Towards Designing Next-Generation Cyber-Physical Systems Part 1: Transdisciplinary Synthesis of Holistic Affordance Intelligence

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Abstract: *The background study underpinning this two-part position paper rests on two assumptions: (i) next-generation cyber-physical systems (NG-CPSs) will be based on a synergistic combination of artificial intelligence approaches, and (ii) their overall design will be oriented toward system operational affordances (SOAs) and will extend to their runtime operation. This first paper elaborates on the first assumption and presents the author's vision that the cognitive abilities of NG-CPSs will rely on holistic affordance intelligence (HAI). Considering contemporary literature, he interprets HAI as a federation of sensorimotor, computational, and embodied intelligence, plus the relevant segments of human natural intelligence (HNI). The study compared the above manifestations of AI from ontological, epistemological, and methodological aspects, and investigated their complementarity and interoperation. As a novel contribution, a framework for realizing HAI has been conceptualized. The synthesis of knowledge for HAI is transdisciplinary in that it integrates concepts, theories, methods, and explanatory frameworks originating from AI, CPSs engineering, cognitive science, systems theory, human-centered design, and philosophy of cognition into a unified affordance-oriented framework for NG-CPSs. The conversion of this framework into an integrative methodology needs to start with the consolidation and testing of the underpinning theory, and the detailed elaboration of context-sensitive procedures, methods, instruments, and criteria. The study argues that HAI is not merely a technical aggregation of AI technologies but an emergent transdisciplinary construct that connects computational, physical, cognitive, and human dimensions of system operation. The paper formulates propositions to advance post-disciplinary research in the above-mentioned directions.*

Keywords: next-generation cyber-physical systems, sensorimotor intelligence, computational intelligence, embodied intelligence, holistic affordance intelligence, viability-dependent integration framework, research propositions.

1 Introduction

1.1 Conceptual background and base of the study

A compelling piece of evidence for scientific convergence is the intersection of artificial intelligence (AI) research and cyber-physical systems (CPSs) research. The former appeared more than 60 years ago, while the latter formed as a distinct discipline only two decades ago. Strong bridges have been formed between them through various forms of non-embodied (generative and agentic) AI research. On the other hand, cognitive design/engineering catalyzed the convergence process by equipping CPSs (manifesting as software- and knowledge-integrated systems) with the intellect needed to solve real-life problems/tasks using both standard and tailored knowledge-processing methods.

Contemporary AI research is often presented as a unified field of technical development, not considering its long historical progression and technological milestones. However, closer inspection reveals that fundamentally different assumptions have been made about what intelligence is, how it can be known, and how it can be reconstructed. These assumptions are not addressed explicitly, yet they define the articulation of AI and the structure of AI systems at the bottom (Erden, Z.D., 2025). The intended contribution of this position paper is to take the AI manifestations relevant to next-generation CPSs (NG-CPSs) into account, scrutinize the ontology, epistemology, and methodology of the concerned ones, show how they obey different internally coherent constraint regimes, and frame how these manifestations may complement each other to form what counts as operational and behavioral intelligence for the target systems.

The central claim of the study is that the alternative manifestations of AI correspond to internally coherent but distinct configurations of ontological, epistemological, and methodological commitments. These configurations of the alternative manifestations are not arbitrary. They are constrained by internal consistency of requirements, understood as the absence of contradiction among what is assumed to exist, what counts as knowledge, and how systems are constructed (Baltezarević, B.V., & Battista, D., 2025). Given the intertwined evolution of the system-paradigm of CPSs, likewise the sophistication of creative AI technologies, it can be forecast that NG-CPSs will be intellectualized, socialized, personalized, and naturalized ecosystems. The primary hypothesis of the work is that it will be supported by a federation of sensorimotor artificial intelligence (SAI) (Mathis, M.W., 2026), computational artificial intelligence (CAI) (Denning, P. et al., 2025), and embodied artificial intelligence (EAI) in an integral and complementary manner (Duan, J. et al., 2022).

Why is the coexistence of SAI, CAI, and EAI in NG-CPSs important? The answer lies in (i) the fundamental limitations of CAI alone, (ii) the need to include physical grounding in system intelligence, (iii) to utilize the novel assets of physical AI, and (iv) the demand to extend the intellectualization of complex NG-CPSs to multi-layer intelligence. It has been widely recognized that pure CAI has fundamental limitations in the context of NG-CPSs. The two major ones concern CAI's current capabilities and the envisioned functionalities of NG-CPSs. Most current AI systems rely on purely symbolic, sub-symbolic, and meta-symbolic representations, with limited use of post-symbolic representations. Typically, their processing mechanisms rely on data-driven 'statistical' algorithms running in virtual environments. These entail limitations such as (i) lack of physical grounding, (ii) restricted causal understanding of real-world dynamics, and (iii) poor generalization across environments. While CAI excels at various representation-related tasks (e.g., pattern recognition), it struggles with corporeal phenomena, material interaction, energy constraints, the incorporation of time, and physical uncertainty. By contrast, SAI is intended to address a part of these limitations by integrating sensing, morphology, and physical interaction. At the same time, EAI is expected to exploit the natural basis of intelligent physical behavior and material computation (Liu, H. et al., 2025). This position paper aims to explore a paradigm shift (a radical change in basic assumptions) and to set up a conceptual framework for an anticipatory research agenda (Horváth, I., & Ábrahám, G., 2025). The intent is to inspire and provoke further studies with the conceptual framework and to withstand scrutiny.

1.2 A transdisciplinary Synthesis of Holistic Affordance Intelligence

The challenges posed by NG-CPSs cannot be adequately addressed within the boundaries of a single discipline. The intellectualization, socialization, personalization, and naturalization of NG-CPSs require integration of knowledge originating from systems engineering, AI, cognitive science, cybernetics, design theory, philosophy of cognition, and human-centered innovation. Consequently, this study adopts a transdisciplinary perspective. In this paper, transdisciplinarity is understood as more than collaboration among disciplines. It denotes the creation of a common conceptual framework that transcends disciplinary boundaries and assists in the synthesis of heterogeneous forms of knowledge into a coherent explanatory and operational structure.

Unlike interdisciplinary approaches, which transfer methods between disciplines, cross-disciplinary and multidisciplinary approaches, which place disciplinary insights side by side, post-disciplinary synthesis seeks integrative concepts that can organize and relate multiple academic domains of knowledge. A transdisciplinary approach even extends it with societal knowledge.

The overall proposition of this paper is that HAI can serve as a transdisciplinary foundation for the affordance-oriented design and operation of NG-CPSs. HAI is proposed as such an integrative concept. It connects the operational logic of cyber-physical systems, the representational and learning capabilities of computational AI, the situated interaction principles of sensorimotor intelligence, the viability-oriented perspective of embodied intelligence, and the contextual and normative contributions of human intelligence. An important element of the methodological approach is the development of transdisciplinary collective design intelligence, as discussed by Ford, L.D., & Ertas, A., (2024). Therefore, the synthesis spans multiple ontological, epistemological, and methodological traditions.

1.3 Approach to Work and the Paper

This work aims to combine SAI, CAI, and EAI and to investigate the possible influences on the design of NG-CPSs. Thus, the ambitions are not modest. Three fundamental research questions are addressed:

- R1 What differentiates sensorimotor, computational, and embodied artificial intelligence from ontological, epistemological, and methodological aspects?
- R2 If they are based on different ontological commitments, what framework can support merging them into a holistic system-level intelligence?
- R3 What changes in system operation can be expected of holistic system-level intelligence in the context of NG-CPSs?

The overarching goals have been defined as (i) a foundational analysis of the above AI manifestations, and (ii) synthesis (design) of a conceptual framework that could be realistically transferred into both forward-looking concrete research agendas/projects and dedicated educational programs. The latter involves conceptualizing and structurally characterizing holistic system-level intelligence within the conceptual framework of NG-CPSs, and achieving notional coherence, academic rigor, and potentially high impact. Towards this end, foundation models related to the evolution of symbolic versus connectionist versus physical AI technologies, and their limits (grounding problem, embodiment gap) have been studied.

Drawing on a focused yet comprehensive review of recent literature and integrating it with the author's conceptual vision, this position paper advances the discourse in a strongly argumentative manner. It articulates and synthesizes key ontological, epistemological, and computational perspectives on SAI, CAI, and EAI, and explores their potential convergence into a holistic system-level intelligence. The backbone of the structured argumentative synthesis includes (i) focused literature analysis and integration (focusing on AI technologies, cyber-physical systems, and embodied cognition), (ii) notional unification and conceptual abstraction, (iii) symbolic formalization where proper, and (iv) formulation of propositions to support future research. As a central contribution, the paper proposes and logically defines a conceptual framework for holistic system-level intelligence in NG-CPSs. The framework introduces symbolic constructs to capture interactions among SAI, CAI, and EAI. The framework also identifies critical gaps requiring further

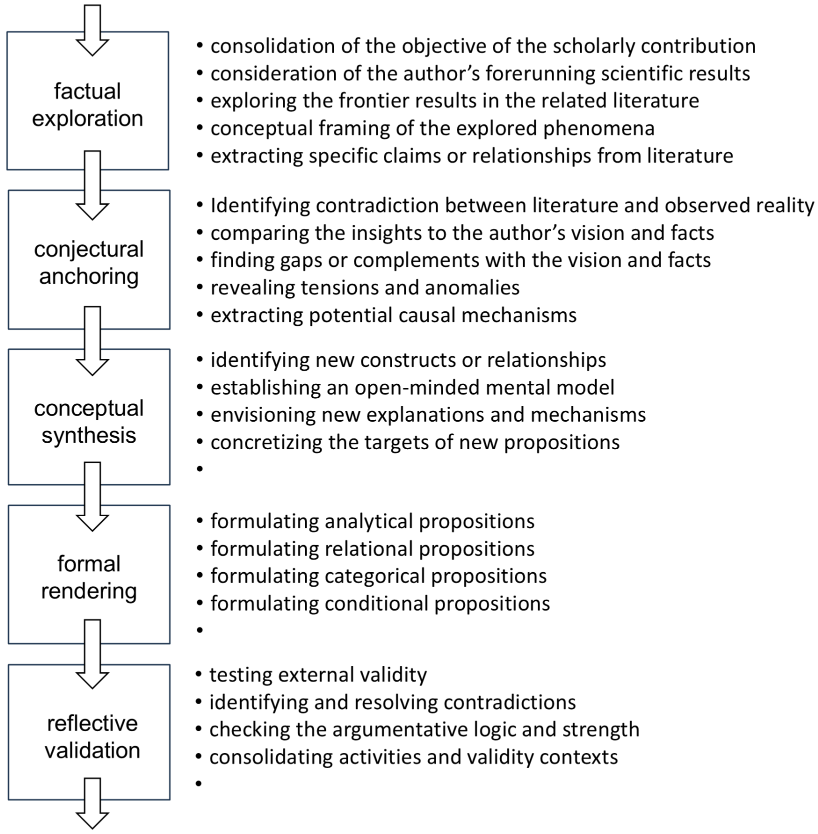

Figure 1: *The stages and actions in the research process.*

investigation and formalization. The reasoning process alternates between analytic decomposition (characterizing Sections 2–3) and synthetic integration (presented in Sections 4–5), often purposefully adapting earlier formulations and examples.

The content generation process was driven by the strong intention to consider the most recent developments. The elaboration process (steps and considerations) followed what is usual for an argumentative position paper for a specialized scientific community. The stages and actions are shown in Figure 1. The paper formulates a set of propositions to stimulate post-disciplinary and transdisciplinary research and to bridge artificial intelligence, systems engineering, cognitive science, and human-centered design. It concludes that the transition from coexistence to true integration of SAI, CAI, and EAI necessitates a reconceptualization of intelligence as a distributed, multi-layered, and context-embedded phenomenon, with significant implications for the design and operation of NG-CPSs.

The paper is organized as follows: Section 2 provides an overview of the evolution of the cyber-physical systems paradigm, the manifestation and intellectualization of NG-CPSs, and the challenges in their affordance-driven design and operation. Section 3 analyzes sensorimotor, computational, methodological, and manifestation aspects. Section 4 elaborates on the synthesis of holistic system-level intelligence and the complementary elements of human natural intelligence. Section 5 presents the author's propositions, and Section 6 concludes the paper.

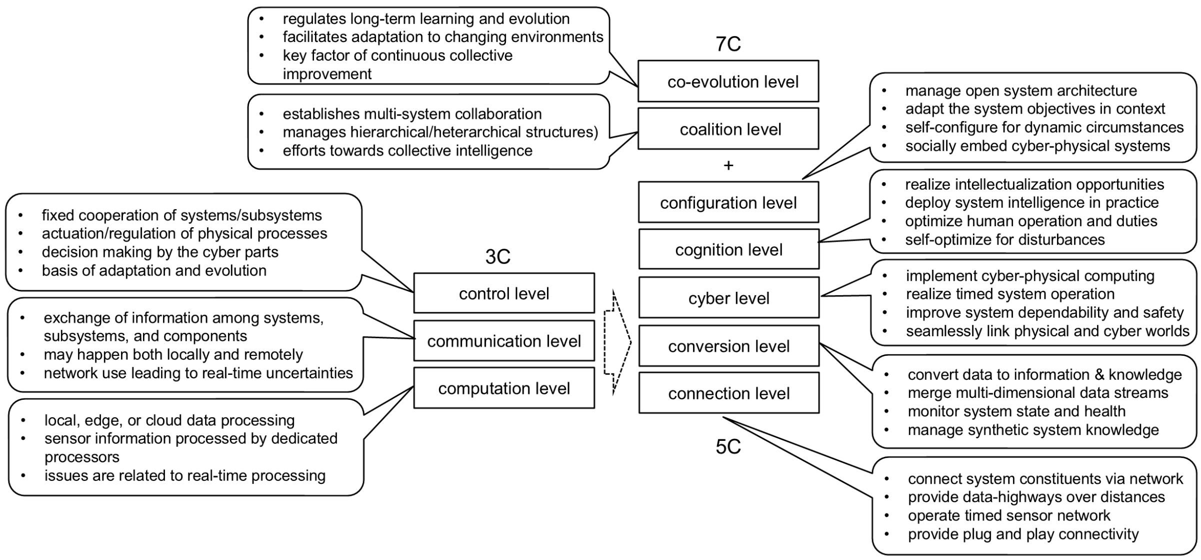

Figure 2: *The combined stratified models of cyber-physical systems.*

2 Evolving Paradigm of Cyber-Physical Systems

2.1 Paradigmatic Development of CPSs

When we ask five experts what CPSs are, we can expect ten different answers, often at a high level of abstraction. This is caused partly by the complexity of the system paradigm, partly by its rapid evolution (Eslami, Y. et al., 2023). The essence of CPSs was first described by the 3C model and characterized by a tight integration of computation, communication, control, and physical processes. The design features of traditional CPSs are (i) deterministic control, (ii) predefined functionality and architecture, (iii) data-based and software-integrated operation, and (iv) design-time completeness. The originally involved hardware, software, and cyberware knowledge domains have gradually been augmented with cognitive, social, and ecological knowledge domains. To account for growing intellectual knowledge and social behavior, this overly simple 3C model has been extended to the stratified 5C and 7C models (Figure 2) (Yin, D. et al., 2020).

The contemporary CPS literature recognizes the paradigm shift, but it frames it in an AI-related, yet layered way (Uddin, M.A., & Salam, H., 2025). The identified drivers of paradigmatic development are distributed problem-solving intelligence, context-dependent adjustment of operational goals, autonomous adaptive operation, openness of environmental coupling, and sociotechnical integration. Across surveys and position papers, CPS evolution is usually described along three coupled trajectories: (i) increasing convergence, integration, and complexity, (ii) increasing intelligence, autonomy, and creativity, and (iii) increasing openness, context-sensitivity, and runtime decision-making. The trend in paradigm evolution is from pre-specified, deterministic, function-executing closed systems to open systems featuring holistic system-level intelligence, operational affordance handling, situational context-awareness, and self-managed evolution. These abilities are often treated as generation markers. An evolution-over-generations model has been proposed by Horváth, I. et al. (2017).

Current CPSs are framed as products of convergence between hardware, software, cyberware, and knowledgeware. The consideration of biological, cognitive, social, and ecological domains has led to formulations of models like cyber-physical-social systems (CPSSs), human-in-the-loop (HITL) environment models, and system-in-the-loop (SITL) models. The major drivers towards NG-CPSs are intellectualization, socialization, personalization, and naturalization of the manifestations of this family of systems

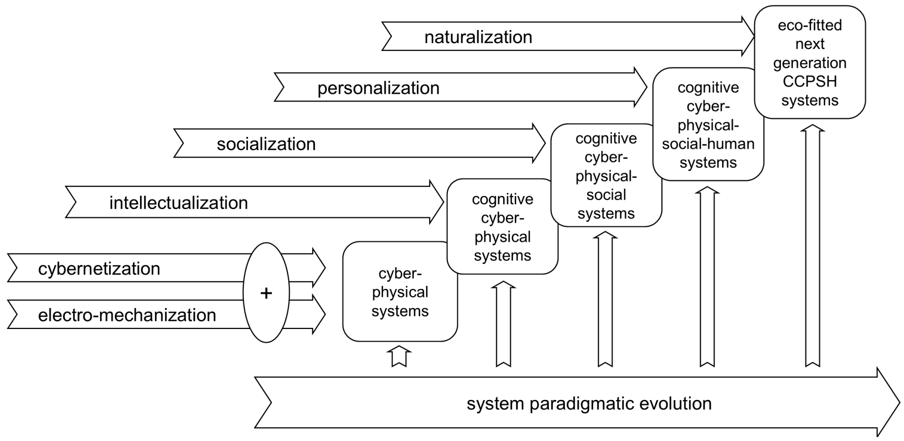

Figure 3: *Paradigmatic evolutionary model of CPSs towards NG-CPSs.*

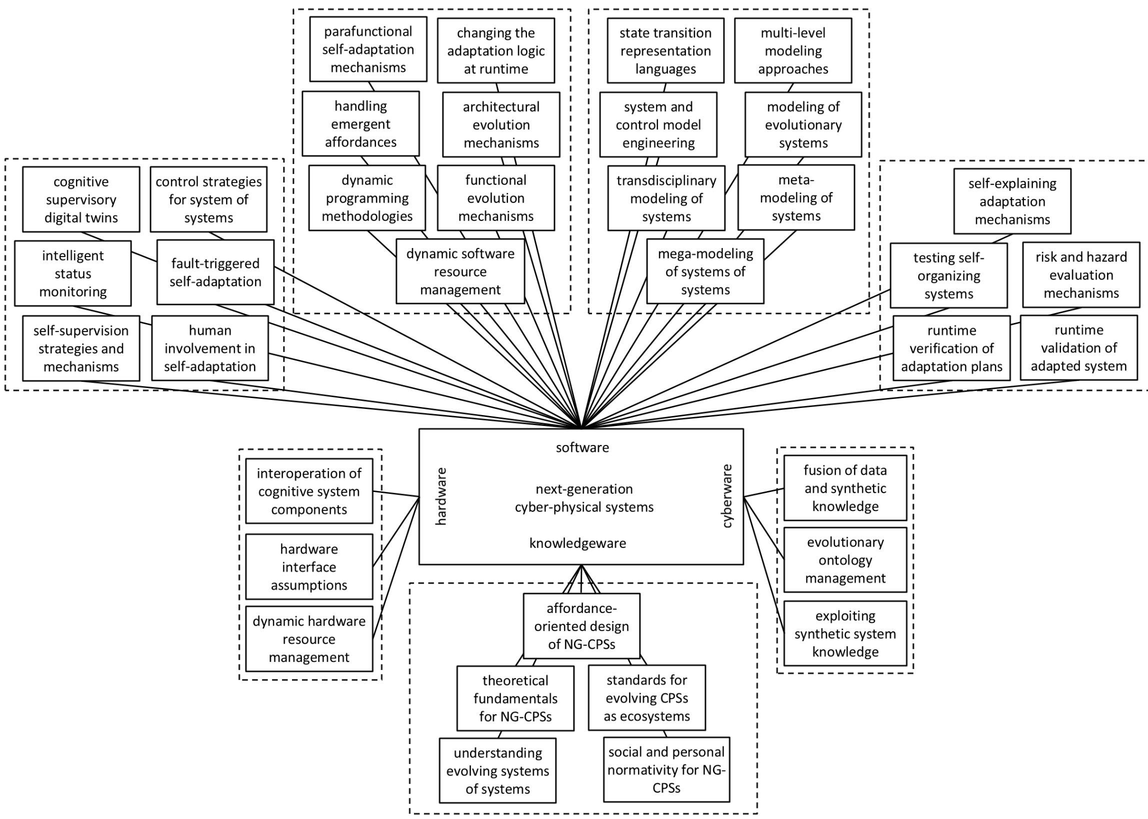

Figure 4: *Operational complexity involved in NG-CPSs.*

(Figure 3). NG-CPSs can be foreseen to feature high-level self-awareness, self-adaptation, self-organization, and self-determined learning, while showing huge operational and architectural complexity and challenges (Figure 4). They will be able to work under uncertainty and with evolving goals, reason about context, and dynamically configure their behavior.

The self-* abilities manifest not only in specific operational functions, but also in the growing potential

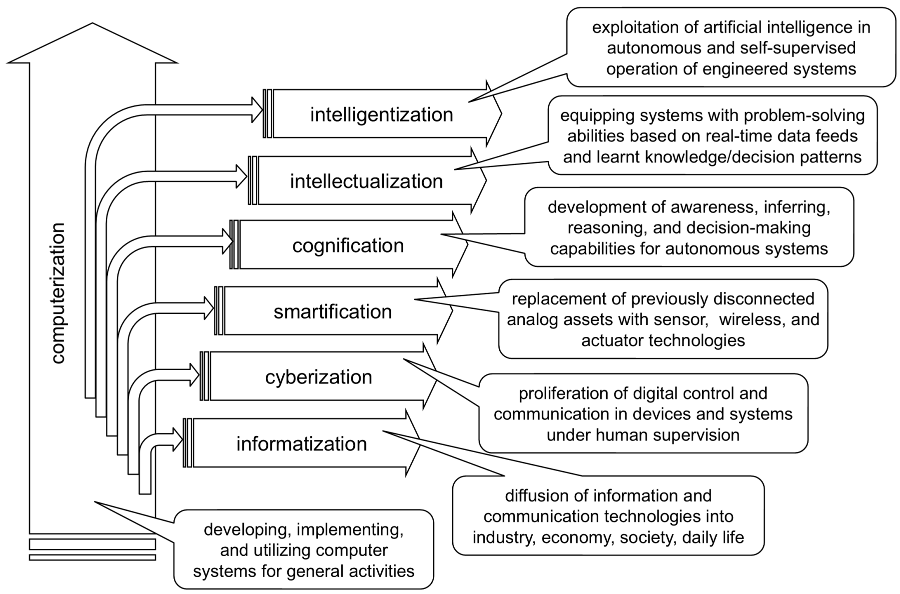

Figure 5: *Shifting objectives of cognitive engineering of systems.*

of operational affordances (Albrechtsen, H. et al., 2001). These changes strongly challenge the currently typical multi-disciplinary or cross-disciplinary system design methodologies. Several researchers have recognized this and tried to develop theories and frameworks for highly adaptive and/or evolving CPSs. However, despite rapid developments, the design theory of social-cyber-physical systems is still in its infancy. This raises the need for new post-disciplinary and transdisciplinary research into design and engineering theories and methodologies that can manage the emergent behaviors and compositional synergy of the elements of the complex, networked CPSs.

2.2 Intellectualization of NG-CPSs

The information-processing and cognitive-reasoning capabilities of application systems are continuously enhanced (Figure 5). Authors reported on the development of intelligent systems, including CPSs. I must frankly state that I am an advocate for denying the existence of authentic intelligence in any living being other than humans and have reservations about the human-like intelligence of digitally computed systems. Therefore, I insist on the following differentiation concerning engineered systems. As a technological advancement, intellectualization (and system intellect) means equipping systems with cognitive abilities and resources, provided by humans, to solve problems and learn adaptive behaviors across varying environments and contexts. Intelligentization (and system intelligence) means the acquisition of cognitive abilities and resources by the system for problem-solving, autonomous learning, and evolving behaviors within dynamic environments and contexts (Horváth, I., 2025). Eventually, it goes together with the teleological problems of system self-intelligentization and the possibility of autopoietic engineered systems (Zönnchen, B. et al.,2025). Despite the current hype, I think intellectualization is a more realistic approach, considering the current prospects of demand for systems and the techno-economic feasibility of the development goals[1]. Intelligentization and self-intelligentization may be goals for the far future (if these are realistic and workable at all). Towards this end, even more sophisticated AI technologies are indispensable.

The intellectualization of NG-CPSs improves their abilities to perceive, interpret, reason, adapt, cooperate, evolve, and, act autonomously. It (i) goes beyond adding AI technologies and points toward the

[1]Contrary to the above position statement, I will use the phrases 'intelligence' and 'system intelligence' to avoid contradiction with the vocabulary of the present literature, where it is logically needed.

emergence of systems with synthetic operational knowledge, contextual awareness, and para-functional capabilities, (ii) extends classical autonomic computing ideas toward intent-driven multi-system operation, and (iii) makes the transition from feedback-type reactive regulation to proactive and anticipatory automated operation possible. It also enables self-organization, higher-level operational autonomy, and consequent reconstruction of reality in dynamic environments. Intellectualization also increases context awareness and situational cognition, and enables semantic interoperability, mission-aware adaptation, dynamic role allocation, and cooperative social behavior. Examples are collaborative robotic environments, resilient energy infrastructures, autonomous manufacturing ecosystems, and adaptive mobility systems.

The complex problem of application-oriented intellectualization is addressed by cognitive engineering, which deals with both non-AI-based intellectualization (model-driven, rule-driven, logic-driven, formally engineered, deterministic) and AI-based intellectualization (learning-driven, data-centric, probabilistic, and adaptive cognition). In practice, NG-CPSs will be hybrid cognitive systems that combine both approaches. It must be emphasized that non-AI-based intellectualization approaches are as important as AI-based approaches, although they are sometimes underestimated today (Chami, M. et al., 2022). They stay critically important for reasoning, regulation, adaptation, predictability, explainability, traceability, safety, trustworthiness, and certifiability.

A typical non-AI-based intellectualization approach is model-based systems engineering (MBSE) that uses application-specific intellectualization mechanisms. In MBSE, explicit system knowledge models are developed for intents, functions, structure, behavior, constraints, and dependencies (Henderson, K., & Salado, A., 2021). Conditions for the development of comprehensive and robust system models are, on the one hand, the stability of the operational knowledge and, on the other hand, the formalizability of domain expertise. MBSE becomes especially powerful, as well as challenging, when integrated with runtime adaptation. Standard procedures for runtime model development are scarce in autonomous systems. Executable mathematically based models for perception, classification, prediction, planning, anomaly detection, and optimization are associated with procedurally defined formal computational methods, as well as foundational ontologies, semantic concept networks, causal knowledge graphs, and semantic reasoning engines. They support reflective adaptive control and guarantee explicit semantics, computational stability, high interpretability, and operational reachability, liveness, and safety. Digital twins can intellectualize CPSs without using computational AI by enabling simulation-based anticipation, operational constraint propagation, prognostic scenario evaluation, and runtime synchronization (Zheng, X. et al., 2022). At the same time, innovative, hybrid twin architectures may combine physics-based, process-induced, and AI models.

The AI-based intellectualization approaches typically rely on self-learning, adaptation, inference, or generative reasoning. The literature shows, from multiple perspectives, that purely AI-based intellectualization faces problem-coverage limitations, deployment rigidity, scalability limits, instability risks, explainability challenges, a lack of explicit time management, limited adaptability, certification barriers, and, therefore, trust deficits. Bridging neural learning, statistical and symbolic reasoning, and explicit knowledge structures, neuro-symbolic approaches are one of the strongest candidates for NG-CPS intellectualization because they improve explainability, support reasoning, and enable formal constraints. Probabilistic generative AI and nondeterministic LLM-based cognition may serve as semantic coordinators, planners, contextual interpreters, and mediators of human interaction, but bounded autonomy, runtime verification, and supervisory architecture have become essential, particularly in the case of distributed intelligence (Chen, R. et al., 2025). Their potential roles include intent interpretation, mission decomposition, multi-agent coordination, procedural reasoning, and synthetic documentation generation. The follow-up sections provide further information.

Intellectualization provides an opportunity for NG-CPSs to accumulate operational wisdom, transfer learned behaviors, share synthetic knowledge across ecosystems, and support continual capability evolution. This paves the way toward symbiotic cognition, cooperative decision-making, adaptive human-machine teaming, co-construction, and socially aware CPSs that are characterized by high resilience and anti-fragility. Nevertheless, intellectualization strives not only for system self-intelligence but also for human-system co-intelligence, which enables richer human-in-the-loop, human-on-the-loop, and even human-out-of-the-loop cooperation regimes. Together, these foster the formation of a holistic system-level intellect needed by goal enhancement, evolving operation, anomaly detection, predictive maintenance, attack prevention, runtime repair, and graceful degradation in NG-CPSs. Also shown in publications is that synthetic system intelligence (SSI) plays a growing role in self-managing systems. SSI is self-produced by NG-CPSs at runtime, either based on coded human knowledge (helping boot up) or on runtime learning and model building (Chae, J. et al., 2023). A particularly important opportunity is the generation and exploitation of machine-generated operational knowledge, learned system experiences, and emergent procedural know-how. If the principles of packaging and transferring are elaborated and standardized, SSI may become an industrial asset in the age of intellectualized systems (Horváth, I., 2024).

As a result of intensive intellectualization, NG-CPSs are increasingly becoming self-adaptive and capable of operating in partially open and unpredictable environments. The emerging concept of meta-intellectualization assumes systems that can reason about their own physical and cognitive processes, evaluate their own competence, and move toward self-evolving architectures, reflective behavior, and epistemic awareness. This trend offers an opportunity to create systems that survive disruptions, reorganize under overload, and improve through disturbances. Certain proposed early frameworks try to correct unsafe AI actions at runtime in CPSs.

The system design of NG-CPSs is supposed to shift toward situated (runtime-defined) operations. Visionary experts assume that the function-oriented design will be complemented by affordance-oriented design (Sareh, P., & Loudon, G., 2024). This assumption may motivate us to investigate the genesis of affordances in the context of NG-CPSs and to develop effective approaches to affordance management. However, it implies the need to reinterpret the concept of affordances and to have novel mental models of system conceptualization, cognitive engineering, and practical deployment. Currently, the issues of affordance-enabling resources and affordance-enabled operation of NG-CPSs are not yet covered in contemporary literature. In the next sub-section, a thematic detour is taken to (i) summarize the existing notion of affordances, (ii) gain deeper insight into the current affordance theories, and (iii) introduce a new concept of operational affordances in the context of NG-CPSs. It is hoped that the detour will be useful and clarify why a synthesis of the three genres of artificial intelligence technologies will be necessary.

2.3 From User Affordances to System Affordances

The notion of affordance appears explicitly in the design literature, although it has not yet been universally adopted. They have been defined and categorized from human perspectives. Gibson's definition refers to affordances as features and qualities of an artifact that suggest possible actions to its users (Gibson, J.J., 1977). The identification of types of affordances also reflects this view. The type 'explicit affordances' includes clearly visible cues that imply an action. The type 'implicit affordances' includes subtle cues that suggest functionality through design, such as a raised surface hinting that it can be pressed. The type 'perceived affordances' involves possible actions that depend on whether users recognize and put action possibilities into operation. The type 'real affordances' includes those features or qualities that exist regardless of user perception. One issue is that these categories of affordances cannot be used directly to decide what affordances exist from a system-internal perspective (i.e., how an intellectualized NG-CPS can recognize, select, use, and supervise such assets). This issue needs extensive further research.

Davis, J.L. & Chouinard, J.B. (2016) introduced the mechanisms-and-conditions framework of affordances. This framework shifts the orienting question from what technologies afford to how they afford, whom they afford for, and under what circumstances? Mainly, it deals with the problem of binary applications and presumed universal subjects in affordance analyses. The operational mechanisms implied by affordances mean that technologies can request, demand, encourage, discourage, refuse, and allow social action, variously conditioned according to users' perception, dexterity, and cultural and institutional legitimacy in relation to the technological object. Davis, J.L. (2023) presented an applied affordance framework to help consider affordances in the design of machine learning systems and their operational models, which both reflect and shape the social worlds in which these systems work, as argued.

Gaver, W.W. (1991) defined four types of affordances: (i) correct, (ii) perceptible, (iii) hidden, and

(iv) false. Correct affordances are manifested in artifacts in ways that enable a correct chain of actions. Perceptible affordances originate in the perceptual characteristics of an artifact itself and shed light on available and desired action possibilities. These obvious properties prompt users to use the affordance as intended. Hidden affordances do not present themselves as obvious affordances. In human-computer interaction (HCI), users must often rely on experience and/or trial and error to point out possible actions of user interfaces. False affordances are look-alike affordances that do not have any real function, meaning that the user perceives possibilities for action that are nonexistent. A good example of a false affordance is a placebo interface indicator. Hartson, R. (2003) defined four additional types to consider in HCI: (i) physical (the perceptual characteristics show users what to do), (ii) cognitive (design features that help users notice or know about things), (iii) sensory (design features that help users sense something), and (iv) functional (design features that help users achieve goals).

In the above-cited paper, the term 'intended functionality' is used interchangeably with 'functional affordance'. For this reason, it is justified to state that the term 'functional affordance' has nothing to do with the concept of 'operational affordance'. The latter (i) happens by chance (serendipitous), (ii) manifests in the physical reality of a system (system-internal), and (iii) makes a purposeful action in its operation process when invoked. It means it is not a kind of higher-level user enablement that is perceivable when information is available so that an actor can perceive and then act upon the existing affordance. As discussed above, such user-oriented affordances, action patterns (action prompts to users), and memes (action prompts to users) are major concerns in user interface design for artifacts and interactive systems. These different interpretations led to specific implementations of affordances, with a focus on relationality and a centralization of the role of values in affordance theory (Pedrola, F.P., & Vitari, C., 2023). Eventually, they are useful for both socio-technical analysis and socially informed design.

Despite the interpretational differences, the above-cited authors kept four common conceptual elements. Namely, affordances (i) are action possibilities in the relation between an artifact and its user(s), (ii) they are external to interactively operated systems, (iii) do not belong to the artifact but manifest in the perceptive, cognitive, and motor relations between artifact and user, and (iv) the developed theories are about what the users can do with a system (rather than about what a system can do with its own affordances). Furthermore, from a design perspective, they are designed features (characteristics or properties) of the artifact that provide clues about the intended or possible uses. In contrast, this work assumes that an affordance may exist associated with the physical operation of a system. Such affordances, called system operational affordances (SOAs), are (i) system-internal (i.e., handled by the system itself), (ii) emergent (i.e., may appear in certain contexts), (iii) implicitly manifested (i.e., not directly designable), and (iv) resource-related (i.e., depends on the availability of enablers).

The issues for later studies are exactly these. On the one hand, comprehensive theories are needed to reveal the essence of system-managed affordances. On the other hand, adaptable technological solutions are to be developed to cast and process such affordances in various application contexts. Runtime modeling (inferable ampliative representations) of operational affordances seems indispensable, but also an enormous challenge. It is unlikely that system-internal affordances can be managed (self-managed) in any other way in (and by) prevailing digital computing-supported systems. Also, SOAs-oriented operation of NG-CPSs entails unique design thinking. What should designers include in systems to support the emergence and handling of operational affordances? How can they maximize the use and efficiency of operational opportunities and minimize or prevent operational errors and incompetence? In human involvement, how can they improve interoperability and reduce cognitive friction?

These are complicated questions without trivial answers. And the searches completed using the terms "affordance self-management by system" and "self-managed system affordances" have not resulted in any useful clues . . .

2.4 Operational Affordances and Affordance-Oriented NG-CPSs

The earlier sections said that NG-CPSs will increasingly work autonomously (define and manage their operation) in open, dynamic, and uncertain environments. Therefore, their operation cannot be completely specified at design time. A dual design challenge is to manage their adaptive/evolving operations, and, concurrently, to guarantee reliable and resilient operation under these conditions. The growing complexity of AI-enabled autonomous systems shifts the emphasis of design from predefined functionality toward context-dependent, actionable operation profiles. It also means that classical function-centered cross-disciplinary (software-integrated) engineering becomes insufficient for designing or co-creation of such systems (Anasuri, S., & Pappula, K.K., 2024). We need not only a new affordance theory for NG-CPSs, but also new methodologies to manage their non-traditional behavior.

The demand for SOAs is further reinforced by socialization, personalization, and naturalization of NG-CPSs, as well as the regulatory, ethical, and safety requirements for their context-aware autonomous decision-making. SOAs may also improve human-machine collaboration by exposing intelligible possibility structures rather than isolated functional modules. This perspective aligns naturally with adaptive autonomy, high-level intellectualization, and self-managed operation coordination. At the same time, it raises incomparable epistemic and procedural complexities. There is no such thing as a 'predefined affordance' because the phare is inherently contradictory. The system possesses SOAs only as implicit capabilities. They are previously unspecified operational possibilities that appear as a set of probabilities to choose from and become recognizable by consideration of changing operational states, evolving system configurations, and dynamic operational environments.

Research in robotics shows that affordance is not only a theoretical concept from psychology (Hauser, H. et al., 2023). In object grasping and manipulation, robots need to learn the affordance of objects in the environment, i.e., to learn from visual perception and experience (a) whether objects can be manipulated, (ii) to learn how to grasp an object, and (iii) to learn how to manipulate objects to reach a particular goal. As an example, the hammer can be grasped, in principle, with various hand poses and approach strategies, but only a limited set of effective contact points and the associated best grip allow efficient performance of the goal.

SOAs-oriented operation assumes that NG-CPSs can reason about emerging opportunities, constraints, and alternative operational pathways at runtime. Notwithstanding this, how can an intellectualized NG-CPS, having been designed for a particular functionality, owning a given set of architectural elements, working under a given control regime, and striving for best operation, recognize its own operational affordances at runtime? Not only that, but other related questions are also difficult to address in general. For instance, based on what information can the existence of a set of SOAs (possible operation-modifying actions) be detected? What information is necessary to reason about which specific SOA is applicable in a particular state of NG-CPSs, and how should that SOA be activated? The system itself should excavate such information as needed. Advances in real-time distributed sensing, reasoning in context, cognitive digital twins, semantic interoperability, and runtime simulation are expected to make SOAs computationally workable. New operational principles, such as superseding strict recovery to nominal states by preserving viability of operational actions, may also favor SOAs-oriented design. The system may work with multiple relational representations of what actions are possible, permissible, and practical in a specific situation. Consequently, the engineering of NG-CPSs should evolve from function-centric architectures to complementing affordance-oriented operational frameworks that can support adaptive, resilient, and context-sensitive operations.

The context-dependent operations of NG-CPSs can be derived from affordances, which are a set of possible actions on various operational levels. The logic of working with affordances can be schematized in the following way: a system (i) perceives affordances (possibilities for action in context), (ii) interprets the state, context, and a proper objective, (iii) identifies necessary/possible operation regarding the objective, (iv) instantiates the operation by defining the actions and organizing the resources, and (v) realizes the operation and detects its effects. This logic is a reversal of the classical flow of design, which is typically organized as an iterative specification procedure of purposes, requirements, functions, structures, embodiments, and behaviors of a system. The affordance-oriented flow is closer to the following flow: perceived situation, implications of situation, range of affordances, selected/constructed operation, instantiated operation, experienced behavior.

An important forerunning conclusion is that affordances cannot be designed up front. They are runtime-emergent relations and action possibilities inferred from the interactions among goals, states, structures, behaviors, situations, intentions, and viability constraints. The identification and feasibility investigation of SOAs assumes exploration not only of the actual operation space and relation spaces, but also the space of operationally reachable future possibilities. This leads us to difficult-to-grasp concepts such as operational identities, intentions, and normativity. Operational identities refer to how an intellectualized system self-defines its role through practical actions, aggregated skills, and tangible behaviors, and how it transforms operational possibilities into experiential and measurable on-the-ground performance. Considering the high-level mission goals in specific contexts, operational intentions refer to the feasibility and utility of the system's action plan. Operational normativity refers to obeying formal and informal (regulatory and practical) action-guiding rules that govern the system's operation and behavior. There are no control models for these yet.

Operational affordances are not identical to a specific manifestation of system intelligence. Rather, they are context-conditioned operational possibilities that appear from the actual constellation of system-internal (state relationships) and/or system-external (environment interactional) relations. Nothing included in this definition requires intelligence. Nevertheless, to develop a new theory of affordance, two fundamental assumptions should be considered. One assumption is that operational affordances have causal existence. Another assumption is that operational affordances are deterministic (i.e., they can be reliably recognized, evaluated, and exploited). If both assumptions stand, then SOAs can be treated as an ontological bridge to a holistic system-level intelligence that includes organizational, contextual, and environmental constituents. Sensorimotor AI can be associated with relations between system-internal states and behavioral patterns (internal operational possibilities). Computational AI can learn contextual relations and reason about situational possibilities during operation (context-dependent interactions). Embodied AI can realize local adaptations reflecting environmental possibilities, dynamics, and constraints (physicality-mediated couplings) (Liu, Y. et al., 2025). Consequently, SOAs depend on the relational conditions that enable SAI, CAI, and EAI to create intelligent behavior in cooperation. The total of the relational conditions makes up the operational possibility space of the system. Therefore, the different forms of intelligence can be understood as mechanisms for discovering, evaluating, and exploiting operational affordances rather than creating them.

If the mentioned manifestations of AI are integrated, SOAs can be viewed as causally efficacious relational properties. They are neither purely subjective perceptions nor purely objective physical properties. Rather, they exist as real constraints and opportunities created by the coupling of system, context, and environment. The affordance exists because the relational structure exists, regardless of whether it is recognized. Intelligence acts upon these affordances but does not necessarily generate them. These are the aspects of the actual manifestation of the causality assumption.

The SAI-CAI-EAI synthesis also suggests a nuanced reflection on the second assumption. The existence of affordances may be objectively figured out by the relational configuration the system owns at a point in time. The recognition and exploitation of that affordance are contingent upon the intelligence available to the system. The existence of SOAs is potentially deterministic, but their recognition and evaluation are dependent on system intelligence. That is, exploitation of SOAs is both context-dependent and intelligence-reliant. This disposition is important because it separates the ontology of affordances from the epistemology of intelligence. Based on this thinking, we can position SOAs as the unifying construct for intelligence from the cognition of affordances to their exploitation. It is also important that this reasoning gives affordance theory a foundational role concerning the intellectualization of NG-CPSs. Intelligence is not the source of affordances but the capability by which such systems navigate and exploit an already existing affordance-landscape generated by the (non-designable) emergent interplay of resources and the coupled system–context–environment nexus. For a post-disciplinary theory of NG-CPSs, this provides a natural ontological foundation for integrating SAI, CAI, and EAI into a single affordance-centric framework. However, integration should take into consideration all important ontological, epistemological, and methodological aspects analyzed below.

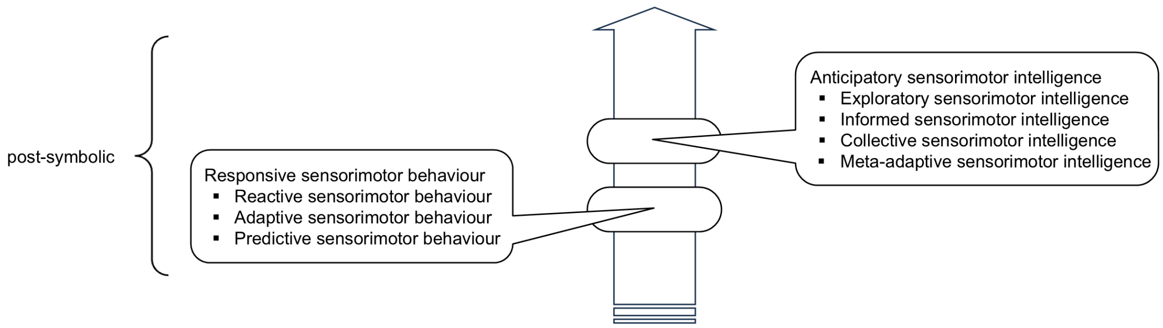

Figure 6: *Classes of sensorimotor artificial intelligence.*

3 Comparative Analysis of Categories of Enabling Artificial Intelligence

3.1 Ontological Features of the Considered AI Approaches

In the human context, SAI has been defined as situated perception-action coupling between agents and the environment. This dynamic interaction, together with the goal-driven regulation of processes, determines its enactive ontological commitment. The primary assumptions of SAI are: (i) the human mind has adaptive behavior in a closed loop (core metaphor), (ii) cognition is situated and generated in bodily interaction, (iii) perception, reasoning, and action are inseparable, (iv) intelligence emerges from embodied cognition and lawful enactivism (Ward, D. et al., 2017), (v) the encapsulating environment is partly physical, partly virtual, (vi) the implementation of the sense-reason-act loop is enacted through computational coupling to physical elements, and (vii) the actors (agents) are inseparable from their body and environment. This means that cognition does not happen inside a closed reasoning system but is distributed across agent-system-environment state dynamics. Consequently, SAI rejects the notion that cognition is purely internal computation over representations and offers an ontologically stronger (that is, not only digital representation-based) model of intelligence. SAI shifts the focus from internal representations to structured relations between perception and action (Travis, I.L., 1990). The core ontological unit of SAI is therefore not representation, but interaction trajectory. Based on post-symbolic operational models, SAI can be responsive or anticipatory (Figure 6).

The so-called 4E (embodied, embedded, enactive, and extended) school of cognitive science emphasizes the conceptual importance of purposeful everyday interactions with the external world, such as navigating the environment, rather than taking 'higher cognition' to be the primary phenomenon of interest (McGregor, S., 2026). From a system perspective, researchers have found the ontological essence of SAI as a replication of natural human enactment. Sensorimotor activity refers to planned and controlled actions that enable systems to learn about their physical environments (i.e., the embedding environment) by combining sensory input (seeing, hearing, touching) with planning and performing motor actions (grasping, moving, crawling) to generate both cognitive and motor outputs. Activities, such as grasping, rocking, or exploring textures, are essential for both operation and cognitive development.

Situated operational processes have naturally appeared and reached widespread deployment in CPSs due to the need for state-dependent and autonomous control, without symbolic computation over detached representations. From a system control point of view, it may alternatively mean operation adjustment and operation adaptation (Figure 7). In intellectualized systems, knowledge-boosted sensing-reasoning-planning-acting loops are implemented. Also driven by the demand for managing complex problem-solving, interactions, and decision-making effectively in operational processes, SAI has reached a prominent level of sophistication. SAI is also often used in ontogenetic systems, which change in their architecture, form, function, or behavior over their lifespan, rather than only across their evolving generations.

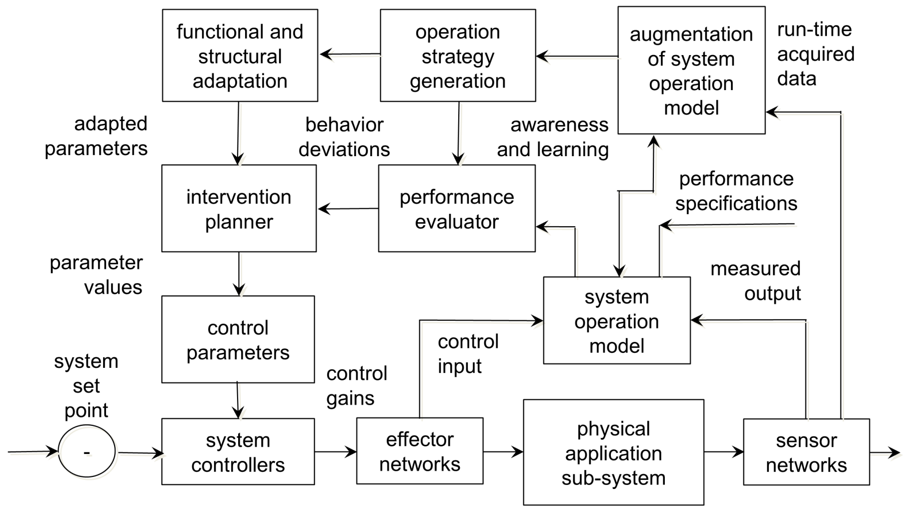

Figure 7: *A functional view of the control levels of adaptive CPSs.*

The ontological commitment of CAI is that cognition is a product of computation over (various symbolic) representations. This is rooted in computationalism, symbolic reasoning, statistical inference, and representational cognition. Practically, this assumption has been the guiding principle of all computational trajectories of AI research, from the beginning up to today. Thus, the key ontological properties are (i) disembodiment (no intrinsic physical coupling), (ii) abstraction (works on symbolic or vector representations), and (iii) substrate-independence (hardware-agnostic logic). Ranging from symbolic reasoning engines to contemporary deep learning architectures, CAI systems work through abstract representations, algorithmic transformations, and data-driven optimization processes executed on computational substrates. Though intelligence in biological systems is inherently embodied and action-oriented, CAI abstracts away embodiment and interaction, and strives to capture only a restricted projection of intelligence (Krzanowski, R., & Polak, P., 2022).

Based on the grounding representations, three families of approaches populate the onto-methodological landscape of CAI, which are based on (i) pure symbolic, (ii) sub-symbolic, or (iii) meta-symbolic representations (Figure 8). CAI is most frequently used in epistemic (cognitive reasoning-oriented) systems because it is grounded in the view that intelligence consists in the manipulation of internal symbolic, sub-symbolic, or meta-symbolic representations through computations governed by reasoning and learning principles, independent of physical embodiment. Over the last 50 years, multiple approaches have been conceptualized, which use different internal computational policies and can be overviewed only with omissions (Horvitz, E., & Mitchell, T.M., 2024). There are also efforts to develop CAI based on post-symbolic representations that account for the natural physicality of cognition. Idejiora-Kalu, N. (2024) emphasized the importance of “possession of feelings” by AI systems (spirit-based AI), which is a major setback in the acceptability (indeed, trust) and utilization of AI.

EAI radicalizes the critique of disembodied cognition and is aligned with embodied cognition and enactivism (Korteling, J.E. et al., 2021). Its ontological commitment is that intelligence manifests as viability-preserving corporeal regulation under dynamical constraints in systems. It is based on the following assumptions: (i) the basis of the embodied cognition and intelligent behavior is a physically instantiated system, (ii) often regarded as substantiated or simulated body, the whole of the system is constitutive of cognition, not an auxiliary implementation substrate, (iii) intelligence manifests as a corporeally realized behavior and regulation, including morphology, energy constraints, and dynamical coupling with the environment, (iv) the potential operation of a system is determined by its resources and state of operation, (v) intelligence is inseparable from the changes of physical embodiment, material constraints, energy flows,

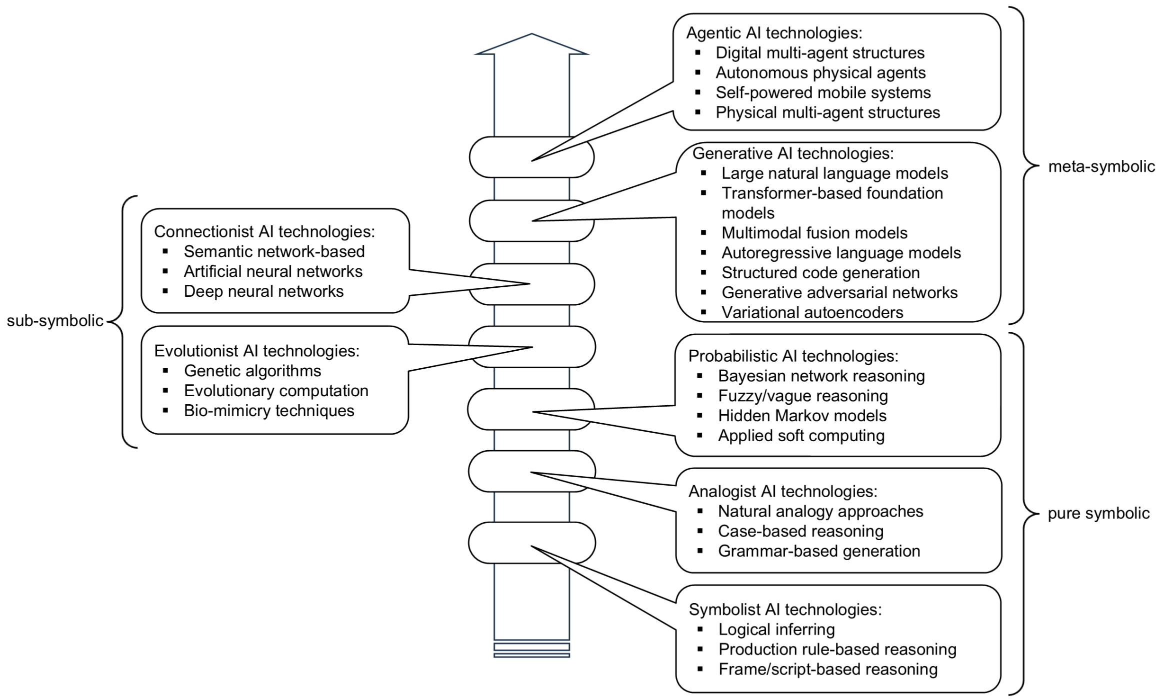

Figure 8: *The onto-methodological landscape of CAI.*

morphological structure, or environmental coupling, and (vi) operational feasibility, physical limitations, and environmental accessibility result in a viability region of the system (Hadi Sadati, S.M. et al., 2022). The latter defines the admissible state space within which the system can continue working via a set of viability constraints. Eventually, EAI can be regarded as the system's capability to keep its existence within practical regions of state space. Thus, this ontological commitment of EAI contrasts with both SAI and disembodied CAI (Ni, H., & Cui, L., 2025).

While CAI has reached an unprecedented level of maturity, EAI has still been comparatively under-theorized and fragmented in its development (Sun, F. et al., 2024). This is especially true regarding CPSs and NG-CPSs, which lend themselves to the use of both SAI and CAI. Nevertheless, EAI has been enriched by variously named implementations, such as reservoir computing (Nakajima, K., 2020). A probably incomplete overview is shown in Figure 9. Their common assumptions are that the body serves as an operational participant, and its morphology and actions play a role (Müller, V. C., & Hoffmann, M., 2017). Embodiment serves both as a constraint and an enabler. Morphology contributes to adaptation as passive dynamics, means of stabilization, or physical actor intelligence.

3.2 Epistemological Differences and Commodities of AI Approaches

Various theoretical traditions and frameworks have been used to explain or underpin the epistemology of SAI. They differ significantly in what they regard as 'knowledge'. The theory of enactivism, as proposed by Varela, F. et al. (2017), explains the cognitive core of SAI as the enactment of a meaningful world through sensorimotor activity. Knowledge arises from structural coupling with the environment, recurrent perception-action loops, and autonomous maintenance of organization (self-organization). In the context of CPSs, it refers to sensing- and reasoning-based adaptive participation in a dynamic environment.

The theory of embodied cognition, articulated by Lakoff, G., & Johnson, M. (1999), argues that sensorimotor structure constrains what can be known, and cognition depends on bodily capabilities. For systems

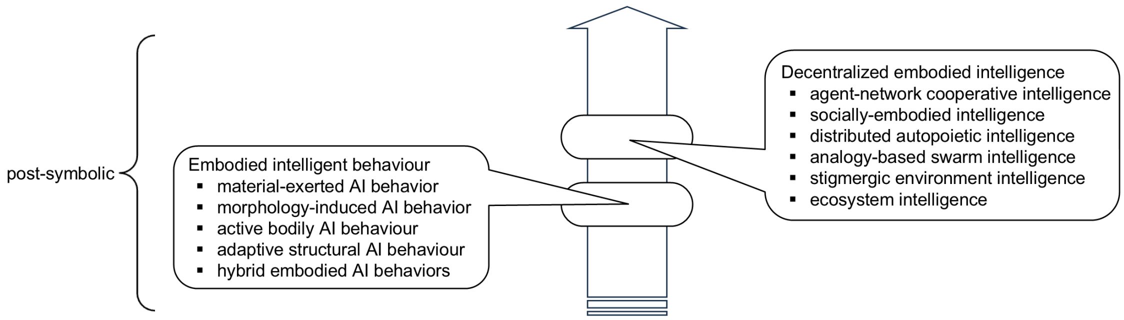

Figure 9: *Classes of embodied artificial intelligence.*

engineering, it means that sensors and actuators partly form the system's epistemic architecture and are not merely interfaces. Developed by O'Regan, J.K., and Noë, A. (2001), the sensorimotor contingency theory is based on the central idea that perception consists of mastering lawful relations between actions and sensory changes. It claims that procedural actions systematically transform future sensory states and that knowledge is associated with the mastery of sensorimotor contingencies. The general cognitive systems theory, often attributed to Thelen, E., and Smith, L. (1994) views knowledge of continuously evolving dynamical systems as an emergent property of coupled dynamics.

According to the 'free-energy principle' theory of Fritson, K. (2010), knowledge is modeled as minimizing prediction error or variational free energy. Considering CPSs, it implies that SAI of systems is supposed to predict sensory inputs, act to realize predictions, and update internal generative models promptly. The abstraction of the assumed factors offers a mathematically rigorous epistemology coupling sensing, reasoning, learning, and action. In the context of highly adaptive NG-CPSs, the viability theory of adaptive systems, elaborated by Aubin, J.-P. (1990), interprets SAI knowledge as the means of keeping operation trajectories within viability constraints (over admissible states). In this interpretation, SAI may contribute to the detection of affordances, the choice of workable actions, and the preservation of viability.

In the context of NG-CPSs, it is also an epistemological issue how a hybrid of the above and other theories can regulate how they acquire, maintain, and use knowledge through monitoring themselves and keeping sensorimotor coupling. Considering the epistemological framework of SAI, system knowledge, and semantic models (meaning, context, and relationships) appear in ongoing sensorimotor coupling rather than through reasoning on symbolic representations alone. The nature of the systems and their environment strongly defines the needed knowledge. There are no universal operation models for the environment $\leftrightarrow$ perception $\leftrightarrow$ reasoning $\leftrightarrow$ planning $\leftrightarrow$ action $\leftrightarrow$ adaptation $\leftrightarrow$ state cycles. It means that the epistemological characterization of SAI cannot be separated from signal/data acquisition, information processing, and state manipulation. Learning is the outcome of adaptive interaction, environmental exploration, embodied experimentation, and closed-loop adaptation. The validation of the knowledge assumes viability, robustness, task closure, and adaptive stability. This aligns with ideas like sensorimotor contingencies. Thus, the epistemic stance of SAI is participatory rather than observational (it works with participatory knowledge and uses it as the basis of system-level control). The conversion of input to output is based on digital computing. It is supported by CAI, which internalizes knowledge into representations (Müller, V.C., 2007).

The epistemological framework of CAI includes both traditional computational theories and modern computational technology and cognitive theories. The classical foundation comes from computationalism, the cognitive revolution, and classical symbolic AI, associated with scholars such as Newell, A., Simon, H.A., and Fodor, J. The basic assumptions are that (i) knowledge can be represented internally in computer architectures, (ii) reasoning is computation over representations, and (iii) intelligence is the manipulation of symbolic structures. The foundation has been extended with classical cybernetics, which reduces knowledge to information processed through computational transformations. The epistemological framework has been put onto its contemporary foundation by the incorporation of probabilistic representations and reasoning, based on the theory of Bayes, T., which considers that belief is updated by evidence and knowing means supporting justified probabilistic beliefs. Combined with the statistical learning theory of Vapnik, V. (2013), it has shifted the focus from representation to prediction in CAI due to its generalizing character.

Current CAI approaches are supported by the theory of connectionism as well as by various theories of neural computation, cultivated by Rumelhart, D., McClelland, J., and others. System knowledge is reflected by the state of the network configuration (i.e., distributed across the values of network parameters). Typically, no explicit symbolic representations (or representations that aim to capture semantics, such as concept ontologies, semantic graphs, and relational knowledge bases) are used. This limits the explainability of the knowledge owned by the network. The system 'knows' because it has obtained a useful internal structure through learning, and the more information it receives during training, the more and better it knows. In comparison with explicit model-based intelligence, often associated with SAI, it is implicit model-based intelligence working as implicit reasoning algorithms. Formulated by Wiener, N., and Ashby, W.R., the cybernetic regulation theory explains the usefulness of knowledge provided by CAI, considering its ability to control (i.e., to what extent it can enable effective regulation). This sets up contact with SAI.

Instead of directly enacting the world, systems intellectualized by CAI construct models of the world using observational and representational knowledge. The sources of knowledge are various predictive information structures (data, rules, patterns, and repositories). The knowledge is derived through computation (information processing through symbol manipulation and typically encoded. Pure symbolic, sub-symbolic, and meta-symbolic are typical categories of syntactic knowledge representation. Knowledge is derived by logic-based, statistical, probabilistic, or analogical inference mechanisms. Learning occurs through parameter estimation, probabilistic inference, statistical generalization, or functional optimization, and the validity of the knowledge is achieved through generalization across samples. The richness and expressiveness of the symbolic representations influence the accuracy of representational mapping, and the sophistication of coding enhances both ampliative reasoning and thematic learning. Validation of the inferred knowledge is established through predictive accuracy, generalization performance, statistical robustness, and benchmark evaluation.

In general, CAI alone is still insufficient for NG-CPSs because it lacks physical grounding, (ii) embodied viability regulation, (iii) situated operational understanding, and (iv) continuous environmental coupling. From the aspect of the epistemic stance, knowledge is what a spectator (rather than an insider) usually has, because human-type awareness and intuitive semantics are approximated only with restricted fidelity. This limitation motivates efforts to integrate CAI with SAI and EAI. Embodied cognition theories jointly argue that cognition is enacted physically (appears through body-environment interaction). The theories, frameworks, and models proposed to explain the epistemological essence and the knowledge related to EAI from various disciplinary perspectives accept this assumption.

Major theories claim that it is constitutive under physical constraints and is of continued existence. The major theories of EAI are as follows: (i) theory of embodied cognition (TEC), (ii) theory of holistic enactivism (THE), (iii) theory of situated cognition (TSC), (iv) theory of extended mind (TEM), (v) theory of dynamical systems (TDS), (vi) theory of morphological computation (TMC), (vii) theory of predictive processing (TPP), and (viii) theory of sensorimotor contingency (TSM). A common feature of most of these theories is that they challenge the AI research's classical assumption that intelligence is disembodied and largely context independent. However, their claims about how intelligence appears from the interaction of brain, body, and environment differ significantly.

TEC is rooted in cognitive science and philosophy of mind. Its core idea is that cognition is grounded in bodily experience (i.e., in some form of sensorimotor activity). This theory rejects the view that thinking is purely symbolic or bound to the brain. Eventually, THE is a stronger form of embodied cognition. It assumes that cognition arises through active engagement of a system with its incorporating environment (world) and claims that intelligence is enacted, rather than represented. It emphasizes the system's autonomy and sensorimotor coupling. TSC concentrates on how cognition depends on context and environment.

It presumes that intelligence is situated in real-world tasks rather than abstract reasoning and that social coordination plays a role. TEM proposes that cognition extends beyond the brain into tools and the environment. It recognizes the influence of information processing tools and digital environments on the human memory and the TDS models cognition as a continuous, time-evolving interaction between brain, body, and environment. However, it rejects discrete symbolic representations based on the assumption that intelligence is an emergent pattern in coupled systems. TMC, as interpreted within the framework of info-computational constructivism, explores how an agent's physical shape, material properties, and mechanical dynamics can generate emergent behavior, process semantic information, offload computational load from digital control, and exploit passive adaptability, while adapting to the operational state and the environment (Ghazi-Zahedi, K. et al., 2017). TPP proposes that the brain is an active prediction machine (generates internal assumptions about the world and continuously updates them based on incoming sensory data) rather than merely reacting to stimuli as a passive receiver of information. TSM claims that perception is not something the brain does to create 'pictures' of the external world passively, but an active process of physical exploration relying on the practical, embodied knowledge of how actions (e.g., movements) affect the senses.

In simple words, the key epistemological tension originates in the following: (i) SAI asks: 'What interaction and control keep the system viable and model intelligence as sophisticated relational control?' and (ii) CAI asks: 'What is the correct representation and ampliative reasoning, developing growing models as representation?' Whereas EAI asks 'What behaviour can be expected from the bodily actors of the system and how can it be modeled as part of intellectualized behaviour?' These differences should be resolved or at least mitigated. Thus, the epistemological insufficiency of isolated intelligence paradigms for NG-CPSs is a general motivation behind striving for holistic integration of intelligence (and holistic affordance intelligence) (Hadorn, B. et al., 2015).

3.3 Methodological Characteristics of AI Approaches

Methodological approaches should be viewed from two aspects in the context of artificial intelligence. On the one hand, they guide the process of bringing AI manifestations into existence. On the other hand, they also guide the process of deploying AI in systems. Usually, they are distinguished terminologically by referring to the former as a construction methodology and the latter as an operational methodology. The construction principles of the SAI are rooted in the already mentioned perception-action cycles, environmental coupling, and situated interaction control. The development of SAI can be described as an interaction-centric methodology. The goal is to construct intelligence through effective coupling with the environment, rather than through internal models of physical behavior. The main stages of the development methodology are (i) define the physical operation process and environment, (ii) define the associated sensors and actuators, (iii) set up purposeful perception-action loops, (iv) learn sensorimotor regularities, and (v) adapt through procedural/physical interaction. The development is strongly experimental and ecological, and the central object of design is proper penetration into real-life processes and infrastructure (the system-environment coupling).

The operational methodology of SAI relies on abilities such as changing physical or simulated embodiments, distributed multi-modal sensing, online closed-loop learning, real-time adaptation, and long-term evolution. The operational methodology of SAI is based on (i) closed-loop interaction, (ii) policy learning through experience, and (iii) continuous adaptation in perception–action cycles. The concrete methods of operation are often drawn from control theory, dynamical systems theory, cognitive engineering, and complex systems design.

The core metaphor of the operational methodology of CAI is that the mind works as a program. The principal assumptions are that (i) cognition is substrate-independent, (ii) the world can be made accessible internally through (encoded, abstracted, and manipulated) models, (iii) cognition occurs inside the representational domain, (iv) intelligence can be derived by formal transformations of signal or symbol representations, (v) the cognitive agent is fundamentally disembodied (even if deployed in a CPS like a robot) (Perez, J.A. et al., 2018), (vi) reasoning can be approximated by algorithmic manipulation, (vii)

Figure 10: *The floating wheel of a truck – as a well-known example of structurally enacted situated behavior.*

learning can be based on recognition and composition of patterns, and (viii) the semantics of knowledge can be representationally encoded. These align with both classical cognitivism and, in modern form, large-scale statistical models (e.g., deep learning).

Fundamentally, the development methodology of CAI relies on the assumption that intelligence can be designed by constructing proper computational structures. The development is driven by some underlying representation, enabling a way of digital cognition (Hsu, H.P., 2025). The typical workflow is (i) define the application problem, (ii) define relevant variables and states, (iii) construct models using digital representations, (iv) train, infer, reason, or optimize knowledge by the computational mechanism, and (v) evaluate the overall performance. The primary task of designers is to design or learn internal models (model-first development).

EAI features an engagement-centric operational methodology, with some slight intertwining with the model-first and the interaction-first development methodologies. From a design viewpoint, it is a concurrent progression with targeted system behaviors, enabling actors (agents), and environment coupling (Howard, D. et al., 2019). Thus, it applies the 'system-agent-environment-first' strategy. Embodiment forces simultaneous consideration of the system's physical manifestation, active structural elements, behavioral constraints, materials/metamaterials, energies/transformations, morphologies/physical properties, adaptation opportunities, sensing actions, actuation actions, sensorimotor/computational cognition, embedding environment, and social interaction. Behavior patterns of EAI can be interpreted at multiple organizational levels. At the lowest level, morphology-conditioned micro-behaviors emerge through local physical interactions and sensorimotor feedback loops. At higher levels, recurrent coordination structures stabilize into operational patterns that support adaptive task execution under varying environmental conditions. Over longer temporal horizons, learning processes modify the admissibility and prioritization of affordances, thereby restructuring the system's operational repertoire.

The developer designs not merely algorithms or couplings but an entire embodied ecology (Hughes, J. et al., 2022). The process typically involves phases such as (i) defining the embodied actors (passive and active agents), (ii) defining their functional capabilities, (iii) defining adaptation opportunities, (iv) computational and sensorimotor coupling of actors, (v) enabling adaptive learning and self-organization, (vi) defining environmental contexts, and (vii) maintaining operational viability across changing conditions. Therefore, development becomes inherently integrative. Figure 10 presents an example where the above procedure was applied in practice without considering the deployment of computational and sensorimotor AI.

From a systems-theoretic perspective, in the context of CPSs and NG-CPSs, the application methodologies are intended to make the most of the cognitive capabilities that AI genres contribute to the overall operation (Jiang, Y. et al., 2022). For example, the application methodology of CAI emphasizes diagnosis, prediction, decision support, planning, and optimization. The environment is regarded as an implicit object to be modeled, and the system operates by consulting internal knowledge structures. The application methodology of SAI emphasizes exploration, penetration, learning-in-action, adaptation of physical processes, and discovery of operational affordances. The environment is treated as a source of actionable opportunities, and the system operates by maintaining effective interaction. The approach of deploying EAI emphasizes (i) the optimal selection of physical actors, (ii) sustained autonomy of actors, (iii) context-sensitive adaptation, (iv) harmonized co-adaptation of the actors, (v) resilience of the entire system, and (vi) ensuring operational viability under a dynamic environment. Therefore, the environment is not merely modeled or explored, but it becomes part of the operational reality of an intellectualized system. The system operates by maintaining successful engagement.

The comparative analysis presented above demonstrates that SAI, CAI, and EAI are not merely alternative technological solutions. Each originates in different scientific traditions and embodies different assumptions regarding the nature of intelligence, cognition, knowledge, embodiment, and adaptation. SAI draws heavily on ecological psychology, enactivism, and cognitive science; CAI emerged from computer science, mathematics, logic, and information theory; EAI incorporates concepts from biology, neuroscience, robotics, dynamical systems theory, and morphology-based computation. Consequently, any attempt to integrate these manifestations into a coherent operational framework is inherently transdisciplinary. Consideration of design and use aspects places it in the domain of transdisciplinarity. McGregor, S.L. (2024) argued that transdisciplinarity has cemented itself as a promising strategy for addressing complex systems problems. HAI should therefore be understood not only as a technological synthesis but also as a synthesis of disciplinary worldviews concerning system intelligence, adaptive behavior, and design issues.

4 Synthesis of Holistic Affordance Intelligence

4.1 Conceptual Disposition of Holistic Affordance Intelligence

The background study underpinning this two-part position paper rests on two assumptions: (a) NG-CPSs will be based on a synergistic combination of artificial intelligence approaches, and (ii) their overall design will be oriented toward system operational affordances (SOAs) and will extend to their runtime operation. Related to the first assumption, the previous sections discussed computational, sensorimotor, and embodied intelligence as partially distinct concepts of cognition. However, alone, none of these concepts appears sufficient to explain and support the operational requirements relevant to NG-CPSs, which are expected to adapt operational goals at runtime, interact continuously with their changing physical environments, collaborate with humans, and preserve viable operation under uncertainty and incomplete knowledge. Under such conditions, intelligent operation can no longer be reduced to predefined functional execution, purely reactive adaptation, or isolated computational optimization. To meet the concurrent needs for system operation intelligence and affordance-oriented system operation, the concept of HAI is proposed. Its conceptualization should address these needs as conceptual twins from a system design perspective.

Behind holistic affordance intelligence is a transdisciplinary synthesis, also involving both academic and civil knowledge (Figure 11). HAI is defined as distributed cyber-physical-human operational intelligence through which an NG-CPS recognizes, evaluates, regulates, and operationalizes situated affordances while preserving viable continuation of operation under dynamically evolving conditions. Since they were originally defined as disjunct concepts, SAI, CAI, and EAI must be brought into a synergistic relationship (Figure 12). Towards this, HAI should therefore not be interpreted as a monolithic reasoning mechanism, but rather as a coordinated operational and/or architectural framework of complementary intelligence manifestations in affordance-oriented system operations. In this framework, SAI contributes situated environmental coupling and embodied interaction; CAI contributes abstraction, prediction, optimization, and symbolic manipulation, and EAI contributes various forms of physical behaviors and morphology-conditioned adaptations. Complementing these, HNI contributes contextual interpretation, normativity, and strategic operational guidance (Popa, E., 2021). The operational relevance of HAI lies in the continuous coordination of these heterogeneous capabilities during affordance management.

From an operational perspective, HAI should govern the transformation of open operational possibility fields into viable, executable operational trajectories (Paolo, G. et al., 2024). This regulation involves multiple tightly coupled processes: perception of environmental and internal conditions, generation of affordance hypotheses, viability-oriented admissibility evaluation, ranking of admissible affordances, synthesis of executable operational structures, and recursive monitoring of operational consequences. Consequently,

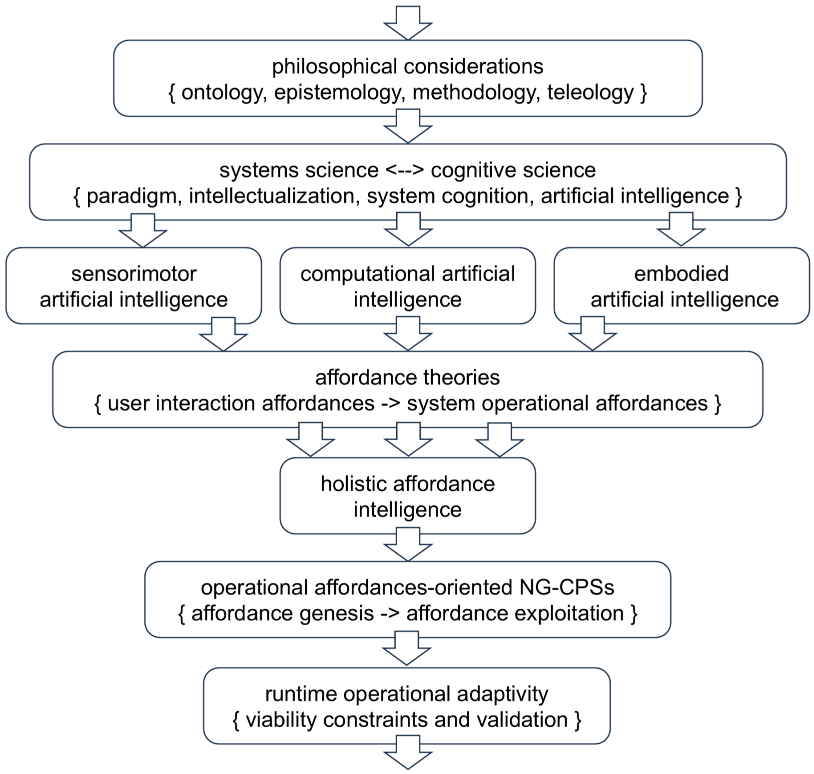

Figure 11: *Transdisciplinary synthesis leading to holistic affordance intelligence.*

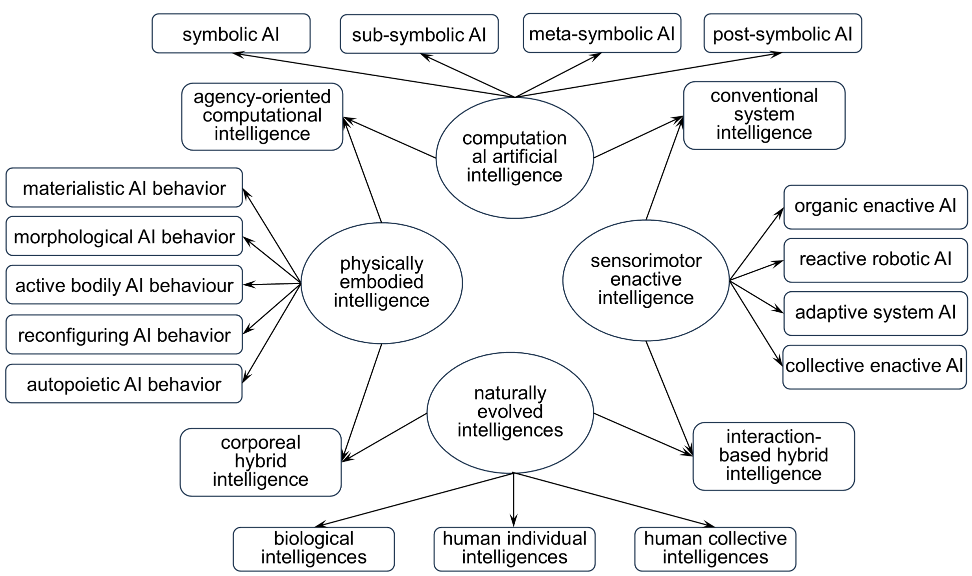

Figure 12: *Sources of HAI.*

HAI should act less as a static controller and more as a continuously restructuring operational mediation mechanism between the system and its situated environment. Therefore, the integration problem is not merely computational. It also concerns reasoning mechanisms, methodological unification, and architectural embedment of heterogeneous representational forms, temporal scales, embodiment constraints, learning mechanisms, and human-system interaction principles. The implementation challenge becomes particularly difficult because affordance management is inherently prospective. The system must evaluate not only immediate operational feasibility but also the future operational consequences of activating particular affordances. This requires predictive simulation, recursive self-modeling, uncertainty management, and viability-preserving operational planning.

Thus, HAI is not purely artificial intelligence. It is hybrid operational intelligence that also changes the interpretation of autonomy in NG-CPSs. Autonomy can no longer be understood exclusively as independence from external intervention. Instead, it increasingly refers to the system's ability to regulate situated operational possibilities while preserving viability, adaptability, and sociotechnical acceptability under dynamically evolving conditions. Thus, autonomy becomes viability-regulated operational self-organization rather than deterministic self-execution. This situation motivates the introduction of HAI as an integrative operational framework that provides the capability for a cyber-physical-human system to recognize, evaluate, regulate, and operationalize situated affordances while preserving viable continuation of operation under dynamically evolving conditions.

This definition emphasizes important characteristics. First, HAI is fundamentally situated. Operational meaning emerges relative to current operational conditions, environmental structures, system capabilities, contextual constraints, and sociotechnical requirements. Second, HAI is relational. Affordance is not an intrinsic property of isolated objects or environments. Instead, they emerge through the relation between the operational capabilities of the system, the characteristics of the environment, and the operational objectives and constraints of the situation. Third, HAI is viability regulated. Not every recognized affordance should be operationalized. Operational admissibility depends on whether realization of a given affordance preserves operational continuation, adaptability, safety, future operational flexibility, and sociotechnical acceptability. Fourth, HAI is dynamically adaptive. The admissibility and relevance of affordances may evolve continuously due to environmental change, operational disturbances, self-managed learning, embodiment changes, human interaction, and/or evolving mission objectives. Consequently, intelligent operation cannot be based exclusively on static predefined operational structures. Finally, HAI is sociotechnical. Human participants remain constitutive components of operational intelligence by contributing contextual interpretation, normative regulation, strategic adaptation, and collaborative operational coordination.

4.2 Architectural Implementation of Holistic Affordance Intelligence

From the perspective of a system-level designer, the critical issue is not the conceptual distinction of the three artificial intelligence manifestations, but how they can be operationally integrated into a realizable runtime operation architecture supporting affordance-oriented operation. As argued above, strategic integration of SAI, CAI, and EAI into HAI does not mean a synthesis into a novel compound intelligence. Instead, HAI is supposed to emerge as a system intelligence functionally integrated during system operation. In other words, the concept of HAI is realized by an implementable system architecture, and the design challenge is fundamentally architectural. The problem that is faced is not simply how to exchange data between AI modules, but how to establish runtime co-regulation of operational possibilities by HAI. It involves novel system engineering issues, such as viability-aware operational synthesis, dynamic affordance management, embodiment-conditioned execution, and recursive predictive adaptation.

The solution may be a multi-layer operational architecture in which HW, SW, CW, and KW constituents cooperate continuously through dedicated runtime interfaces. The implementation framework of the layered architecture proposed for affordance-enabled runtime operation management is shown in Figure 13. It is based on the design assumption that affordance-oriented NG-CPSs operate through continuous runtime reduction and restructuring of operational possibility spaces (Liao, Y.C., & Holz, C., 2025). Consequently, the layer interfaces themselves must support possibility management rather than simple command exchange. The framework identifies eight tightly coupled operational layers and a bus

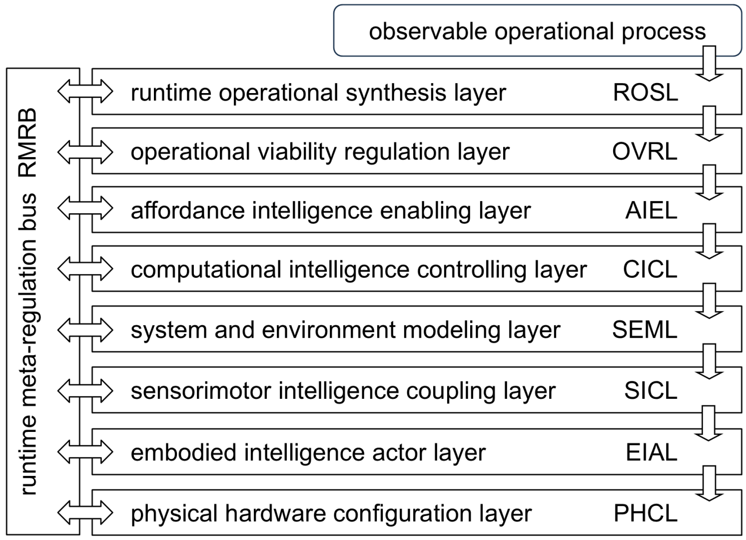

Figure 13: *Layered architecture for affordance-enabled runtime operation management.*

that supports the coordination of the layers and exchange of content and control information at runtime. PHCL is dedicated to the physical body of the system, including all hardware assets (components), processed material and energy flows, and their physical dynamics. EIAL manages both the localized (e.g., compliant material-exerted, morphology-induced, active bodily, adaptive structural, etc.) actors and the decentralized (e.g., cooperative agent-network, socially embodied, distributed autopoietic, analogy-based swarm, etc.) actors of embodied behaviour. SICL monitors the state of sensor networks, provides active perception, enables motor adaptations, provides feedback in interaction loops, actuator arrangements, sensorimotor prediction, and environmental probing. SEML is concerned with the digital models, both design-time created and runtime generated system models, sensorimotor–computational interface, sensorimotor–embodiment interface, cognitive digital twins, multi-modal fusion, temporal abstractions, and uncertainty estimation.

CICL manages mechanisms of digital inference, probabilistic assessment, ampliative reasoning, machine learning, deep learning, decision-making, operational explanations, semantic searches, chats/recommendations, socialization and personalization, and system security. AIEL is dedicated to the permanent management of operational affordances, including operating state assessment, affordance generation, operational context prediction, affordance ranking, affordance activation, process adaptation, computational–embodiment interface, and operational memory. While AIEL focuses on specific SOAs, OVRL focuses on maintaining overall system operation. It manages operational process interfaces, viability kernels, future-option preservation, constraint management, forecasting simulations, physical stabilization, and performance assessment. ROSL is assigned to managing evolutionary advancements, adapting the active interaction modules, harmonizing with system users, and regulating interoperation with other systems. RMRB is the most critical architectural element and is not a classical middleware bus. It acts as (i) an operational synchronizer (maintains coherent affordance representations across SAI, CAI, and EAI), (ii) viability regulator (propagates mission, embodiment, energy, human, and safety constraints), (iii) temporal coordinator (synchronizes sensorimotor loops, embodiment adaptation, digital strategic planning), (viii) affordance-space manager (predicted operational trajectories, viability risks, future-option reductions, instability indicators), and predictive orchestration asset (conduct recursive Self-Monitoring to track degradation, uncertainty accumulation, capability evolution, and operational drift).

The availability of HAI has implications not only for the operational processes but also for the architectural aspects of NG-CPSs. Before everything, it implies a deviation from the traditional CPS architecture, which primarily supports predefined functionality, deterministic execution, and design-time operational completeness. In contrast, affordance-oriented NG-CPSs increasingly require architectural constituents (hardware, software, and cyberware) that can support affordance-related functionality, e.g., runtime affordance recognition, admissibility evaluation, predictive viability assessment, adaptive operational synthesis, continuous human-system coordination, and dynamic operational restructuring.

4.3 Complementing Elements of Human Intelligence

The term 'cognizant element' refers to a component, aspect, or feature that possesses, enables, or represents awareness, knowledge, or active understanding within a specific system. It is used in diverse fields, including philosophy (specifically Eastern spiritual philosophy), system design, and sometimes in legal or technical analysis, indicating the 'part that perceives' or the 'part that knows'. Despite the comprehensiveness and potential of the 'cognizant element' of NG-CPSs, they cannot miss human participation. Therefore, it should also be considered in the context of HAI. The main point is that human participation may introduce forms of regulation that cannot be reduced solely to computational optimization. Characteristic examples include ethical norms, institutional constraints, legal requirements, cultural expectations, and collaborative priorities. They are important because they may influence social embedding but may also continuously shape affordance admissibility. That is, humans contribute forms of operational regulation not reducible to computational optimization, even in the presence of HAI.

Conceptually, the considered segments of HNI remain indispensable because they provide contextual interpretation, strategic prioritization, sociotechnical coordination, sociocultural adaptation, abductive/intuitive/heuristic reasoning, normative/ethical judgment, operational meaning attribution, and legal awareness. The integration of these cognitive dimensions transforms operational intelligence into a distributed cyber-physical-human co-decision process. Humans remain constitutive operational participants rather than external supervisors. Consequently, HAI must be interpreted as cyber-physical-human co-intelligence. At the same time, the implementation of such co-intelligence is not a simple matter due to the high-level cognizance introduced by HAI.

Importantly, embodiment should continuously constrain operational realization. SOAs cannot be interpreted as purely symbolic entities detached from operational reality. Physical embodiment is supposed to determine the accessibility of operational possibilities, the realizability of actions, and operational interaction dynamics. At the same time, human participation introduces forms of regulation that cannot be reduced solely to computational optimization. Ethical norms, institutional constraints, legal requirements, cultural expectations, and collaborative priorities influence the admissibility of affordances. Consequently, HAI should not be interpreted as purely artificial intelligence – eventually, it manifests as hybrid intelligence. Rather, it represents a broader operational intelligence emerging through coordinated interaction among computational, embodied, environmental, and human processes.

4.4 Affordance Regulation as the Core Operational Mechanism

The central operational mechanism of HAI is operational affordance regulation (OAR), which refers to the continuous management of operational possibility spaces under situated continuation requirements. Computationally, OAR comprises multiple interconnected sub-processes, including affordance recognition, affordance admissibility evaluation, affordance prioritization, runtime operational synthesis, viability preservation, and adaptive updating of operational structures (Figure 14). These sub-processes collectively determine which operational possibilities become realizable under specific operational conditions. In addition, OAR expands operational openness by identifying potentially realizable actions relative to current system capabilities and environmental conditions. However, unrestricted expansion of operational possibilities may rapidly lead to combinatorial explosion, operational instability, or decision paralysis. Consequently, affordance-oriented operation requires additional mechanisms to reduce the space of operational possibilities (SOPs).

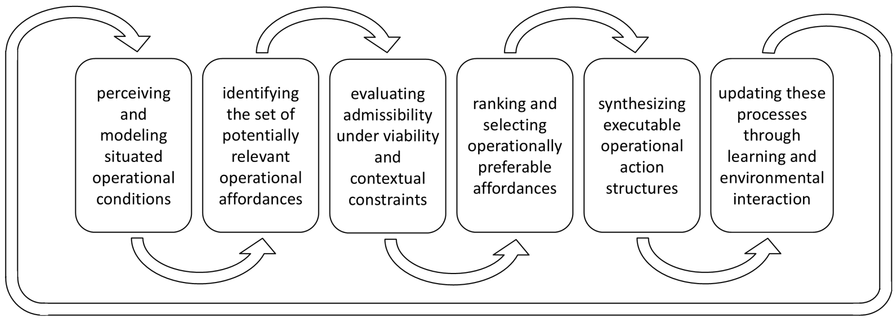

Figure 14: *High-level process of operational affordance regulation.*

The reduction of SOPs cannot be interpreted as a simple optimization sub-process. Instead, admissibility emerges through interaction among multiple partially overlapping constraints, including viability preservation, embodiment limitations, resource restrictions, contextual relevance, future-option preservation, and human normative considerations. Thus, OAR becomes a continuous balancing process between operational openness and operational coherence. Too little reduction may result in instability and uncontrolled operational complexity, whereas excessive reduction may produce rigidity, premature closure, and loss of adaptability. Accordingly, intelligent operation increasingly depends on maintaining dynamically balanced affordance regulation rather than maximizing isolated operational objectives alone. It is assumed that using viability theory to filter and rank affordances may be useful. Viability theory provides a suitable conceptual and mathematical basis for regulating the transition from recognized affordance spaces toward operationally admissible affordance sub-sets. The essential objective is not merely to determine whether an affordance is executable at a given moment, but whether its operationalization preserves the system's optimal future behavior.

5 Propositions

5.1 Proposition One

The presented analysis shed light on the differences in methodological foci of AI genres: SAI targets the construction of physical and procedural coupling, and the ampliative coordination of perception and action, CAI supports model construction and develops methods for reasoning about the world, while the methodological approaches of EAI concentrate on utilizing physical phenomena and provide useful behaviour for the system in a changing environment. This reconfirms that NG-CPSs require simultaneous synthesis of all three methodologies, SAI to perceive and act, CAI to model and predict, and EAI to adapt and be autonomous. Research may explore whether they are common strategies for integrating them into HAI, and shareable principles for implementing them in various application contexts.

5.2 Propositions Two

The transition towards holistic affordance intelligence in NG-CPSs is no longer optional but inevitable. This work argues that affordances must be elevated to first-class design constructs, formalized as set-valued mappings from system–environment states to actionable possibilities and grounded in viability-theoretic principles to guarantee sustained operation under evolving constraints. This suggests that the development of NG-CPSs may consider layered architecture, including (i) a sensorimotor layer to build affordance-sensitive perception-action loops, (ii) a computational layer to build representations and predictive models, and (iii) an embodiment layer to organize the overall agent-environment system to maintain viability. To utilize operational affordances requires not only enabling the fusion of sensorimotor, computational, embodied, and human intelligence, but also computational mechanisms capable of learning and updating sets of affordances in closed-loop interaction. Research must establish experimental holistic intelligence systems and benchmark cases that expose the possibilities and limitations of affordance-oriented operation of NG-CPSs.

5.3 Propositions Three

Traditional CPS paradigms primarily interpret intelligent behavior as the execution and optimization of predefined functions under anticipated conditions. However, NG-CPSs will increasingly operate in open, dynamically changing environments where relevant operational possibilities cannot be fully predefined at design time. From this perspective, system intelligence shifts from static functional execution toward dynamic regulation of situated operational possibility spaces. Embracing this shift will redefine the epistemological and engineering foundations of NG-CPS design. Post-disciplinary research is needed to develop design methodologies for affordance-oriented design of NG-CPSs and to demonstrate their superior behaviour, viability, adaptability, and generative capacity. Investigation of highly adaptive/evolving operations is needed, with a shared attention on the capability of systems to (i) recognize emerging operational possibilities, (ii) evaluate their admissibility under changing constraints, and (iii) operationalize viable actions during runtime.

5.4 Propositions Four

HAI is not bestowed upon genuine AI systems but on complex, cognitively active application systems, such as NG-CPSs. Advancing towards HAI in NG-CPSs calls for focused research directions. First, affordances may be formalized as set-valued mappings from system–environment states to admissible action possibilities, which can be embedded in viability-theoretic frameworks to support sustained operation under dynamic constraints. Second, computational approaches are needed to approximate and adapt these affordance sets in closed-loop interaction, enabling the coordinated integration of sensorimotor, computational, embodied, and human intelligence. Third, systematic evaluation through experimental dual implementation and benchmark cases could support the comparison of function-oriented and affordance-oriented design methodologies, particularly regarding the developmental trade-offs. These research directions could support a gradual consolidation of theoretical foundations, methodological approaches, and their translation into engineering practice.

6 Conclusions

The first part of the position paper addressed the probable nature of the holistic system-level intelligence of NG-CPS. It investigated three manifestations of computational, sensorimotor, and embodied intelligence through three analytic lenses (ontology, epistemology, and methodology). It also sheds light on what segments of human natural intelligence remain indispensable for system supervision (Conway, A.R., & Kovács, K., 2015). It conceptualized a framework that combines them into a consistent common substance, considering one constraint principle (non-contradictory coherence across the triple). An additional professional goal was to turn a high-dimensional conceptual triangulation into a convincing argumentative conceptual structure without losing its force. It was hypothesized that the primary distinction among the three manifestations is essentially ontological, implying different epistemologies and methodologies.

The concept of holistic system-level intelligence has been consolidated with a view to the assumed affordance-driven operation of NG-CPSs and described by the notion of holistic affordance intelligence. The expectation against HAI is not only to provide a synergistic co-existence of three current implementations of AI, but also to support affordance-oriented operation of future systems. This is needed because, as 'being-intelligence', SAI and CAI focus on rationality, wisdom, and alignment of the system's cognitive elements. At the same time, EAI is about their 'behavior-intelligence', and focuses on the manifestation of operating and acting (i.e., it is about practical utility). The major assumption of this position paper is that HAI can be a seamless application-dependent federation of the four constituents.

While the constituents of HAI are widely discussed in the literature, the conjunctive relationships among them are much less investigated and theoretically explained. The perspective of operational control of NG-CPSs, which combines operational functions and affordances, is a typical example. That is why the paper not only elaborates on the essence and role of the constituents of HAI but also presents the author's view on their complementary nature and integration for affordance management. HAI is not interpreted as the next isolated intelligence paradigm competing with computational, embodied, or human intelligence. Rather, it denotes the coordinated operational capability that emerges through the interaction of these forms of intelligence during situated system operation. The need for such integration also stems from the observation that intelligent operation increasingly depends on the capability to recognize, evaluate, regulate, and operationalize situated possibilities for action under continuously changing operational conditions.

Beyond its technological implications, the proposed framework contributes to the emergence of a transdisciplinary theory of intelligent cyber-physical systems. By integrating concepts originating from artificial intelligence, systems engineering, cognitive science, cybernetics, philosophy of cognition, and human-centered design, holistic affordance intelligence provides a common conceptual language for future research on affordance-oriented NG-CPSs. The author therefore views HAI not only as a candidate operational architecture but also as a transdisciplinary scientific construct capable of bridging previously disconnected research traditions.

As proposed, extensive post-disciplinary/transdisciplinary research is needed across the interrelated knowledge domains. Beyond the concrete research proposals formulated in the propositions, there are countless research trajectories and additional other topics deserving investigation, such as pragmatic approaches to deep methodological transition, construction of a formal viability-kernel for affordance spaces, affordance dynamics analysis based on runtime edited graphs, recursive operational admissibility, meta-regulation theory for HAI, affordance-inclusive operational digital twins, metrics and indicators for affordance entropy, or runtime filtering/compression of operational possibility-spaces.

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References

Albrechtsen, H., Andersen, H.H., Bødker, S., & Pejtersen, A.M. (2001). Affordances in activity theory and cognitive systems engineering. *Research Report Risoe-R* No. 1287. Risø National Laboratory. Denmark. Forskningscenter Risoe. (EN), 1-39.

Anasuri, S., & Pappula, K.K. (2024). Human-AI co-creation systems in design and art. *International Journal of AI, BigData, Computational and Management Studies,* 5(1), 102-113.

Aubin, J.-P. (1990). A survey of viability theory. *SIAM Journal on Control and Optimization,* 28(4), 749-788.

Baltezarević, B.V., & Battista, D. (2025). Artificial intelligence and cognitive boundaries: a critical examination of intelligence, understanding, and consciousness.*Knowledge-International Journal,* 69(1), 61-66.

Chae, J., Lee, S., Jang, J., Hong, S., & Park, K.J. (2023). A survey and perspective on industrial cyber-physical systems (ICPS): From ICPS to AI-augmented ICPS.*IEEE Transactions on Industrial Cyber-Physical Systems,* 1, 257-272.

Chami, M., Abdoun, N., & Bruel, J.M. (2022). Artificial intelligence capabilities for effective model-based systems engineering: A vision paper. In: *Proceedings of the INCOSE International Symposium,* (Vol. 32, No. 1, pp. 1160-1174).

Chen, R., Jiang, W., Qin, C., & Tan, C. (2025). Theory of mind in large language models: Assessment and enhancement. In: *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics,* (Volume 1: Long Papers) (pp. 31539-31558).

Conway, A.R., & Kovács, K. (2015). New and emerging models of human intelligence. *Wiley Interdisciplinary Reviews: Cognitive Science,* 6(5), 419-426.

Davis, J.L. (2023). 'Affordances' for machine learning. In: *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency,* (pp. 324-332).

Davis, J.L., & Chouinard, J.B. (2016). Theorizing affordances: From request to refuse. *Bulletin of Science, Technology & Society,* 36(4), 241-248.

Denning, P., Odlyzko, A., Walker, M., Delic, K., Yaffe, P., & Picton, P. (2025). Artificial intelligence: foundational technologies of artificial intelligence.*Ubiquity,* 2025(July), 1-10.

Duan, J., Yu, S., Tan, H.L., Zhu, H., & Tan, C. (2022). A survey of embodied AI: From simulators to research tasks. *IEEE Transactions on Emerging Topics in Computational Intelligence,* 6(2), 230-244.

Erden, Z.D. (2025). Evolution, future of AI, and singularity. *arXiv preprint* arXiv:2507.02876.

Eslami, Y., Franciosi, C., Ashouri, S., & Lezoche, M. (2023). A review and analysis of the characteristics of cyber-physical systems in Industry 4.0. SN *Computer Science,* 4(6), 825.

Ford, L.D., & Ertas, A. (2024). Systems engineering transformation: Transdisciplinary endeavor. *Transdisciplinary Journal of Engineering & Science,* 15, 1-39.

Friston K. (2010). The free-energy principle: a unified brain theory? *Nature Reviews Neuroscience,* 11(2), 127-138. DOI: 10.1038/nrn2787.

Gaver, W.W. (1991). Technology affordances. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems,* (pp. 79-84).

Ghazi-Zahedi, K., Deimel, R., Montúfar, G., Wall, V., & Brock, O. (2017). Morphological computation: the good, the bad, and the ugly. In: *Proceedings of the 2017 IEEE International Conference on Intelligent Robots and Systems,* (pp. 464-469).

Gibson, J.J. (1977). Chapter 8: The theory of affordances. In: *The Ecological Approach to Visual Perception,* Hilldale, USA, 1(2), 67-82.

Hadi Sadati, S.M., ElDiwiny, M., Nurzaman, S., Iida, F., & Nanayakkara, T. (2022). Embodied intelligence & morphological computation in soft robotics community: Collaborations, coordination, and perspective. In: *Proceedings of the IOP Conference Series: Materials Science and Engineering,* (Vol. 1261, No. 1, p. 012005). IOP Publishing.

Hadorn, B., Courant, M., & Hirsbrunner, B. (2015). Holistic integration of enactive entities into cyber physical systems. In: *Proceedings of the 2015 IEEE 2nd International Conference on Cybernetics,* (pp. 281-286). IEEE.

Hartson, R. (2003). Cognitive, physical, sensory, and functional affordances in interaction design, *Behaviour & Information Technology,* 22(5), 315-338, DOI: 10.1080/01449290310001592587

Hauser, H., Nanayakkara, T., & Forni, F. (2023). Leveraging morphological computation for controlling soft robots: Learning from nature to control soft robots. *IEEE Control Systems Magazine,* 43(3), 114-129.

Henderson, K., & Salado, A. (2021). Value and benefits of model-based systems engineering (MBSE): Evidence from the literature. *Systems Engineering,* 24(1), 51-66.

Horváth, I., & Ábrahám, G. (2025). Transdisciplinary shifts in system paradigm-driven disciplines: Mechatronics as an example. *Transdisciplinary Journal of Engineering & Science,* 16, 177-207. DOI: 10.22545/2025/00276

Horváth, I. (2024). Utilization of synthetic system intelligence as a new industrial asset. *Journal of Integrated Design and Process Science,* 27(2), 111-133.

Horváth, I. (2025). A first inventory of investigational concerns for prognostic systems thinking based on an extended conceptual framework. *Journal of Integrated Design and Process Science,* 28(2), 68-85.

Horváth, I., & Tavčar, J. (2022). Designing cyber-physical systems for runtime self-adaptation: Knowing more about what we miss... *Journal of Integrated Design and Process Science,* 25(2), 1-26.

Horváth, I., Rusák, Z., & Li, Y. (2017). Order beyond chaos: Introducing the notion of generation to characterize the continuously evolving implementations of cyber-physical systems. In: *Proceedings of the International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (Vol. 58110, p. V001T02A015). ASME.

Horvitz, E., & Mitchell, T.M. (2024). Chapter 8: Scientific progress in artificial intelligence: History, status, and futures. In: *Realizing the Promise and Minimizing the Perils of Artificial Intelligence for the Scientific Community,* University of Pennsylvania Press, 147-194.

Howard, D., Eiben, A. E., Kennedy, D. F., Mouret, J. B., Valencia, P., & Winkler, D. (2019). Evolving embodied intelligence from materials to machines. *Nature Machine Intelligence,* 1(1), 12-19.

Hsu, H.P. (2025). From programming to prompting: developing computational thinking through large language model-based generative artificial intelligence. *TechTrends,* 69(3), 485-506.

Hughes, J., Abdulali, A., Hashem, R., & Iida, F. (2022). Embodied artificial intelligence: Enabling the next intelligence revolution. In: *Proceedings of the IOP Conference Series: Materials Science and Engineering,* (Vol. 1261, No. 1, p. 012001). IOP Publishing.

Idejiora-Kalu, N. (2024). Epistemology in AI (Transdisciplinary AI). *Transdisciplinary Journal of Engineering & Science,* 15, 135-152.

Jiang, Y., Li, X., Luo, H., Yin, S., & Kaynak, O. (2022). Quo Vadis artificial intelligence?. *Discover Artificial Intelligence,* 2(1), 4.

Keller, F. (2023). The concept of embodied human intelligence: power and limits.*Acta Philosophica: Rivista Internazionale di Filosofia,* 32, 1, 2023, 55-74.

Korteling, J.E., van de Boer-Visschedijk, G.C., Blankendaal, R.A., Boonekamp, R.C., & Eikelboom, A.R. (2021). Human-versus artificial intelligence. *Frontiers in artificial intelligence,* 4, 622364.

Krzanowski, R., & Polak, P. (2022). The meta-ontology of AI systems with human-level intelligence. *Philosophical Problems in Science,* (73), 197-230.

Lakoff, G., & Johnson, M. (1999). Philosophy in the flesh: The embodied mind and its challenge to Western thought. New York: Basic Books.

Liao, Y.C., & Holz, C. (2025). Redefining affordance via computational rationality. In:*Proceedings of the 30th International Conference on Intelligent User Interfaces,* (pp. 1188-1202).

Liu, H., Guo, D., & Cangelosi, A. (2025). Embodied intelligence: A synergy of morphology, action, perception and learning. *ACM Computing Surveys,* 57(7), 1-36.

Liu, Y., Chen, W., Bai, Y., Liang, X., Li, G., Gao, W., & Lin, L. (2025). Aligning cyber space with physical world: A comprehensive survey on embodied AI. *IEEE/ASME Transactions on Mechatronics,* 1-36.

Mambo, W. (2022). Aligning software engineering and artificial intelligence with transdisciplinary. *Transdisciplinary Journal of Engineering & Science,* 13, 21-36.

Mathis, M.W. (2026). Leveraging insights from neuroscience to build adaptive artificial intelligence.*Nature Neuroscience,* 29(1), 13-24.

McGregor, S. (2026). Embodied sensorimotor (hyper) intensionality. *Logic and Logical Philosophy,* 1-26.

McGregor, S.L. (2024). Shifting paradigms: Bringing transdisciplinarity into the light. *Transdisciplinary Journal of Engineering & Science,* 14, 303-316.

Müller, V. C., & Hoffmann, M. (2017). What is morphological computation? On how the body contributes to cognition and control. *Artificial Life,* 23(1), 1-24.

Müller, V.C. (2007). Is there a future for AI without representation?. *Minds and Machines,* 17(1), 101-115.

Nakajima, K. (2020). Physical reservoir computing - an introductory perspective. *Japanese Journal of Applied Physics,* 59(6), 060501.

Ni, H., & Cui, L. (2025). Embodied intelligence: A literature review. *Journal of Computer Science and Frontier Technologies,* 1(3), 23-32.

O'Regan, J.K., and Noë, A. (2001). A sensorimotor account of vision and visual consciousness. *Behavioral and Brain Sciences,* 24, 939-1031.

Paolo, G., Gonzalez-Billandon, J., & Kégl, B. (2024). A call for embodied AI. *arXiv preprint* arXiv:2402.03824.

Pedrola, F.P., & Vitari, C. (2023). Affordance theory for information systems project implementation: a process and organizational outlook. In:*Proceedings of the Americas Conference on Information Systems,* 1-11.

Perez, J.A., Deligianni, F., Ravi, D., & Yang, G.Z. (2018). Artificial intelligence and robotics. *arXiv preprint* arXiv:1803.10813, 147, 2-44.

Popa, E. (2021). Human goals are constitutive of agency in artificial intelligence (AI). *Philosophy of Technologies,* 34, 1731–1750.

Sareh, P., & Loudon, G. (2024). The form-affordance-function (FAF) triangle of design. *International Journal on Interactive Design and Manufacturing,* 18(2), 997-1017.

Sun, F., Chen, R., Ji, T., Luo, Y., Zhou, H., & Liu, H. (2024). A comprehensive survey on embodied intelligence: Advancements, challenges, and future perspectives. *CAAI Artificial Intelligence Research,* 3(9150042), 1.

Thelen, E., & Smith, L.B. (1994). *A dynamic systems approach to the development of cognition and action.* Boston: MIT Press.

Travis, I.L. (1990). Knowledge representation in artificial intelligence. *Clinic on Library Applications of Data Processing,* (27th: 1990).

Uddin, M.A., & Salam, H. (2025). Beyond rule-based context awareness: Large language models as adaptive cognitive layers in cyber-physical systems. In:*Proceedings of the AAAI Symposium Series,* 6(1), 140–147. https://doi.org/10.1609/aaaiss.v6i1.36045

Vapnik, V. (2013). The nature of statistical learning theory. Berlin: Springer Science & Business Media.

Varela, F.J., Thompson, E., & Rosch, E. (2017). *The embodied mind, revised edition: Cognitive science and human experience.* Boston: MIT Press.

Ward, D., Silverman, D., & Villalobos, M. (2017). Introduction: The varieties of enactivism. *Topoi,* 36(3), 365-375.

Yin, D., Ming, X., & Zhang, X. (2020). Understanding data-driven cyber-physical-social system (D-CPSS) using a 7C framework in social manufacturing context. *Sensors,* 20(18), 5319.

Zheng, X., Lu, J., & Kiritsis, D. (2022). The emergence of cognitive digital twin: vision, challenges and opportunities. *International Journal of Production Research,* 60(24), 7610-7632.

Zönnchen, B., Dzhimova, M., & Socher, G. (2025). From intelligence to autopoiesis: rethinking artificial intelligence through systems theory. *Frontiers in Communication.* 10:1585321. DOI: 10.3389/fcomm.2025.1585321.