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Theoretical Article (Hypothesis & Theory)

Vol. 1, Issue 2, July-December 2026 | ISSN: 3139-6267

Journal of Artificial Intelligence and Digital Health

From Cognitive Intelligence to Systemic Intelligence: A Transdisciplinary Framework for Emergence, Adaptation, and Societal Transformation

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Received: July 13, 2026; **Manuscript No:** JAID-26-7504; **Editor Assigned:** July 17, 2026; **PreQc No:** JAID-26-7504 (PQ); **Reviewed:** July 31, 2026; **Revised:** August 12, 2026; **Manuscript No:** JAID-26-7504 (R); **Published:** September 08, 2026

Citation: Moleka P (2026). From Cognitive Intelligence to Systemic Intelligence: A Transdisciplinary Framework for Emergence, Adaptation, and Societal Transformation. J. Artif. Intell. Digit. Health. Vol.1 Iss.2, September (2026), pp:144-159.

ABSTRACT

Traditional conceptions of intelligence have largely confined the concept to human cognition, psychometric performance, or computational capability. While these perspectives have generated significant advances in psychology, artificial intelligence, and cognitive science, they provide only a partial understanding of intelligence in an increasingly interconnected world. This article develops a broader conceptual framework by proposing Systemic Intelligence as an emergent property of complex adaptive systems rather than an isolated characteristic of individual agents. Drawing on systems theory, complexity science, evolutionary biology, philosophy, governance studies, and contemporary artificial intelligence research, the paper argues that intelligence arises through dynamic interactions, feedback mechanisms, network structures, and adaptive learning processes operating across multiple scales.

The proposed framework demonstrates how intelligence manifests in biological ecosystems, social institutions, technological infrastructures, educational systems, and collaborative governance arrangements. Rather than viewing intelligence as a localized cognitive function, the article conceptualizes it as a relational capacity that enables systems to organize information, coordinate action, generate innovation, and continuously adapt to changing environments. This perspective bridges traditionally separate disciplines by integrating insights from collective intelligence, distributed cognition, cybernetics, complexity theory, and human–AI collaboration into a unified conceptual model.

The study further explores the implications of systemic intelligence for leadership, governance, education, technological innovation, and sustainability, arguing that societies facing global challenges require institutional arrangements capable of mobilizing distributed intelligence rather than relying solely on centralized decision-making. By reframing intelligence as a foundational organizing principle of complex systems, the article contributes a transdisciplinary theoretical foundation for future empirical research on adaptive governance, resilient organizations, hybrid human–AI systems, and transformational innovation. The framework ultimately positions systemic intelligence as a key explanatory concept for understanding how complex systems evolve, learn, and generate sustainable transformation in the twenty-first century.

Keywords: Systemic Intelligence; Complexity Science; Emergent Systems; Collective Intelligence; Distributed Cognition; Adaptive Governance; Human–AI Collaboration; Systems Thinking; Innovation; Transformation

INTRODUCTION

For much of modern intellectual history, intelligence has been conceptualized primarily as a property of individual minds. In psychology, it has commonly been associated with capacities such as reasoning, memory, learning, and problem-solving. In computer science, intelligence has increasingly been operationalized through computational processes involving search, learning, prediction, pattern recognition, and algorithmic problem-solving [1-2]. Philosophical traditions have likewise associated intelligence with reason, understanding, consciousness, and rational agency. These approaches have generated important advances, but they generally locate intelligence within identifiable agents rather than within the wider systems through which information, cognition, action, and adaptation are coordinated.

This agent-centered conception is becoming increasingly difficult to sustain in an environment characterized by artificial intelligence (AI), digital infrastructures, interconnected databases, networked organizations, and complex socio-technical systems. Contemporary AI is rarely deployed in isolation. It operates through relationships among algorithms, users, professionals, institutions, datasets, sensors, platforms, regulatory structures, and physical environments. The significance of AI therefore depends not only on what an algorithm can compute but also on how its outputs are interpreted, validated, communicated, acted upon, and incorporated into subsequent cycles of decision-making. In healthcare, this distinction is particularly important because AI is being developed and deployed across diagnosis, clinical decision support, medical imaging, health research, disease surveillance, public-health analysis, and health-system management [3-4].

Digital health makes visible a problem that conventional accounts of intelligence often leave unresolved. A health system may contain highly capable algorithms without necessarily becoming an intelligent system. Conversely, a system can produce effective adaptive responses through the interaction of human expertise, institutional knowledge, data infrastructures, computational tools, and community participation. The intelligence of such a system cannot be attributed exclusively to the physician, the epidemiologist, the algorithm, the database, or the institution. It arises through their interaction.

The distinction becomes especially significant in public health. Public-health problems are rarely confined to a single level of analysis. Disease surveillance, outbreak response, population health, health inequalities, environmental risks, and health-system resilience involve interactions among biological processes, individual behavior, communities, healthcare organizations, laboratories, governments, digital infrastructures, and environmental conditions. AI can contribute to these processes through risk prediction, surveillance, spatial analysis, disease forecasting, epidemic modeling, and other analytical functions, but its effectiveness depends on the broader organizational and institutional environment in which it is embedded [5].

This article therefore proposes a conceptual shift from understanding artificial intelligence primarily as the intelligence of an artificial agent toward understanding systemic intelligence as an emergent property of interconnected human, technological, institutional, and environmental systems. The central proposition is that intelligence may be distributed across relationships rather than localized exclusively within individual agents.

The article advances the Intelligence Field Hypothesis, defined as the proposition that intelligence can emerge as a distributed, relational, adaptive, and systemic property of interacting agents and infrastructures. The hypothesis does not deny individual human intelligence or artificial intelligence. Instead, it argues that some forms of intelligence become visible only when the analytical unit is expanded from the individual agent to the interacting system.

The notion of a field is used here as a theoretical metaphor rather than as a claim that intelligence constitutes a physical field equivalent to gravitational or electromagnetic fields. The metaphor describes a distributed configuration of information, cognition, interaction, feedback, and adaptive organization. The purpose is to capture a form of intelligence that is produced through relationships and that cannot be adequately explained by examining individual components independently.

This proposition extends existing discussions of collective intelligence, distributed cognition, and human–AI collaboration. Hutchins, demonstrated that cognition can be distributed across people, tools, representations, and environments, while Surowiecki, showed how groups can generate collective problem-solving capacity through decentralized participation and information aggregation [6-7]. Contemporary AI introduces another layer to this architecture by enabling computational systems to participate in processes of prediction, classification, information processing, and decision support.

Yet the existence of human–AI collaboration does not automatically establish systemic intelligence. Recent evidence indicates that combinations of humans and AI do not consistently outperform the strongest human or AI component. Their effects vary according to task characteristics, system design, and the configuration of the collaboration [8]. This finding is theoretically important for the present argument because it suggests that intelligence is not generated simply by adding AI to human decision-making. Rather, it depends on the quality of the relationships through which human and artificial capabilities are organized.

The Intelligence Field Hypothesis therefore asks a broader question than whether an algorithm is intelligent: How does intelligence emerge from the interaction of human, artificial, institutional, social, and environmental components within complex systems?

This question is particularly relevant to digital health because digital technologies increasingly connect clinical, administrative, epidemiological, and community-level information. The World Health Organization's classification of digital interventions recognizes digital technologies as components of broader health services and systems rather than as isolated technical artifacts [9]. Digital health consequently provides a suitable domain for investigating systemic intelligence because it combines information infrastructures, professional expertise, computational systems, patients, institutions, and public-health functions.

The contribution of this article is therefore threefold. First, it develops a philosophical and historical foundation for conceptualizing intelligence as relational and systemic. Second, it integrates systems theory, complexity science, distributed cognition, collective intelligence, artificial intelligence, and human–AI collaboration into a common theoretical architecture. Third, it applies this framework to AI-enabled digital health and public health, where intelligence increasingly depends on the coordination of computational and human capacities.

The originality of the framework does not lie simply in extending the meaning of intelligence. It lies in relocating the analytical unit through which intelligence is examined. Instead of asking only how intelligent an individual person or artificial system is, the framework asks how intelligently a system can sense, interpret, coordinate, learn, adapt, and transform.

This shift has important implications for AI research. An AI model may produce a prediction, but the prediction becomes consequential only through a larger system of interpretation and action. A public-health surveillance algorithm may identify a potential anomaly, but epidemiologists must interpret the signal, laboratories may need to verify it, institutions must determine whether action is warranted, communities may need to respond, and subsequent outcomes must be incorporated into future assessments. The intelligence of the system therefore emerges through a recursive process rather than from the algorithm alone.

The article proceeds from the historical and philosophical foundations of systemic intelligence to systems theory and complexity science before developing the Intelligence Field Hypothesis as a framework for understanding intelligence across human, technological, organizational, and public-health systems.

Historical and Philosophical Roots of Systemic Intelligence

Understanding intelligence as systemic requires reconsidering the intellectual history through which intelligence has been conceptualized. Although modern approaches have often emphasized individual cognition, philosophical and scientific traditions have repeatedly raised questions concerning the relationship between intelligence, order, interaction, knowledge, and larger structures.

Aristotle and the Notion of Nous

Aristotle's conception of nous provides an early philosophical point of departure for considering intelligence in relation to broader structures of intelligibility. In Metaphysics, Aristotle distinguishes different dimensions of intellectual activity and examines the relationship between knowledge, actuality, and intelligibility [10]. His conception should not be identified directly with contemporary systemic intelligence, but it demonstrates that intelligence has historically been treated as more than a simple measurable psychological capacity.

The present framework does not claim a direct historical continuity between Aristotelian nous and contemporary AI. Rather, Aristotle provides an early illustration of the philosophical problem that continues to concern theories of intelligence: whether intelligence should be understood only as a property possessed by an individual or as a capacity connected to wider structures of order, relation, and intelligibility.

This question becomes particularly significant when intelligence is embedded in technological systems [11]. An AI model can generate predictions or classifications, but those outputs do not acquire meaning independently of the environment in which they are interpreted and used. In healthcare, the significance of an algorithmic output depends on clinical expertise, institutional procedures, patient circumstances, available evidence, and the purposes for which the system has been designed.

Descartes and the Mechanistic Mind

René Descartes' distinction between res cogitans and res extensa contributed to a powerful intellectual tradition in which thinking and material extension were conceptually separated [12]. The Cartesian framework helped establish a model in which rational cognition was strongly associated with the thinking subject while the physical world was increasingly approached through mechanical explanation.

Modern computational approaches to AI inherited aspects of this intellectual trajectory by attempting to formalize cognitive functions as processes of information manipulation and computation. Such approaches have produced major scientific and technological advances, but they can also reinforce a binary distinction between intelligence located in the human mind and intelligence implemented in the machine.

The systemic perspective developed here moves beyond this binary. It does not ask whether humans or machines are the true bearers of intelligence. Instead, it examines how human and artificial capabilities become organized within larger systems.

In digital health, for example, an AI decision-support system does not operate independently of physicians, patients, electronic health records, laboratories, institutional procedures, and regulatory requirements. The resulting capacity for diagnosis, monitoring, or decision support is therefore distributed across an interacting configuration.

Popper, Kuhn, and the Social Organization of Knowledge

Twentieth-century epistemology further demonstrated that knowledge is produced through processes of criticism, interaction, interpretation, and institutional organization. Popper emphasized conjectures and refutations, showing that knowledge develops through the continuous testing and correction of claims. From this perspective, intelligence involves not merely possessing information but developing mechanisms through which information can be challenged, revised, and improved [13].

Kuhn similarly demonstrated that scientific knowledge is shaped by communities, paradigms, anomalies, institutional practices, and historical transformations. Scientific intelligence therefore cannot be understood exclusively as the cognitive capacity of individual researchers. It also involves laboratories, instruments, professional communities, standards of evidence, institutional arrangements, and processes of collective evaluation [14].

This epistemological insight has direct relevance to AI-enabled health systems. An AI-generated prediction is not self-validating. It becomes part of a larger knowledge process involving clinical interpretation, scientific evidence, institutional protocols, patient experience, and public accountability. A system becomes more intelligent when it possesses mechanisms for comparing machine-generated signals with other forms of evidence and for learning from errors.

Systemic intelligence therefore includes the capacity for critical evaluation, contextual interpretation, error correction, and collective learning.

Hegel and Intelligence as Relational Development

Hegel's dialectical conception of development provides another philosophical precursor to systemic approaches to intelligence. In Hegel's account, development occurs through relations, contradictions, and transformations rather than through the isolated unfolding of independent entities [15].

The Intelligence Field Hypothesis does not depend upon Hegel's complete metaphysical system. Nevertheless, the dialectical perspective is relevant because it draws attention to the possibility that higher-order patterns can emerge through interactions among different elements.

Human–AI collaboration can be understood in a related way. Human expertise and machine-generated analysis do not need to be identical to become jointly productive. Humans can contribute contextual interpretation, ethical judgment, experience, accountability, and social understanding, while AI can contribute rapid computation, large-scale information processing, pattern recognition, and prediction.

The crucial point is that complementarity does not guarantee successful collaboration. The evidence synthesized by Vaccaro demonstrates that the performance of human–AI combinations varies substantially across tasks. Human–AI collaboration should therefore be understood as a designed relationship whose outcomes depend on how the respective capabilities are coordinated rather than as an automatic synthesis of human and artificial intelligence [8].

Systems Thinking: Bertalanffy and the Emergence of Wholes

The transition from philosophical reflection to modern systems theory provides a more direct foundation for systemic intelligence. Bertalanffy, challenged reductionist approaches by emphasizing that organisms and other complex systems cannot always be adequately understood through the isolated examination of their components [16].

The central systems insight is that relationships matter. Components interact, exchange information, influence one another, and participate in feedback processes. As a consequence, system-level properties may arise that are not directly observable within individual components [17].

This principle is fundamental to the Intelligence Field Hypothesis. If intelligence involves information integration, coordination, adaptation, learning, and problem-solving, then some forms of intelligence may emerge from the relationships among agents rather than from agents considered separately.

Wiener's cybernetics further developed this perspective through its emphasis on communication, feedback, regulation, and control. Cybernetic systems demonstrate how adaptive behavior can arise through continuous interaction between a system and its environment [18].

Digital health systems increasingly display these characteristics. Health information is generated through patients, clinicians, laboratories, sensors, mobile devices, electronic records, and public-health surveillance. AI systems can process portions of this information and generate predictions or recommendations. Human actors then interpret outputs and make decisions, while interventions generate new observations that feed back into subsequent cycles.

The result is not a simple sequence in which a human supplies information and a machine returns an answer. It is a recursive process of sensing, interpretation, action, observation, and learning.

THEORETICAL FRAMEWORK

From Collective Intelligence to Human–AI Intelligence

The emergence of collective intelligence and distributed cognition further challenges the assumption that intelligence is located exclusively within individual agents. Hutchins demonstrated that cognitive processes can be distributed across people, artifacts, representations, and environments. Surowiecki, similarly examined how decentralized groups can generate forms of collective problem-solving capacity [6,19].

Contemporary AI introduces an additional component into this architecture. Human–AI systems combine biological cognition with computational capabilities, creating configurations in which humans and machines participate in common problem-solving processes [20].

However, hybrid intelligence and systemic intelligence are not synonymous. Hybrid intelligence focuses primarily on the productive combination of human and artificial capabilities. Systemic intelligence includes human–AI interaction but extends beyond the human–machine relationship to encompass institutions, infrastructures, communities, governance structures, data environments, and feedback processes.

The distinction is particularly important in healthcare. A physician working with an AI decision-support system constitutes a human–AI configuration. A public-health system involving physicians, epidemiologists, laboratories, patients, electronic records, algorithms, public institutions, regulatory arrangements, communication systems, and community organizations constitutes a much broader systemic intelligence architecture.

The distinction is not merely semantic. It changes the object of analysis. Human–AI research can ask whether people and algorithms perform better together. Systemic intelligence asks how the entire configuration generates, distributes, validates, and uses intelligence.

Synthesis: Toward the Intelligence Field Hypothesis

Across these intellectual traditions, a recurring pattern becomes visible. Intelligence increasingly appears not simply as an isolated possession but as something that can be generated through relationships, interactions, feedback, knowledge systems, and adaptive processes.

From Aristotle's nous to systems theory, from epistemic communities to distributed cognition, the conceptual trajectory supports a movement toward relational understandings of intelligence.

The Intelligence Field Hypothesis extends this trajectory by proposing that the appropriate unit of analysis for some forms of intelligence is not the individual agent but the interacting system.

This proposition does not diminish individual intelligence or artificial intelligence. Instead, it situates them within a broader architecture. Human intelligence, AI, collective intelligence, distributed cognition, and hybrid intelligence can be understood as distinct but interacting components of systemic intelligence.

This framework is especially relevant to AI-enabled digital health, where intelligence can emerge through the continuous interaction of algorithms, health professionals, patients, institutions, data infrastructures, communities, and public-health systems.

Systems Thinking and Emergent Intelligence

The conceptual movement toward systemic intelligence becomes clearer through systems thinking. General Systems Theory, cybernetics, complexity science, distributed cognition, and contemporary research on socio-technical systems all demonstrate that system-level properties can emerge from interactions among components.

Foundations of Systems Thinking

Bertalanffy's systems approach emphasizes that biological organisms, social organizations, and technological networks must be understood as interconnected wholes. Their behavior depends not only on their components but also on relationships, information flows, feedback mechanisms, and interactions with their environments [16].

This perspective reframes intelligence as a system-level capacity involving the ability to sense conditions, integrate information, coordinate action, learn from outcomes, and adapt.

Wiener's cybernetics provides a complementary foundation. Feedback enables systems to compare states, detect differences, regulate behavior, and respond to environmental changes. Intelligence, from this perspective, involves not merely information processing but the use of information to guide adaptive action [18].

Healthcare provides a useful illustration. Data generated by patients and health services can inform analytical systems. Analytical outputs can support professional decisions. Interventions produce new observations, and these observations can modify subsequent decisions. The system therefore operates through recursive feedback.

The intelligence of the system lies partly in its capacity to maintain and improve this cycle.

Complexity Science and Adaptive Systems

Complexity science provides an additional explanation of how higher-order intelligence can emerge. Complex adaptive systems contain multiple interacting agents whose local interactions can generate global patterns [21-23].

The properties of such systems include nonlinearity, feedback, self-organization, adaptation, distributed control, path dependence, emergence, and interaction across multiple levels.

These properties are increasingly visible in digital health ecosystems. Healthcare is not simply an aggregation of hospitals, clinicians, patients, technologies, and institutions. It is a dynamic network in which information, decisions, resources, behaviors, and institutional responses continuously influence one another.

AI adds another layer of complexity by introducing computational systems capable of processing large and heterogeneous datasets and producing predictions, classifications, recommendations, or other analytical outputs. Rajpurkar et al note that medical AI has developed across multiple domains, including medical imaging and non-image data, while identifying human–AI collaboration as an important area of ongoing research [24].

The Intelligence Field Hypothesis therefore proposes that AI should be evaluated not only in terms of the intelligence of individual algorithms but also according to the systemic intelligence generated when AI interacts with human and institutional components.

Distributed and Collective Cognition

Distributed cognition provides an important bridge between cognitive science and systemic intelligence. Hutchins demonstrated that cognitive processes can extend across individuals, artifacts, representations, and environments [6].

Clinical reasoning already operates through distributed arrangements. Healthcare professionals work with patient histories, laboratory results, imaging, guidelines, colleagues, databases, monitoring devices, institutional protocols, and other forms of evidence. AI adds another cognitive resource to this distributed architecture.

An AI-enabled clinical or public-health system can therefore be understood as a network of interacting cognitive resources rather than simply as a machine that replaces a human decision-maker.

This distinction is crucial. The Intelligence Field Hypothesis does not claim that AI possesses all of the intelligence necessary to manage complex health problems. Rather, it proposes that systemic intelligence may emerge when heterogeneous forms of intelligence are coordinated within an adaptive architecture.

From Digital Networks to Digital Health Ecosystems

Digital technologies transform distributed cognition by increasing the speed, scale, and connectivity of information flows. Electronic health records, telemedicine, mobile health platforms, laboratory information systems, wearable technologies, Internet-of-Things devices, public-health surveillance systems, and AI analytics can become interconnected components of digital health ecosystems.

The World Health Organization's second edition of its Classification of Digital Interventions, Services and Applications in Health provides a common language for describing how digital technologies address individual and health-sector needs. It also recognizes the importance of health-system challenges, including equity, and the variety of services and applications through which digital technologies contribute to health systems [9].

From a systemic perspective, these technologies should therefore be analyzed as components of an ecosystem rather than as isolated applications. Their intelligence depends on relationships among data, technologies, professionals, patients, institutions, and governance arrangements.

A public-health surveillance system provides an illustrative example. An AI system may identify an unusual pattern across epidemiological data. Epidemiologists may interpret the signal, laboratories may provide confirmation, public-health authorities may determine an appropriate response, and communities may contribute information about local conditions and responses. Subsequent outcomes generate new data that can alter later assessments. The intelligence of the surveillance system is therefore distributed across the network.

Human–AI Collaboration as a Systemic Process

Human–AI collaboration is particularly important because it represents an increasingly common configuration through which intelligence is produced in contemporary organizations.

AI systems can process large datasets, identify statistical patterns, generate predictions, and support information retrieval. Humans contribute contextual reasoning, professional knowledge, ethical judgment, experiential understanding, social interpretation, and responsibility.

However, recent evidence cautions against assuming that these capabilities automatically combine into superior performance. Vaccaro, in a systematic review and meta-analysis of more than one hundred experimental studies, found substantial variation in human–AI performance across tasks. Their findings indicate that human–AI combinations can perform worse than the better-performing human or AI component, demonstrating that the design of the interaction matters [8].

This finding strengthens rather than weakens the Intelligence Field Hypothesis. It suggests that systemic intelligence cannot be reduced to the mere presence of multiple intelligent components. What matters is the architecture through which those components exchange information, interpret outputs, allocate responsibility, detect errors, and learn from consequences.

Human–AI collaboration should therefore be understood as a dynamic systemic process involving sensing, computational interpretation, human contextualization, collective decision-making, intervention, and feedback.

Complexity, Public Health, and Adaptive Intelligence

Public health offers a particularly appropriate domain for examining systemic intelligence because public-health problems are inherently interconnected.

Disease outbreaks, for example, involve biological processes, human behavior, mobility, healthcare capacity, communication, institutional decisions, environmental conditions, and social inequalities. No single expert and no single computational model can independently represent all relevant dimensions.

AI can contribute through disease surveillance, risk prediction, spatial modeling, misinformation monitoring, disease forecasting, epidemic modeling, and diagnostic support [5]. At the same time, public-health professionals contribute epidemiological interpretation, contextual judgment, institutional authority, and knowledge of local populations. Communities contribute situated knowledge and behavioral information. Institutions provide coordination and implementation capacity.

The systemic intelligence of public health therefore emerges from the coordination of multiple forms of intelligence.

This also changes how AI performance should be evaluated. Algorithmic accuracy remains important, but it is insufficient as a measure of systemic intelligence. A system must also be capable of integrating relevant evidence, detecting errors, interpreting information in context, coordinating appropriate responses, learning from outcomes, and adapting to changing circumstances.

WHO guidance emphasizes that AI for health should be developed and used with human autonomy, safety, transparency, accountability, inclusiveness, equity, and public interest in view [4]. These requirements can be interpreted not merely as external ethical constraints but as conditions that influence the quality of the intelligence produced by the overall system.

Emergence as the Core Mechanism

The central mechanism connecting systems thinking and intelligence is emergence.

At the micro level, individual agents may perform relatively specific operations. At higher levels, their interactions can generate patterns of coordination, adaptation, learning, and problem-solving that cannot be attributed entirely to any one component.

The Intelligence Field Hypothesis therefore treats emergence as a constitutive mechanism of systemic intelligence.

In an AI-enabled health system, this emergence can be represented conceptually as:

data → computational analysis → human interpretation → institutional decision → intervention → outcomes → feedback → learning

The sequence should not be understood as strictly linear. Each stage can modify the others, and new information can alter earlier interpretations. The system is therefore recursive.

This model also explains why technically sophisticated AI systems may fail to generate intelligent outcomes when embedded in poorly designed organizational environments. Fragmented data, inadequate professional capacity, weak governance, inappropriate incentives, poor communication, exclusion of communities, and ineffective feedback can prevent computational capability from becoming systemic intelligence.

Systemic intelligence is consequently a property not only of technological capability but of relationships, architectures, institutional arrangements, and adaptive processes.

The Intelligence Field Hypothesis

Building on the philosophical, systems-theoretical, and complexity foundations developed above, this article proposes the Intelligence Field Hypothesis: intelligence can emerge as a distributed, relational, adaptive, and non-reducible property of complex systems.

The hypothesis does not claim that intelligence is literally a physical field equivalent to gravitational or electromagnetic fields. The term "field" functions as a theoretical metaphor for a distributed configuration of information, cognition, interaction, feedback, and adaptive organization.

Defining the Intelligence Field

The intelligence field can be defined as the emergent capacity of an interconnected system to sense, acquire, process, integrate, interpret, learn from, and act upon information in ways that enhance adaptation, coordination, innovation, and transformation.

This definition differs from conventional conceptions of intelligence in several important respects. It is relational rather than exclusively individual, distributed rather than localized, emergent rather than reducible, adaptive rather than static, and multi-level rather than confined to a single scale.

The framework consequently shifts the central analytical question from "How intelligent is this agent?" to "How intelligently does this system sense, interpret, coordinate, decide, learn, and adapt?"

This shift is especially significant in digital health. The performance of a health-related AI system cannot be separated completely from the data environment, users, institutional context, workflow, regulatory environment, and populations affected by its outputs. Rajpurkar et al emphasize both the potential of AI to reshape healthcare and the importance of addressing technical and ethical challenges, including data limitations and bias [3].

Distinguishing Systemic Intelligence from Related Concepts

The conceptual contribution of the Intelligence Field Hypothesis becomes clearer when systemic intelligence is distinguished from several adjacent concepts.

Artificial intelligence refers primarily to computational systems capable of performing tasks involving functions such as prediction, classification, learning, pattern recognition, and information processing. Systemic intelligence is broader. AI can contribute to systemic intelligence, but systemic intelligence includes the interactions among AI, humans, institutions, data infrastructures, communities, and environments.

Collective intelligence concerns the capacity of groups or collectives to generate knowledge, solve problems, or coordinate action. Systemic intelligence incorporates collective intelligence but extends the analytical domain beyond human collectives to include technological and institutional components.

Distributed cognition explains how cognitive processes can be distributed across people, artifacts, representations, and environments [6] .Systemic intelligence builds on this insight but emphasizes not only cognition but also adaptation, feedback, coordination, learning, and transformation.

Hybrid intelligence concerns the combination of human and artificial intelligence in collaborative problem-solving. Systemic intelligence includes human–AI collaboration but extends the analytical unit beyond the human–AI dyad to the larger socio-technical ecosystem.

Systemic intelligence therefore refers to the higher-order adaptive capacity generated through interactions among multiple forms of intelligence and the structures through which those forms of intelligence operate.

The distinction is particularly important in healthcare. A clinician using an AI decision-support tool represents a human–AI configuration. A public-health system involving clinicians, patients, epidemiologists, laboratories, electronic records, algorithms, institutions, regulatory arrangements, communication infrastructures, and communities represents a systemic intelligence architecture.

Properties of the Intelligence Field

The Intelligence Field Hypothesis rests on several interconnected properties.

The first is relationality. Intelligence is expressed through relationships among agents, information, tools, and environments rather than existing independently of those relationships.

The second is emergence. System-level intelligence may arise from interactions that are not contained within any single component.

The third is distribution. Intelligence may be distributed across people, algorithms, databases, sensors, institutions, communities, and environments.

The fourth is adaptivity. Intelligent systems modify their behavior in response to changing information and environmental conditions.

The fifth is recursivity. Outputs become inputs into subsequent cycles of interpretation and action.

The sixth is multi-scale integration. Intelligence can operate simultaneously across individual, organizational, societal, technological, and ecological levels.

The seventh is transformative capacity. Systemic intelligence can generate new patterns of organization, innovation, and adaptation rather than merely maintaining existing structures.

These properties are particularly visible in AI-enabled public-health systems, where information and decisions circulate across multiple organizational and social levels.

Mechanisms of Intelligence Field Emergence

The emergence of systemic intelligence can be understood through an interconnected process of sensing, integration, interpretation, coordination, adaptation, and learning.

Sensing involves the acquisition of information through human observation, clinical encounters, laboratories, sensors, databases, digital platforms, and public-health surveillance. Integration connects information originating from different sources. AI can contribute significantly to this process by processing large and heterogeneous datasets.

Interpretation transforms information into meaningful knowledge. This process cannot always be delegated to algorithms because interpretation often depends on professional knowledge, institutional context, values, uncertainty, and local conditions.

Coordination connects interpretation to collective action. Individuals and institutions use information to determine what should be done, who should act, and how resources should be allocated.

Adaptation occurs when the system modifies its behavior in response to changing conditions or observed consequences.

Learning occurs when the system incorporates feedback into subsequent cycles of decision-making.

The six processes therefore constitute a recursive architecture rather than a linear pipeline.

Human–AI Collaboration as an Intelligence Field

Human–AI collaboration provides one of the clearest contemporary manifestations of the Intelligence Field Hypothesis.

In an AI-centered paradigm, the principal analytical object is the algorithm. In a human–AI paradigm, attention shifts toward the interaction between the algorithm and the human decision-maker. In a systemic paradigm, the analytical focus expands again to encompass the wider configuration within which humans and AI operate.

Consider a public-health surveillance system. An AI model may identify an unusual epidemiological pattern. Epidemiologists may interpret the signal in relation to existing knowledge. Laboratories may verify relevant evidence. Health authorities may decide whether intervention is necessary. Communication systems may transmit information to professionals and communities. Communities may respond in ways that affect the subsequent epidemiological situation. New observations then enter the system.

No single component performs the entire intelligence function.

The AI contributes computational analysis. The epidemiologist contributes scientific interpretation. The laboratory contributes empirical verification. The institution contributes authority and coordination. Communities contribute situated knowledge and behavioral responses. The digital infrastructure enables information circulation. Feedback enables learning.

The resulting intelligence is systemic because it emerges through the interaction of these components.

Importantly, this argument does not imply that human–AI collaboration is inherently superior. Vaccaro demonstrate that human–AI combinations can produce heterogeneous outcomes and may sometimes underperform the better individual component. The Intelligence Field Hypothesis therefore directs attention toward the design of the interaction itself: how information is presented, how uncertainty is communicated, how human judgment is incorporated, how responsibility is allocated, how errors are detected, and how feedback is used for improvement [8].

In healthcare, this distinction is essential because AI-supported decisions can affect patients, professionals, and populations. WHO therefore emphasizes human autonomy, safety, transparency, accountability, inclusiveness, equity, and public interest in the governance of AI for health [4].

Systemic Intelligence in AI-Enabled Public Health

Public health provides a particularly important application domain for the Intelligence Field Hypothesis because public-health systems must integrate information across individuals, populations, organizations, technologies, and environments.

AI can contribute to public health through surveillance, disease forecasting, risk prediction, spatial analysis, epidemic modeling, diagnostic support, misinformation monitoring, and policy analysis. Olawade et al identify several such applications while also emphasizing limitations related to infrastructure, data availability, technical capacity, privacy, and ethical concerns [5].

The systemic perspective places these applications within a broader adaptive architecture. A public-health surveillance system does not become intelligent simply because it contains an AI model. It becomes more intelligent when it can transform heterogeneous information into reliable signals, connect those signals to expert interpretation, coordinate institutional action, monitor consequences, and learn from outcomes.

A conceptual representation of this architecture is:

Population and environment → data generation → computational analysis → human interpretation → institutional decision → public-health intervention → population response → new data

The arrows indicate feedback rather than simple one-way transmission. Population responses alter the conditions being monitored, which generates new information and potentially changes subsequent decisions.

This architecture helps explain why systemic intelligence is particularly relevant to public health. Public-health systems operate across multiple levels and cannot rely exclusively on the performance of any single component.

The World Health Organization's digital-health classification further supports this systemic interpretation by treating digital interventions and applications as elements addressing broader individual and health-sector needs rather than as isolated technologies [9].

The Intelligence Field Hypothesis therefore proposes that AI-enabled public health should be understood as a distributed adaptive intelligence system in which computational intelligence, professional knowledge, institutional coordination, community participation, and environmental feedback interact continuously.

Governance and the Quality of Systemic Intelligence

The systemic conception of intelligence also changes the way AI governance should be understood.

If intelligence is distributed across a socio-technical system, responsibility cannot be assigned exclusively to the algorithm. Developers, healthcare professionals, institutions, regulators, technology providers, patients, and communities may all participate in the production and governance of system outcomes.

Governance therefore becomes part of the intelligence architecture itself. Data quality, privacy, transparency, accountability, equity, human oversight, and public participation influence whether a system can learn appropriately and respond effectively to changing conditions.

WHO's, guidance emphasizes that AI for health should protect human autonomy, promote well-being and safety, ensure transparency and explainability, foster responsibility and accountability, promote inclusiveness and equity, and remain responsive and sustainable [4].

The more recent WHO guidance on large multimodal models reinforces the importance of governance as AI systems become capable of processing and generating multiple forms of information and are increasingly considered for healthcare, public health, scientific research, and drug development.

From the perspective of the Intelligence Field Hypothesis, these principles are not external additions to intelligence. They shape the conditions under which intelligence is produced and whether its consequences are beneficial.

A technically sophisticated system that systematically produces inequitable outcomes, excludes relevant knowledge, or lacks mechanisms for correcting errors cannot be regarded as fully intelligent at the systemic level.

Toward a Unified Framework of Systemic Intelligence

The Intelligence Field Hypothesis therefore provides a framework for bringing together several traditions that are often studied separately. Human intelligence concerns the cognitive and practical capacities of individuals. Artificial intelligence concerns computational capabilities implemented through technological systems. Collective intelligence concerns the capacity of groups to generate knowledge and solve problems. Distributed cognition concerns the extension of cognitive processes across people, artifacts, and environments. Hybrid intelligence concerns interaction between human and artificial capabilities [25].

Systemic intelligence encompasses these forms while shifting attention toward the relationships through which they become coordinated.

The conceptual relationship can therefore be expressed as:

Human intelligence + artificial intelligence + collective intelligence + distributed cognition + institutional intelligence + environmental information → systemic intelligence

This expression is conceptual rather than additive. Systemic intelligence does not result from simply accumulating intelligent components. It emerges when those components are connected through relationships capable of information exchange, interpretation, coordination, feedback, learning, and adaptation.The framework consequently shifts AI research from an exclusively agent-centered paradigm toward a system-centered paradigm of intelligence.

In AI-enabled public health, the central question is not whether artificial intelligence can replace human intelligence. It is whether human and artificial capabilities can be organized within systems capable of continuous sensing, interpretation, coordination, learning, and adaptation.

This is the central theoretical proposition of the Intelligence Field Hypothesis: intelligence is not exhausted by the capacities of individual agents; under appropriate conditions, it emerges through the organization and interaction of multiple forms of intelligence within complex systems.

The hypothesis thus provides a theoretical bridge between complexity science, AI, digital health, public health, distributed cognition, and human–AI collaboration. It also establishes the foundation for examining how systemic intelligence may contribute to innovation, resilience, governance, education, organizational transformation, and broader societal adaptation.

Education, Health, and the Development of Systemic Intelligence

Education and health represent two particularly important domains for examining the Intelligence Field Hypothesis because both are complex systems in which knowledge, human judgment, technology, institutions, and social relationships interact continuously. In both domains, intelligence cannot be adequately attributed to a single individual or technological system. It emerges through networks of actors, information infrastructures, institutional arrangements, and feedback processes. The increasing integration of artificial intelligence therefore provides an opportunity to examine how human and computational capabilities can become components of broader intelligence fields.

The application of systemic intelligence to education requires moving beyond the assumption that learning is primarily an individual cognitive activity. Students learn through interactions with teachers, peers, curricula, technologies, families, institutions, and communities. Similarly, healthcare outcomes emerge through interactions among patients, clinicians, laboratories, health information systems, hospitals, public-health institutions, technologies, and wider social and environmental conditions. In both settings, the intelligence of the system depends on its capacity to integrate distributed knowledge, interpret information, coordinate action, learn from feedback, and adapt.

Artificial intelligence introduces an additional layer into these systems. AI can process information at scales that exceed ordinary human analytical capacity, identify patterns, generate explanations, support prediction, and facilitate decision-making. Yet computational capability alone does not constitute systemic intelligence. AI becomes systemically intelligent only when its capabilities are connected with human interpretation, institutional knowledge, ethical judgment, contextual understanding, and mechanisms of accountability.

This distinction is especially important in education and health because both involve high levels of human responsibility. UNESCO's guidance on generative AI in education emphasizes that AI should be integrated through a human-centred approach that protects human agency, equity, inclusion, privacy, and meaningful participation rather than being treated as an autonomous solution to educational challenges [26]. Similarly, the World Health Organization emphasizes that AI in health should be developed and deployed in ways that protect autonomy, safety, transparency, accountability, equity, and the public interest [4]. These principles are consistent with the Intelligence Field Hypothesis because they position AI within broader human and institutional systems rather than treating the algorithm as the primary unit of intelligence.

Systems Thinking and Intelligence in Education

Systems thinking provides a useful foundation for understanding educational intelligence because educational outcomes are produced through relationships rather than isolated variables. Students, teachers, curricula, institutional policies, financing arrangements, assessment systems, families, communities, and technologies influence one another through multiple feedback loops. The RISE Education Systems

Framework, for example, examines relationships involving politics, compact, management, and voice and choice, together with system features such as delegation, finance, information, support, and motivation [27].

From the perspective of the Intelligence Field Hypothesis, these relationships constitute an educational intelligence architecture. Information about learning difficulties may originate with a student, teacher, assessment system, parent, or digital platform. Its value depends on whether it can circulate through the system, be interpreted appropriately, and generate an adaptive response. A system that collects large quantities of educational data but fails to translate them into meaningful decisions cannot necessarily be considered intelligent.

Artificial intelligence can strengthen this architecture by providing adaptive feedback, identifying learning patterns, supporting personalized learning, and assisting teachers with information analysis. However, the impact of AI depends on the wider educational environment. An AI tutoring system may identify a student's difficulty, but the educational system must still determine how that information should be interpreted and acted upon. Teachers remain essential because learning involves motivation, context, social interaction, ethical development, and forms of judgment that cannot be reduced to computational prediction.

This perspective also changes how educational technology should be evaluated. The relevant question is not simply whether an AI system performs a particular task efficiently. The more important question is whether its integration increases the educational system's capacity to learn, adapt, collaborate, and improve. AI should therefore be assessed as part of an educational intelligence field rather than as an isolated technological intervention.

Emergent Intelligence in AI-Supported Learning

Emergent intelligence in education refers to cognitive and adaptive capacities that arise from interactions among learners, educators, technologies, knowledge resources, and institutions. AI-supported learning environments make these interactions increasingly visible because students may now engage simultaneously with teachers, peers, digital resources, and generative AI systems.

Generative AI can provide explanations, alternative perspectives, examples, feedback, simulations, and assistance with problem-solving. Its contribution to learning, however, depends on how learners engage with its outputs. If students simply accept generated information without evaluation, AI may increase access to information without necessarily increasing understanding. If students critically examine, question, compare, revise, and contextualize AI-generated outputs, the technology can become part of a richer learning process.

The distinction is central to systemic intelligence. Intelligence involves not only producing information but determining which information is relevant, evaluating its reliability, connecting it to context, and transforming it into meaningful knowledge and action. Human reflective judgment therefore remains an essential component of AI-supported learning.

UNESCO's guidance on generative AI similarly emphasizes that AI should support rather than displace human capacities and collective action in education [28]. The Intelligence Field Hypothesis extends this position by proposing that educational intelligence is generated through the interaction of human cognition, social learning, institutional structures, and technological capabilities.

AI-Driven Educational Innovation

AI-driven educational innovation includes intelligent tutoring systems, adaptive learning platforms, learning analytics, automated feedback, conversational systems, and generative AI. These technologies can expand the capacity of educational systems to identify learning needs and provide differentiated support.

Earlier research on intelligent tutoring systems demonstrated the potential of AI-supported environments to personalize instruction, although outcomes depend heavily on pedagogical design, implementation quality, duration of use, and contextual conditions [29]. The Intelligence Field Hypothesis builds on this literature by shifting attention from the performance of the individual technology toward the intelligence of the educational system in which the technology operates.

The same principle applies to generative AI. Its value should not be measured only by the sophistication of its outputs but by whether it strengthens learning processes. An educational intelligence field is strengthened when AI helps learners formulate better questions, explore alternative explanations, receive useful feedback, collaborate with others, and reflect on their own reasoning.

This creates a new conception of AI literacy. Students need not only technical knowledge of how to use AI systems but also the capacity to interrogate their outputs, identify uncertainty, recognize bias, verify claims, and understand the limits of automated systems. UNESCO's recent work on AI competency in education similarly emphasizes human-centred competencies and responsible engagement with AI.

The integration of AI consequently requires changes in curriculum, assessment, teacher development, and institutional governance. Assessment systems must increasingly evaluate reasoning, reflection, problem-solving, and the ability to use information critically rather than relying exclusively on final products that may be generated with AI assistance.

Health Systems as Intelligence Fields

Healthcare provides an even more direct demonstration of the Intelligence Field Hypothesis because health systems are inherently distributed. Clinical decisions depend on interactions among patients, physicians, nurses, laboratories, diagnostic technologies, medical records, pharmaceutical systems, hospitals, health authorities, and communities.

Artificial intelligence is increasingly integrated into these systems through medical imaging, clinical decision support, predictive analytics, patient monitoring, digital therapeutics, health information systems, and generative AI. These applications can increase analytical capacity, but their contribution to health intelligence depends on how effectively they interact with human expertise and institutional processes.

The WHO's guidance on AI in health recognizes the potential of AI to improve diagnosis, treatment, research, drug development, surveillance, and outbreak response while emphasizing that ethics and human rights must remain central to design and deployment [4]. The WHO's later guidance on large multimodal models further identifies applications across healthcare, public health, scientific research, and drug development while emphasizing the need for appropriate governance, human oversight, and accountability [30].

From the perspective of systemic intelligence, a clinical AI system should therefore not be considered intelligent in isolation. A diagnostic algorithm may identify a pattern, but the clinician interprets that pattern, the patient provides contextual information, institutional protocols shape the decision, and subsequent outcomes generate feedback. Intelligence emerges through this interaction.

The same principle applies to public health. Surveillance systems integrate clinical reports, laboratory results, demographic information, environmental conditions, mobility data, and community-level information. AI can strengthen the capacity to detect patterns and anomalies across these datasets, but public-health intelligence requires human interpretation, institutional coordination, community engagement, and appropriate intervention.

Healthcare thus provides a concrete environment in which artificial intelligence can become part of a wider systemic intelligence field.

Digital Health Ecosystems and Human–AI Intelligence

Digital health expands the intelligence field beyond hospitals and clinics. Electronic health records, telemedicine platforms, mobile health applications, wearable devices, Internet of Things technologies, laboratories, health information exchanges, and public-health databases increasingly form interconnected digital ecosystems.

These systems create continuous flows of health information. Sensors can generate physiological data; electronic records can provide clinical histories; laboratories contribute diagnostic information; AI systems can identify patterns; clinicians interpret results; and public-health institutions can use aggregated information to understand population-level trends.

The intelligence of such an ecosystem depends on the quality of its feedback loops. Information must move between appropriate actors, be interpreted within context, generate decisions, and return to the system as new evidence. A technically sophisticated digital health infrastructure may therefore remain systemically weak if data remain fragmented, if interoperability is poor, if important populations are excluded, or if patients and professionals do not trust the system.

Digital health consequently illustrates a central proposition of the Intelligence Field Hypothesis: intelligence is generated not simply by data or algorithms but by the relationships through which data become knowledge and knowledge becomes coordinated action.

Leadership, Power, and the Governance of Intelligence Fields

Systemic intelligence is shaped by leadership and power because information, authority, resources, and decision-making are distributed unevenly within organizations and societies. A system may contain substantial knowledge and technological capability while remaining unable to use them effectively if information is concentrated, participation is restricted, or institutional structures prevent learning.

Leadership therefore becomes an important mechanism through which intelligence fields are enabled or constrained. Leaders influence whether information can circulate, whether diverse forms of knowledge are recognized, whether disagreement is permitted, whether experimentation is encouraged, and whether feedback can modify established practices.

Leadership as a Relational Property

In complex systems, leadership cannot be reduced to the actions of a single individual. Foucault's analysis of power emphasizes that power operates through relationships, institutions, knowledge, and social practices. Leadership consequently occurs within a broader relational architecture [31].

Distributed leadership scholarship similarly conceptualizes leadership as emerging through interactions among individuals, organizational structures, and situations [32-33]. This perspective is highly compatible with systemic intelligence because knowledge is distributed across organizational actors.

In healthcare, for example, effective decisions may depend simultaneously on physicians, nurses, laboratory specialists, pharmacists, administrators, patients, data scientists, and AI systems. No single actor necessarily possesses all relevant information. Leadership becomes the capacity to connect these distributed forms of expertise.

In education, the same principle applies to teachers, students, administrators, families, policymakers, and technological systems. Systemic intelligence increases when leadership creates conditions for these actors to contribute knowledge and learn from one another.

Power and the Distribution of Knowledge

Power influences systemic intelligence partly through the control of information. Centralized systems can facilitate coordination, but excessive centralization may restrict the circulation of local knowledge and reduce the diversity of information entering decision processes.

Ostrom's research on collective governance demonstrates that communities can develop institutional arrangements that allow local actors to coordinate and manage complex resources. The significance of this work for systemic intelligence lies in its demonstration that intelligence can emerge through distributed participation rather than requiring centralized control [34].

The same issue arises in AI-enabled systems. AI can centralize analytical capacity because large datasets and computational resources may be controlled by governments, corporations, hospitals, or technology providers. At the same time, digital technologies can potentially distribute information and participation more widely.

The result depends on governance. A health AI system that is technically sophisticated but opaque, inaccessible, or disconnected from patients and health professionals may increase computational power while weakening systemic intelligence. Conversely, a system that combines AI capabilities with transparent governance, professional expertise, patient participation, and institutional accountability can strengthen the intelligence of the wider health ecosystem.

Collaborative Governance and Systemic Intelligence

Collaborative governance provides a framework for organizing distributed intelligence. It enables governments, professionals, communities, civil society organizations, private actors, and knowledge institutions to contribute to collective decision-making.

Ansell and Gash emphasize the importance of dialogue, trust, institutional design, and shared understanding in collaborative governance, while conceptualize collaborative governance through processes of principled engagement, shared motivation, and capacity for joint action [35-36].

AI introduces an additional dimension to this configuration. Algorithms can analyze complex information, but they do not independently determine social legitimacy or ethical priorities. Human actors remain responsible for interpreting evidence, negotiating values, communicating decisions, and accepting accountability.

This creates what may be described as a human–AI governance field. Government contributes institutional authority; professionals contribute expertise; communities contribute situated knowledge; digital infrastructures contribute connectivity; and AI contributes computational analysis. Systemic intelligence emerges when these capabilities are connected through legitimate governance processes.

Leadership in AI-Enabled Health and Education

Leadership becomes particularly important when AI is introduced into health and education because both domains involve vulnerable populations, professional responsibility, and significant asymmetries of knowledge.

In healthcare, leaders must determine how AI recommendations enter clinical workflows, how responsibility is allocated, how errors are detected, and how patients are informed. The WHO emphasizes the importance of human autonomy, safety, transparency, accountability, inclusiveness, and sustainability in AI for health [4].

In education, leaders must similarly determine how AI affects teaching, assessment, student agency, data protection, and teacher roles. UNESCO's guidance stresses the need for regulation, teacher preparation, data protection, equity, and human-centred implementation [28].

Leadership is therefore not simply responsible for adopting AI. It is responsible for designing the institutional conditions under which human and artificial intelligence can interact safely and productively.

Leadership for Systemic Transformation

Adaptive leadership emphasizes sensemaking, experimentation, distributed problem-solving, and learning under conditions of uncertainty. Uhl-Bien and Arena similarly emphasize leadership capable of enabling adaptability and innovation in complex organizations [37-38].

Within the Intelligence Field Hypothesis, leaders can consequently be understood as architects of intelligence conditions. Their role is not to possess all knowledge but to create environments in which knowledge can circulate, differences can be interpreted constructively, experimentation can occur, and feedback can influence decisions.

This conception of leadership is particularly relevant to AI-enabled systems. Leaders must establish how AI-generated information is evaluated, how uncertainty is communicated, when human judgment is required, and how accountability is maintained. The quality of the intelligence field therefore depends partly on the governance architecture created by leadership.

Intelligence, Human–AI Collaboration, and Systemic Transformation

Systemic transformation occurs when changes in knowledge, technology, institutions, relationships, or patterns of behavior alter the functioning of a system. Intelligence contributes to transformation because systems require capacities to sense changing conditions, interpret information, generate alternatives, coordinate action, and learn from consequences.

The Intelligence Field Hypothesis therefore positions intelligence as a mechanism of transformation rather than merely a cognitive attribute. A system becomes more capable of transformation when it can connect information with interpretation, interpretation with decision-making, and decision-making with feedback.

Systemic Intelligence and Innovation

Innovation is one of the principal mechanisms through which intelligence produces systemic change. Christensen's work on disruptive innovation demonstrates how new technologies and organizational models can challenge established systems. Rogers diffusion framework further demonstrates that innovations spread through networks of communication, trust, social learning, and adoption [39-40].

From a systemic perspective, innovation involves more than creating something new. It involves the capacity of a system to detect novelty, evaluate it, adapt it to local conditions, and integrate it into existing structures.

AI can accelerate parts of this process by analyzing large datasets, identifying patterns, generating alternatives, and supporting experimentation. Yet faster generation of alternatives does not necessarily constitute better innovation. Systemic intelligence requires evaluation, contextualization, ethical assessment, and learning from implementation.

Complex adaptive systems illustrate this principle. Organizations, cities, technological networks, and ecological systems evolve through interactions among multiple agents and through feedback between the system and its environment [22-23,41]. Intelligence emerges when these interactions enable the system to respond adaptively rather than merely react mechanically.

Adaptive Intelligence in Healthcare

Healthcare systems are continuously exposed to changing disease patterns, technological innovations, demographic transitions, resource constraints, and public expectations. Their capacity to adapt depends on the integration of clinical knowledge, institutional learning, technological capabilities, and population-level information.

AI can contribute to this adaptive capacity by supporting early detection, clinical analysis, risk prediction, resource planning, and population surveillance. The WHO recognizes the potential of AI for diagnosis, treatment, health research, drug development, surveillance, and outbreak response while emphasizing appropriate governance and human rights.

The Intelligence Field Hypothesis interprets these capabilities as components of an adaptive health intelligence system. AI performs computational sensing and analysis; professionals provide interpretation; institutions coordinate action; patients contribute experiential knowledge; and outcomes provide feedback.

The system becomes intelligent not because one component is exceptionally capable but because the components collectively learn.

Human–AI Collaboration in Clinical Decision-Making

Human–AI collaboration represents a particularly important form of systemic intelligence because it combines computational processing with human contextual judgment.

In clinical decision-making, AI can analyze medical images, laboratory information, clinical histories, or physiological signals. Clinicians then evaluate these outputs against the patient's circumstances, professional knowledge, and clinical priorities. The decision is therefore generated through interaction rather than through the algorithm alone.

This model differs fundamentally from technological substitution. The objective is not to eliminate human judgment but to reorganize the relationship between human and computational capabilities. AI can expand analytical capacity while humans maintain contextual interpretation, communication, ethical reasoning, and responsibility.

WHO guidance on large multimodal models emphasizes that such systems may have applications across healthcare and public health but require careful attention to reliability, accountability, stakeholder participation, human rights, and governance [30].

The Intelligence Field Hypothesis provides a theoretical explanation for why these safeguards are not external constraints on intelligence. They are conditions that enable intelligence to function systemically. Human oversight, transparency, and feedback increase the capacity of the broader system to recognize errors and adapt.

Digital Health Ecosystems and Continuous Intelligence

Digital health technologies create increasingly continuous forms of health intelligence. Wearables, remote monitoring systems, mobile applications, electronic records, telemedicine, laboratory platforms, and IoT devices generate information across different stages of the health cycle.

When connected, these technologies can create feedback loops in which information is continuously generated, processed, interpreted, and acted upon. A physiological signal may trigger an analytical process; the result may inform a healthcare professional; an intervention may follow; and subsequent measurements may provide evidence about the intervention's effectiveness. This creates an architecture of continuous systemic intelligence.

However, connectivity creates new risks. Incomplete datasets, biased algorithms, poor interoperability, privacy violations, or inappropriate automation can weaken rather than strengthen the intelligence field. Systemic intelligence therefore requires governance mechanisms capable of ensuring that technological connectivity translates into meaningful and responsible learning.

AI-Supported Public-Health Intelligence

Public health offers perhaps the clearest illustration of intelligence distributed across scales. Population health depends on information generated by individuals, communities, healthcare providers, laboratories, surveillance systems, environmental monitoring systems, and public institutions.

AI can strengthen public-health intelligence by processing heterogeneous data, detecting anomalies, supporting forecasting, identifying populations at risk, and informing resource allocation. Yet the transformation of prediction into effective public-health action depends on institutional coordination, communication, trust, and community participation.

The Intelligence Field Hypothesis therefore distinguishes between computational prediction and systemic intelligence. Prediction identifies what may happen. Systemic intelligence involves determining how that information should be interpreted, communicated, acted upon, and evaluated.

This distinction is particularly important during health emergencies. A predictive model may identify an emerging risk, but public-health intelligence requires surveillance, clinical confirmation, institutional coordination, public communication, intervention, and subsequent evaluation. The intelligence field is therefore distributed across the entire response system.

From Artificial Intelligence to Hybrid and Systemic Intelligence

Artificial intelligence, collective intelligence, distributed cognition, and hybrid intelligence describe related but distinct phenomena. Artificial intelligence refers primarily to computational systems capable of performing tasks associated with intelligent behavior. Collective intelligence concerns capabilities that emerge from groups. Distributed cognition emphasizes cognitive processes distributed across individuals, tools, representations, and environments. Hybrid intelligence concerns the complementary interaction of humans and artificial systems.

Systemic intelligence extends these perspectives by emphasizing the architecture connecting multiple forms of intelligence. A healthcare system may contain artificial intelligence, professional expertise, collective knowledge, institutional memory, patient experience, and environmental information. Systemic intelligence concerns how these different forms interact to produce adaptive capacity.

The distinction is therefore one of analytical scale and relational structure. The Intelligence Field Hypothesis does not reject existing concepts of intelligence; it situates them within a broader framework in which intelligence can emerge across interconnected human, technological, organizational, and environmental components.

Governance and Societal Transformation

If intelligence is distributed across systems, governance must also be designed to support distributed learning. Policy systems should facilitate information sharing, interdisciplinary collaboration, participation, feedback, and responsible AI integration.

In healthcare, this requires governance arrangements that connect clinicians, patients, technology developers, regulators, public-health institutions, and communities. In education, it requires collaboration among teachers, students, administrators, policymakers, researchers, and technology providers.

The objective should not simply be greater technological adoption. The objective should be the development of systems capable of learning responsibly.

This distinction is fundamental because technological advancement can increase computational power without increasing social intelligence. A system can process more data while becoming less transparent, less equitable, or less accountable. Systemic intelligence therefore requires alignment between technological capability and institutional capacity.

CONCLUSION, LIMITATIONS, AND FUTURE DIRECTIONS

This article has reconceptualized intelligence as a systemic, emergent, distributed, adaptive, and transformative property of complex systems. The Intelligence Field Hypothesis moves beyond the assumption that intelligence belongs exclusively to individuals or computational machines and instead focuses on the relationships through which information, knowledge, cognition, technology, institutions, and environments become connected.

The analysis of education demonstrates that learning intelligence emerges through interactions among students, educators, technologies, curricula, institutions, and communities. AI can expand the informational and analytical capacities of educational systems, but its contribution depends on human agency, critical reflection, pedagogical design, and institutional governance. UNESCO's human-centred approach to generative AI provides important support for this interpretation.

The analysis of healthcare provides an even stronger demonstration of the framework. Health intelligence is distributed among patients, clinicians, laboratories, medical records, diagnostic systems, digital platforms, public-health institutions, and communities. AI can strengthen particular components of this system, including pattern recognition, prediction, decision support, monitoring, and surveillance. Yet systemic health intelligence emerges only when these capabilities are connected through effective human–AI collaboration, institutional coordination, ethical governance, and continuous feedback.

This distinction addresses an important limitation in conventional discussions of artificial intelligence. AI performance alone does not determine the intelligence of a health or educational system. A highly accurate algorithm may produce limited systemic value if it is disconnected from professional workflows, institutional decision-making, patient experience, or public accountability. Conversely, relatively simple technologies can generate substantial systemic value when they improve information circulation, coordination, learning, and adaptation.

The Intelligence Field Hypothesis therefore proposes that the appropriate unit of analysis for increasingly AI-enabled environments is not the algorithm alone but the intelligence architecture of the system in which the algorithm operates.

In digital health, this architecture includes AI systems, healthcare professionals, patients, electronic records, laboratories, wearable technologies, IoT devices, public-health institutions, regulatory systems, and communities. In education, it includes learners, teachers, AI systems, curricula, institutions, assessment structures, and social environments. In both cases, systemic intelligence depends on the relationships connecting these components.

This perspective also clarifies the distinction between artificial intelligence and systemic intelligence. Artificial intelligence concerns the capabilities of computational systems. Systemic intelligence concerns the capacity of an interconnected system to sense, integrate, interpret, coordinate, learn, and adapt. Artificial intelligence can therefore become a component of systemic intelligence without being identical to it.

The framework consequently contributes to the emerging discourse on human–AI collaboration by shifting attention from the performance of individual AI systems toward the adaptive capacity of human–AI ecosystems. This is particularly relevant to healthcare, where AI increasingly participates in diagnosis, monitoring, decision support, research, and public-health surveillance. WHO guidance emphasizes that AI for health must remain grounded in autonomy, safety, transparency, accountability, equity, and public benefit. These principles can be interpreted within the Intelligence Field Hypothesis as institutional conditions necessary for a health intelligence field to function responsibly.

The framework has several limitations. First, the Intelligence Field Hypothesis remains primarily theoretical and requires empirical validation. Although the proposed framework identifies mechanisms involving information integration, distributed cognition, human–AI interaction, feedback, and adaptation, these mechanisms require systematic testing across different settings.

Second, measurement remains challenging. Intelligence distributed across individuals, organizations, technologies, and environments cannot easily be captured through conventional psychometric or machine-performance measures. Future research will therefore need to develop indicators capable of assessing system-level capacities such as information integration, adaptive learning, coordination, resilience, and human–AI complementarity.

Third, systemic intelligence is context-dependent. Cultural values, institutional arrangements, socioeconomic conditions, professional norms, and political structures influence how intelligence is generated and recognized. The framework must therefore remain open to different cultural and epistemic configurations rather than assuming a universal model of intelligence.

Fourth, AI systems themselves are rapidly changing. The emergence of generative AI and large multimodal models creates new possibilities for interaction across text, image, audio, video, and structured data. WHO's recent guidance recognizes that such models may have significant applications in healthcare and public health while also creating new governance challenges [30]. The Intelligence Field Hypothesis will therefore require continuous empirical refinement as AI capabilities evolve.

Future research should move toward operationalizing the framework through measurable dimensions of systemic intelligence. Studies could examine information integration, distributed decision-making, feedback quality, adaptive capacity, human–AI complementarity, institutional learning, and resilience.

Healthcare should constitute a major empirical domain for this research. Comparative studies could investigate AI-supported clinical decision-making, digital health ecosystems, electronic health-record environments, remote patient monitoring, wearable technologies, health-data networks, and AI-supported public-health surveillance. Such research could examine whether different configurations of human and artificial intelligence produce different levels of system-level performance and adaptability.

Education provides a complementary domain. Research could investigate AI-supported learning environments, teacher–AI collaboration, generative AI and assessment, learning analytics, and institutional AI governance. Comparative research across educational systems could determine how organizational structures and cultural contexts influence the emergence of educational intelligence.

Another important research direction concerns human–AI co-learning. Existing approaches often treat humans as users and AI as tools. A systemic perspective instead asks how humans and AI mutually influence decision processes over time. This requires examining feedback, adaptation, trust, error correction, changing expertise, and the evolution of human–AI relationships.

Governance should constitute a further research priority. Future studies should examine how transparency, accountability, participation, privacy, data governance, and institutional design influence the intelligence of AI-enabled systems. This is particularly important in health and education, where technological decisions can affect fundamental rights and social opportunities.

Finally, systemic intelligence should be evaluated not only by efficiency or predictive performance but also by its contribution to human well-being, equity, resilience, and responsible transformation. A system that becomes more computationally powerful but less inclusive, less transparent, or less accountable should not automatically be considered more intelligent.

The central proposition of the Intelligence Field Hypothesis is therefore deliberately broader than the claim that artificial intelligence is becoming more powerful. The deeper transformation is that intelligence itself is becoming increasingly distributed across human, technological, organizational, and environmental networks.

The future of intelligence research consequently requires a shift from asking which entity is intelligent to asking how intelligence emerges across relationships. In education, this means examining how learners, teachers, institutions, and AI collectively generate knowledge. In healthcare, it means examining how patients, professionals, technologies, data infrastructures, and public-health institutions collectively generate health intelligence. In governance, it means understanding how distributed knowledge can become coordinated and accountable action.

From this perspective, AI is neither the endpoint nor the sole source of intelligence. It is one increasingly important component of larger intelligence fields. The transformative challenge is to design systems in which human and artificial capabilities are connected in ways that increase learning, adaptability, resilience, equity, and responsible action.

The Intelligence Field Hypothesis therefore offers a foundation for a broader science of intelligence in complex systems: a science concerned not simply with intelligent individuals or intelligent machines, but with the emergence, organization, governance, and transformation of intelligence across interconnected systems.

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