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Positioning Multi-Intelligence Agents for Healthcare Enterprises: Toward Evolving Cyber-Physical-Social Systems

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Healthcare enterprises, including providers, payers, pharmaceutical and biotech firms, medical device manufacturers, health IT companies, regulators, supply chain actors, and hybrid care models, face the complex challenge of balancing economic viability with equitable and environmentally-responsible care delivery. This challenge is compounded by entrenched asymmetries in access to information, analytical capabilities, and control over resources and decision-making, which constrain responsiveness and obstruct transitions toward inclusive, adaptive service delivery. In this article, the author argues for designing healthcare systems for punctuated evolution, rapid, transformative adjustments to shifting patient needs, emerging technologies, and evolving regulatory or environmental conditions, while operating in a poised equilibrium that balances stability and exploration. A smart service perspective is advanced, prioritizing adaptability, stakeholder alignment, and long-term resilience across healthcare and related domains. The author presents a computational and conceptual framework positioning smart services as evolving cyber-physical-social systems (eCPSS), anchored in the novel construct of multi-intelligence agents (MIAs). The core contribution is a mental model integrating physical, cyber, and social domains to address persistent asymmetries in intelligence, information, and resources. This model operationalizes adaptive intelligence by enabling MIAs to perceive context, learn from interaction, and align behavior with dynamic service goals. It introduces evolvability, the maintained capacity of an eCPSS to generate and retain beneficial variations while remaining viable. The healthcare sector is used to illustrate the framework's relevance, with a discussion of its extensibility to other smart service domains. [DOI: 10.1115/1.4070442]

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1 Introduction

Highly networked complex systems, such as healthcare, urban intelligence, and environmental response, consist of interconnected components that interact in non-trivial ways, exhibiting emergent behaviors, adaptability, and resilience [1]. These characteristics underpin the formation of smart societies [2–5], envisioned in Society 5.0, as human-centered, super-smart environments where cyberspace and physical space converge to enhance quality of life, promote inclusivity, and sustainability [6,7].

Despite the promise of smart-society innovation, sectors such as healthcare continue to face persistent challenges in maintaining economic viability, ensuring equitable access, and upholding environmental responsibility [8–10]. The core problem lies not in the absence of technology but in its fragmented integration across social and ecological frameworks. Asymmetries continue to impede scalable, sustainable transformation of service systems within smart societies. In healthcare enterprises, these asymmetries manifest as unequal access to data, uneven analytical capacity among stakeholders, and limited interoperability between clinical, digital, and organizational systems, barriers that constrain adaptability and sustainability.

To address these challenges, in this article, a shift from static, product-optimization mindsets to a designing-for-service approach is advocated, one that treats services as evolving entities and focuses on enabling conditions for value co-creation, system adaptability, and social return on investment [11–16]. This view redefines the goals of service engineering from efficiency-driven delivery to public value creation, including well-being, empowerment, and long-term sustainability. In healthcare, such a paradigm reframes care delivery from isolated treatment episodes to adaptive learning systems that evolve with patient needs, policy dynamics, and technological innovation. Achieving this transformation is central to the broader smart-society vision, which links individual well-being to social and ecological stability [17,18].

Designing for service extends beyond delivering predefined outputs. It focuses on creating the conditions for continuous

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value co-creation within complex service ecosystems. By embedding adaptability and responsiveness, it ensures that public services can evolve in alignment with shifting needs, stakeholder dynamics, and systemic disruptions. Among public service domains, healthcare exemplifies these dynamics most vividly: it operates at the intersection of technological innovation, social responsibility, and institutional complexity, where adaptability is essential for continuity and equity. This perspective is particularly relevant for retrofitting healthcare infrastructures—from hospitals to digital platforms—to be more inclusive, equitable, and resilient. While frameworks such as Industry 4.0, Industry 5.0, and early Society 5.0 implementations have driven advances in automation, connectivity, and human-centric innovation, they lack the adaptive scaffolding required for socio-technical systems like healthcare to co-evolve with their environments [19]. Healthcare therefore provides an ideal setting in which to examine what such scaffolding requires: the integration of digital and physical infrastructures with human and organizational intelligence. To enable this convergence and sustained adaptability, service systems must be conceived not as static workflows but as evolving socio-technical ecosystems.

This motivates the development of a conceptual framework for designing smart services as evolving cyber-physical-social systems (eCPSSs), In this article, a mental model is proposed for designing smart services as eCPSS, in which physical, cyber, and social spaces converge to form adaptive, resilient, and co-evolving service architectures capable of responding to evolving needs, emerging technologies, and external pressures. The central computational contribution is the introduction of multi-intelligence agents (MIAs), adaptive computational agents that bridge asymmetries across the physical, mental, and artificial domains to enable punctuated evolution in service systems through dynamic role negotiation, real-time orchestration, and ethical decision-making. Their integration advances the intent of initiatives such as Industry 5.0 and Society 5.0 by aligning technological autonomy with societal goals, a relationship exemplified in healthcare, where intelligent systems must reconcile automation with empathy, safety, and equitable access to care.

Building on this foundation, eCPSS is presented as the overarching design context, and MIAs are structured through a three-layer roadmap for analysis, synthesis, and evaluation. The framework provides definitions, modeling patterns, co-agency protocols, prompt templates, and minimal simulation hooks, together with a verification and validation checklist that can be adapted by design researchers, systems engineers, and healthcare technologists. These artifacts are intended for reuse in building, testing, and refining eCPSS scenarios in ways that align with the JCISE emphasis on computational modeling, simulation, and methods for engineering design and systems integration.

The remainder of the article is organized as follows: In Sec. 2, limitations of existing initiatives are reviewed, outlining key asymmetries, and surveys enabling technologies. In Sec. 3, the adaptive intelligence and novel concept of MIAs are introduced. In Sec. 4, a layered design roadmap and guidelines for implementing MIAs are presented. In Sec. 5, the application of MIAs in healthcare diagnostics and validation strategies is explored. In Sec. 6, the insights gained from this healthcare application to outline cross-sectoral generalizability and computational modeling contributions are extended, positioning the framework within the wider design-research context, cross-sectoral generalizability and computational modeling contributions are discussed. The summary of the key insights and outlining the next research directions are presented in Sec. 7.

2 Literature Review and Gap Analysis

2.1 Review of Existing Initiatives. Existing initiatives such as Industry 4.0, Industry 5.0, and the early adoption of Society 5.0 (see Fig. 1) have advanced digital and human-centric innovation but fall short of integrating the economic, social, and ecological dimensions of sustainability [10]. Industry 4.0 emphasizes technological advancement with limited attention to social or environmental impact [19]. Industry 5.0 stresses human prosperity yet lacks clear socio-technical integration [20]. Under early adoption of Society 5.0 highlights social transformation without corresponding economic and technological infrastructure [4].

In Fig. 1, the author illustrates the parallel yet disconnected trajectories of industrial and societal transformation—where the industry track (Industry $4.0 \rightarrow 5.0$) emphasizes innovation and prosperity, and the society track (Society 5.0) focuses on human and social progress—but their lack of convergence into a shared space for co-designing technological capacity, human cognition, and ecological responsibility remains a critical limitation of current approaches.

Consequently, neither industry nor society, in their current trajectories, is equipped to manage the demands of eCPSS. Industrial systems remain brittle under sociocultural disruption, while social systems lack the computational, infrastructural, and economic robustness required for systemic transformation. Despite the value of existing initiatives, their effectiveness is limited by the absence of an integrative, interdisciplinary framework that unites technological advancement with societal and ecological transformation. Moving forward, progress requires a co-evolutionary foundation that bridges industrial and societal trajectories into a unified model for adaptive, resilient, and sustainable service systems.

Addressing this gap requires a shift from the conventional product-centric perspective to a smart service-oriented paradigm. While prior efforts emphasize tangible outputs and technologies, the author explores a critical question: What constitutes a smart service in a smart society? The author proposes that smart services are designed to be adaptive, human-centered, and sustainable by design. Crucially, technology may or may not be an integral component of service delivery, as the focus is on retrofitting and enhancing existing services rather than creating new ones merely to showcase technological superiority.

These initiative-specific shortcomings point to a deeper, systemic issue: the presence of entrenched asymmetries in how resources, information, and intelligence are distributed and used, factors that severely constrain adaptability and sustainability.

2.2 Asymmetries in Current Systems

2.2.1 Resource Asymmetry. Resource asymmetry refers to the unequal distribution and access to resources, which may be tangible or intangible, finite or infinite (Column 1 in Fig. 2). These resources can include natural, human, capital, digital, energy, material, social, cultural, and temporal assets. Such asymmetries often lead to inefficiencies and pose challenges in optimizing resource use across systems. Although notable progress has been made through advances in energy efficiency, renewable technologies, storage solutions, autonomy, and circular economy practices, such as remanufacturing, recycling, and waste management methods (e.g., lean, just-in-time, and reconfigurable manufacturing), resource asymmetries remain a persistent issue [20].

2.2.2 Information Asymmetry. Information asymmetry arises when the flow of information between key actors, namely, the information owner and the information absorber, is disrupted or imbalanced (Column 2 in Fig. 2). Information can exist in two primary forms, original or distorted. Distortion may result from various factors, including intentional manipulation, external influence, hindered transmission, or unawareness. Some progress has been made in reducing these asymmetries. Smart contracts as in Ref. [21] use artificial intelligence (AI), blockchain, and other ledger technologies. Social contracts as in Refs. [22,23] include incentives and penalties. Still, it is difficult to balance access to accurate information. A key challenge is ensuring balanced access to accurate, timely, and contextually appropriate information across system participants.

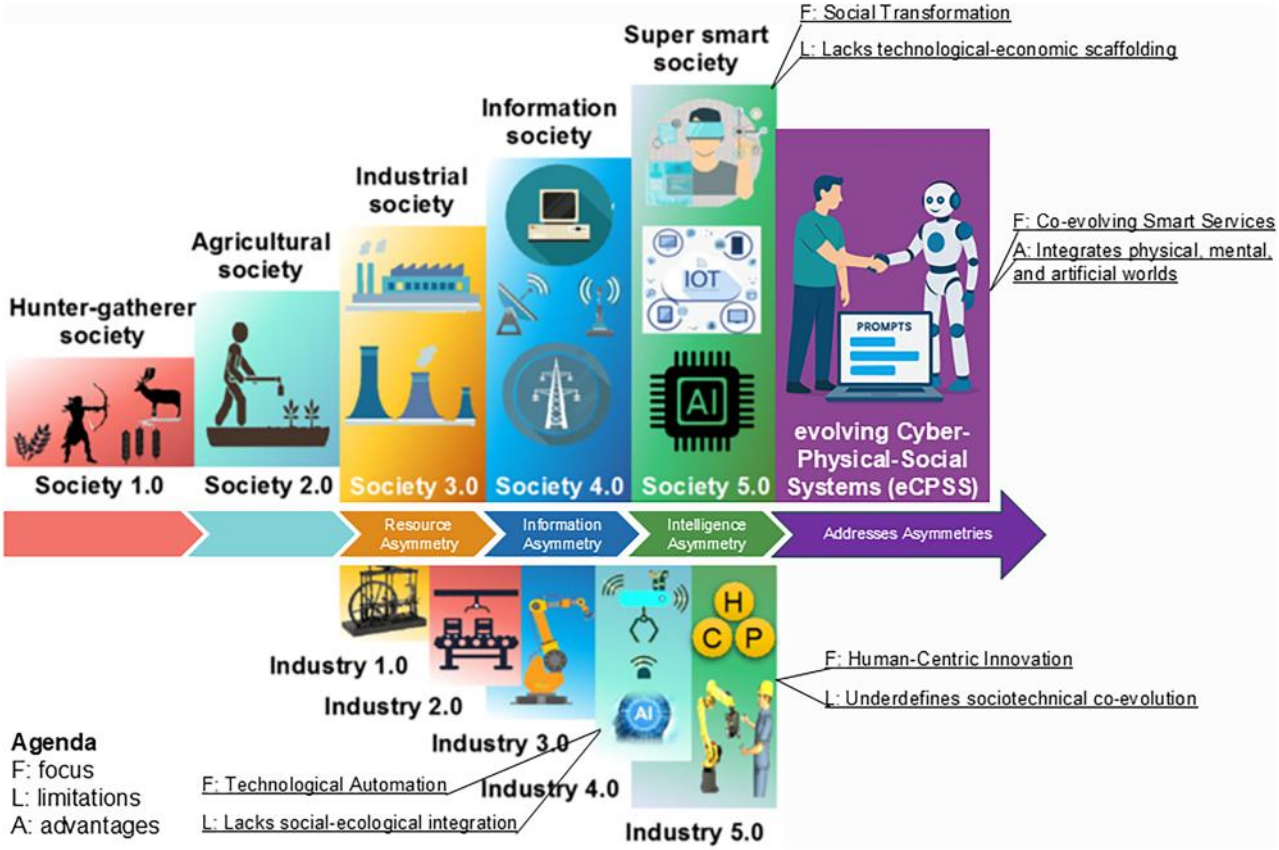


Fig. 1 Society transformation and industry evolution

2.2.3 Intelligence Asymmetry. Intelligence asymmetry refers to the imbalance in access to, use of, and understanding of diverse forms of knowledge across three key dimensions: human, artificial, and organizational (Column 3 in Fig. 2). Human knowledge encompasses various types, such as propositional, non-propositional, a priori and a posteriori, self-knowledge, meta-knowledge, common knowledge, domain-specific knowledge, and both explicit and implicit forms [24]. Artificial knowledge, by contrast, includes declarative, procedural, heuristic, structural, and meta-level forms of representation and reasoning [25]. Organizational knowledge is often embedded in system-level representations, such as models that are prescriptive, descriptive, predictive, normative, exploratory, causal, or theoretical, and may operate at global or local (myopic) scopes [26].

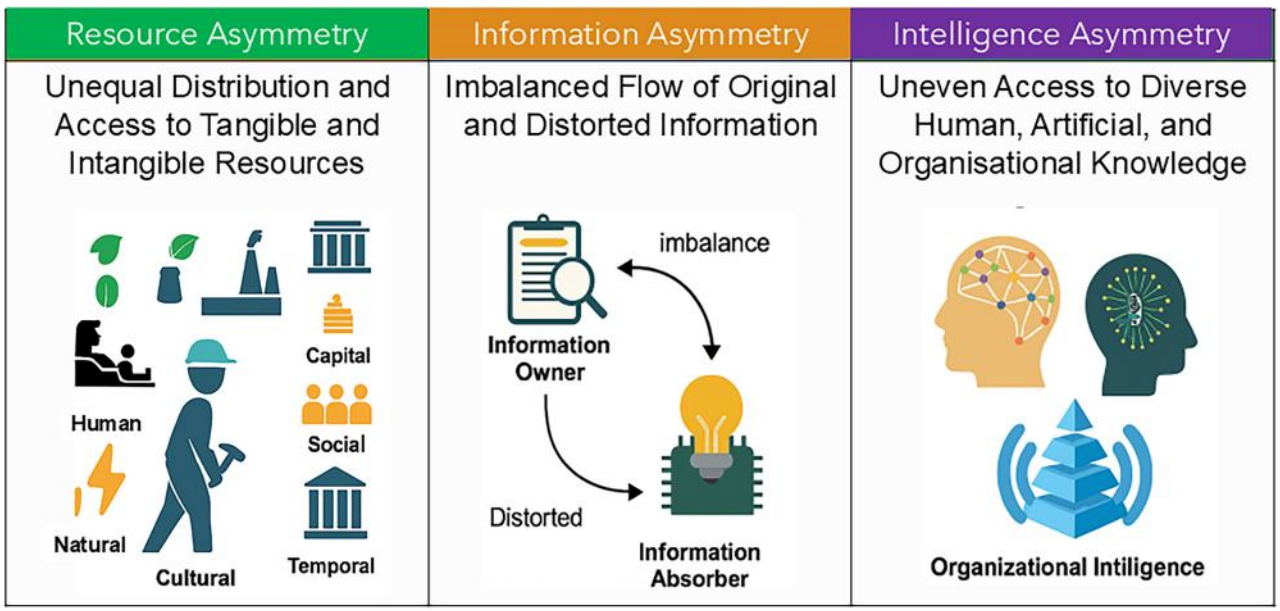


Fig. 2 Persistent asymmetries in current systems

These asymmetries also shape decision-making processes, influencing whether choices are made through selection or compromise strategies [27], and the reasoning methods applied, such as inductive, deductive, abductive, or analogical reasoning [28]. Moreover, diverse perspectives on intelligence—mathematical, epistemological, cognitive, sociological, and instructional—determine how knowledge is structured and applied across different contexts [29]. Despite substantial technological progress, integration among human, artificial, and organizational intelligence remains limited, particularly in bridging the real, mental, and artificial worlds.

Traditional systems often fail to respond adaptively because they are not designed to bridge persistent asymmetries across knowledge domains, decision-making structures, and stakeholder roles. Without mechanisms for co-evolution between human and machine intelligence, these systems remain brittle, static, and misaligned with dynamic (changeable) service needs.

2.3 Technological Readiness. Recent advances across artificial intelligence, orchestration technologies, and adaptive learning frameworks form a critical foundation designing for smart services. However, these advances, while necessary, remain individually insufficient to support the dynamic, socially embedded adaptation required for eCPSS. Over the last 5 years, significant technological progress has laid the groundwork for the kind of adaptive, intelligent services envisioned in this article. Three intersecting domains, agentic AI, orchestration technologies, and adaptive learning frameworks, demonstrate growing maturity and potential for integration into eCPSS. Yet, each remains bounded by architectural, epistemological, or operational limitations.

2.3.1 Agentic Artificial Intelligence: From Task Execution to Contextual Adaptation. Recent advances in agentic AI have produced systems capable of autonomous reasoning, planning, and executing multistep tasks using frameworks such as AutoGPT, LangChain, and reasoning and acting (ReAct). These agents integrate large language models with memory, feedback loops, and tool use, allowing adaptation to user instructions and environmental inputs over time [30,31]. Although they mark a shift from passive tools to semi-autonomous problem solvers, their design remains focused on narrow tasks and often lacks the relational intelligence required for meaningful coordination with human stakeholders in social or institutional contexts [32]. Most frameworks still assume well-defined goal states and static utility functions, which are ill-suited for the ambiguity and interdependence of real-world service environments such as healthcare or public planning. Moreover, because generative AI primarily relies on predictive mimicry—reproducing patterns from training data rather than engaging in principled reasoning—it struggles to operate in dynamic, non-linear contexts where human behavior is unpredictable and highly dependent on situational factors [33].

Gap 1: Current agentic AI systems, though effective in executing structured tasks, remain limited in relational intelligence and context-sensitive coordination. Their reliance on predefined goals and static utility functions makes them poorly suited to environments marked by ambiguity, evolving objectives, and human complexity—such as healthcare or public services. They struggle to negotiate roles dynamically or adapt beyond preset parameters. In healthcare, for example, diagnostic assistants or triage chatbots perform well under fixed protocols but fail to coordinate with clinicians' judgment, patient preferences, and changing care pathways. Addressing this gap requires a shift from task execution to participatory adaptation, where agents continuously learn and adjust in response to system-level dynamics and social context.

2.3.2 Orchestration Technologies: From Control to Coordination. Technologies for orchestration, ranging from edge-cloud architectures [34], swarm robotics [35], to AI-led service orchestration [36], have enabled distributed control across complex systems. These approaches improve scalability, real-time responsiveness, and fault tolerance by decentralizing decision-making and enabling modular composition of services. However, orchestration is still mostly mechanistic. Systems rely on fixed rules or scripted workflows and struggle to adapt when situations change, new goals arise, or social and contextual factors need to be considered.

Gap 2: Current orchestration technologies remain largely mechanistic, relying on deterministic rules and predefined workflows that limit contextual reasoning, social negotiation, and adaptive restructuring. Consequently, they perform poorly under disruption or shifting stakeholder goals, particularly in human-centered, dynamic environments. Within healthcare enterprises, this limitation is visible in hospital operations and workflow-management systems that optimize scheduling or resource use but cannot re-orchestrate care when emergencies, policy shifts, or inter-departmental dependencies occur. Addressing this gap requires a new orchestration approach—socially and semantically aware, continuously learning, and responsive to multidimensional change across cyber, physical, and social spaces.

2.3.3 Adaptive Learning Frameworks: From Incremental Updates to Systemic Learning. The field of adaptive learning has advanced through innovations in meta-learning, continual learning, and human-in-the-loop strategies [37,38], enabling systems to generalize across tasks, incorporate human feedback, and reduce catastrophic forgetting. These approaches are increasingly applied in robotics, education, and personalized healthcare, yet key limitations persist: most systems cannot reconcile human intuition with algorithmic inference, account for power asymmetries among stakeholders, or connect short-term learning with long-term service adaptation.

Gap 3: Existing adaptive learning systems remain largely limited to incremental improvements. They struggle to reconcile conflicting forms of intelligence, such as human intuition versus algorithmic inference, and rarely account for asymmetric power dynamics among stakeholders. Moreover, these systems typically operate within narrow task boundaries, lacking the capacity to integrate learning across different levels of abstraction, from tactical adjustments to strategic shifts in service goals. In healthcare, this shortfall is evident in clinical decision-support and federated analytics systems that update predictive models from new patient data yet fail to translate those updates into systemic learning, such as policy revision, care-pathway redesign, or equitable resource distribution. This constrains their ability to support systemic adaptation in complex, evolving environments. Bridging this gap requires a new learning paradigm, one capable of structural learning and meta-level coordination across diverse intelligences and decision layers.

While these technological advances mark critical progress, they remain fragmented and insufficient without a unifying framework that can integrate human, artificial, and ecological dimensions into an evolving, intelligent service system, necessitating the development of eCPSS.

2.4 The Need for Evolving Cyber-Physical-Social Systems. The gaps identified in the preceding sections as fragmented frameworks that fail to integrate economy, society, and ecology (Sec. 2.1); entrenched asymmetries in resources, information, and intelligence that constrain adaptability (Sec. 2.2); and the limitations of current technological solutions such as agentic AI, orchestration, and adaptive learning (Sec. 2.3), underscore the need for a new systemic paradigm. These challenges are not isolated but interdependent, rooted in the inability of existing models to coordinate across the physical, cyber, and social dimensions of delivery service. In response, in this article, the eCPSS as a model of interconnected systems that explicitly connects these dimensions to enable adaptive, human-centered, and sustainable by design smart services is proposed. By integrating technological capacities with human and ecological needs, eCPSS offers

structural coherence and co-evolutionary potential absent in existing initiatives.

2.4.1 Meeting the Demands of a Smart Society Through Healthcare. To meet the demands of a smart society (as envisioned in Society 5.0), there is a need for services capable of continuous adaptation to human and environmental change. Among all service domains, healthcare most vividly embodies these demands. It must operate under safety-critical conditions, where decisions carry immediate consequences; maintain human oversight over increasingly autonomous technologies; ensure data provenance and interoperability across fragmented digital infrastructures; uphold ethical and regulatory compliance in accordance with frameworks such as GDPR, HIPAA, and NHS Digital; safeguard equity in access and outcomes across diverse populations; and function effectively despite variable data quality and contextual uncertainty, requiring systems that reconcile technological autonomy with human well-being, ethical accountability, and equitable access.

The proposed eCPSS framework provides the foundation for such transformation. Through the integration of MIAs, eCPSS enables adaptive coordination across physical, cyber, and social layers—supporting safe decision-making through real-time feedback, preserving human oversight via co-agency protocols, validating data provenance through traceable knowledge flows, and promoting equitable access through context-aware resource disposition. Together, eCPSS and MIAs create a unified architecture for intelligent and trustworthy healthcare delivery, integrating physical, cyber, and social dimensions into a unified architecture for intelligent care delivery [43–45]. These three layers and their relationships are visualized in Fig. 3.

For clarity, the three constituent worlds of eCPSS are defined as follows:

- Physical world (Fig. 3): The tangible, real-world environment where physical entities and processes operate. Physical space includes infrastructure, geography, machines, devices, and environmental context.
- Artificial world (Fig. 3): The computational layer in which data, algorithms, and AI are used to simulate, predict, and optimize the system behavior. Cyberspace functions as the digital brain of the system, encompassing IoT networks, data infrastructures, control mechanisms, and cybersecurity layers.
- Mental world (Fig. 3): The cognitive and social domain where human values, perceptions, and decisions take shape. Social space includes norms, interactions, roles, collaboration, trust, and ethical dynamics.

Together, these three worlds constitute the operational foundation of the eCPSS model. They provide a shared substrate to model and guide dynamic interactions among humans, intelligent technologies, and ecological systems, aligning these interactions with system-level goals under real-world conditions and systemic feedback. These interactions already occur organically, therefore, the role of eCPSS is to mediate and align them via shared representations across the mental, artificial, and physical worlds.

As shown in Sec. 2.2, persistent asymmetries in resources, information, and intelligence often constrain efforts to design smart services. Meeting key service design requirements, such as effective resource disposition (what, when, how, whom, where), information flow (what, to/from whom, how, when), and knowledge sharing (what, to/from whom, how, when), requires a model like eCPSS that can bridge these divides across the physical, cyber, and social layers.

Realizing the potential of eCPSS depends on overcoming persistent asymmetries in resources, information, and intelligence that hinder adaptive decision-making, disrupt collaboration, and limit system-level optimization. Addressing these challenges calls for computational models and design principles that enable continuous co-evolution among human, artificial, and organizational actors

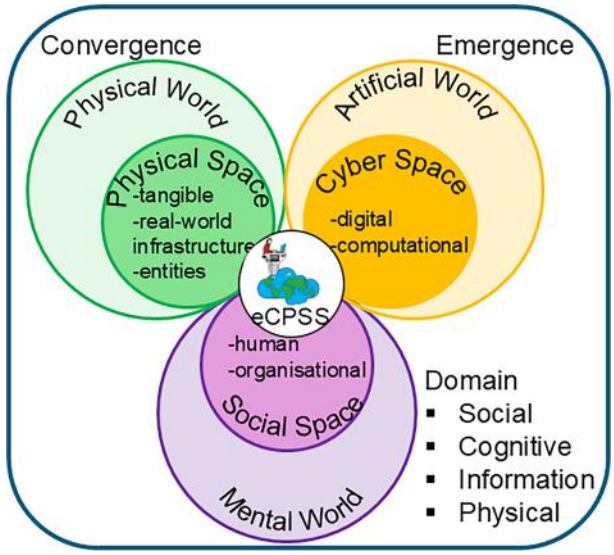


Fig. 3 The philosophical foundation for eCPSS

across physical, mental, and social domains. In Sec. 3, MIAs are introduced, a computational innovation that operationalizes this integration and directly addresses the asymmetries identified above [40].

2.4.2 Limitations of Existing Cyber-Physical Systems in Healthcare. Healthcare provides a critical testbed for eCPSS. Existing cyber-physical system (CPS) frameworks connect medical devices, digital infrastructure, and human actors, but they often remain technology-centric and lack contextual intelligence. An agent-based health-monitoring system that integrates wearable sensors and software agents for real-time supervision has been developed, and broader agent-based computing applications across healthcare and life sciences have been surveyed [39,40]. These studies illustrate distributed coordination yet reveal limited reasoning and ethical awareness.

Concepts from industrial CPS, such as the modular and holonic architectures of [41,42], have been adapted to hospital operations and medical-asset management. More recent digital-twin and federated-learning frameworks extend CPS to personalized diagnostics and data-secure collaboration. Nevertheless, these implementations display three persistent gaps: (1) weak coupling across physical, cyber, and social layers; (2) lack of continuous, multi-stakeholder learning; and (3) minimal capacity for ethical validation. These shortcomings substantiate the need for an eCPSS paradigm, in which MIAs act as adaptive mediators aligning clinical, organizational, and computational intelligence. MIAs directly address the asymmetries in information, reasoning, and resource disposition that limit current healthcare CPS solutions.

3 Conceptual Framework: Adaptive Intelligence and Multi-Intelligence Agents

3.1 Redefining Intelligence for Smart Services. Conventional knowledge systems, such as augmented intelligence and cognitive intelligence, often regard intelligence as static, composed of rules and instructions that govern human or machine action [42]. While effective in structured environments, these approaches fall short in complex, evolving service ecosystems where uncertainty, ambiguity, and interdependence dominate.

In contrast, adaptive intelligence redefines knowledge as dynamic, relational, and evolving, emerging from continuous interaction between human creativity and machine learning [43]. This shift provides the epistemological foundation for designing smart

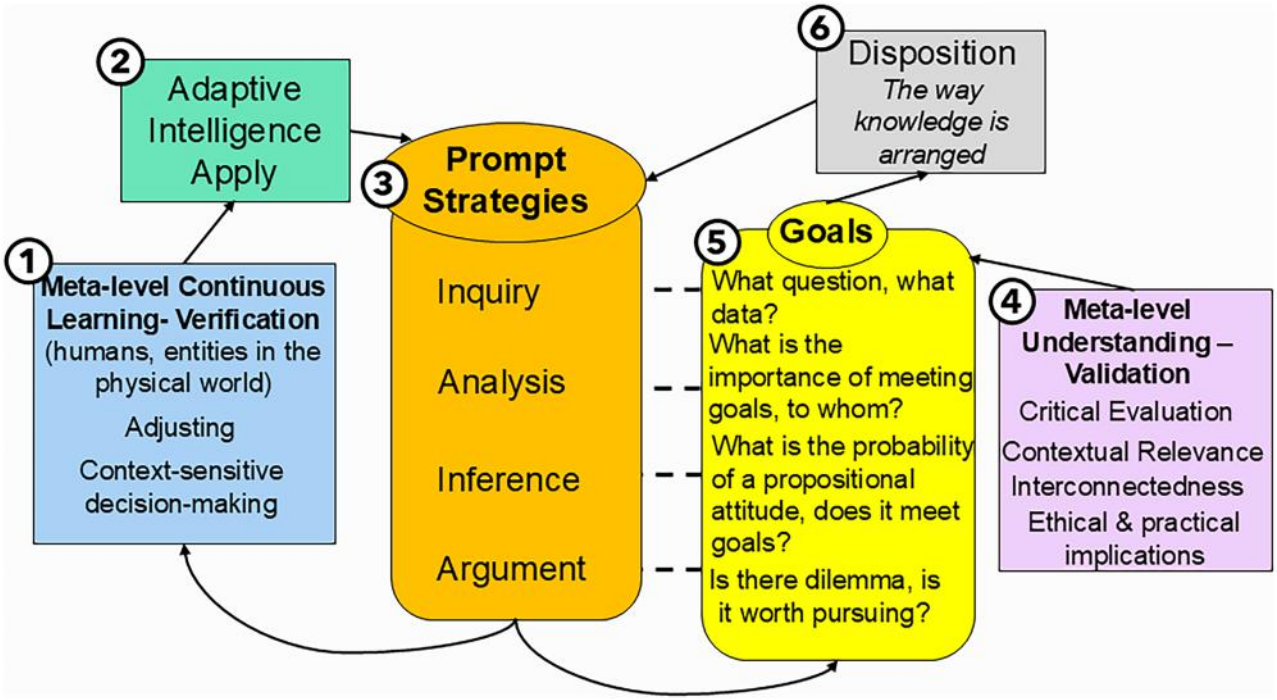


Fig. 4 Adaptive-intelligence reasoning framework underpinning MIAs

service as eCPSS, where intelligence is shaped by context, feedback, and social engagement.

To move from conceptual insight to practical implementation, there is a pressing need for foundational models that can bridge fragmented knowledge domains and connect human designers, users, and computational systems. Adaptive intelligence facilitates this by supporting the co-evolution of human and machine capabilities, enabling innovation that is responsive, ethical, and aligned with system-wide goals.

To operationalize this vision, the author introduces a new type of computational agent, MIAs, designed to bridge asymmetries across physical, social, and cyber spaces.

3.2 Defining and Structuring Multi-Intelligence Agents. MIAs enact adaptive intelligence by enabling punctuated evolution [44] designed to manage asymmetries across physical, cyber, and social realms. They are not static tools, but evolving computational entities capable of redefining their function, role, and behavior through ongoing learning and context-sensitive decision-making. They leverage higher-order cognitive processes, such as reasoning, abstraction, and knowledge synthesis, to continuously reshape their structural role within a system.

Inspired by Gardner's theory of multiple intelligences [45], MIAs are fine-tuned from foundational models trained on diverse human intelligences, such as linguistic, logical-mathematical, spatial, interpersonal, and others, enabling them to interface more effectively with human users and social systems.

Three core asymmetries are central to the challenges MIAs aim to overcome:

(1) Intelligence asymmetry to enhance machine capability: Humans excel at complex, nuanced reasoning, including emotional intelligence, ethical judgment, and social context awareness. In contrast, agents often exhibit limited reasoning scope or domain-specific capabilities. Bridging this asymmetry involves expanding the cognitive and contextual sophistication of machines to better align with human intelligence.

(2) Information asymmetry to interface machine capabilities and human abilities: Information may be accessed, interpreted, and trusted differently by humans and machines. Humans are prone to cognitive bias and selective attention; agents may struggle with relevance, ambiguity, or contextual cues. Agents must mediate these differences to facilitate shared understanding, equitable access, and trustworthy decision-making.

(3) Resource asymmetry to extend human abilities: While humans are constrained by time, attention, fatigue, and cognitive load, machines face limitations in sensory fidelity, processing power, or environmental adaptability. Agents play a critical role in augmenting human capacity, automating routine tasks, managing complexity, and adapting dynamically to shifting conditions to support more resilient decision-making.

By embedding adaptive intelligence into their design, MIAs serve as the connective tissue across these asymmetries, enabling systems to evolve more responsively and intelligently in the face of contextual change.

MIAs operate through a layered and iterative process of interaction with their environment, spanning six steps that correspond to the worlds of the eCPSS framework. This cycle enables MIAs to continuously learn, adapt, and act in line with dynamic (changing) system goals:

- Step 1 in Fig. 4, context interpretation: MIAs begin by interpreting the identity, needs, and goals of users, determining not just what service should be delivered, but when and how. This includes continuous learning from real-world feedback in the physical world.
- Step 2 in Fig. 4, application of adaptive intelligence: At the core of their decision logic, MIAs apply adaptive intelligence to adjust their behavior based on historical learning and environmental signals.
- Step 3 in Fig. 4, prompt strategies: MIAs use strategies such as inquiry, analysis, inference, and argumentation to process real-time information and navigate uncertainty.

- Step 4 in Fig. 4, meta-level validation: MIAs evaluate the relevance, ethical soundness, and systemic coherence of their conclusions, integrating insights across domains to deepen decision quality.
- Step 5 in Fig. 4, alignment with system goals: MIAs assess which data and actions are needed, for whom the goals matter, and whether goal pursuit is probabilistically and ethically justified.
- Step 6 in Fig. 4, disposition and structuring: Finally, MIAs translate insights into operational logic, dynamically structuring knowledge, rules, and tasks to support system-wide adaptation.

This adaptive cycle enables MIAs to bridge cognitive, technological, and environmental divides, maintaining relevance and system alignment as service contexts evolve.

Modeling such multi-layer interactions inherently involves significant complexity arising from heterogeneous data, feedback rates, and contextual variability across physical, cyber, and social domains. Rather than eliminating this complexity, MIAs manage it by structuring information through layered ontologies and temporal knowledge graphs that allow partial, evolving representations to remain interpretable and adaptive over time.

This reconceptualization of knowledge and agency offers a new foundation for understanding human–machine co-evolution in designing for smart service systems. However, to bring MIAs from concept to application, their design, fine-tuning, and deployment must be guided by a solid theoretical grounding that integrates insights from cognitive, social, and systemic disciplines.

3.3 Foundational Theories. MIAs are rooted in a multi-theoretical foundation that synthesizes insights from diverse disciplines to support their adaptive and integrative capabilities. The Triarchic theory of intelligence [46] provides a framework for analytical, creative, and practical cognition, enabling MIAs to reason, innovate, and act in complex environments. Complementing this, Gardner's multiple intelligences theory (MIT) [45] expands the cognitive repertoire of MIAs by incorporating linguistic, logical-mathematical, visual-spatial, and interpersonal intelligences, ensuring that varied modalities of human reasoning are reflected in machine processes.

Vygotsky's sociocultural learning theory [47] introduces the importance of social interaction and context in shaping intelligence, while Piaget's constructivism [48] emphasizes developmental learning through active engagement with the environment—principles essential for MIAs to learn and adapt over time. The theory of constraints (ToC) [49] is applied to help MIAs identify and focus their intelligence on systemic bottlenecks, enhancing the efficiency of decision-making and service orchestration. Finally, living systems theory (LST) [50,51] positions MIAs as dynamic subsystems embedded within broader ecosystems, capable of evolving alongside the social, technical, and ecological systems they serve positioning MIAs as dynamic subsystems within living ecosystems These theories provide the scaffolding for MIAs to operate not just as reactive tools, but as proactive agents shaping and being shaped by their environment.

Each of these foundational theories directly informs the six-step architecture of MIAs, providing the cognitive, social, and ecological scaffolds that enable them to function as intelligent agents in eCPSS—from interpreting context (Step 1) and adaptive learning (Step 2) through strategic decision-making (Steps 3–5) to dynamic knowledge structuring (Step 6). Their combined influence ensures that MIAs are not just algorithmic executors, but co-evolving actors capable of reasoning, adapting, and learning within complex service environments.

These foundational theories not only shape the architecture of MIAs but also frame the critical research questions and hypotheses that guide their systematic design, fine-tuning, and deployment across service domains.

3.4 Research Question and Hypothesis. The concept of MIAs offers a transformative approach to addressing the complexities of adaptive intelligence, yet a critical gap remains in how to systematically design and fine-tune such agents to operate effectively across diverse domains. This gap leads to the overarching research question underpinning this article:

What foundational model can capture multiple intelligences and be fine-tuned to specific AI agents, enabling the integration of social factors with intelligent technologies to foster adaptive intelligence and strengthen the relationship between the physical, mental, and artificial worlds?

The author hypothesizes that developing MIAs, fine-tuned from foundational models trained on diverse forms of intelligence, such as visual-spatial, linguistic-verbal, logical-mathematical, and interpersonal, can help bridge the divide between human values and intelligent technologies. As noted in the previous conceptual framing, this approach draws inspiration from Gardner's theory of multiple intelligences, effectively giving AI "different types of smarts" that enable it to integrate social factors more meaningfully into real-world contexts. Through this diverse training, MIAs can support the emergence of adaptive intelligence, the ability to learn, adjust, and build knowledge systems that connect the physical, mental, and artificial worlds in evolving service systems.

4 Engineering the Multi-Intelligence Agents: Roadmap for Implementation

To implement the hypothesis outlined in Sec. 3.4, a structured framework is needed to translate foundational theory into practical design logic. In this article, a three-layer autonomy roadmap is proposed, see Fig. 5, which systematically minimizes asymmetries in intelligence, information, and resources by aligning theoretical constructs with targeted design guidelines. This roadmap provides a progression across layers of autonomy in MIAs, from human-guided learning to agent-led orchestration.

This layered roadmap operates at a poised equilibrium [52] allowing MIAs to remain functional while continually adapting to new environmental and informational constraints. Operating at a poised equilibrium, balancing stability, exploration, and complexity, MIAs remain functional while transforming environmental variability into beneficial variations that sustain evolvability.

4.1 Operational Mechanism and Example Instantiation. Building on this framework, presented in Fig. 5, is an adaptive control structure through which MIAs continuously reduce asymmetries in intelligence, information, and resources. The multi-layer structure itself reflects the inherent complexity of eCPSS interactions; each layer decomposes this complexity into interpretable functions that allow the system to remain adaptive without oversimplifying real-world variability. Layer 1 (adaptive intelligence) captures human reasoning, establishes ethical and cognitive boundaries, and provides feedback that guides agent learning. Layer 2 consists of two interacting sub-layers that together enable self-organization. The intelligence layer abstracts reasoning patterns, priorities, and heuristics from Layer 1, translating human cognitive intent into computable forms, while the representation layer mirrors the physical world by encoding environmental states, constraints, and resources as evolving ontologies and temporal knowledge graphs. Together, they form a bidirectional interface between cognition and execution: the intelligence layer communicates intent downward, and the representation layer conveys contextual feedback upward. Layer 3 (disposition and execution) then transforms validated representations into executable actions across digital and robotic subsystems, closing the loop through contextual feedback.

For example, in healthcare diagnostics, in Layer 1, MIAs learn clinical reasoning from physicians; in Layer 2, it encodes this reasoning into adaptive diagnostic rules linked to patient data streams; and in Layer 3, it re-allocates analytical or robotic resources to

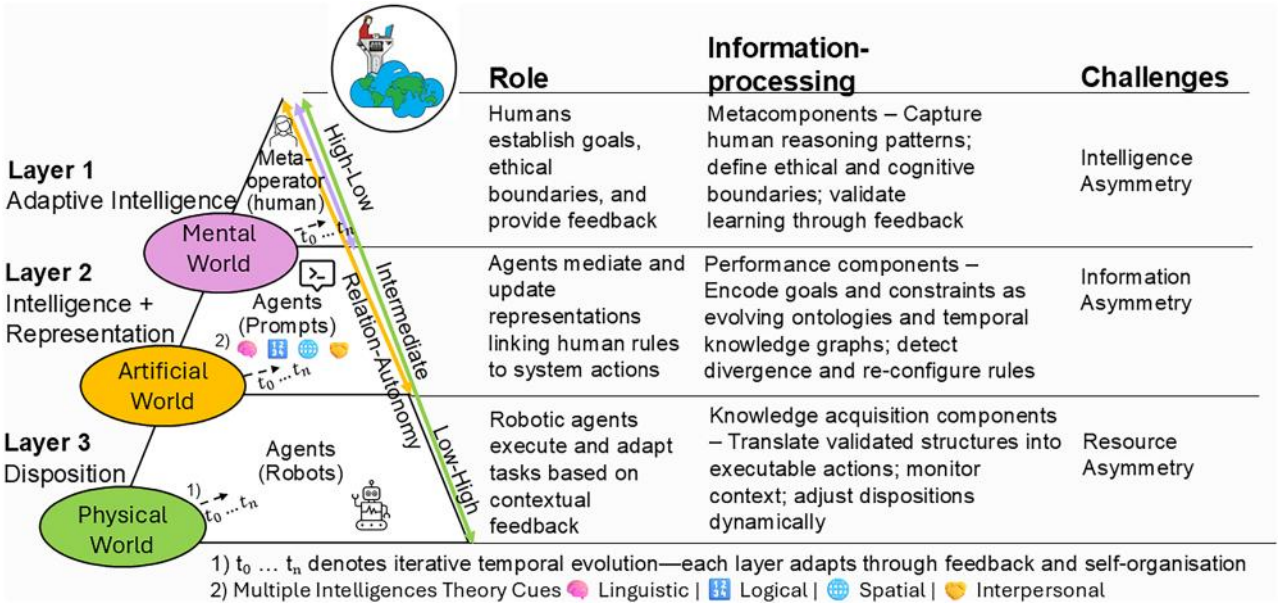


Fig. 5 Layered roadmap for MIAs in eCPSS

refine predictions and deliver updated recommendations. This iterative cycle of sensing, reasoning, and acting maintains functional stability while generating beneficial variations in goals, roles, and interfaces, demonstrating evolvability within an operationally viable framework.

In the context of MIAs, evolvability emerges from the continuous learning and restructuring of relationships across the mental, artificial, and physical layers, preserving design freedom while enabling long-term system adaptation.

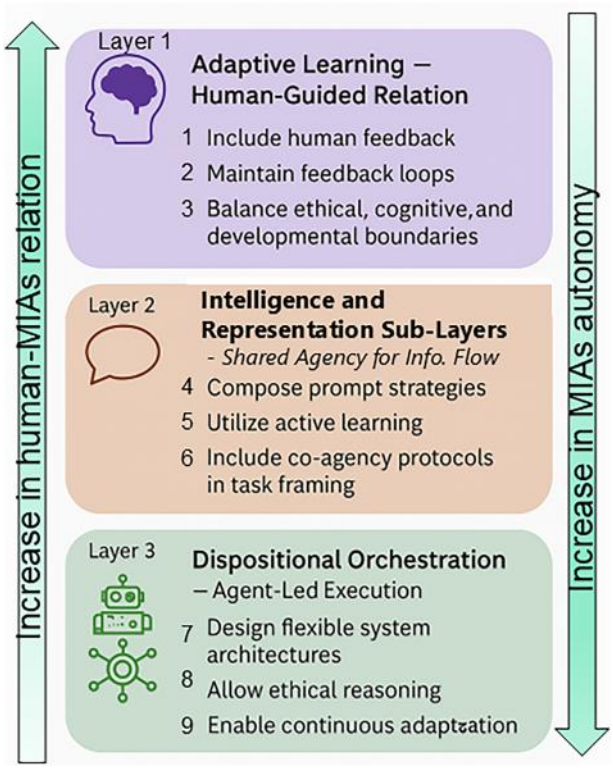


Fig. 6 Design guidelines structured to systematically reduce intelligence, information, and resource asymmetries

4.2 Three-Layered Autonomy Mechanism. *Layer 1 in Fig. 5, Adaptive Learning: Human-Guided Relation*

At the foundational layer, MIAs engage in adaptive learning driven by human guidance. Humans establish overarching goals, define ethical boundaries, and provide feedback on early system behavior. This corresponds to the "mental world" in Fig. 3, where humans act as strategic governors of knowledge co-creation.

At this layer, the key research question that needs to be answered is "What are the principles of engagement between humans and intelligent technologies to minimize intelligence asymmetries?"

The working hypothesis is that foundational engagement principles, drawn from theories such as MIT, sociocultural theory, Piaget's constructivism, ToC, and LST, can guide the development of MIAs as adaptive knowledge systems aligned with human goals.

Design guidelines presented in Layer 1 in Fig. 6 are as follows:

1. Implement modular learning structures that can scaffold new knowledge through contextual human feedback.
2. Integrate feedback loops and meta-cognitive validation to support relational learning and reduce mismatches in intelligence representation.
3. Align learning strategies with ethical, cognitive, and developmental boundaries defined by human collaborators.

Layer 2 in Fig. 5, Prompt Strategy: Shared Agency for Information Flow

In the second layer, MIAs operate with medium autonomy, organizing and restructuring information through interacting intelligence and representation sub-layers. The intelligence sub-layer abstracts human cognitive intent from Layer 1, reasoning patterns, priorities, and heuristics, and translates them into computable forms. The representation sub-layer mirrors the physical world, encoding environmental states, constraints, and resources as evolving ontologies and temporal knowledge graphs. Working together, these sub-layers maintain coherence between human intent and environmental context, allowing MIAs to self-organize information flows and update rules dynamically. Agents take initiative to interpret rules, mediate contexts, and learn from multi-modal sources. This layer operates primarily within the "artificial world" in Fig. 3, reflecting semi-autonomous reasoning.

At this layer, the key research question is "What strategies can prompts employ to organize information and update rules to minimize information asymmetries?"

Table 1 Research opportunities through the lenses of punctuated evolution

Key aspects	MIAs role	Research opportunities
Personalized healthcare	MIAs enable adaptive care by learning from individual patient data, providing tailored and evolving care plans that respond to changing needs.	F: *How can MIAs and healthcare providers co-evolve to improve the prediction of patient health trajectories and care plans?* B: *How can the system's learning behavior evolve to integrate more complex treatment models as new data becomes available?* S: *What structural adjustments are necessary to allow the system to evolve its capabilities while maintaining patient-centered care?*
Multidisciplinary integration	They bridge diverse knowledge domains, synthesizing insights from medical professionals, patients, and administrators for a holistic approach to care.	F: *How can the MIAs progressively evolve to integrate multidisciplinary insights, adapting to the collaborative environment?* B: *How can the system's behavior adapt to feedback from diverse healthcare stakeholders to improve integration over time?* S: *What structural evolution is necessary to enable MIAs to better support cross-disciplinary collaboration in real-time?*
Real-time decision support	MIAs offer continuous learning and real-time decision-making, ensuring healthcare providers have up-to-date insights for effective patient care.	F: *How can the system's functional evolution support a more nuanced and context-sensitive decision-making process?* B: *What behavioral changes are necessary to support more autonomous, adaptive decision-making as new patterns and data emerge?* S: *How can the system's structural elements evolve to manage and process larger data volumes without losing decision quality?*
Process automation	MIAs optimize administrative tasks and resource allocation, increasing efficiency in healthcare delivery and reducing the burden on professionals.	F: *How can MIAs progressively learn to automate more complex processes by incorporating human feedback and operational data?* B: *How does the system's behavior need to change to increase the smoothness and adaptability of process automation over time?* S: *How can the system's structure evolve to allow for greater automation, while retaining the ability to learn from human users?*
Enhanced collaboration	They improve communication among patients, providers, and administrators, ensuring efficient information sharing and team coordination.	F: *What functional improvements are needed to ensure seamless communication in an evolving healthcare network?* B: *In what ways can the behavior of the system be refined to better facilitate communication and coordination as new collaboration models emerge?* S: *How can the system's structure evolve to accommodate new, flexible models of collaboration in the healthcare sector?*
Ethical validation	MIAs support ethical decision-making by validating AI-driven actions to ensure patient care is both effective and aligned with ethical standards.	F: *What functional evolutions are needed to ensure ethical compliance and fairness in dynamic healthcare environments?* B: *What behavior adaptations are necessary to ensure the MIAs remain ethical and aligned with evolving norms and patient needs?* S: *How should the system's structural evolution incorporate mechanisms for ethical validation that can evolve with healthcare advancements?*

Note: F—function, B—behavior, S—structure.

The working hypothesis is that prompt-based learning methods, such as fine-tuning, human-in-the-loop approaches, and multimodal input processing, can help balance agent initiative with accountability to human-intended service outcomes.

Design guidelines presented in Layer 2 in Fig. 6 are as follows:

4. Develop composable prompt strategies to enable real-time contextual reasoning across cognitive and digital layers.
5. Use active learning and co-prompting to restructure information dynamically for new domains and stakeholder needs.
6. Design agents with co-agency protocols.

Layer 3 in Fig. 5, Dispositional Orchestration: Agent-Led Execution

At the highest layer, MIAs autonomously manage orchestration across robotic agents and digital subsystems. This corresponds to the "physical world" in Fig. 3, where MIAs translate insights into action with minimal human oversight.

At this layer, the key research question is "What rules for agent disposition enhance the ability to perform tasks and follow instructions to minimize resource asymmetries?"

The working hypothesis is that dispositional orchestration models—integrating adaptive rules, feedback mechanisms, and role reconfiguration—can enable MIAs to align service delivery with systemic goals in dynamic conditions.

Design guidelines presented in Layer 3 in Fig. 6 are as follows:

7. Create flexible disposition architectures.
8. Implement goal alignment and ethical reasoning modules to ensure agent-led decisions are context-appropriate and socially aligned.

9. Use continuous monitoring and adaptive correction protocols to sustain resilience and task fidelity during autonomous execution.

Together, these layered guidelines establish MIAs as adaptive, context-sensitive computational agents capable of bridging asymmetries and co-evolving with human and systemic needs across dynamic service environments.

5 Engineering Application: Evolving Healthcare Diagnostics

5.1 General Use Cases Across Domains. The MIA architecture is designed to be modular and context-aware. Its general principles are demonstrated here through the healthcare diagnostics domain, which provides the most complex and socially critical setting for validation.

In healthcare, MIAs provide clinicians, administrators, and researchers with real-time diagnostics, predictive analytics, and personalized treatment recommendations, while also supporting cost management, drug development, and health system optimization to improve population health outcomes. Agents have been employed in decision-support systems for chronic disease management, hospital workflow optimization, and drug interaction analysis [39,40].

5.2 Case Focus: Diagnostics in Healthcare. In this section, the focus is on providing an overview of how MIAs can support the design of healthcare as an evolving service responsive to changing patient needs, emerging technologies, and adaptive care models. In Table 1, critical research questions related to the evolving function, behavior, and structure of the MIAs within healthcare are highlighted.

By leveraging their multi-intelligence and multi-level autonomy, MIAs enable healthcare to operate as a dynamic, evolving service that adapts to patients, practitioners, and institutional contexts. The proposed framework supports a healthcare ecosystem that is more efficient, personalized, and responsive, evolving in line with technological advances and social needs.

Healthcare diagnostics face persistent asymmetries in resources (unequal access to care), information (fragmented or incomplete records), and intelligence (limited integration between human expertise and AI). Addressing these challenges requires systems that are both data-rich and adaptively intelligent. MIAs support early and precise diagnostics, reduce delays, and improve outcomes while aligning with goals of equity, scalability, and resource efficiency. Validation will target chronic conditions (e.g., diabetes, cardiovascular disease) and acute scenarios (e.g., stroke, sepsis) through simulation modeling (e.g., Vensim), controlled hybrid workspaces, and pilot studies in real-world diagnostic settings.

As summarized in Table 1, the healthcare case reveals a set of functional, behavioral, and structural research opportunities that extend beyond the immediate application. These questions frame the conditions under which MIAs can sustain co-evolutionary adaptation and ethical accountability in complex service systems.

5.2.1 Limitations Related to Data Sensitivity. The healthcare domain involves unique challenges of data privacy, security, and ethical governance. Although MIAs are designed to mediate information asymmetries, their application in healthcare requires compliance with data protection frameworks, such as GDPR, HIPAA, and NHS Digital standards. Future implementations will incorporate privacy-preserving learning (e.g., federated or edge intelligence) and differential access control to ensure that sensitive patient data remain secure while still enabling adaptive, context-aware service delivery. These requirements are recognized as central to the safe and ethical deployment of MIAs in healthcare.

6 Cross-Comparative Positioning and Prospective Generalization of the Multi-Intelligence Agents Framework

The contribution of this work extends beyond healthcare, offering a computational model of intelligence orchestration applicable across engineering and service domains. At its core, the MIA

Table 2 MIAs design guidelines applied to domains

Layer	Design guideline	Urban infrastructure	Energy grid reconfiguration	Environmental monitoring
Layer 1	1. Modular learning structures	Enable MIAs to learn from commuter feedback and contextual factors like rush hour dynamics	Train MIAs on regional energy consumption patterns and grid load behavior	Enable MIAs to learn from seasonal and regional patterns of air/water quality data
	2. Feedback loops and meta-cognition	Use real-time feedback from traffic sensors and public input to recalibrate route suggestions	Use feedback from smart meters and operators to refine energy distribution strategies	Integrate sensor feedback and expert annotations to improve anomaly detection
	3. Ethically bounded learning	Ensure learning goals align with fairness in public transit access	Respect energy equity policies and environmental targets	Constrain model learning to align with ecological protection standards
Layer 2	4. Composable prompt strategies	Develop prompts that synthesize real-time traffic data, policies, and weather updates	Construct prompts that factor in real-time grid load, pricing, and renewable input	Develop prompts that trigger alerts based on pollution thresholds and meteorological data
	5. Active learning and co-prompting	Incorporate feedback from different city departments and citizens	Allow MIAs to refine strategies as new usage behaviors or energy sources emerge	Incorporate co-prompting from environmental scientists and community monitors
	6. Co-agency protocols	Negotiate between human planners and agents for shared control of traffic interventions	Support shared authority with energy dispatch operators	Allow MIAs to share decisions with environmental agencies for actionable alerts
Layer 3	7. Flexible disposition architectures	Reassign traffic priorities dynamically during congestion or events	Reallocate grid resources to balance supply and demand under changing conditions	Reassign monitoring focus during natural disasters or abnormal events
	8. Goal alignment and ethical modules	Ensure route planning aligns with equity and accessibility guidelines	Align energy decisions with sustainability and reliability mandates	Ensure environmental responses align with public health and regulatory requirements
	9. Continuous monitoring and correction	Monitor traffic efficiency metrics and adjust MIAs routing logic	Track power fluctuations and adapt load balancing strategies	Continuously monitor sensor calibration and detection accuracy

architecture provides a reusable, modular design pattern for implementing layered autonomy in complex eCPSS. This modularity does not remove the underlying modeling complexity of such systems; rather, it allows MIAs to cope with it by decomposing heterogeneous, cross-domain interactions into interpretable layers that remain adaptive and transferable across contexts. The author uses this model to address persistent asymmetries of intelligence, information, and resources through a structured, agent-driven framework that is computationally tractable and semantically rich.

Across domains, such as urban planning, education, environmental monitoring, and supply chains, MIAs minimize the systemic asymmetries outlined in Sec. 2.2 through a consistent six-step cycle (Fig. 4) of context interpretation, adaptive-intelligence application, prompt strategy, meta-validation, goal alignment, and disposition structuring. This consistency supports:

- Model-based reuse, as the same computational architecture adapts to new domains with minimal redesign.
- Parameterization, allowing learning behavior and decision rules, can be tuned to different actor types, system constraints, and performance criteria.
- Scalability, as the agent-layer can grow modularly while maintaining coherence with human input and system objectives.

The three-layer roadmap (Fig. 5) provides a computational lens for modeling service intelligence evolution, from low-autonomy learning to full orchestration, each layer verifiable through agent-based, discrete-event, or hybrid CPS simulations. In Table 2, it is illustrated how these principles apply across domains, from demand-responsive public transport and energy grid optimization to adaptive environmental monitoring. While healthcare remains the principal domain of validation, in Table 2, prospective extensions for other service contexts are illustrated.

6.1 Comparison With Existing Design Approaches. Existing approaches to designing intelligent or service-oriented systems, such as multi-agent systems, cognitive architectures, and design-for-service frameworks, offer valuable foundations but remain limited when applied to eCPSS.

Multi-agent systems typically coordinate autonomous entities within a shared environment to achieve distributed control or optimization [53–55]. However, they assume fixed goal structures and lack mechanisms for representing human cognition or social negotiation, which are essential for service co-evolution. Cognitive architectures such as ACT-R and SOAR provide models of individual reasoning and learning [56,57] but do not extend to systemic adaptation or multi-layer orchestration across human and machine intelligences. Design-for-service approaches in engineering and management science emphasize the process efficiency and user experience [13,14], yet they treat technological, social, and ecological factors as separate domains.

The proposed MIAs framework advances these approaches by embedding adaptive intelligence within a layered autonomy structure that unites human, artificial, and organizational intelligences. MIAs continuously learn across mental, artificial, and physical worlds, enabling self-organization, temporal adaptation, and reduction of asymmetries in information, intelligence, and resources. This integration positions MIAs as a next-generation computational design construct capable of realizing sustainable, evolving smart-service systems.

6.2 Distinction From Existing Implementations. While current intelligent systems, such as multi-agent-based models or intelligent tutoring systems, demonstrate autonomy and limited adaptivity, they are typically domain-specific and operate within fixed rules or reward structures. These systems optimize behavior for predefined objectives but do not evolve their own roles, goals, or interaction rules as the environment changes. In contrast, MIAs are designed for meta-adaptation. This requires advancements in representation learning, meta-reasoning, and multi-level orchestration that integrate symbolic and connectionist methods within a common adaptive framework. Consequently, MIAs move beyond incremental optimization to provide a foundation for co-evolving, self-organizing smart-service systems that sustain performance and ethical alignment under continuous change (see Table 3).

The contribution here is a generalizable computational design guidelines that integrates human-centered design principles, learning logic, and orchestration strategies, bridging the gap between the agent architecture and system-level impact.

7 Closing Remarks and Outlook

Designing for smart services as eCPSS reframes engineering from product optimization to service evolution. This perspective establishes adaptability, intelligence alignment, and evolvability as the primary design objectives for resilient and equitable systems. Through the healthcare diagnostics domain, this article proposes that MIAs can operationalize these objectives by mediating between human cognition, artificial reasoning, and system behavior to deliver adaptive, ethical, and reliable care. Through the healthcare diagnostics domain, this study demonstrates how MIAs operationalize these objectives by mediating between human cognition, artificial reasoning, and system behavior to deliver adaptive, ethical, and reliable care.

As discussed in Sec. 5, the healthcare application illustrates that adaptive intelligence, rather than automation alone, determines whether future service systems can remain both functional and transformative under uncertainty. The healthcare case illustrates that adaptive intelligence, rather than automation alone, determines whether future service systems can remain both functional and transformative under uncertainty. By embedding MIAs across physical, cyber, and social layers, healthcare services can sustain a poised equilibrium between stability and exploration, balancing innovation with patient safety, data governance, and ethical accountability. The framework also provides a structured pathway for mitigating asymmetries in resources, information, and intelligence that continue to constrain clinical decision-making and service delivery.

While the proposed eCPSS–MIA framework is conceptually generalizable to other domains, its immediate significance lies in healthcare, where regulatory complexity, ethical sensitivity, and organizational interdependence create the most demanding conditions for adaptive system design. The healthcare application

Table 3 Comparison of existing system-design approaches and the proposed MIAs framework

Approach	Primary focus	Limitation	Distinct feature of MIAs
Multi-agent systems [53–55]	Distributed coordination and task automation	Limited social/context awareness; static goal structures	Context-sensitive co-evolution and learning across domains
Cognitive architectures [56,57]	Individual cognition and adaptive reasoning	No multi-layer orchestration or social feedback	Layered autonomy integrating human and machine intelligences
Design-for-service [13,14]	Process and experience design in socio-technical systems	Separation of technological, social, and ecological dimensions	Unified, adaptive framework for evolving service ecosystems

therefore serves as an illustrative context through which the framework's capacity to integrate technical autonomy with human oversight and societal goals is explored. The healthcare application therefore serves as the primary validation of the framework's capacity to integrate technical autonomy with human oversight and societal goals.

Moving forward, the emphasis lies in refining and critically examining the proposed mental model—clarifying its theoretical boundaries, methodological implications, and relevance for design research. Rather than prescribing implementation pathways, the next step is to frame the conceptual and empirical questions that will determine how adaptive-intelligence systems such as MIAs can be designed, evaluated, and governed across contexts. In future work, the focus is on extending this foundation by quantifying evolvability and adaptive capacity, developing benchmarks for system resilience, and testing the scalability of eCPSS architectures in additional service contexts. Such efforts will strengthen the evidence base for adaptive-intelligence design and expand the applicability of MIAs beyond healthcare, contributing to the broader evolution of human-aligned, sustainable smart societies.

The research opportunities outlined in Table 1 crystallize the interplay of function, behavior, and structure in evolving healthcare systems. They highlight that sustaining adaptive intelligence requires not only algorithmic innovation but also organizational and ethical evolution. Future studies should therefore operationalize these questions—evaluating how MIAs can translate between clinical and computational logics, restructure workflows dynamically, and embed ethical validation into system architectures. Although developed through healthcare, these functional–behavioral–structural lenses offer a transferable methodology for analyzing evolution in other socio-technical domains.

7.1 Questions for the Design-Research Community. Building on the research opportunities outlined in Table 1, these questions broaden the inquiry from healthcare diagnostics to the wider design of adaptive, evolving service systems. They invite design researchers, systems engineers, and educators to refine, test, and extend the proposed eCPSS–MIA mental model through prototypes, simulations, and stakeholder co-design. Design researchers, systems engineers, and educators are invited to test and refine the position that MIAs can help people design and operate eCPSS. This article frames future inquiry through five interrelated questions that can be investigated via prototypes, simulations, and stakeholder co-design.

(1) How can researchers formalize evolvability for MIAs as a measurable design property—defining testable mechanisms and indicators that capture the thresholds separating functional stability from exploratory evolution under uncertainty and resource asymmetry? Can researchers define evolvability for MIAs as a set of testable mechanisms and measurable indicators, and estimate the thresholds that separate functional stability from exploratory evolution under uncertainty and resource asymmetry?
(2) How can investigators structure matched prototyping and simulation studies so evaluators can compare MIA-enabled performance with current practice, while stakeholders co-define goals, constraints, and acceptance criteria?
(3) How can theorists specify reviewer-checkable indicators for learning, stability, variation, selection, and retention, and connect those indicators to measures of equity, resilience, and adaptive capacity?
(4) How can experimenters vary representation updates at the representation layer and attribute observed changes in global performance and resilience to those local interventions rather than to exogenous policy or data shifts?
(5) How can organizers establish governance and verification protocols that keep humans in charge of safety-relevant decisions while enabling reproducible studies across healthcare, urban infrastructure, and environmental monitoring?

Together, these questions can turn a position into accountable evidence and advance design practice with clarity, discipline, and care.

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Conflict of Interest

There are no conflicts of interest.

Data Availability Statement

The author attests that all data for this study are included in the article.

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