage, decision trails, and outcome metrics can be systematically tracked across care settings.

An emerging frontier in this governance landscape concerns the integration of large language models with FHIR-based interoperability infrastructure. Recent evidence shows that large language model agents deployed on HL7 FHIR-structured data can navigate complex, resource-based clinical data models to answer interoperable clinical questions across health systems. This capability depends on interoperability governance being in place before deploying the artificial intelligence layer.[30] FHIR-Retrieval-Augmented Generation (RAG) architectures, which combine retrieval-augmented generation with real-time FHIR data retrieval via Substitutable Medical Applications and Reusable Technologies (SMART) on FHIR protocols, enable patient-specific, guideline-concordant clinical recommendations by grounding large language model outputs in longitudinal patient records.[31] These agentic FHIR stacks illustrate the practical stakes of interoperability governance. Without standardized, governed data exchange, large language models operating on fragmented or proprietary electronic health record schemas cannot achieve the cross-institutional generalizability that clinical utility requires. The governance-first principle documented across the systematic corpus thus reappears in the latest generation of artificial intelligence-integrated health data architectures.

The AI-HI augmentation cycle

Interoperable data infrastructures catalyze a synergistic augmentation cycle in which artificial intelligence and human intelligence enhance each other's capabilities, reconfiguring healthcare work and evolving workforce competencies. Artificial intelligence applications achieve higher diagnostic accuracy and clinical utility when deployed on comprehensive, longitudinal, interoperable datasets.[9,13] This performance improvement shifts human clinical work from data gathering toward data interpretation and contextual judgment, requiring deliberate organizational redesign. Pandemic implementations provide illustrative evidence: Aanestad et al.[24] document that interoperable surveillance platforms enabled public health officers to use artificial intelligence to detect epidemiological patterns while concentrating human effort on policy interpretation, community engagement, and ethical resource allocation.

Citizen co-production extends the augmentation cycle: when integrated through interoperable channels, patient-contributed data from wearable devices, health portals, and self-reported outcomes, including well-being indicators, sleep patterns, and social connectivity, create the longitudinal datasets required for artificial intelligence-supported

population-level early detection of depression, anxiety, and burnout.[10,11]

Human capital development is a notable outcome of the augmentation cycle. Gilboa's[27] Israel case documents systematic workforce investment: health information technology professionals acquired competencies in data architecture and standards implementation; clinicians underwent upskilling in data literacy and algorithmic interpretation; and new roles emerged, notably data governance officers mediating between technical systems and clinical workflow needs. Reddy[32] demonstrates that workforce development must be treated as a co-requisite of artificial intelligence adoption, not a downstream consequence. Health administrations that build interoperable systems without simultaneous investment in training frontline workers, community nurses, and social workers in data governance will find that technical capacity outpaces human capacity, generating workarounds and system disuse.

Moreira et al.[20] document an empirical failure mode of this cycle in a Brazilian reference hospital. The absence of organizational interoperability inverted the augmentation cycle: a nurse with enterprise resource planning experience was assigned to information technology support rather than to training, reinforcing dependency with every intervention. Managers could not act without information technology support; institutional knowledge resided in individual technicians rather than documented processes; workforce turnover reset organizational competence to baseline. Annual losses exceeded US$4 million not because of a lack of technology, but because the absence of organizational and semantic interoperability prevented the deployed technology from functioning as designed. Technology without interoperability governance amplifies fragmentation rather than resolving it.

SDG pathways enabled by interoperable health systems

Beyond organizational outcomes, interoperability provides foundational infrastructure for health systems to contribute to multiple Sustainable Development Goals. For Universal Health Coverage (SDG 3.8), Dixon et al.[33] and Gilboa[17] provide convergent evidence that interoperable health information exchanges reduce service duplication, lower patient costs, and improve access to longitudinal records across care settings. Open interoperability standards advance SDG 9 by democratizing health innovation in low-resource settings.[34] Nordic pandemic data infrastructures demonstrate the role of interoperability in equitable resource distribution (SDG 10).[24] Interoperable telehealth platforms reduce travel-related emissions, while integrating climate-health data enables artificial intelligence-driven predictive models for climate-sensitive diseases (SDGs 12 and 13).[25]

Mental health data integration represents an emerging SDG pathway that the reviewed literature has underexplored. SDG 3.4 requires not only clinical intervention but also population-level prevention, which depends on data. In most health systems, mental health services generate fragmented data; crisis episodes in emergency departments are not linked to outpatient psychiatric records, which are siloed from primary care encounters and community mental health assessments. This fragmentation prevents artificial intelligence-supported early detection and the coordinated care pathways that reduce preventable hospitalization. Regional and municipal health authorities that govern preventive mental health programs, including depression screening, workplace burnout prevention, and adolescent well-being initiatives, face a direct governance barrier because interoperable mental health information systems are absent. Linking mental health data across education, housing, employment, and health services reflects the intersectoral coordination SDG 3.4 requires. Still, most jurisdictions are currently impeded by a lack of semantic and organizational interoperability among mental health data systems.

Discussion

Interoperability as governance capability and augmentation prerequisite

This review's central finding is that interoperability is not passive information technology infrastructure but an active, dynamic governance capability. Successful health information exchange implementations, from Israel's National Health Information Exchange to Nordic pandemic data infrastructures, establish legal frameworks, ethical protocols, and institutional accountability structures before technical integration. This governance-first architecture emerges as a convergent pattern across the reviewed implementations, not as a statistically validated predictor from a controlled comparative analysis, but as a finding consistent across geographically and structurally diverse health systems, including Israel, the Nordic countries, the United States, and the United Kingdom.[16-18,,24,27,28] Evidence across these contexts supports governance-first sequencing as a meaningful implementation principle, while acknowledging that causal inference remains a priority for future longitudinal research. For health system administrators, interoperability investment decisions are decisions about organizational capability: the skills, agreements, and governance processes that make technical standards clinically operational. The evidence also refutes the framing of artificial intelligence and human intelligence as competing capabilities.[35] Artificial intelligence accuracy improves with longitudinal, interoperable datasets,[9,13] while human clinical roles are elevated toward interpretation and patient engagement.[8,32] This

augmentation dynamic is contingent on governance infrastructure; without it, as the Brazilian reference hospital case demonstrates,[20] technology amplifies fragmentation, and workforce development cannot be treated as a downstream benefit.

Mental health informatics and policy implications

Mental health interoperability represents a governance challenge that the health informatics field has underaddressed. SDG 3.4 and the clinical imperative to reduce preventable psychiatric hospitalization both require interoperable mental health data infrastructure. Research should address governance mechanisms for cross-setting data sharing, patient-facing design principles that balance clinical utility with privacy and stigma concerns, and implementation pathways for resource-constrained settings. The state of the research infrastructure corroborates the characterization of mental health interoperability as underexplored: despite the existence of catalogues documenting over 55 longitudinal mental health cohort studies and more than 4,000 measures of mental health and well-being,[36] the interoperability of these datasets with routine clinical systems remains limited. Recent harmonization efforts using the International Classification of Functioning, Disability and Health framework to align mental health measures across datasets demonstrate both the technical feasibility and the governance complexity of cross-study data integration.[37] The INSPIRE Network initiative in sub-Saharan Africa illustrates that longitudinal mental health data integration is achievable when common data models and interoperability standards are applied, but that governance frameworks for consent, data access, and cross-institutional accountability remain the binding constraint.[38]

Implications for practice

For health system administrators, the findings yield a practical governance framework. First, interoperability investment should be framed as strategic dynamic capability-building,[3,4,39] requiring legal clarity on data ownership, cross-institutional governance agreements, multidisciplinary artificial intelligence oversight structures,[14,33] and workforce development programs,[32,40] rather than as information technology procurement. Second, municipal and regional health administrations need dedicated support for interoperability governance, including capacity-building resources, legal templates for data-sharing agreements, and workforce training programs aligned with the governance maturity of local health systems. Third, deploying artificial intelligence in health systems should be contingent on demonstrable interoperability governance; without it, the augmentation cycle documented in this review will not materialize, and the risk of clinical and organizational failure, as empirically documented,[20] is substantial. Fourth, mental health information systems should be a priority for the next wave of interoperability investment, given the size of the governance gap and the scale of the public health burden.

Conclusion

This systematic review synthesizes evidence from 40 peer-reviewed studies to demonstrate that interoperability in healthcare is a critical dynamic capability that mediates collaboration between artificial and human intelligence, rather than merely a passive information technology infrastructure. Three empirically grounded themes, interoperability as a meta-governance mechanism, the artificial intelligence and human intelligence augmentation cycle, and sustainable development goal pathway enablement- collectively indicate that the conditions for sustainable, equitable, artificial intelligence-enabled health systems are organizational and governance-based rather than technical.

The evidence does not support framing artificial and human intelligence as competing capabilities. Artificial intelligence effectiveness and human clinical competency are interdependent in interoperable environments, and this augmentation relationship extends to encompass citizens as co-producers of the health data ecosystems on which artificial intelligence governance depends. Governance-first implementations invest in human capital, participatory governance, and multilevel coordination alongside technical standards; those that do not produce the fragmentation and dependency documented in the empirical literature.

The practical implication is clear: treat investment in health data interoperability as strategic governance capability-building for artificial intelligence-enabled, citizen-responsive, multilevel health systems. For clinical informaticians, health system administrators, and policymakers, this means prioritizing governance frameworks, legal clarity, workforce development, and participatory design alongside technical standards, with deliberate attention to the governance conditions of low- and middle-income country health systems, where the gap between interoperability potential and implementation capacity remains a structural barrier.

These findings suggest several research directions. Comparative implementation studies in low- and middle-income country contexts are needed to examine how resource constraints and governance cultures mediate the dynamics of interoperability between artificial and human intelligence. Longitudinal workforce studies should track how clinical roles and skill requirements evolve as interoperable health information systems progressively integrate artificial intelligence tools. Research addressing the governance and organizational barriers to mental health data integration across primary care, specialist, and community settings represents an urgent priority given the scale of the public health burden. Developing and validating metrics that link specific interoperability investments to progress on sustainable development goal indicators, including health equity, access, and climate-health outcomes, would advance the field considerably. Finally, studies examining

the minimum organizational maturity required before interoperability investment can yield the governance and clinical outcomes documented in this review, with reference to the governance failure mode described by Moreira et al., [20], would provide actionable guidance for health system administrators in resource-constrained settings.

Data Availability Statement

The data supporting this review's results consist of the published studies included in the systematic literature review corpus. All included studies are identified in the reference list. No primary dataset was generated. The structured extraction template used for data collection is available from the corresponding author upon reasonable request.

AI use declaration

During the preparation of this study and manuscript, the authors used Claude Sonnet 4 (Anthropic, 2024) to support thematic synthesis, condense manuscript sections to meet journal word limits, and review academic language for terminological consistency. The authors also used Grammarly to review grammar and style in the English-language manuscript, and Consensus to verify bibliographic references. The authors declare that they have reviewed and edited the output and accept full responsibility for the content of this publication.

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