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SPECIAL FOCUS PAPER

Global Agentic Healthcare Intelligence: A Sociotechnical Framework for Digital Innovation, Governance, and Early Detection in Ageing Health Systems

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ABSTRACT

Artificial intelligence (AI) connected biomedical devices, wearable sensing, medical imaging analytics, electronic health record (EHR) intelligence, genomics, smart home monitoring, and telehealth platforms have opened new possibilities for proactive detection. Yet their impact remains constrained by fragmented implementation, limited interoperability, insufficient clinical integration, and unresolved governance challenges. This paper develops global agentic healthcare intelligence (GAHI) as a sociotechnical framework for integrating AI-enabled healthcare intelligence technologies in ageing systems. It introduces the sociotechnical health intelligence transformation model (SHITM), which explains transformation as the alignment of technological intelligence, healthcare value creation, and societal legitimacy. Using comparative framework synthesis and integrative literature review methods, the article evaluates 30 healthcare intelligence technologies based on clinical relevance, early detection capability, AI maturity, scalability, governance risk, ageing applicability, and implementation readiness. The analysis proposes an early detection capability index (EDCI) and a governance risk score (GRS) to support structured evaluation. GAHI is then articulated as a six-layer architecture comprising data acquisition, intelligence processing, agentic decision systems, clinical intelligence, governance and compliance, and population health intelligence (HI). The framework advances biomedical engineering, health informatics, AI governance, gerontechnology, and sustainable health-system design by moving from isolated digital applications toward interoperable, explainable, privacy-preserving, and clinically actionable intelligence ecosystems.

KEYWORDS

agentic healthcare intelligence, ageing health systems, biomedical engineering, digital health, early detection, federated artificial intelligence (AI), health informatics, sociotechnical governance

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1 INTRODUCTION

Population ageing is no longer just a marginal demographic phenomenon; it has become an inherent feature of health system reform. With the changing composition of populations around the world into older age groups, the clinical repercussions take the form of increasing prevalence of multiple diseases, frailty, impaired cognition, polypharmacy, heart disease, diabetes, and declining functioning [1], [2]. Traditional episodic models of care (which rely on clinic visits, hospital encounters, or acute symptom presentation) are fundamentally misaligned with the gradual, temporal structure of ageing-related deterioration [3]. Accordingly, there is an increased need for early detection. Older people may be experiencing clinical change well before they meet diagnostic criteria. There are usually some clues before one suffers a fall, decompensates from heart failure, develops delirium, suffers from medication toxicity, experiences cognitive impairment, or becomes metabolically unstable. However, these early signals remain invisible when healthcare systems depend primarily on intermittent clinical measurements [4]. Digital health and biomedical engineering technologies offer a viable pathway to extend clinical visibility into homes, communities, and everyday routines. Wearable systems can continuously monitor activity, sleep, gait, rhythm, and physiological instability; imaging artificial intelligence (AI) supports diagnostic recognition; EHR analytics identify longitudinal risk; and smart home systems detect deviations in daily living patterns [5–6]. The rapid acceleration of medical AI has catalyzed interest in these proactive, personalized paradigms. Machine learning (ML) and deep learning methods are used for risk assessment, diagnosis, imaging, telemonitoring, natural language processing, and clinical decision support [7–8]. However, technological advancement has outpaced the development of necessary frameworks for trustworthy adoption. AI algorithms that perform well on well-curated data often struggle in real-world settings, including multimorbidity, missing values, population heterogeneity, complexity of clinical procedures, and differences across institutions [9]. This is indicated by the development of reporting extensions such as CONSORT-AI, SPIRIT-AI, and DECIDE-AI, which suggest a need for transparency in data, environment, human-AI interaction, error analysis, and clinical evaluation [10], [11], [12]. This operational challenge deepens with the advent of agentic AI. In this context, agentic AI will not mean the independent substitution of clinicians. Instead, it means explainable, governance-based systems that can detect risk signals, contextualize them, make suggestions on what to do next, coordinate workflows, and learn from feedback. This limited definition is critical in gerontology since one cannot entrust the clinical accountability to automation. The primary function of agentic intelligence is to mitigate fragmentation, prioritize risk, and facilitate timely intervention. To operationalize this approach, this paper introduces Global Agentic Healthcare Intelligence (GAHI), a sociotechnical framework designed to evaluate, integrate, and govern AI-enabled technologies within ageing health systems. The framework is grounded in the sociotechnical health intelligence transformation model (SHITM), which posits that digital health transformation succeeds only when technological intelligence, healthcare value creation, and societal legitimacy are explicitly aligned. GAHI directly addresses the persistent challenges of fragmented digital health implementation, insufficient governance, limited interoperability, and the weak integration between early detection tools and definitive clinical action [13].

The structural contributions of this study are fivefold. First, it operationalizes GAHI as a six-layer framework for integrating healthcare intelligence technologies. Second, it proposes SHITM as an original theoretical model explaining the translation

of technological intelligence into clinical and societal value. Third, it evaluates thirty healthcare intelligence technologies through a structured comparative synthesis. Fourth, it introduces the early detection capability index (EDCI) and governance risk score (GRS) as decision-support tools for technology assessment. Fifth, it applies the critical economic lens of biomedical neocapitalism to examine predictive health markets, insurance optimization, genomics, and preventive biomedical services (See Figure 1) [14]. Three core research questions (RQ) guide this inquiry:

RQ1: How can AI-enabled healthcare intelligence technologies be systematically evaluated for early detection in ageing health systems?
RQ2: How do the social and technical mechanisms interplay to transform digital health tools into integrated agentic healthcare intelligence ecosystems (HIE)?
RQ3: How can GAHI be governed in a less risky and clinically meaningful environment for early detection?

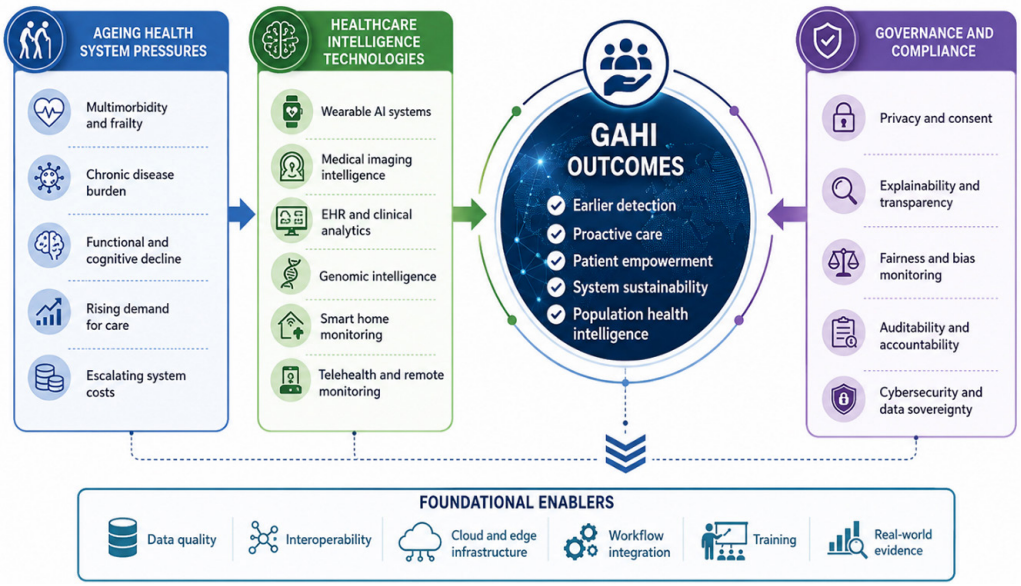


Fig. 1. Research framework for GAHI

2 LITERATURE REVIEW

2.1 Artificial intelligence-enabled healthcare intelligence

Artificial intelligence functions as a strategic necessity in gerontological care because older patients typically exhibit concurrent, interacting physiological decline rather than isolated pathologies. Computational models process heterogeneous datasets across electronic records, continuous sensor streams, neuroimaging, speech patterns, pharmacy records, and patient-reported metrics. This synthesis isolates latent risk patterns before physiological deterioration necessitates emergency admission [15]. However, demographic shifts expose predictive frameworks to significant biological and clinical heterogeneity. Older cohorts frequently present with overlapping disease profiles, atypical symptom presentations, frailty, distinct socioeconomic vulnerabilities, and patchy longitudinal digital histories. These compounding variables regularly undermine algorithmic generalization across different clinical

cohorts [16]. Deploying ML in these settings avoids engineering automation for its own sake. Instead, it generates anticipatory clinical capacity. Operative models assist clinical teams by isolating true physiological deterioration from benign, age-associated variance, targeting high-risk individuals for timely clinical contact. To achieve clinical utility, evaluation frameworks must measure real-world clinical workflows, institutional usability, equity metrics, and objective patient outcomes alongside traditional statistical verification [17], [18], [19].

2.2 Agentic intelligence and early detection

Agentic AI introduces goal-directed task coordination across distributed, multi-institutional clinical operations. Within regulated medical spaces, these architectures function as bounded decision-support tools rather than autonomous clinical proxies [20]. They parse risk parameters, organize triage queues, recommend evidence-based clinical steps, route administrative tasks, and track patient follow-up [21], [22]. Final diagnostic and therapeutic accountability remain anchored to human professionals and institutional legal frameworks [23], [24]. This operational boundary protects patient safety within complex gerontological care pathways. Older patients routinely navigate disjointed networks spanning primary care, medical specialties, community pharmacies, rehabilitation centers, home health agencies, informal family care networks, and emergency departments. Agentic coordination mitigates this structural fragmentation by linking cross-institutional risk signals to the appropriate clinical actors. Conversely, unmanaged agentic deployment risks creating legal ambiguities regarding malpractice liability, clinical escalation protocols, and competing triage priorities [25]. Early detection tools aim to identify physiological risk or functional vulnerability before acute medical crises require hospitalization. While wearables, remote monitoring applications, computer-aided diagnostics, genomic sequencing, smart home sensors, and digital twins support this objective, utility depends entirely on clinical actionability [22]. A risk alert that fails to trigger a specific clinical assessment, specialty referral, pharmacological titration, physical rehabilitation protocol, or emergency triage pathway adds to administrative workloads without shifting the patient's prognostic trajectory [23], [24], [25], [26], [27]. Within ageing health infrastructures, effective early tracking must be longitudinal and sensitive to individual baselines. Isolated metrics for heart rate, sleep duration, or gait symmetry are routinely less informative than deviations from an individual's historical norm. This analytical reality requires multimodal data stream processing coupled with human interpretation. GAHI structures early detection as a closed-loop operational cycle: continuous data acquisition, algorithmic interpretation, clinical prioritization, targeted intervention, and empirical feedback on outcomes [28], [29], [30], [31], [32], [33], [34], [35].

3 THEORETICAL FOUNDATION: SOCIOTECHNICAL HEALTH INTELLIGENCE MODEL

The SHITM explains how AI-enabled healthcare technologies generate value in ageing health systems. The model rests on a simple but often neglected premise: the introduction of advanced technology does not, by itself, constitute transformation. Transformation occurs when technological intelligence becomes clinically meaningful, organizationally actionable, ethically legitimate, and socially trusted [36], [37]. SHITM contains three interacting domains. Technology intelligence consists

of sensors, biomedical equipment, AI algorithms, data architecture, interoperability principles, cloud computing, and edge computing, among others. Value creation in healthcare involves early detection, accurate diagnosis, care coordination, precision medicine, patient empowerment, and the reduction of unnecessary utilization. Societal impact is defined by governance, equity, trust, data sovereignty, regulation, workforce changes, and preventive health economics [38], [39], [40]. The model supports integration by clarifying how the GAHI layers relate to one another. Data acquisition and intelligence processing create technical capacity. Agentic decision systems and clinical intelligence convert capacity into care value. Legitimacy, accountability, equity, and sustainability are facilitated by governance, compliance, and population HI. SHITM therefore prevents GAHI from becoming a technical architecture detached from clinical and societal conditions [41], [42], [43].

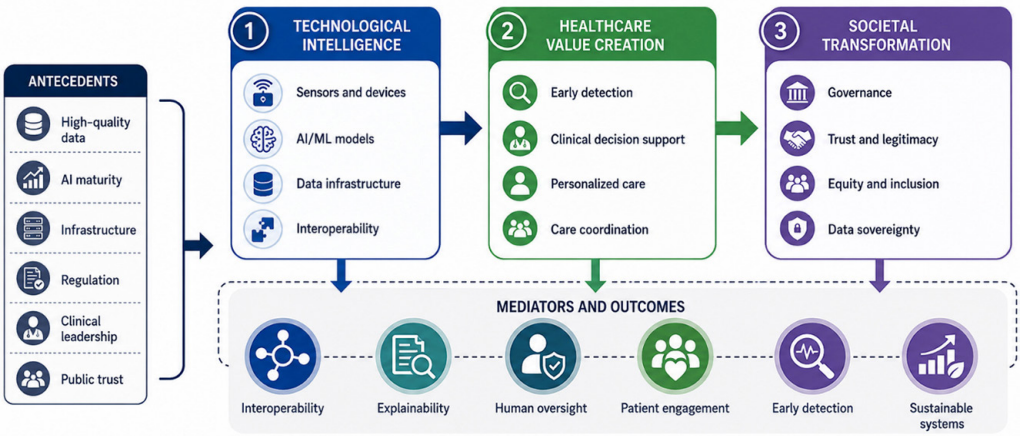


Fig. 2. Sociotechnical health intelligence transformation model

Figure 2 operationalizes the SHITM by visually aligning the three theoretical domains described in the text: Technological Intelligence, Healthcare Value Creation, and Societal Transformation. The figure clarifies that AI-enabled healthcare transformation happens when technical capabilities are converted into clinically actionable value and then legitimized through governance, trust, equity, and institutional accountability [36], [37]. The top-middle area is Technological Intelligence and symbolizes the technical basis of GAHI. This consists of biomedical sensors, connectivity, AI/ML models, data architecture, cloud computing, interoperability standards, and privacy infrastructure (See Table 1 for all research propositions). The Technological Intelligence area relates to Proposition P1: Technological Intelligence enhances early detection ability when the data are longitudinal, multimodal, and clinically interpretable. In the figure, the arrow from Technological Intelligence to Healthcare Value Creation shows that technical capability must produce usable clinical intelligence rather than isolated data streams. Healthcare Value Creation Domain–Lower-left domain, which explains the significance of technical intelligence to the delivery of healthcare. These are early detection, risk prediction, clinical decision making, precision medicine, care coordination, and patient empowerment. The propositions that apply to this area are P2, P3, P5, and P6. P2 is represented by interoperability as a mediating mechanism linking technological intelligence to care value. P3 is represented by explainability, which enables clinicians to interpret AI outputs and adopt them safely. P5 is evident in the connection between agentic coordination and care continuity, while P6 is reflected in the patient-and-caregiver engagement pathway. Societal Transformation, in the lower-right corner, refers to

the broader institutional and ethical context in which healthcare intelligence operates. The topic discussed relates to Propositions P4, P7, and P8. P4 emerges from the connection between governance and social trust, emphasizing that ethical governance will influence the relationship between AI adoption and societal trust. P7 is seen in federated and privacy-preserving infrastructure, allowing for scalability and intelligence without centralized data collection. P8 is shown as the outer alignment logic connecting all three domains, indicating that sustainable transformation occurs only when technological, clinical, and societal components are jointly aligned [38], [39], [40], [41], [42], [43].

Table 1. Theoretical propositions derived from SHITM

P	Statement	Reference
P1	Technological intelligence increases early detection capacity when data are longitudinal, multimodal, and clinically interpretable.	[5]–[9], [17], [22], [49]–[55]
P2	Interoperability strengthens the relationship between technological intelligence and the creation of healthcare value.	[18], [19], [37]–[43], [59]
P3	Explainability mediates the relationship between AI-generated intelligence and clinical adoption.	[24], [31]
P4	Ethical governance positively moderates the relationship between healthcare intelligence adoption and societal trust.	[13], [24]–[31]
P5	Agentic healthcare intelligence improves care continuity by coordinating risk signals, clinical priorities, and intervention pathways.	[33], [41]–[43], [57]
P6	Patient and caregiver engagement mediates the effect of early detection technologies on healthcare value.	[20], [24], [52], [53]
P7	Federated and privacy-preserving architectures increase global scalability by enabling collaborative learning without centralized data extraction.	[60]
P8	Sustainable transformation occurs when technological intelligence, healthcare value creation, and societal governance are aligned.	[36]–[43]

4 RESEARCH METHODOLOGY

This study adopts a comparative framework synthesis methodology supported by an integrative literature review and structured technology assessment. This design is appropriate because the aim is to develop and refine a conceptual and governance framework rather than to evaluate a single intervention using primary clinical data [44], [45]. The approach combines conceptual synthesis, comparative analysis, and technology classification to build an analytically defensible framework for ageing HI [46]. The unit of analysis is the healthcare intelligence technology category. Thirty technologies have been chosen since they apply to early diagnosis, ageing care, biomedical engineering, health informatics, AI-based clinical practice, and HI. The following selection criteria were considered: clinical relevance, scalability, AI maturity, data availability, and applicability to ageing care. A category of technology was kept if it satisfied at least four of these criteria. The following dimensions were used to evaluate each technology: clinical relevance, ability to detect early, AI maturity, scalability, potential for data integration, governance risk, suitability for an ageing population, and implementation readiness. The assessment scale consisted of five points. Reliability was supported by consistent criteria, a shared coding protocol, transparent scoring logic,

and internal consistency checking across tables. Construct validity was strengthened by defining each evaluation dimension before analysis, while analytical validity was supported by comparing multiple technology classes rather than relying on a single use case [47], [48]. The comparative analysis considers 30 health care intelligence technologies that can aid early detection, continuous monitoring, risk prediction, decision-making, and long-term planning in health care systems for an ageing population. The evaluation is purposefully socio-technical, and addresses clinical relevance, scalability, governance capacity, and fitness for the ageing population [49], [50].

5 RESEARCH FINDINGS: ASSESSMENT OF HEALTHCARE INTELLIGENCE TECHNOLOGIES

5.1 Early detection capability index

The EDCI is introduced as a structured interpretive tool for comparing the contribution of different technologies to early recognition of disease, deterioration, or functional decline. It is not a diagnostic score and should not be used to claim clinical efficacy. Its purpose is to support technology prioritization and framework synthesis by assessing the proactive value of each technology [51], [52]. Five aspects characterize the EDCI framework: signal sensitivity, longitudinal monitoring capability, clinical actionability, multimodal integration potential, and ageing-specific relevance. The first one, signal sensitivity, refers to the extent to which the technology can detect early changes in physiological, behavioral, cognitive, environmental, and clinical aspects. The longitudinal monitoring aspect concerns the ability to detect such changes over time. The third aspect, the clinically actionable aspect, concerns the output's ability to elicit a response. The multimodal integration potential refers to the connection to the electronic health record (EHR), imaging, genomics, pharmacy information, smart home, and patient-reported outcomes [53], [54]. EDCI is determined using the equation EDCI = SS + LMC + CA + MIP + ASR, in which each constituent has scores between 1 and 5. A very high EDCI score is one that lies in the range of 21–25, a high score falls within 17–20, a moderate score ranges between 13–16, a low score is one that has scores of 9–12, and a very low score is one that lies within 5–8. A high EDCI score denotes proactive potential [55].

Table 2. Early detection capability index results

Technology	EDCI/25	Interpretation	Reference
Wearable AI systems	23	Very high	[17], [22], [49], [50]
Medical imaging intelligence	22	Very high	[5]–[8], [32]
EHR analytics	24	Very high	[19], [56], [59]
Genomic intelligence	18	High	[23], [54], [55]
Smart home monitoring	22	Very high	[21], [51]
Conversational AI	16	Moderate	[20], [24], [70]
Predictive analytics platforms	24	Very high	[15]–[17], [35], [56]
Digital twins	21	Very high	[5], [8]
Healthcare robotics	18	High	[49], [50]

(Continued)

Table 2. Early detection capability index results *(Continued)*

Technology	EDCI/25	Interpretation	Reference
Remote patient monitoring	24	Very high	[17], [20], [52], [53]
Biosensors and implantable	22	Very high	[17], [22], [49]
Fall detection systems	22	Very high	[21], [22], [49], [51]
Gait and mobility analytics	23	Very high	[21], [22], [49]
Sleep monitoring systems	19	High	[17], [22], [49]
Cardiovascular monitoring AI	24	Very high	[5]–[8], [17], [22]
Diabetes and metabolic intelligence	24	Very high	[17], [22], [52], [53]
Cognitive decline detection	21	Very high	[15], [16], [21]
Medication adherence technologies	20	High	[20], [52], [53]
Telehealth intelligence platforms	19	High	[20], [52], [53]
Clinical decision support systems	21	Very high	[41]–[43], [57]
NLP for clinical notes	21	Very high	[7], [8], [19], [56]
Federated learning systems	18	High	[60]
Explainable AI platforms	18	High	[24], [31]
Privacy-preserving analytics	16	Moderate	[52], [54]–[58]
Population health surveillance	23	Very high	[1]–[4], [39], [40]
AI-enabled rehabilitation	19	High	[49], [50]
Voice biomarker analytics	18	High	[15], [16], [24]
Nutrition and lifestyle intelligence	18	High	[17], [22], [52]
Mental health monitoring systems	18	High	[24], [26]–[28], [51]
Emergency risk prediction systems	24	Very high	[8], [15]–[17]

Table 2 assesses how well each healthcare intelligence technology can contribute to the proactive identification of disease, deterioration, or loss of functionality before any adverse clinical event occurs. These results confirm yet another key principle postulated within the GAHI model: the primary benefit of healthcare intelligence is that it enables the recognition of emerging risks long before they become critical issues. Systems such as EHR analytics, predictive analytics, cardiovascular monitoring, and remote patient monitoring have earned the highest EDCI points because they provide both continuous monitoring and clinical knowledge. It is interesting that emerging systems such as digital twins and cognitive decline detection also possess strong preventive capabilities.

5.2 Governance risk assessment

Governance risk arises because early warning systems, which perform best, are highly dependent on sensitive, continuous, predictable, or recognizable data. The GRS measures privacy sensitivity, consent complexity, algorithmic transparency, risk of bias and representativeness, accountability complexity, and cybersecurity/data

sovereignty risk [56], [57]. The GRS is computed using the formula: GRS = PS + CC + AO + BR + AC + CDSR. The scores lie between 6 and 30. If the score lies between 25–30, then it shows very high governance risk; if the score lies between 19–24, then it shows high governance risk; if it lies between 13–18, then it shows moderate governance risk; if it lies between 6–12, then it shows low governance risk. Table 3 demonstrates that technological capability and governance complexity often increase simultaneously. The technology solutions that demonstrate the best ability to predict and detect events early are also among the greatest governance risks.

Table 3. Governance risk assessment

Technology	GRS/30	Risk Level	Reference
Wearable AI systems	22	High	[17], [22], [24], [28], [49]
Medical imaging intelligence	21	High	[5]–[8], [32]
EHR analytics	27	Very high	[19], [26], [56], [59]
Genomic intelligence	28	Very high	[23], [27], [28], [54], [55]
Smart home monitoring	26	Very high	[21], [28], [51]
Conversational AI	24	High	[20], [24]
Predictive analytics platforms	28	Very high	[15]–[17], [26], [35], [56]
Digital twins	29	Very high	[5], [8], [17]
Healthcare robotics	20	High	[49], [50]
Remote patient monitoring	23	High	[17], [20], [52], [53]
Biosensors and implantables	24	High	[17], [22], [49]
Fall detection systems	20	High	[21], [22], [49], [51]
Gait and mobility analytics	20	High	[21], [22], [49]
Sleep monitoring systems	20	High	[17], [22], [49]
Cardiovascular monitoring AI	23	High	[5]–[8], [17], [22]
Diabetes and metabolic intelligence	22	High	[17], [22], [52], [53]
Cognitive decline detection	27	Very high	[15], [16], [28]
Medication adherence technologies	21	High	[20], [52], [53]
Telehealth intelligence platforms	22	High	[20], [52], [53]
Clinical decision support systems	24	High	[24], [41]–[43], [57]
NLP for clinical notes	27	Very high	[7], [8], [19], [26], [56]
Federated learning systems	26	Very high	[60]
Explainable AI platforms	17	Moderate	[24], [31]
Privacy-preserving analytics	23	High	[52], [54]–[58]
Population health surveillance	29	Very high	[1]–[4], [13]
AI-enabled rehabilitation	20	High	[49], [50]
Voice biomarker analytics	27	Very high	[15], [16], [24]
Nutrition and lifestyle intelligence	20	High	[17], [22], [52]
Mental health monitoring systems	28	Very high	[24], [26]–[28], [51]
Emergency risk prediction systems	29	Very high	[8], [15]–[17]

Genomics, digital twins, EHR analysis, population health monitoring, and detection of cognitive decline all saw increases in GRS due to the highly sensitive nature of the personal data they involve. These findings directly support the governance dimension of GAHI and the societal transformation domain of SHITM [58]. Figure 3 presents a visual comparison of healthcare intelligence technologies with respect to their EDCI and GRS. This figure shows one of the core features of the GAHI approach–that technologies with the greatest potential for proactive detection usually pose the most significant governance issues. This feature is clearly shown in Table 3, where genomic intelligence, EHR analysis, cognitive decline detection, digital twins, and population health surveillance are characterized by high GRS due to the sensitivity of the personal data involved, complex ethical issues, and accountability requirements.

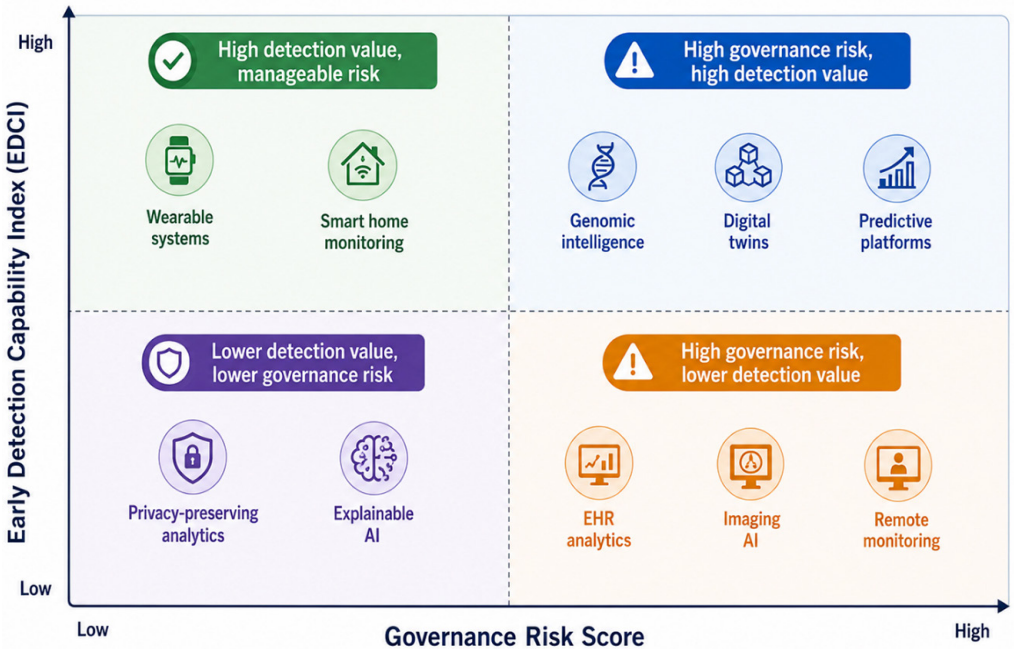


Fig. 3. Comparative technology analysis

6 RESEARCH DISCUSSION

As shown in Figure 4, the six-layer framework proposed by GAHI includes data, models, agent-based coordination, clinical decision support, governance, and public HI (See Figure 4). GAHI is not a one-way pipeline but rather works in a loop process, wherein results, errors, warnings, interventions, and policies are fed back into the system [59], [60]. Taken together, the results indicate that the value of healthcare intelligence does not arise from any individual technology in isolation, but from how these technologies fit together over the course of care. Technologies with significant capabilities for early detection, such as EHR analytics, predictive technologies, telemonitoring technologies, cardiovascular AI, diabetes intelligence, and emergency risk prediction technologies, are especially valuable because they can detect signs of deterioration long before they become clinically significant [51]. On the other hand, these technologies need to be treated with great caution, as high predictive capabilities are usually achieved using very sensitive, longitudinal data, which may not always be complete [52].

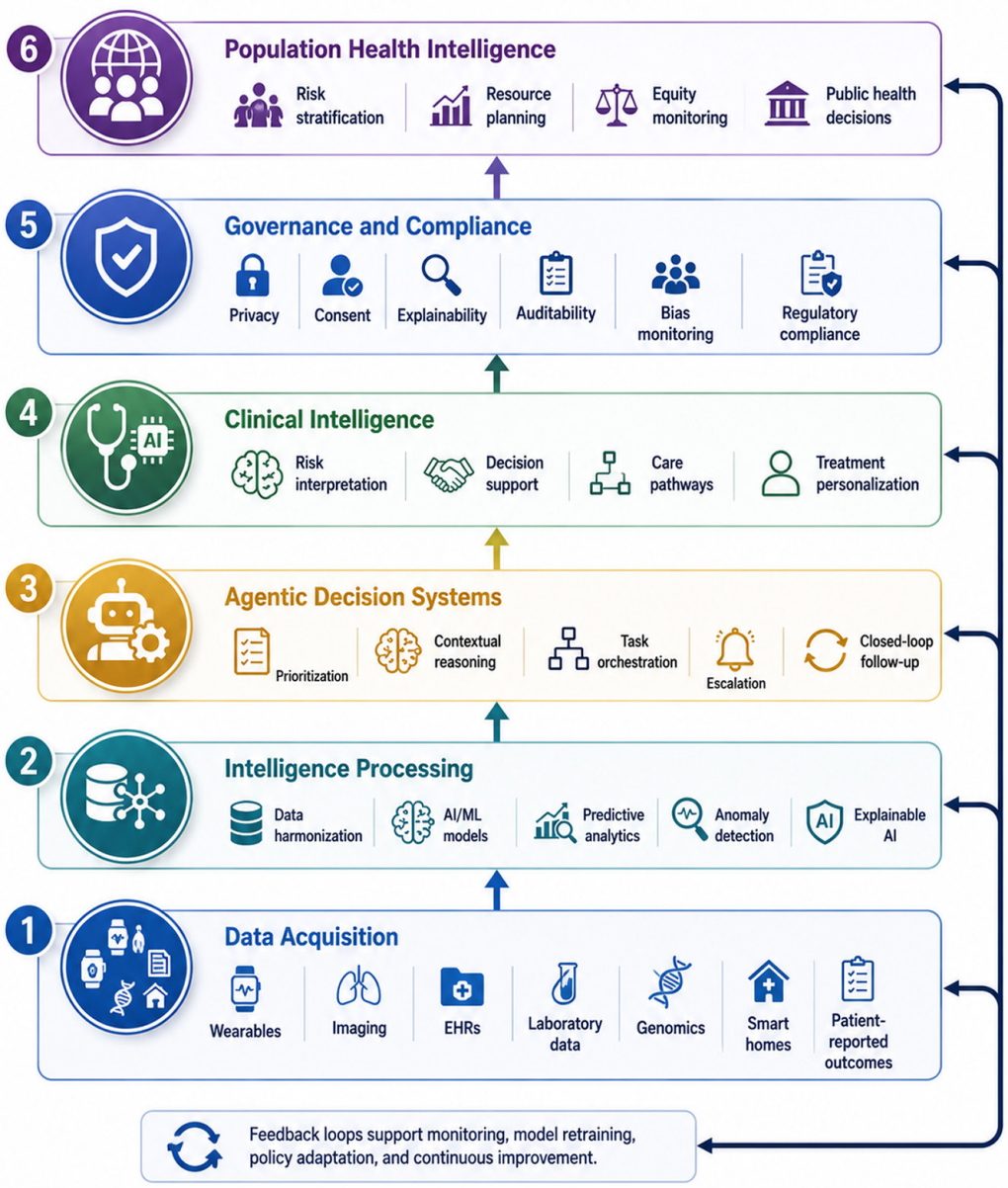


Fig. 4. Six-layer architecture of GAHI

In addition, the results on governance highlight a real-world dilemma at the core of AI-driven gerontology practice. Genomic analysis, digital twins, population health surveillance, NLP in clinical notes, identification of cognitive decline, and federated learning are technologies with tremendous potential but pose complex challenges regarding consent, privacy, bias, accountability, and data sovereignty [43]. It suggests these technological applications need to be slowed, made more open, and better controlled. In a decent healthcare system, seniors should not feel that innovation is done to them, but that it is done for them and for their benefit. GAHI, therefore, treats governance as part of clinical quality, not as an administrative layer added after implementation [44]. A human-centred interpretation of the findings implies that technologies must be ranked based on their utility and practicality. Devices such as wearables, smart homes, gait analysis systems, fall detection systems, sleep monitors,

medication compliance systems, and telehealth platforms are useful for making healthcare more relevant to people's everyday lives [45]. On the other hand, such devices may induce feelings of fatigue, anxiety, digital overload, and surveillance if not properly explained. For ageing populations, success depends on simplicity, dignity, caregiver involvement, and clinicians' ability to respond appropriately when a signal is generated. The purpose of early detection is not to produce more alerts; it is to create enough time for a safer and more compassionate intervention [36], [47], [58]. The implementation of GAHI depends on how healthcare professionals evaluate and adopt new AI-enabled technologies [49], [60]. *Healthcare organizations* need to move away from evaluating and implementing systems based on performance or efficiency alone and instead consider clinical usability, explainability, workflow integration, patient-centred value creation, and governance risks of such innovations [27]. For *policymakers*, the development of intelligence ecosystems needs to align with regulatory and governance policies. This includes establishing criteria for validating and monitoring AI systems, ensuring their explainability and transparency, governing data, detecting and mitigating biases, protecting patients' rights, and ensuring interoperability across borders [58, 59]. It is clear that *biomedical engineers* are a vital part of the GAHI ecosystem, as they develop devices, sensing technologies, and analytical systems through which healthcare intelligence will be generated. In addition to high device accuracy, there is also the need to ensure patient comfort, ensure safety, manage data quality, and integrate with clinical practices, especially for older patients with multiple comorbidities [60]. *Technology developers* are also responsible for ensuring that ethical and governance considerations are incorporated at the very beginning of the system development process. [41], [52].

7 CONCLUSION

Global agentic healthcare intelligence advances the current state of knowledge by creating a hierarchical model comprising six interlinked levels: data collection, intelligence processing, agentic decision system, clinical intelligence, governance and compliance, and population HI. This model demonstrates that biomedical signals, AI models, clinical pathways, patient engagement, governance measures, and public health strategies can be integrated into a single intelligence ecosystem. The main theoretical contribution of the study is SHITM, the theory explaining transformation as the process of aligning technological intelligence, healthcare value creation, and societal legitimacy. The main practical contribution is the creation of EDCI and GRS, enabling comparison of technologies based on proactive value and governance sensitivity. The use of GAHI will lead to better patient outcomes by ensuring that ageing healthcare moves away from delayed treatment towards anticipating problems. Early detection will ensure fewer preventable hospital admissions, better management of chronic diseases, fewer falls, safer medication use, earlier detection of cognitive impairments, and ageing-in-place solutions. Future healthcare for ageing should use AI not just for automation but for responsible intelligence that detects early, explains more, coordinates faster, governs data responsibly, and retains human clinical judgment.

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