Scholarly Article

Service-Dominant Logic in the AI Era

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Abstract

The rapid growth of artificial intelligence (AI) reflects its widespread adoption across various industries and occupations. Yet, much of the discourse still conceptualizes AI narrowly as a property of computational machinery. Within marketing and service scholarship, such mechanistic framings obscure the relational and systemic dimensions of intelligence that become salient in AI-enabled service interactions. Drawing on service-dominant (S-D) logic, this paper reconceptualizes intelligence as an emergent property of adaptive, self-organizing service ecosystems, foregrounding the systemic processes and relational configurations through which actors and their capacities take form. As intelligent technologies become increasingly entangled in service exchange, they render more visible and consequential the ongoing interactions through which human and non-human actors are co-constituted, underscoring the need for a clearer relational-ontological grounding of S-D logic. We conceptualize adaptation and intelligence as a generative duality: adaptation captures the adjustments enacted within a service ecosystem, whereas intelligence denotes the systemic capacity enabling those adjustments through feedback, learning, and institutional co-evolution. This perspective strengthens S-D logic's relational foundations by showing that AI exemplifies—rather than disrupts—the emergent, relational processes through which service ecosystems coordinate, evolve, and create value.

Keywords

service-dominant logic, artificial intelligence, service ecosystems, distributed intelligence, emergence

> "Intelligence is the ability to adapt to change" (Stephen Hawking), making "cognition the very process of life" (Capra and Luisi).

Introduction

Conversations about artificial intelligence (AI) have become central to discourse as society faces significant shifts in work, daily life, and human potential. The rapid adoption of AI across industries and regions reflects its ubiquity and potential to reshape society. McKinsey's global survey on AI (Singla and Sukharevsky 2024) found that more than two-thirds of respondents across almost all regions reported using AI in various areas of their organizations. The rise of large language models (LLMs) such as ChatGPT has accelerated this trend, contributing to an exponential increase in global AI adoption and investment. This acceleration has sparked both enthusiasm and concern, underscoring the promises and risks of AI across various areas of life. Yet, while discussions of AI's impact have permeated popular, practitioner, and academic literature (Belk 2021; Bostrom 2014; Noble 2018), the dominant conceptualization of AI remains narrowly focused.

In marketing and service research, AI has been studied largely as a property of computational machinery—increasingly sophisticated algorithms embedded in technological artifacts designed to automate tasks and replicate human intelligence (Huang and Rust 2018) and even emotions (Huang and Rust 2024). This micro-theoretical framing has provided important insights into the computational aspects of information processing and how AI is being utilized in business and society. However, it remains anchored in a Newtonian mechanistic worldview, which, when applied to the concept of intelligence, commonly leads to conceptualizations of intelligence as a property of discrete, independent entities functioning within (somewhat) predictable systems. By contrast, contemporary intelligence research across fields such as cognitive science, systems theory, and neurobiology suggests that intelligence is not merely a computational capability but an emergent, dynamic phenomenon that arises from interactions within complex systems (Capra and Luisi 2014).

These systemic perspectives challenge mechanistic assumptions by emphasizing intelligence as a relational, emergent phenomenon. A prominent expression of this shift is the literature on collective intelligence (CI) (Flack et al. 2022), which examines how cognitive capacities arise across interacting groups rather than within isolated entities. Broadening prevailing conceptions of intelligence beyond narrow AI-centric views and toward collective and systemic perspectives underscores the need for marketing and service research to engage more deeply with contemporary perspectives on intelligence, as failing to do so risks obscuring how AI-driven interactions cocreate value, transform markets, and reconfigure systems of value cocreation and service exchange. As Russell (2016, p. 7), a leading AI scholar, emphasizes, AI's aim is not to mimic human cognition but to "create and understand intelligence as a general property of systems, rather than as a specific attribute of humans." This systemic view of intelligence opens the door to conceptualizing both human and technological intelligence as emergent capacities of dynamic systems rather than properties of isolated entities. However, while CI research moves beyond individual cognition, it often struggles to explain how heterogeneous actors come to participate in and contribute to such intelligence. This limitation stems from treating actors as pre-defined units that then interact, leaving unanswered how their capacities emerge within systems. In other words, prior research in CI presupposes the very entities whose collective capabilities it seeks to explain.

The need to expand our understanding of the source and nature of intelligence in the AI era raises an important theoretical question for marketing and service research: How should intelligence—and AI in particular—be conceptualized once it is understood as an emergent property of service ecosystems rather than as a computational capacity of isolated actors? To address this question, we apply the service-ecosystem perspective of service-dominant (S-D) logic (Vargo and Lusch 2004, 2008, 2016) as an organizing framework (Vargo 2023). S-D logic provides a transcending lens for conceptualizing the cocreation of intelligence in dynamic systems of service exchange. It is established as an indigenous theoretical tradition within marketing and service research that has gained substantial traction in contemporary work (Bolton 2020; Sheth, Parvatiyar, and Uslay 2022). Moreover, S-D logic and its service ecosystem lens naturally align with established systems-based conceptions of intelligence but have not yet been applied in developing a framework for intelligence in general, and AI more specifically. We integrate S-D logic with insights from systems thinking, assemblage theory, and quantum theory to develop a framework for (artificial) intelligence as an emergent property of adaptive, self-organizing service ecosystems. This framework reveals conceptual limitations in prior S-D logic work while extending its account of emergent properties and processes in service ecosystems.

As intelligent technology is increasingly integrated in service exchange (Jim et al. 2022), the boundaries between human and non-human actors blur, demanding a richer theorization of how their roles and capacities are mutually constituted. Rather than treating technology as an external tool or passive enabler, AI foregrounds its active participation in shaping value creation and coordination. This perspective aligns with *relational ontologies*, which view agency as *emerging within interactions rather than being inherent to discrete entities*—a perspective sometimes referred to as intra-action (Barad 2007). From this standpoint, the rise of AI necessitates a reconsideration within S-D logic of how cognition, value creation, and governance emerge through recursive sociotechnical relationships. By highlighting the entanglement of human and non-human contributions, AI draws attention to residual traces of anthropocentric assumptions in some S-D logic interpretations, even as S-D logic has increasingly moved toward distributed, relational views of agency and meaning-making. In doing so, AI foregrounds coordination and institutional emergence as distributed, relational processes through which intelligence, as a systemic capacity, enables adaptive adjustments that sustain the viability of service ecosystems over time.

Accordingly, this manuscript has two aims: (a) to develop an S-D-logic–based framework for understanding the processes and functions of AI in service ecosystems and (b) to extend and refine S-D logic's ontological foundations by incorporating relational and systems-oriented perspectives necessary for conceptualizing intelligence as an emergent, ecosystemic phenomenon. We proceed as follows: First, we examine dominant conceptualizations of AI in marketing and service literature, highlighting their reliance on mechanistic assumptions. Next, we synthesize insights from intelligence theory, cognition, and complex systems to develop a framework that conceptualizes intelligence as an emergent capacity of service ecosystems, extending and refining S-D logic's grounding in relational and systemic ontologies. Finally, we explore the implications for AI's role in creating value in service ecosystems, offering a pathway forward for advancing research, managerial practice, and policy in an era of increasingly intelligent (i.e., adaptive) technology.

Intelligence as a Systemic Phenomenon

The marketing and service fields offer several important frameworks at the intersection of AI and strategic marketing, service provisions, and retail adoption (e.g., Davenport et al. 2020; Guha et al. 2021; Huang and Rust 2021). As shown in Table 1, these frameworks generally focus on midrange theoretical developments, assuming that AI is well understood. In fact, they describe AI in a very similar manner, as the property of a "computational machinery" (Huang and Rust 2021, p. 31), sets of "programs, algorithms, systems and machines" (Davenport et al. 2020, p. 25) that "emulate capabilities inherent in humans"

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Table 1. AI Literature Comparison.

Paper Elements	Current Article	Huang and Rust (2018; 2021)	Huang and Rust (2024)	Davenport et al. (2020)	Guha et al. (2021)
Research Type	Conceptual article	Conceptual articles	Conceptual article	Conceptual article	Empirical article with propositions
Main Purpose	Reconceptualizing intelligence as an emergent property of service ecosystems.	Explaining mechanical, cognitive, and feeling AI and their strategic deployment.	Conceptualizes customer care as a GenAI-enabled journey from emotion recognition to emotional connection.	Explaining AI's impact on marketing activities and decisions.	Examining AI adoption in retail contexts.
Level of Abstraction	Meta-theoretical	Midrange—theoretical	Midrange—theoretical	Midrange—theoretical	Midrange—theoretical
Level of Analysis	Service ecosystems and relational constitution.	AI systems, marketing tasks, and human—AI role allocation.	Human—AI interactions in emotionally charged service encounters.	Task-level and organizational-level AI applications.	AI—customer and AI—employee interactions in retail.
Definition of AI / Intelligence	Relationally emergent intelligence arising from interactions among human and non-human actors.	"Manifested by machines that exhibit aspects of human intelligence (HI)." (Huang and Rust 2018).	"Feeling AI" oriented toward emotion recognition, empathy, and emotion management.	"Refers to programs, algorithms, systems and machines that demonstrate intelligence" (Shankar 2018, p. vi).	"A system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation."
AI and HI Contrast	Ontological parity; intelligence emerges relationally.	AI parallels or approximates multiple forms of human intelligence.	AI simulates empathy but differs from humans in sincerity and commonsense reasoning.	See Huang and Rust (2018), machines can parallel types of human intelligence."	AI intelligence below or comparable to humans, depending on task.

Note. AI = artificial intelligence; HI = human intelligence.

Table 2. Adaptation as a Fundamental Manifestation of Intelligent Behavior.[1]

HI	AI
"[. . .] is judgement, otherwise called good sense, practical sense, initiative, the faculty of *adapting* one's self to circumstances." (Binet and Simon 1905)	"[is] any system [. . .] that generates *adaptive* behavior to meet goals in a range of environments can be said to be intelligent." (Fogel 1995)
"[. . . is] the capacity to meet novel situations, or to learn to do so, by new *adaptive* responses." (Drever 1952)	"Intelligence is the ability for an information processing system to *adapt* to its environment with insufficient knowledge and resources." (Wang 1995)
"[. . .] adjustment or *adaptation* of the individual to his total environment, or limited aspects thereof[. . .] (Freeman quoted in Sternberg 2000)..	[. . .] requires a highly *adaptive*, general-purpose system that can autonomously acquire an extremely wide range of specific knowledge and skills and can improve its own cognitive ability through self-directed learning." (Voss 2007)
"Ability to *adapt* oneself adequately to relatively new situations in life." (Pinter quoted in Sternberg 2000)	"[. . .] in any real situation behavior appropriate to the ends of the system and *adaptive to* the demands of the environment can occur, within some limits of speed and complexity." (Newell and Simon 2007)
"[. . .]certain set of cognitive capacities that enable an individual to adapt and thrive in any given environment they find themselves in[..]" (Simonton 2003)	

Note. AI = "Artificial" Intelligence; HI = human intelligence.

(Huang and Rust 2021, p. 31), machines mimicking "intelligent human behavior" (Syam and Sharma 2018, p. 136), and intelligence "comparable to humans" (Guha et al. 2021, p. 29). More recently, Huang and Rust (2024) advance this line of work by introducing "feeling AI" and a GenAI-enabled customer care journey; however, their framework remains grounded in an understanding of intelligence as a machine capability.

At the same time, some work within and adjacent to this literature begins to problematize this purely machine-centered understanding of AI by questioning whether intelligence can be meaningfully attributed to isolated artifacts. Earlier work by Huang and Rust (2018, p. 161), for example, points out that advances in "the Internet and communication technologies significantly scale up AI's self-learning ability to the entire network rather than individual machines," resulting in more complex and emergent forms of intelligence. Similarly, Hoffman and Novak (2018) argue that consumer experiences in the Internet of Things are shaped by assemblages of everyday objects communicating with each other and consumers via the Internet. Extending this argument further, Crawford (2021) emphasizes that AI is not autonomous but relies on extensive resources, labor, and infrastructure.

This critique of machine-centered, human-like conceptions of AI gains further force when considering the absence of a unified definition of human intelligence (HI) itself. As Sternberg et al. (1981, p. 6) point out, "there seem to be almost as many definitions of [HI] as there were experts asked to define [it]." Likewise, Legg and Hutter (2007, p. 2) state that "Despite a long history of research and debate, there is still no standard definition of intelligence," and in their review of 71 definitions, the authors identify three common attributes of HI: (a) "a property that an individual agent has as it interacts with its environment or environments," (b) "related to the agent's ability to succeed or profit with respect to some goal or objective," and (c) "how able the agent is to adapt to different objectives and environments" (Legg and Hutter 2007, p.9). That is, while the traditional HI literature views intelligence as a property of an individual actor, it converges on the notion that intelligence can only be understood in the context of goal-driven interaction and adaptation processes in relation to an environment, echoing the need for a more systemic view of intelligence. As shown in Table 2, adaptation emerges as a fundamental feature of intelligent behavior across both *human* and *artificial* intelligence domains.

The definitions in Table 2, consistent with the frameworks in Table 1, generally link adaptive capabilities to the cognitive functions of humans or computational machinery. However, the concept of adaptation has its intellectual roots in systems thinking, where fields such as evolution and ecology have long provided foundational insights into adaptive behavior. In the study of "minimal cognition," for example, recent research finds that plants exhibit adaptive, anticipatory, and goal-directed behaviors consistent with Legg and Hutter's (2007) conceptualization of intelligence. Calvo Garzón and Keijzer (2011, p. 157) observe that "plants are sensitive to a variety of signals" that yield future advantages, such as roots adjusting growth based on future mineral and water acquisition. Those signals include light, soil structure, and competition—demonstrating that "plant cognition [is]. . . adaptive, flexible, anticipatory, and goal-directed" (Segundo-Ortin and Calvo 2022, p. 3). While work on minimal cognition centers on a focal actor (i.e., the plant), it shows that cognition is not limited to mental processes of an individual brain or species but emerges as biological systems "interact at many levels" (Calvo Garzón and Keijzer 2011, p. 159).

Similarly, HI cannot be separated from the systemic interactions in which it operates (Schlinger 2003). In fact, in what has become known as the Santiago Theory of Cognition, Maturana and Varela (1991) argue that cognition needs to be reframed from an individual human phenomenon to a systemic one. Specifically, they reframe cognition from the mental activities related to acquiring and processing information to the distributed, autopoietic processes through which all living networks self-generate and self-perpetuate. Cognition, in this view, transcends individual brains, becoming a primary mechanism for life's self-perpetuation across ecosystems, or as Capra and Luisi (2014, p. 253) state, "cognition [is] the very process of life."

S-D logic as a Foundation for Conceptualizing Intelligence

As noted, we propose that an S-D logic, service ecosystems perspective can serve as an organizing theoretical framework (Vargo 2023) for understanding the root of "artificial" intelligence, as it accommodates a more contemporary understanding of intelligence while connecting directly with the service and marketing literature. In doing so, it aligns naturally with and helps interpret other frameworks that conceptualize intelligence as a dynamic, relational, and systemic phenomenon (e.g., Beer 2004; Capra and Luisi 2014).

S-D logic is a metatheoretical shift in thinking about value creation and markets that argues for service, or the application of resources, as the basis of exchange (Vargo and Lusch 2004, 2008). Recently, Sheth, Parvatiyar, and Uslay (2022) described S-D logic as a leading candidate for the development of a general theory of marketing. Similarly, Kotler et al. (2021) referred to S-D logic as the "grand theory" of marketing, and Bolton (2020) believes that many marketing academics have already adopted S-D logic thought, especially its cocreative and systemic orientations, although many without realizing it. In the service context, Field et al. (2021) further reinforce the importance of S-D logic in understanding and designing sustainable service ecosystems.

The S-D logic service ecosystems perspective emphasizes how *value is cocreated through dynamic interactions among various actors* in socioeconomic systems. Service ecosystems are defined as "relatively self-contained, self-adjusting system[s] of resource-integrating actors connected by shared institutional arrangements and mutual value creation through service exchange" (Vargo and Lusch 2016, pp. 10–11). This definition, grounded in systems thinking—including complexity theory (Vargo and Lusch 2016)—reframes value "from a property of output to an experiential outcome, a measure of a change in viability, [or] well-being" of a system (Vargo and Lusch 2017, p. 54). Institutional arrangements—comprising interdependent norms, rules, and meanings—guide these cocreative processes, fostering adaptation and innovation.

Importantly, any given ecosystem comprises multiple overlapping subsystems that are themselves nested within higher- and lower-order systems. Thus, a system's viability can be assessed from numerous viewpoints and levels, and at any point in time, viability will vary across its nested and overlapping components. From this perspective, brains and computational machinery are higher-level systemic aggregates themselves because brains are composed of dynamic networks of molecules, cells, and tissues (Watson and Levin 2023), while computational machinery operates through interconnected graphics processing units (GPUs), algorithms, and user interactions. This nested structure, as Capra and Jakobsen (2017, p. 835, emphasis added) note, means that "each individual system is an *integrated whole and, at the same time, part of larger systems*." Thus, the *actor–environment dualism* commonly invoked in intelligence research *arises from the observer's analytical lens, not from any inherent division within the relational dynamics that constitute intelligence.*

S-D logic's ecosystems perspective provides an organizing framework for reconceptualizing the sociotechnical and systemic nature of AI because of its institutional grounding, which makes it reconcilable with well-established and emerging conceptualizations of the social construction of technology (Bijker 1997; Orlikowski 1992; Pinch and Bijker 1987; Vargo, Wieland, and Akaka 2015), as well as those of technological governance (Vargo, Fehrer, et al. 2023). At the same time, this institutional grounding is fundamentally relational, blurring distinctions between human and non-human actors and emphasizing the governance mechanisms that sustain systemic adaptation.

From this relational standpoint, understanding intelligence requires moving beyond interactions among pre-existing actors and toward the relational processes through which actors and their capacities are continually formed and transformed. Although S-D logic has long emphasized interaction, it *has yet to fully develop the relational ontology required to account for this co-constitutive view of actors and action*. By engaging complementary frameworks—CI, systems thinking, and relational ontologies—we argue that system viability is not a function of individual actors' computational capabilities but of the dynamic, interdependent processes through which intelligence becomes expressed in ecosystems. This requires attention to the capacities that emerge through interactions among heterogeneous actors, as it is this relationally generated intelligence that enables adaptation and, ultimately, system viability. The generative nature of service ecosystems requires further development of S-D logic to shift attention from the attributes of actors and their interactions to the relational constitution of capabilities, revealing service ecosystems themselves as autopoietic and cognitive systems. A natural starting point for developing this ecosystemic account of intelligence is the literature on CI, which demonstrates how collective capabilities emerge from distributed interactions rather than from individual actors.

How (Artificial) Intelligence Supports System Viability

Collective Intelligence

In this section, we introduce CI as an empirically grounded perspective for understanding how adaptive capacities emerge from distributed interaction rather than from isolated actors. CI is a body of work spanning fields such as "computer science, sociology, neuroscience, biology, political science, physics, and management" (Flack et al. 2022, p. 2). In business literature, studies show that crowds can outperform individuals and even firms (Boudreau and Lakhani 2013). Biology contributes insights through studies of beehives and ant colonies (Malone and Bernstein 2022), where insects collectively respond to environmental challenges—a concept also applied to robotic systems, where swarm behavior enhances adaptation (Parker 2007). Swarm intelligence illustrates how complex coordination can emerge from simple local interactions among agents (Bonabeau, Dorigo, and Théraulaz 1999). Through decentralized feedback and minimal communication, swarm systems achieve coherence, resilience, and adaptability—properties mirrored in AI-enabled networks and service ecosystems. Just as swarms organize through distributed sensing and self-adjustment, service ecosystems evolve through recursive exchanges and feedback loops that sustain value cocreation and systemic viability (Vargo, Akaka, and Wieland 2020).

However, as Malone and Bernstein (2022) observe, CI lacks a widely accepted definition, just as HI has long faced similar definitional challenges. Lévy (1997, p. 16) describes CI as a form of "universally distributed intelligence," constantly enhanced, coordinated in real time, and resulting in the effective mobilization of skills." In contrast, Smith (1994, p. 1) defines it as "a group of human beings [carrying] out a task as if the group, itself, were a coherent, intelligent organism working with one mind, rather than a collection of independent agents." Such dynamics have been observed in marketing organizations, where individual and collective cognitions converge to produce superior coordination and performance (Rust, Moorman, and van Beuningen 2016). These perspectives converge on the idea that CI emerges from interactions among actors who cocreate value. Historically, studies have focused on homogeneous groups (e.g., human groups, ant colonies, robotic swarms) in settings like families, armies, or organizations. However, as technology advances, there is a growing interest in CI arising from human-technology interactions. Malone and Bernstein (2022), for example, identify human computation, crowdsourcing, and collaborative technologies as critical to contemporary CI research.

Recent work increasingly frames this shift toward human-technology CI in terms of advances in AI itself. In particular, the shift from artificial narrow intelligence (ANI) to artificial general intelligence (AGI) further contributes to this growing focus on human–computer interactions (Guha et al. 2021; Müller and Bostrom 2016). ANI encompasses AI systems designed for specific tasks within a limited scope, unable to operate beyond their predefined functions. AGI, in contrast, represents AI capable of understanding, learning, and applying knowledge across diverse tasks and domains. With the progression toward AGI, computational technologies are increasingly seen as "smart enough" to engage in CI. For example, Weld, Lin, and Bragg (2015) show that AI technologies enhance efficiency in human interactions and are increasingly viewed as participating actors rather than mere support tools. Nevertheless, work on CI often sustains a distinction between humans and technological artifacts—a divide that, implicitly, is only bridged once technologies are deemed "smart" or anthropomorphic enough to qualify as CI participants.

While prior research highlights the cognitive advantages of CI over isolated brains, it often struggles to explain how heterogeneous actors come to participate in and contribute to such intelligence. The limitation stems from treating actors as independently constituted units that then interact, leaving unanswered how their capacities emerge within a system. To address this, we draw on theoretical perspectives that support and extend S-D logic by emphasizing that, in heterogeneous networks, *actors and their capacities emerge from the relational arrangements that constitute them*. From this perspective, the emergent intelligence observed in service ecosystems arises not simply from exchanges among distinct entities but from the *continual formation of actors within evolving assemblages of relations.*

Relational Ontologies

In this section, we draw on assemblage theory and actor–network theory to demonstrate how heterogeneous human and non-human actors are constituted through relations rather than treated as pre-given entities. Assemblage thinking—associated with the work of Deleuze and Guattari (1987)—offers a powerful lens for understanding the distributed and relational nature of intelligence in the AI era. An assemblage is "a multiplicity which is made up of many heterogeneous terms and which establishes liaisons, relations between them, across ages, sexes and reigns—different natures" (Deleuze and Parnet 1987, p. 69), emphasizing that outcomes arise from connections among diverse human and non-human elements. This is particularly salient for AI, which is never a single technological artifact but a sociotechnical configuration of algorithms, data, infrastructures, institutions, and human practices.

Hoffman and Novak (2018) note a growing adoption of assemblage theory and actor-network theory (ANT) in consumer culture, marketing, and "consumption" research. ANT, sometimes viewed as assemblage theory's "empirical sister-in-arms" (Müller 2015, p. 30), is recognized for emphasizing the dynamic and interconnected nature of social and material elements. Law (2009, p. 141) describes ANT as "a disparate family of material-semiotic tools, sensibilities, and methods of analysis that treat everything . . . as a continuously generated effect of the webs of relations within which they are located." ANT asserts that entities have no inherent form or reality outside the enactment of their relationships. Arguably, by dissolving dualisms such as "human versus machine" or "social versus technical," ANT provides the ontological footing needed to conceptualize AI as a co-constituted service actor rather than an external tool.

From this perspective, ANT shares significant overlap with the service ecosystems view. Both perspectives prioritize relationships among heterogeneous actors—individuals, organizations, resources, and technologies—and suggest that value emerges from these collaborative relationships (Vargo and Lusch 2016). Through their interdependencies, these actors form a system in which the social and technical are inseparably intertwined, creating a dynamic that enables value cocreation.

Latour (1996, p. 8), in a study of computerized work sites, posits that human cognition has become "distributed" and "situated" and "is now shared with many intellectual technologies to the point where studying a human is studying a field of forces and transfers of documents, instruments, ideographies, through a collective of similarly distributed fellows, some of them look anthropomorphic but many don't." As "intelligent technology" has become increasingly ubiquitous beyond such sites, the need to reconceptualize intelligence has only intensified. In this way, both assemblage theory and ANT offer core insights into the evolution of AI within service ecosystems.

> "With so many intellectual technologies being introduced from writing to laboratories, from rulers to pebbles, from pocket calculators to material environments, the very distinction between natural, situated, tacit intelligences and artificial, transferable, disembodied ones has been blurred. Intelligence no longer seems a psychological or even a cognitive property, but something more akin to heterogeneous engineering and world making, a distributed ability to link, associate, tie, fragments of reasoning, stories, action routines, subroutines, and to hang them to many holders some of them look like neurone nets, other like softwares, other like graphics, still other like conversations and rituals" (Latour 1996, p. 8).

That is, assemblage thinking aligns with, and informs S-D logic, by pointing to the fact that neither the intelligence of a human nor a non-human actor is embedded in brains or computational devices but emerges through webs of interactions and the practices that carry them. Categorizing AI in terms of how artificially intelligent machines take on human characteristics distracts from the more important understanding of how intelligence is continuously generated through webs of relations among human and non-human actors.

S-D logic and assemblage thinking further share an emphasis on *emergence, wherein* outcomes arise from the interactions among system elements and cannot be reduced to the properties of any individual component. As DeLanda (2006, p. 11) explains, "the properties of the component parts can never explain the relations which constitute a whole." Similarly, Vargo et al. (2023) describe emergent properties as arising from relational dynamics among system elements and as being qualitatively distinct. Hoffman and Novak (2018) elaborate on this by noting that new capacities of the assemblage emerge as a result of interactions between humans and technology. This emergent behavior of systems means that neither the intelligence of a technology nor that of a human can be fully explained without considering the interactions within a system and the relationships through which systems are established and maintained.

Systems Thinking, Quantum Relationality, and Adaptive Viability

Across S-D logic, CI, and assemblage theories runs a shared relational insight: technologies are not autonomous entities but sociotechnical assemblages enacted through interactions among heterogeneous human and non-human actors (e.g., Pinch and Bijker 1987; Vargo, Wieland, and Akaka 2015; Wieland, Hartmann, and Vargo 2017). Systems thinking and quantum-relational perspectives deepen this insight by explaining how such relational configurations sustain system viability through feedback, adaptation, and co-constitutive processes over time. AI technologies make this systemic logic particularly visible, as their capabilities emerge only through ongoing interactions with data, infrastructures, users, and institutional arrangements that define their purposes and meanings.

One might argue that this co-constitutive view of technology occupies only a minor place within broader ontological debates. However, as Capra and Luisi (2014, p. 65) point out, systems thinking—"thinking in terms of connectedness, relationships, patterns, and context"—and the stated understanding that the whole is greater than the sum of its parts has increasingly become adopted by many fields (e.g., biology, psychology, ecology, and physics) and can be found in multiple ontological perspectives (Murphy 2021). In contrast to Newtonian reductionism, where intelligence or causality can be located in discrete entities, systems thinking suggests that intelligence arises through feedback, adaptation, and co-dependence among system components. This is especially apparent in service ecosystems involving AI actors, where learning and feedback continually shape system behavior.

The ongoing shift to relational ontologies has been accelerated by insights from quantum theory, which reveal that "interaction is an inseparable part of [any] phenomenon" (Rovelli 2022, p. 140). Moreover, quantum theory *replaces deterministic certainties with probabilistic tendencies*, foregrounding a world in which outcomes are not predetermined but emerge from the relational configuration of possibilities. These insights resonate strongly with AI systems, whose behavior cannot be understood by examining algorithms or data in isolation but only through their entangled interactions with users, infrastructures, and institutional contexts. In this sense, AI represents a paradigmatic expression of quantum-relational thinking, revealing forms of cognition that are *probabilistic, context-dependent, and enacted through entangled processes of value cocreation* among human and non-human actors.

This quantum-relational worldview has also been adopted in the social sciences, where theorists such as Karen Barad and Alexander Wendt draw on quantum principles to challenge traditional distinctions between human and non-human actors. Barad's (2007) concept of intra-action reframes agency as an enactment rather than an attribute of pre-existing entities, while Wendt (2015, p. 260) describes agents and structures as "mutually constitutive" and co-emergent. These perspectives highlight that systemic relations—among people, institutions, and technologies—continuously reshape social structures. Governing mechanisms (i.e., institutions) therefore play a pivotal role in sustaining and directing the emergence of intelligence within these dynamic systems.

This suggests that understanding how technology becomes intelligent requires an interconnected quantized conceptualization since, as Rovelli (2022, p. 140) states, "all nature is quantum." Importantly, a systemic perspective does not deny the necessity of computing power, algorithms, or neural architectures in AI systems; rather, it recognizes that these elements only become constituted and intelligent through their participation in wider networks. It is through the interactions among heterogeneous actors that adaptations in systems occur and system viability is sustained. In the next section, we build on these insights to examine how the interplay of technology, governance, and intelligence forms a higher-order framework for understanding the adaptive nature of service ecosystems.

Building Blocks of (Artificial) Intelligence

Traditionally, the concepts of intelligence, technology, and governance are treated as distinct categories, a separation that appears so intuitive that it rarely invites scrutiny. However, when viewed through an S-D logic, service ecosystem lens, this division loses its relevance. Instead, intelligence as adaptive capacity, technology as an agentic resource (Akaka and Vargo 2014), and governance as institutions (Vargo 2011) are *best understood as intertwined aspects of dynamic, evolving service ecosystems that sustain system well-being through self-regulation and adaptation.* In this view, all three participate in the broader process of cognition (cf. Capra and Luisi 2014). In the context of technological intelligence, these interdependencies become particularly visible, making AI an ideal setting for examining how intelligence, technology, and governance co-emerge.

Technology

The concept of technology is complex and multifaceted, often defying simple definitions. Pinch (2008) highlights its elusiveness, noting that the term has acquired various and often restrictive meanings, especially in relation to material constraints. To address this, prior S-D logic research (Akaka and Vargo 2014) has built on Orlikowski's (1992) sociomaterial perspective and Arthur's (2009) idea of technology as "assemblages of practices and components" designed to achieve human goals. This perspective encompasses both tangible hardware and intangible processes or methods. For instance, LLM platforms are combinations of both hardware and software as these AI systems are composed of databases, GPUs, machine learning programming languages, training data, and prompt engineering (Davenport et al. 2020), all of which are embedded in broader sociomaterial and natural ecosystems that shape and are shaped by ongoing interactions among human and non-human actors.

Other definitions of technology, such as those by Hughes (1989) and Mokyr (2004), also avoid a clear demarcation between physical components and processes by framing technology as an endeavor to "arrange the world for problem-solving" or as "useful knowledge." These definitions resonate with systems thinking in that they view technology as inseparable from the sociotechnical practices through which it is developed and used. Arthur (2009) describes technological evolution as a combinatorial process in which new elements are synthesized from existing ones, continually generating new "building blocks" for future developments. In AI systems, this combinatorial process is often amplified and accelerated, as algorithms, data sources, and computational architectures continually feed into one another's evolution.

Combinatorial evolution underpins not only technological innovation but also *broader institutional change*. Vargo and Lusch (2016) suggest that institutional change follows a similar combinatorial process. Actors reshape institutional arrangements by recombining elements of existing ones, fostering collaborative reflection and redefining collective action (Thornton and Ocasio 2008). In line with Kant's notion that the whole exceeds the sum of its parts, these recombinations generate emergent wholes whose properties cannot be inferred from the components alone. From an ecosystemic perspective, *technological change* is, in essence, *institutional change*. Technology embodies institutional arrangements and co-evolves with the social systems that constitute those arrangements. Both AI and HI emerge from the (re)combination of resources, where networked interactions among humans and non-human actors shape meanings, perceptions of usefulness, and governance systems that uphold social order.

Governance

Understanding technologies as institutional arrangements implies that *governance is an intrinsic part of the intelligence processes through which service ecosystems adapt and evolve*. Accordingly, Palay (1984, p. 265) characterizes governance as "a shorthand expression for the institutional framework" within which behaviors, rules, and norms are "initiated, negotiated, monitored, adapted, and terminated." This perspective challenges recent discussions on AI, which present governance as an external (to technology) responsibility (Zaidan and Ibrahim 2024). Such discussions often narrowly focus on the responsibilities of two types of actors—AI-creating companies and the regulating authorities. While the White House, for example, points out that the "private sector has an ethical, moral and legal responsibility to ensure the safety and security of their products" (i.e., a call for corporate digital responsibility [CDR]), others call for governmental regulations (McCabe 2023).

This actor-centric view of governance is not unique to the AI discourse; it mirrors broader work on exchange, where governance is often perceived to be limited to government regulations, legal contracts, and other enforceable rules. However, research has long noted that this limited focus on legally enforceable governance is insufficient (Cannon, Achrol, and Gundlach 2000). The institutional perspective of S-D logic offers an alternative view by framing governance as a collaborative process involving numerous actors and their interactions, embedded in systems of service exchange. Since *technologies are institutional arrangements and technological change is institutional change*, technologies cannot exist without gaining shared perceptions of governance structures across interaction and value cocreation (e.g., perceptions of usefulness). In other words, as technology emerges through interactions, so does the governance required to integrate, adapt, and exchange technology.

From this perspective, AI governance is also an emergent property of service ecosystems, arising from the recursive interactions among developer communities, platform infrastructures, users, and institutional arrangements. Through these interactions, norms of responsible use and value creation take shape. This ecosystemic view reframes governance from a top-down mechanism of control to a distributed, emergent property of interaction—an expression of the same adaptive and self-regulating principles that underlie S-D logic's conception of service ecosystems.

This relational–institutional view of governance also reshapes how we understand markets. Far from the static, predetermined constructs of neoclassical economic thought, markets are dynamic, shaped by social, sociomaterial, political, discursive, and systemic influences (Fligstein 1996; Giesler 2008; Humphreys 2010; Nenonen et al. 2014; Rosa et al. 1999; Wieland, Hartmann, and Vargo 2017). From an ecosystemic perspective, markets function as governing institutions that define and regulate the conditions of participation, resource access, and coordination among heterogeneous actors. In the context of AI, this means *that markets themselves play a central role in governing how AI is developed, deployed, evaluated, and adapted*. Market arrangements shape the expectations placed on AI systems, the distribution of responsibilities among actors, and the norms that guide responsible use. Actors who deviate from market "rules," for instance, may face unfavorable conditions or be excluded from exchanges. Given this institutional grounding for technology and governance, markets can be viewed as technologies themselves, serving as "assemblage[s] of practices and components" (Arthur 2009, p. 28) designed to meet human needs, such as facilitating efficient and equitable exchanges. In the following section, we leverage an institutional and relational approach to explore AI as an ecosystemic phenomenon.

Understanding AI as an Ecosystemic Phenomenon

The integration of AI into service ecosystems makes the fundamental processes through which intelligence, technology, and governance coevolve increasingly visible. Within an S-D logic perspective, intelligence is not an attribute of isolated entities but a property that arises from continuous adaptation, feedback, and resource integration across systems of human and non-human actors. In this sense, the increasing use of AI reveals—rather than replaces—what can be understood as an *ecosystemic view of intelligence*: the *distribute*d capacity of service ecosystems to learn, self-adjust, and sustain viability through ongoing interactions and, more fundamentally, intra-actions that reflect a relational ontology in which actors' *capacities are constituted within relations rather than prior to them.*

Here, adaptation and intelligence form a generative duality—two inseparable manifestations of the same systemic process. *Adaptation* represents the enacted adjustments and responses within a service ecosystem, while *intelligence* denotes the generative capacity that gives rise to those adjustments through feedback, learning, and institutional co-evolution. This duality captures the recursive interplay between what systems do and the deeper cognitive potential that enables them to do so. Framing adaptation through an ecosystemic view of intelligence thus deepens S-D logic's account of how service ecosystems sense, respond, and reorganize—how they adapt—in the face of technological change.

From this standpoint, *AI is not a technological artifact endowed with intelligence but an institutional phenomenon that materializes through the recursive intra-actions among human and non-human actors* (see Figure 1). Each instance of AI deployment—whether in generative systems, recommender platforms, or autonomous agents—illustrates how service ecosystems collectively enact intelligence. Technological design, user feedback, and institutional norms coalesce to form feedback loops that continually reconfigure how value is cocreated and evaluated, underscoring the relational constitution of actors, roles, and capacities.

S-D logic's system orientation aligns with this understanding. Value creation and adaptation occur not only through interactions among "intelligent" actors but also through interactions with "nonintelligent" components—datasets, interfaces, physical infrastructures—that enable and constrain interaction. Furthermore, interactions do not presuppose actors to possess predefined or aligned goals; rather, goal orientations emerge through the relational and institutional dynamics in which actors are continually (re)formed, thereby sustaining the heterogeneity essential to ecosystem viability.

Drawing on Capra's (1997) foundational work on networks, feedback, and self-organization, the adaptability of ecosystems with AI actors can be viewed as the outcome of intertwined positive and negative feedback loops. Algorithmic learning mechanisms amplify successful patterns (morphogenesis), while governance structures and ethical constraints counterbalance and stabilize system behavior (morphostasis) (Maruyama 1963; Vargo, Akaka, and Wieland 2020). The dynamic interplay between these forces determines how the system evolves and maintains viability. In this respect, the intelligence of AI systems is not "artificial" but relational—emerging from the capacity of the service ecosystem to sense, respond, and reorganize itself in pursuit of ongoing value creation.

This perspective shifts our understanding of AI from a substitute for human intelligence to a mirror of ecosystemic cognition. Intelligence becomes observable in the ways AI-enabled service systems maintain coherence and adaptability through recursive human–machine interactions. Just as living systems exhibit cognition through self-maintenance (Maturana and Varela 1991), service ecosystems exhibit intelligence through the recursive co-constitution of human and non-human actors, ongoing institutional reconfiguration, and the continual renewal of service exchange.

Thus, AI provides a tangible expression of S-D logic's core principles, illustrating value creation as systemic adaptation, technology as a co-constitutive element in service exchange, and institutions as evolving patterns of coordination shaped by feedback and learning. In this sense, AI does not create a new form of intelligence; rather, it makes visible the adaptive and self-organizing capacities already inherent in service ecosystems.

As human and technological actors interact, feedback mechanisms foster learning, innovation diffusion, and governance adaptation, thereby sustaining the autopoiesis of the broader system (Vargo, Wieland, and Akaka 2015). In this way, AI is both a participant in and a manifestation of an ecosystemic view of intelligence. This framework solidifies S-D logic's foundation in a relational ontology and extends it to account for cognition, adaptation, and co-evolution in the AI era.

Discussion

Traditional approaches to both HI and AI assume that intelligence resides within individual actors and is reflected in their computational or behavioral competencies. We shift this focus by conceptualizing intelligence as an emergent, ecosystemic phenomenon—one that arises through the relations that constitute actors and their collective capacities rather than within the individual actors themselves. Drawing on an S-D logic service-ecosystems lens, and informed by theories of intelligence, systems, and technology (especially as articulated in relational ontologies), we position intelligence and technology as systemic, intra-actional processes generated within evolving service relationships.

This relational reframing provides the foundation for the remainder of the discussion. It enables us to reconsider the relationship between human and technological intelligence, to examine how governance and technology co-emerge within service ecosystems, and to articulate how an ecosystemic view of intelligence advances the theoretical development of S-D logic by expanding our understanding of the mechanisms that enable service ecosystems to survive, thrive, and even cease to exist.

Reframing the Relationship Between Human and Technological Intelligence

Framing intelligence as a localized manifestation of cognition, as seen in the comparison between HI and AI, invites a sense of competition in which AI appears to rapidly outpace human cognitive abilities. This trajectory, particularly in the shift from ANI to AGI, has raised significant ethical and societal concerns regarding potential risks, such as diminished human control over AI, unintended consequences, and broader impacts of highly autonomous systems. For example, while a simple, specialized AI like a smart thermostat (ANI) is perceived as fully controllable, the idea of AGI—an AI capable of solving diverse problems autonomously—stirs apprehension about superintelligent entities that could exceed human capabilities in most domains, as Bostrom (2014) cautions.

However, an ecosystemic view of intelligence reframes the relationship between HI and AI within a relational ontology, in which intelligence arises not from human beings or technologies themselves but from the configurations of relations that bring both into being. In this view, human and non-human actors alike are continually constituted through nested and overlapping systems of institutions, technologies, and value cocreation processes that generate adaptive capacities. In this context, AI is best understood as an artifact in the same sense as other human-designed systems, rather than as something exceptional in kind (Simon 1996).

Viewed through this relational–ecosystemic lens, intelligence becomes evident at the level of entire societies. One of the most effective indicators for the adaptive capacities of ecosystems might be the development of the world's GDP over time. As Bostrom (2014) shows, in the past 100 years, the world's GDP has grown exponentially. This is because social systems, such as cities and economies, can use the variety of interactions within their assemblages to achieve increasing returns to scale—i.e., they can scale superlinearly (West 2017). This suggests that superintelligence (i.e., intelligence that greatly exceeds the cognitive performance of the human brain) is not so much a future, potential state of technological artifacts but rather a characteristic of technologically driven human society, of which what we are now calling AI, is just the latest iteration.

Governance Mechanisms Are Integral to the Creation and Adoption of AI

Our exploration suggests that technology, intelligence, and governance co-emerge through the ongoing interactions among diverse actors, each contributing to shared perceptions of usefulness and value. Hinings, Gegenhuber, and Greenwood (2018, p. 54) point out that "private actors orchestrate digital institutional infrastructures", such as OpenAI, Google, and Microsoft in the case of AI, but the institutionalization of new technologies always involves the (re)combination of institutional building blocks from existing "assemblage[s] of practices and components" (Arthur 2009, p. 28), the legitimatization from users, and the broader establishment of a "governance system reproducing social [i.e., institutional] order, and questions of value appropriation and control [i.e., markets]" (Hinings, Gegenhuber, and Greenwood 2018, p. 54). Alternatively stated, while central or top-down governance is important, its significance is often exaggerated, as it represents only part of the overall governance process. The interplays of technological and market developments are also institutional phenomena (Vargo, Wieland, and Akaka 2015) and thus serve as governance mechanisms, typically the core mechanisms.

In short, governance is not something that happens *to* technology, and therefore to adoption; it is integral to it. Arguably, human actors are commonly concerned about emerging technologies because, as explicated by our framework, technologies are situated within a multitude of concurrent and continuous actions and interactions that occur within broader sociomaterial and natural contexts. In the context of developing governance mechanisms for technologies, Rycroft (2006, p. 281) explains that "the speed with which modern technologies are innovated seems to be accelerating and there appears to be some consensus that faster technological change is likely to create substantial problems for public policymakers." Similarly, Popper (2003, p. 86) states that "we see a growing divergence between time cycles of government and those of technology development." According to Popper (2003, 86), "this presents government operations with a Hobson's choice: Either live within a shorter response time and run the concomitant risk of ill-considered actions (or inactions) or see government input become less relevant and assume reduced stature."

However, an ecosystemic view of intelligence broadens the participation in the creation of governance mechanisms from dyadic technology-developing practitioners and regulating policymakers to "spatially dispersed actors and their involvement in the political struggles and the interactions among them" (Vargo, Wieland, and Akaka 2015, p. 68) (see also Hardy and Maguire 2008; Lawrence and Suddaby 2006). Rejeski (2011, p. 51), for example, views a "wide class of players" in policy systems as "part of a diverse, complex, and dynamic innovation ecosystem, not [as] isolated observers sitting on some external perch." Our ecosystemic view also challenges the notion that rapid technological advancements create governance vacuums due to regulatory delays. Since intelligent technologies represent institutional arrangements and technological change represents institutional change, the evolution of governance structures is inherently part of technological development. Legal institutions, while sometimes delayed, are simply one facet of broader governance mechanisms that shape all technological progress. More foundationally, given the inherent unpredictability of emergent service ecosystems, prescriptive legislation based on foresight may be inherently flawed.

How an Ecosystemic View of (Artificial) Intelligence Informs S-D Logic

An ecosystemic conceptualization of intelligence offers a unifying framework for investigating AI and reveals how S-D logic can be deepened through a relational reconceptualization of *intelligence* and *technology*. While S-D logic has historically utilized a relational, systemic lens, it has not yet fully shifted its focus from individual actors to the interactions—or "intra-actions," per Barad (2007)—that define their identities, roles, and capacities. Russell's (2016, p. 7) argument that intelligence is "a general property of systems" reinforces the need for S-D logic to move fully from an actor-centric to an interaction-centric understanding of cognition and value creation. When intelligence is not a property of discrete actors but arises from their interrelations, S-D logic must foreground intra-action, feedback, and systemic coherence to explain intelligent behavior in service ecosystems.

Prior research suggests that technological adoption is driven by practice adaptation and the relationships among materials, meanings, and competencies (Akaka, Schau, and Vargo 2022). What makes AI a particularly compelling context for the further development of S-D logic is not the technology itself, but the speed, scale, and scope at which it is being adopted and integrated into daily life. The emergence of AI is unique in that it provides extraordinary evidence for the infinite capacity of adaptation, based on its exponential market growth and steep adoption trajectory across global industries and regions (Singla and Sukharevsky 2024). This exponential expansion creates a novel environment for examining how value co-creation dynamics unfold within service ecosystems. S-D logic emphasizes the importance of relational interactions in value cocreation, and AI provides a rich context for observing how adaptive capacities emerge through these interactions at scale. As AI is integrated into diverse practices, the resulting interactions reconfigure the roles of actors, institutions, and resources, highlighting new opportunities to study how institutional arrangements and governance structures form and evolve within these dynamic ecosystems.

The ongoing debate of the promise of AI—as both an opportunity and a threat—further enriches the study of S-D logic by providing a lens through which the tensions between innovation and control, openness and regulation, can be explored. The evolving interaction between AI and governance structures sheds light on how institutions adapt and respond to the increasing complexity of technological systems, offering insights into the ways S-D logic can inform the design of more resilient and equitable institutional arrangements in the face of rapid technological change.

Implications for Research and Practice

Implications for Research

As AI's role in business and society continues to expand, calls for further research—particularly at the intersection of AI and

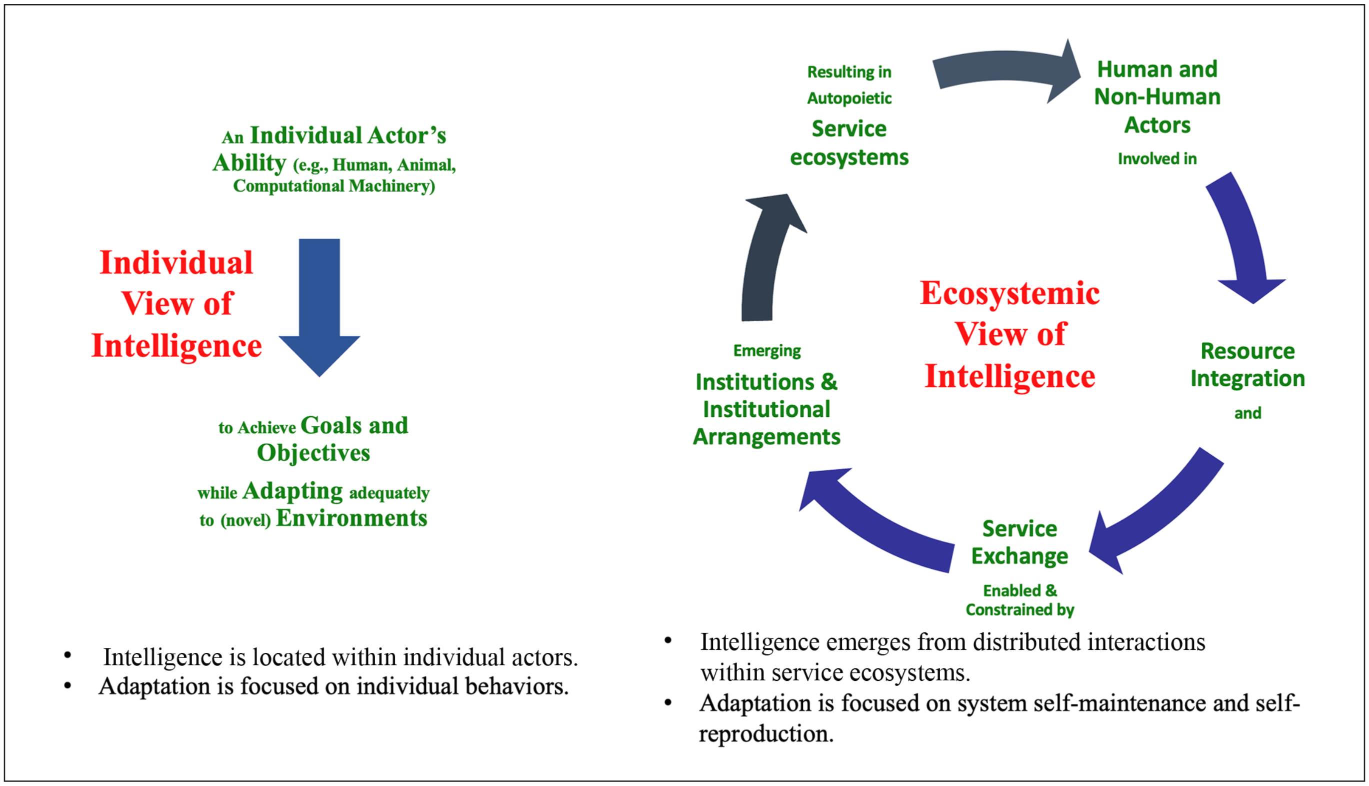

Figure 1. Contrasting individual and ecosystemic intelligence.

service—have intensified. This sense of urgency is often framed in ethical terms, as service contexts are widely regarded as key sites where debates about responsibility, fairness, and societal impact unfold (Belk 2021). Similarly, Wirtz et al. (2023) underscore the heightened risks associated with AI in service, given the extensive customer data involved and the opaque and complex nature of AI-enabled service delivery. While these concerns are well-founded, they have also contributed to a research landscape in which normative prescriptions frequently outpace the development of clearly articulated theoretical relationships.

Foundational to many research agendas at the intersection of service and AI seems to be an underlying assumption that AI is so unique and different from other technologies that it requires new frameworks and models, and is potentially so dangerous that resulting normative theories and recommendations are urgently needed. While we agree with the importance of studying AI, we caution against an "upside-down" approach in which normative theories are developed without sufficient foundational, positive theories. As Hunt (2002) emphasizes, strong normative guidance rests on strong positive theory.

A service-ecosystem perspective, informed additional relational ontologies, provides a solid foundation for studying the role and process of AI in marketing and service research. This perspective emphasizes intelligence, adaptation, governance, and value cocreation as relationally constituted phenomena that unfold through ongoing interactions among human and non-human actors. Building on this foundation, we advance a set of research propositions that specify the core conceptual relationships through which these processes operate in AI-enabled service ecosystems. These propositions are not hypotheses, but theory-building statements that open distinct empirical problem spaces and guide methodological engagement. Together, they delineate how AI can be studied as an ecosystemic and relational phenomenon.

The ubiquity of AI further amplifies these opportunities for S-D logic research. On one hand, the rapid expansion of AI across practices is generating new sociotechnical complexities, revealing emergent patterns and tensions that reshape service ecosystems. On the other hand, AI's rapid growth introduces profound complexities that [may] disrupt long-established institutional arrangements and governance structures. As AI participates in reshaping service ecosystems, future research must attend to how institutional dynamics evolve in response to tensions between innovation, coordination, and governance. Such research can deepen our understanding of how AI influences value cocreation processes and either stabilizes or disrupts existing structures.

Kleinaltenkamp, Kleinaltenkamp, and Karpen (2023) argue that S-D logic's theorizing embodies a tension between substance-ontological and process-ontological perspectives, using Barad's philosophy to describe these opposing views. This debate about whether entities have form outside their interactions or only within associations (Müller 2015) is also evident in work on systems and assemblage theories. We agree with Kleinaltenkamp, Kleinaltenkamp, and Karpen (2023) that reconciling these ontological tensions within S-D logic is an important task, and our relational, intra-actional perspective contributes to this effort while highlighting the need for continued research. A stronger embrace of relational ontology—consistent with intra-action and emergent constitution—can help unify these perspectives. From a research perspective, this shift *foregrounds processes, relations, and feedback dynamics*—rather than stable entities—as the primary units of analysis.

Thus, we encourage future research on S-D logic to further synthesize and reconcile systems thought and related ontologies. Both promote a flat ontology and a move away from Newtonian mechanics and its deterministic focus. Adopting such an ontology has important implications for how scholars examine AI-enabled service ecosystems. A relational, intra-actional view of intelligence foregrounds emergence, co-constitution, and systemic adaptation—features that traditional actor-centric approaches and purely deductive methods struggle to capture. Consequently, future research must consider how this ontological shift reshapes the kinds of questions we ask and the analytical frames we employ.

This relational perspective raises methodological questions about what should be observed and at what scale, given that actors and capacities emerge through relations rather than preexist them. This invites inquiry into how researchers frame their analyses, since intra-actions unfold across service ecosystems in ways that exceed any single study's observational scope. Decisions to foreground localized encounters or broader relational configurations reflect analytic necessity rather than differences in the nature of intra-action. Much like in quantum measurement, the analytic lens itself becomes part of the relational configuration being traced. These choices shape how coordination, meaning-making, and systemic adaptation are identified and interpreted.

Building on this agenda, scholars should explore methods capable of capturing the dynamic and emergent properties of relational service ecosystems. Agent-based modeling, for example, can simulate how heterogeneous actors co-evolve through intra-actions to produce system-level outcomes. More broadly, approaches that leverage AI's capabilities for complex system modeling, predictive analytics, or dynamic adaptation offer promising avenues for investigating relational value cocreation and institutional evolution. Through the continued development of robust theoretical and methodological frameworks, AI may ultimately appear less exceptional and more clearly understood as a manifestation of ecosystemic processes.

Building on these conceptual and methodological implications, Table 3 articulates the paper's research propositions and specifies the empirical phenomena and methodological approaches through which they may be engaged. Rather than enumerating isolated future research topics, the table structures a coherent, theory-driven agenda that links relationally grounded propositions to distinct empirical problem spaces for studying AI as an ecosystemic phenomenon in service research.

Implications for Public Policy

As stated, public policy discussions frequently center on how regulatory policymakers should aim to control technology developers. These implications often manifest as debates between CDR and governmental regulations (Floridi 2021; Wirtz et al. 2023). A recurring issue in these debates is a perceived temporal gap between the fast-moving processes of companies and the slower pace of regulatory institutions (Popper 2003; Rycroft 2006). While Wirtz et al. (2023), for example, argue that governments need to step in when a firm's CDR fails, Floridi (2021, p. 622) claims that CDR has broadly failed already and that "self-regulation needs to be replaced by the law; the sooner, the better." The recently published open letter by a group of AI experts that calls for a slowdown in the development of certain AI to give regulating policymakers more time supports this line of thinking.

Arguably, however, the best way to prepare for unforeseeable problems is not to impose moratoriums on AI but to encourage policymakers to shift to a holistic perspective that considers the interconnectedness of various system components and elements. Such a holistic perspective includes implementing regulatory governance that emphasizes adaptability and flexibility, such as creating dynamic regulatory frameworks that can be quickly updated in response to technological emergence, utilizing large assemblages of collaborative stakeholders to gather diverse perspectives, and implementing real-time data monitoring to inform policy adjustments. Additionally, policymakers can foster interdisciplinary research and collaboration to enhance the understanding of complex systems while investing in education and training programs to equip themselves with the necessary skills to manage AI. Such measures allow for continuous adjustment and improvement in response to emerging challenges rather than relying solely on predictive foresight, thereby ensuring a more resilient and responsive approach to governance.

Implications for Practice

Although we do not claim to have a complete blueprint for applying the "systems turn" in S-D logic, our framework suggests a growing need for practitioners to adopt systems thinking that extends beyond traditional, linear, deductive approaches. This shift would involve probabilistic thinking and a proactive awareness of the opportunities and risks associated with emergent phenomena. We concur with Rejeski's (2011, p. 50) idea that governance in technology requires a "new operating system," one that transitions from the rigid, step-by-step model of Newtonian mechanics to a more dynamic model akin to evolutionary biology. This model would prioritize learning, adaptation, and co-evolution over lengthy processes of issue identification and sequential implementation.

Practitioners, therefore, play a crucial role in this shift, especially since they are often directly engaged in monitoring

Table 3. Research Propositions and Future Research Directions.

Research Propositions	Phenomena to be Examined	Empirical and Methodological Guidance
P1. *AI-enabled Institutional Reconfiguration* The integration of AI into service ecosystems constitutes a process of institutional reconfiguration through feedback, learning, and institutional co-evolution.	Examine the reconfiguration of institutional elements (e.g., roles, responsibilities, and decision frameworks) in AI-enabled service ecosystems.	Longitudinal, multi-level studies can trace institutional evolution over time. Agent-based modeling can simulate feedback-driven institutional reconfiguration. Comparative ecosystem analyses can reveal divergent reconfiguration trajectories.
P2. *Value Cocreation and Learning in Human–AI Assemblages* In AI-enabled service ecosystems, value cocreation emerges through distributed learning processes.	Examine how value cocreation and learning unfold in service practices within human–AI assemblages.	Ethnographic and digital-trace studies can capture co-learning processes in situ. Simulation and experimental designs can model adaptive feedback within specific segments of service ecosystems.
P3. *Ecosystem Viability and Adaptive Reconfiguration* AI participation in service ecosystems alters the ecosystem's adaptive capacity, thereby reshaping system viability over time.	Investigate how AI-enabled interactions affect system-level resilience and viability across service ecosystems.	System dynamics and network analysis can trace resource flows and interdependencies. Machine learning analytics can identify emergent coordination patterns.
P4. *Governance as Emergent Coordination* Governance in AI-enabled service ecosystems emerges primarily from distributed processes among heterogeneous actors.	Examine how governance norms and structures emerge through distributed participation in AI-enabled service ecosystems.	Multi-stakeholder case studies and institutional ethnographies can reveal emergent governance patterns. Discourse and text analysis can trace the evolution of norms across digital and regulatory contexts.
P5. *Intelligence as Intra-actional Emergence* Intelligence in service ecosystems emerges through recurring intra-actional processes that constitute actors and their capacities.	Examine recurring patterns of responsiveness, sensemaking, and adaptation through which intelligence becomes observable.	Conceptual modeling and relational operationalizations can identify intra-actional patterns. Multi-level structural equation models or agent-based modeling can examine their evolution through nested feedback dynamics.
P6. *Emergent Ethical Norms in AI-enabled Service Ecosystems* Shared evaluations of appropriateness and fairness in AI-enabled service ecosystems emerge through ongoing intra-actions.	Examine how ethical norms and fairness perceptions emerge, stabilize, and vary across AI-enabled service ecosystems.	Participatory action research and scenario-based modeling can assess emergent ethical dynamics. Cross-cultural comparative studies can trace the evolution of fairness and ethical norms.

Note. AI = artificial intelligence.

institutional changes and in the development of AI technology platforms that both adapt to and shape these changes. Even as uncertainty grows around the risks associated with AI, we advocate for practitioners to continue leveraging these tools to enhance the adaptability, or "intelligence," of their service ecosystems. Embracing CDR is essential to ensure that AI technologies not only align with but also actively promote societal well-being. This responsibility calls for intentionality in aligning technology with ethical considerations, societal values, and the overarching goal of creating positive social impact.

Conclusion

We have shown that applying S-D logic to explore and explain the AI era compels a clearer account of system viability and how service ecosystems adapt, learn, and sustain value creation through recursive human–technology interactions. Rather than proposing a new theoretical model, our goal has been to demonstrate the continued explanatory power of S-D logic when confronted with intelligent technology. The service ecosystem view provides an organizing foundation for understanding AI as a manifestation of systemic and institutional adaptation, revealing cognition and coordination as core processes of value cocreation.

In doing so, we illustrate not only how S-D logic accommodates contemporary developments in technology and systems thinking but also how these developments motivate a further deepening of S-D logic's relational and intra-actional foundations. S-D logic continues to serve as (a) an indigenous, service-based theoretical framework for marketing (Bolton 2020; Hunt 2020; Kotler et al. 2021; Vargo, Wieland, and O'Brien 2023), (b) a framework compatible with other systemic orientations, emphasizing system well-being (or viability) and recognizing adaptability as a foundation of cognition and smartness, and (c) an institutionally grounded perspective reconcilable with established and emerging conceptualizations of the social construction of technology (Vargo and Lusch 2016; Vargo, Peters, et al. 2023) and technological governance (Vargo, Fehrer, et al. 2023). Yet the rise of AI highlights aspects of intelligence and coordination that require S-D logic to more explicitly articulate the relational constitution of actors, capacities, and institutions within service ecosystems.

Building on this need for conceptual deepening, our framework moves beyond framing intelligence in terms of a distinction between human and artificial forms and instead emphasizes a generative duality between adaptation and intelligence using a service ecosystems lens. In this view, "intelligent" or "not intelligent" is not an intrinsic property of any single actor but an emergent quality of collective resource application and collaboration across human and non-human participants. By conceptualizing AI within S-D Logic, the paper reaffirms S-D Logic's status as a living, evolving metatheory for marketing and service research—one that continues to adapt to new empirical and technological realities.

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Note

1. The quotes were chosen from Legg and Hutter (2007) collection of definitions of intelligence.

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