



Conceptualizing hybrid intelligent service ecosystems

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Abstract

With the proliferation of artificial intelligence (AI) technologies, the collaboration of human and AI actors in value co-creation processes permeates various application domains. In this conceptual paper, we integrate concepts from human-AI collaboration and service research and present a conceptual framework for hybrid intelligent service ecosystems (HISE). The framework extends the existing conceptualizations of service ecosystems as put forward by the service-dominant logic (S-D logic) by emphasizing how actors deliberately configure human and artificial agencies to co-create value via hybrid intelligent service exchange and how this impacts ecosystem formation and evolution. Our conceptualization highlights that value co-creation in HISE is guided and facilitated by shared resources and institutional arrangements, which differ from previous service ecosystems through the emergence of hybrid agency. We demonstrate the applicability of our framework with five illustrative HISE scenarios and provide five theoretical propositions. Our findings extend existing knowledge by theorizing on how to incorporate hybrid intelligence into value co-creation processes. Thereby, we provide a foundation for future interdisciplinary research on human-AI collaboration at the intersection of information systems, human-computer interaction, and service research with S-D logic as a unifying theoretical lens.

Keywords Hybrid intelligence · Service ecosystems · Value co-creation · Artificial intelligence

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Introduction

With the proliferation of artificial intelligence (AI) technologies, we observe a fundamental shift in how people interact with these technologies individually and collectively in service ecosystems (Huang & Rust, 2018). This evolution enables leveraging the potential of *hybrid intelligence* by allocating tasks to either human or AI agents, depending on their respective strengths (Dellermann et al., 2019). The widespread adoption of generative AI applications, such as ChatGPT, highlights hybrid intelligence's transformative impact on value co-creation processes. By strategically assigning tasks based on the context, hybrid intelligence enables outcomes that neither humans nor AI could achieve independently (Hemmer et al., 2023). In particular, the ability to employ "AI as a service" is expected to continuously fuel the growth of hybrid intelligent service opportunities (Newlands, 2021) because it allows individuals to access and use AI capabilities without the need for significant investment in infrastructure and expertise. However, despite advancements

in resolving traditional technical constraints related to AI deployment (e.g., scalability, cost) and regulatory constraints concerning AI safety (e.g., governance of high-risk AI systems), the full potential of human-AI collaboration in co-creating value remains underutilized. This disparity suggests the need for a framework that helps describe and understand how humans and AI co-create value in service ecosystems through interaction and resource integration.

The service-dominant logic of marketing (S-D logic), which is based on the fundamental assumption that service is the basis of all economic exchange, provides an established theoretical lens to study value co-creation through service exchange between actors in service ecosystems (Vargo & Lusch, 2004, 2016). A service ecosystem is a “relatively self-contained, self-adjusting system of resource-integrating actors connected by shared institutional arrangements and mutual value creation through service exchange” (Vargo & Lusch, 2016, pp. 10–11). As such, it represents “a spontaneously sensing and responding spatial and temporal structure of largely loosely coupled, value-proposing social and economic actors interacting through institutions, technology, and language to (1) co-produce service offerings, (2) engage in mutual service provision, and (3) co-create value” (Vargo & Lusch, 2011, p. 185). This view of service ecosystems emphasizes the importance of institutions in value co-creation and service innovation. It explicates the complex and dynamic nature of the social systems through which service is provided (Vargo & Akaka, 2012). Furthermore, it assumes that “service ecosystems are systems of systems in which the various systems interact, and different levels of analysis can be applied: micro (actor engagement), meso (sets of actors and their resources), and macro (ecosystem and institutional logics)” (Storbacka et al., 2016, p. 3009). Vargo and Lusch (2011) further emphasize that technology development, in particular, drives the evolution and performance of service ecosystems, enabling actors to sense and respond more and more spontaneously.

The ascendance of AI technologies and the growing importance of human-AI collaboration in both day-to-day work practices and private contexts are forces that shape service ecosystem evolution. For example, the rapid development of generative AI technologies has led to a surge of AI innovations (e.g., chatbots, image generation) entering the market, impacting the institutional logics (at the macro level). This influx of new technologies updates the resource structures of actors by integrating more advanced AI tools into the service ecosystem, thereby altering resource integration patterns of actors (at the meso level), and creates hybrid actors who allocate tasks to human or AI agencies (at the micro level). In response to these developments, regulatory bodies like the European Union are proposing and implementing legislation such as the EU AI Act (European Union, 2024) to regulate AI use intended to reshape existing

institutional arrangements (at the macro level), ensuring ethical standards and safety. Consequently, organizations like Meta decided to withdraw certain AI models and products from the EU market, which limits the resources available to EU citizens and potentially inhibits service exchange and value co-creation (at the meso level). This example illustrates how institutional arrangements on the macro level both guide meso-level resource integration patterns and evolve through micro-level actor interactions, continuously shaping and reshaping the dynamics of value co-creation in hybrid intelligent service ecosystems (HISE).

While many human-AI collaborations are inherently service-oriented (Knote et al., 2021), and there are already studies that have explored AI’s role in specific service contexts such as marketing (e.g., Wedel & Kannan, 2016), customer service (e.g., Adam et al., 2021; Knote et al., 2021), and broader service research (e.g., Wirtz et al., 2018), there remains a significant lack of understanding of how human and AI agencies can be configured to optimize resource integration and value co-creation within service ecosystems (Breidbach & Brodie, 2017). This under-researched area limits our ability to study and design current and future service ecosystems effectively and to predict their evolution. Addressing this issue is critical and requires a conceptual framework to navigate the evolving resources and shifting institutional arrangements in these service ecosystems, which alter resource integration patterns in service exchange over time.

Despite significant contributions from both service research (e.g., Knote et al., 2021; Wirtz et al., 2018) and hybrid intelligence research (e.g., Dellermann et al., 2019), there is a lack of integration between these fields that leaves the phenomenon of HISE under-conceptualized. To build human-centered solutions aligned with modern imperatives of value co-creation and collaboration, we need integrated knowledge that leverages the strengths of both domains to understand how to systematically describe, explain, analyze, and design human-AI collaboration in service ecosystems. Unresolved questions about HISE refer to the various service ecosystem elements and their interplay, including, e.g., how actors and their resources are configured and evolve in HISE, how to design and manage service ecosystems that enable hybrid intelligent service exchange, and what role institutional arrangements play in this regard.

The lack of a comprehensive understanding of HISE is not just relevant from a theoretical perspective, but it can also have profound implications across diverse application domains (e.g., mobility, elderly care, software engineering, agriculture, IT customer support). This knowledge gap can lead to a negative bias toward human-AI collaboration despite its potential for fostering more effective and sustainable future service ecosystems (Dwivedi et al., 2023). For example, there is an erosion of trust due to unclear

cost-benefit analyses for hybrid intelligent applications and a lack of transparency concerning their employment (Gkinko & Elbanna, 2023; Hildebrand & Bergner, 2021; Schuetz & Venkatesh, 2020). Conversely, the reported significant growth of AI applications in sectors like retail, healthcare, IT and telecommunications, manufacturing, energy (Mordor Intelligence, 2024), and public services (Hernandez, 2022) highlights the potential benefits organizations perceive in integrating AI into their value co-creation processes. Hence, understanding and conceptualizing value co-creation in such settings is critical for researchers and practitioners aiming to design and manage service ecosystems effectively.

Therefore, this paper proposes a conceptual framework to advance our understanding of HISE. By adopting a service ecosystem perspective that is rooted in S-D logic, we aim to describe the complex interplay between different kinds of actors—including humans, AI, and hybrids—and their impact on value co-creation practices and institutional arrangements in HISE. Thereby, we explore the interrelationships of value co-creation, resources, and their mobilization, as well as institutional arrangements concerning AI-driven service offerings and service interactions. In this paper, we define HISE as service ecosystems that leverage human and AI to configure human and AI agencies as human-AI hybrids. By employing an S-D logic lens, we understand HISE as evolving systems that continuously evolve from the configurations of agency through actors by fostering the evolution of both human and artificial agencies, improving the efficiency and effectiveness of hybrid intelligent service. In this view, HISE are able to continuously improve the co-created value for all actors as potential beneficiaries.

By conceptualizing HISE, we make three key contributions to the academic knowledge base: First, the HISE framework is the first to provide a conceptual foundation to study phenomena at the intersection of human-AI collaboration and value co-creation in service ecosystems. Second, it equips researchers and managers with a tool to understand, design, and manage HISE as state-of-the-art service ecosystems that leverage the potential of AI. Third, we present five propositions alongside the conceptualization that guide high-impact future research on HISE, building on our proposed framework.

We demonstrate the versatility and applicability of our framework through a variety of scenarios—semi-autonomous driving, elderly care, sustainable coding, precision agriculture, IT customer support—that encompass diverse service ecosystems that stem from a wide range of industries, from smart products like semi-autonomous vehicles to human-centered services such as elderly care, and from intangible services like software development and IT support to tangible farming processes in agriculture. These scenarios capture a broad spectrum of service interactions and

ecosystem dynamics, showcasing the framework's flexibility to be applied to diverse hybrid service encounters involving actors such as technology providers, service providers, end users, regulators, and environmental factors. While previous studies have focused on AI's transformative role in specific sectors like tourism (Soraya González-Mendes et al., 2024), our conceptual study broadens this perspective by exploring the role of hybrid intelligence across various industries.

The remainder of the paper is structured as follows: Sect. 2 describes the theoretical underpinnings of the study, outlining human-AI collaboration, hybrid intelligence, service ecosystems from a S-D logic perspective, and agency research in information systems (IS). In Sect. 3, we outline our behavioral conceptual research approach, which structures the subsequent Sect. 4, in which we conceptualize HISE and apply the framework to five illustrative scenarios. In Sect. 5, we present five propositions that can guide future research on HISE before concluding the paper in Sect. 6.

Theoretical background

Hybrid intelligence and human-AI collaboration

Hybrid intelligence refers to the combination of human and AI agents, leveraging their complementary strengths to form a socio-technical ensemble (Dellermann et al., 2019; Malone, 2018). It is the outcome of human-AI collaboration (Fügner et al., 2022). This view on human-AI collaboration recognizes that AI systems have unique capabilities, such as processing large amounts of data, pattern recognition, natural language processing, image recognition, and predictive analysis (Goodfellow et al., 2016; LeCun et al., 2015; Russell & Norvig, 2021), which can complement human intelligence in various tasks (Davenport & Kirby, 2016). Similarly, human intelligence provides creativity, empathy, and contextual understanding, which can complement the limitations of AI systems (Brynjolfsson & McAfee, 2014), such as biases arising from training data (Caliskan et al., 2017) or lack of explainability in their decision-making processes (Arrieta et al., 2019). However, hybrid intelligence does not simply involve inserting human intelligence into the AI loop or to automate simple tasks through machine learning. Rather, it seeks to solve complex problems by deliberately allocating and coordinating tasks among heterogeneous algorithmic and human agents, thereby enabling actual human-AI collaboration.

Hybrid intelligence research has sought to explore the interplay between human agents and AI agents in various contexts, such as decision-making (Jarrahi, 2018), problem-solving (Woolley et al., 2010), and team performance (Anthony et al., 2023; Siemon et al., 2022). However, even capabilities previously associated with humans, such as

creative activities, can be enhanced in a hybrid intelligence setting of AI systems together with humans (Jia et al., 2023; Siemon et al., 2022). A key insight from this research stream is that the collaboration between human and AI agents can lead to outcomes that are superior to what either agent could achieve individually (Dellermann et al., 2019; Hemmer et al., 2023). For instance, Woolley et al. (2010) found that hybrid teams can outperform teams of human agents working alone on complex problem-solving tasks. In addition, Stieglitz et al. (2021), for example, study the effects of human behavior in terms of social loafing or delegating responsibility to an AI in a team. Siemon et al. (2022) show how humans in a collaborative creative process react to the critical voices of an AI on their own ideas.

Similarly, Fügner et al. (2022) corroborate through their experimental study that human-AI ensembles perform superiorly in classification tasks when compared to the results achieved by both actors individually. Of particular relevance, however, is that this ensemble only achieves superior performance when the AI can actively delegate tasks to the human and thus has its own agency to influence the collaboration dynamics. Furthermore, Gkinko and Elbanna (2023) show that sustainable hybrid intelligent work scenarios only emerge when AI is perceived as a personal assistant with its own capabilities and scope for action and not just as a tool. These recent studies indicate that AI agency plays an increasingly active and equitable role in hybrid intelligence settings.

Additionally, early pioneering studies exist that describe the effects of AI in ecosystems, for example, concerning ethical implications of AI for innovation ecosystems (Stahl, 2022), data network effects, user decentralization on data- and AI-driven digital platforms (Clough & Wu, 2022; Gregory et al., 2022). However, these studies do not address hybrid intelligence or human-AI collaboration specifically. Moreover, while research on hybrid intelligence has provided valuable insights into the potential of human-AI collaboration, it has primarily focused on the individual and team levels (including their dynamics and influences) (e.g., Dellermann et al., 2019). For example, Recker et al. (2023) propose the size and heterogeneity of a human-AI ensemble (one-to-one, one-to-many, many-to-one, or many-to-many), its control sequence (human-first, machine-first, or synchronous), the nature of the problem domain (well-structured or poorly structured), and the overarching innovation goal (problem-driven or solution-driven) as important aspects that determine task allocation in the agency configuration process. Fabri et al. (2023) present a taxonomy of human-AI hybrids, which we would equate with the configured agency in our framework, and identify five configuration archetypes (AI pre-worker, outsourcing AI, superpower-giving AI, assembly-line AI, collaborator AI) based on clustering 101 human-AI hybrids. However, the agency configuration

of human and AI agencies is still a nascent research topic that is radically changing due to new technological advancements, new forms of deep integration of AI into pre-existing practices, and the ongoing transformation of these practices and value co-creation patterns in general.

To conclude, regarding our aim of conceptualizing HISE, research to date in this field has primarily focused on micro-level interactions between humans and AI but has not sufficiently considered the interplay with the meso and macro levels of service ecosystems in which humans and AI interact. In particular, the hybrid intelligence literature has not fully addressed how the collaboration between human and AI agents can influence value co-creation, resources, and institutional arrangements, which are central elements in service ecosystems.

Service-dominant logic and service ecosystems

S-D logic emerged as a foundational paradigm shift in marketing and service research, offering a well-accepted theoretical lens with which to study economic exchange (Vargo & Lusch, 2004). It positions all economic exchange as service-for-service or skill-for-skill exchange among actors, with emphasis on broader societal and economic systems (Vargo & Lusch, 2016). In this regard, Lusch and Vargo (2006, p. 283) (re-)define service as “the application of specialized competencies (knowledge and skills), through deeds, processes, and performances for the benefit of another entity or the entity itself.”

Since its inception, S-D logic has undergone further development, leading to revisions of its foundational premises and their consolidation into five axioms. As part of an “institutional and dyad-to-network-to-systems turn” (Vargo & Lusch, 2016, p. 6), recent work highlights the importance of a service ecosystem view “to allow a more holistic, dynamic, and realistic perspective of value creation, through exchange, among a wider, more comprehensive (than firm and customer) configuration of actors” (Vargo & Lusch, 2016, p. 5 f.)

Accordingly, S-D logic treats all participants in economic and social exchange as generic actors (Ekman et al., 2016; Hönigsberg & Dinter, 2024; Wieland et al., 2012) who adopt various roles in value co-creation processes rather than being relegated to traditional categories such as “supplier” or “customer” (Vargo & Lusch, 2016, 2017). An actor can thus be any market participant involved in actor-to-actor exchanges (Vargo & Lusch, 2016). Hence, actors can be individuals, organizations, or groups (Storbacka et al., 2016; Wieland et al., 2012) and can be nested in collections of actors, like a group of individuals where both the group and its individuals are conceptualized as actors from an S-D logic perspective (Vargo & Lusch, 2011). Actors can be entities within (e.g., a department, function, or local branches) or external

to an organization (e.g., another company) (Schymietz & Jonas, 2020). Storbacka et al. (2016) further suggest that, with advancing technology, machines can also be considered actors, extending the scope of actor-to-actor interactions. Recognizing this multiplicity of intertwined co-creating actors—individuals, organizations, or other service systems—shifts the focus from value creation as a linear, firm-centric process to a more dynamic and interactive process involving various actors within a service ecosystem (Chandler & Lusch, 2015). For instance, entities such as cities, industries, and markets can themselves be viewed as service ecosystems (Sarno et al., 2024).

In the service science literature, actors are commonly conceptualized as “service systems” (Vargo & Lusch, 2011, p. 186). This concept encompasses entities at any level of aggregation—from single individuals as atomic service systems to entire communities or organizations (Spohrer et al., 2008; Vargo & Lusch, 2011). While it may be counterintuitive to label a single individual a “system,” from a service science perspective, each person integrates resources (e.g., personal skills, knowledge, technologies, social connections) to create value for themselves and others—just like larger collectives (Spohrer et al., 2008). Thus, even an individual can function as a service system because they engage in mutual service-for-service exchanges within broader networks (Vargo & Lusch, 2011). At the same time, superordinate service systems (e.g., firms, neighborhoods, or nations) are themselves composed of interdependent individual service systems interacting and co-creating value.

The same rationale applies to “service ecosystems,” defined as nested constellations of service systems (Storbacka et al., 2016). Conceptually, “a service ecosystem may be nested within or be part of a larger system. Hence, service ecosystems are systems of systems in which the various systems interact” (Storbacka et al. 2016, p. 3009). Scholars frequently compare the terms “service system” and “service ecosystem,” noting that both refer to multi-actor arrangements engaged in value co-creation (Wieland et al., 2012). A key difference lies in the idea of *analytical zoom*: service ecosystems emphasize broader, emergent networks of interacting actors zooming out from dyadic interactions and discrete transactions to more complex actor-to-actor networks, whereas a service system can refer to any entity—be it an individual or collective—engaged in value co-creation via resource integration (Vargo & Lusch, 2017; Poeppelbuss et al., 2022).

By zooming out, service research has moved from studying isolated service systems (e.g., service firms or service delivery systems) to analyzing the more dynamic, interdependent contexts of entire service ecosystems, in which numerous actors simultaneously co-create value (Brozovic & Tregua, 2022). Because service ecosystems “are constantly adapting to changing contextual requirements and

are simultaneously creating these changing contexts in the process” (Wieland et al., 2012, p. 15), small-scale and large-scale shifts in ecosystem properties can be understood as emergent changes or phase transitions (Vargo et al., 2023; Polese et al., 2021).

When conceptualizing HISE, we thus draw on recent S-D logic literature, which predominantly employs service ecosystem terminology. Taking a systems perspective on service (Barile et al., 2016; Wieland et al., 2012) and understanding service ecosystems as systems of systems (Storbacka et al., 2016) has inspired various conceptualizations of aggregation levels according to S-D logic (see Table 1).

For instance, Vargo and Lusch (2017) distinguish among three levels of aggregation in service ecosystems—micro, meso, and macro—corresponding respectively to dyadic exchanges (e.g., transactions, sharing), an industry or market, and broader societal entities (e.g., local, national, or global communities). Chandler and Vargo (2011) likewise move from dyads to triads and complex networks as units of analysis, thereby clarifying how service-for-service exchange can be scaled up from rather direct to more complex and indirect interactions. They also introduce the concept of a dynamic meta layer (not level) that “represents [the] evolution of these levels, which occurs simultaneously [over time]” (Chandler & Vargo, 2011, p. 41). In this sense, the meta layer “covers all the levels of service-for-service exchanges such that they together constitute service ecosystems” (Chandler & Vargo, 2011, p. 44). Storbacka et al. (2016) similarly distinguish three levels—micro (actor engagement), meso (sets of actors, their resources, engagement platforms, and resource integration patterns), and macro (the overall ecosystem with its institutional arrangements). Barile et al. (2016) propose a “tri-level approach,” linking the service system concept from service science (Maglio & Spohrer, 2008) with the service ecosystem concept from S-D logic (Vargo & Lusch, 2011). Specifically, they illustrate how service systems, networked service systems (also labeled as service networks), and service ecosystems each represent distinct yet intertwined analytical levels in service research. Vink et al. (2021) apply the micro-meso-macro distinction to a process model for service ecosystem design, designating the micro level as the focal instance of service ecosystem design, the meso level as encompassing both aligning and conflicting design and non-design processes, and the macro level as the emerging institutionalized patterns of value co-creation.

It is generally assumed that actors can interact at all levels of aggregation and that changes in one level affect the others (Polese et al., 2021). Sarno et al. (2024), for example, describe a “domino effect” in which modifications within one nested service ecosystem can propagate outward to a broader service ecosystem, often beginning with interactions and adjustments at the micro level and then “spread[ing] to the macro level.” Meynhardt et al. (2016)

Table 1 Aggregation levels according to S-D logic

Service ecosystem levels	Vargo and Lusch (2016), Vargo and Lusch (2017)	Chandler and Vargo (2011)	Storbacka et al. (2016)	Barile et al. (2016)	Vink et al. (2021)
Micro	Individual and dyadic structures and activities involved in dyadic exchange (e.g., transactions, sharing)	Units of analysis are dyads with service-for-service exchange among actors	Actor engagement (including co-production and value-in-use activities)	Service systems, which are dynamic configurations of resources (people, technology, information, organizations) connected internally and externally through value propositions	The focal instance of service ecosystem design as a feedback loop of reflexivity and reformation (design) embedded within the process of reproduction (non-design)
Meso	Midrange structures and activities (e.g., market, industry, brand community, cartel)	Units of analysis are triads with service-for-service exchange among dyads (e.g., two dyads of actors a and b and b and c, with indirect service-for-service exchange between actor a and c through actor b)	Sets of actors and their resources (including engagement platforms as intermediaries between actors and evolving resource integration patterns)	Networked service systems (service networks) that evolve through technology, knowledge, culture, business, and society	The interplay between both conflicting and aligning design and non-design processes
Macro	Broader societal structures and activities (e.g., society, national, global, or local community)	Units of analysis are complex networks with service-for-service exchange among triads. When complex networks successfully institutionalize resources, they become joined together as a service ecosystem	Ecosystem and institutional logic	Service ecosystems, which are relatively self-contained, self-adjusting systems of resource-integrating actors, connected by shared institutional logics and mutual value creation through their service exchanges	The patterns of value co-creation that emerge between design and non-design processes within actor collectives

similarly discuss bottom-up emergence and top-down enslavement as dynamics in service ecosystems: macro-level properties can *emerge* from micro-level interactions in ways not fully determined by any one element, and these macro-level properties can, in turn, reshape (“*enslave*”) individual (micro-level) elements.

Vargo and Lusch (2016, p. 17) caution that such distinctions of levels are “relative, rather than absolute and thus these assignments are somewhat arbitrary” within S-D logic. Indeed, they exist “as analytical levels only and do not exist independently of each other. Rather, they represent perspectives related to levels of aggregation” (Vargo & Lusch, 2016, p. 18). It is also important to not confuse levels of aggregation (i.e., micro-meso-macro views of multi-actor networks) with levels of abstraction for building theory in research (i.e., meta theory, midrange theory, and micro theory) (Vargo & Lusch, 2017).

The key takeaway for our conceptualization of HISE is that “service ecosystems” refer to sets of interconnected actors and their relationships, and analysts can zoom in on dyadic actor-to-actor exchanges or zoom out to examine entire industries or societies. The relationships become more complex at higher levels of abstraction, where not all actors are directly connected anymore (Chandler & Vargo, 2011), and it is the researcher who “must determine the relevant service ecosystem(s) and its boundaries for a particular analysis” (Lusch et al., 2016, p. 2960).

Irrespective of how we define or constrain a service ecosystem, all actors within it engage in *resource integration* (Vargo & Lusch, 2008). This process involves combining both operant resources (e.g., knowledge, skills, and abilities) and operand resources (e.g., raw materials or tangible assets) to create value (Vargo & Lusch, 2017). Resource integration underpins core assumptions of S-D logic by emphasizing that every actor in a service ecosystem is a resource integrator who actively shapes value co-creation by combining and applying resources from various sources (Vargo & Lusch, 2016). A central distinction here is between operand resources, which are generally passive and require external action to become valuable (Constantin & Lusch, 1994; Hunt, 2004), and operant resources, which are dynamic and knowledge-based, offering the ability to act upon other resources to create value (Constantin & Lusch, 1994; Hunt, 2004). For example, human skills and organizational capabilities exemplify operant resources that confer strategic and competitive advantage (Vargo & Lusch, 2016).

The service ecosystem perspective further highlights that value is co-created within multi-actor systems that are bound to shared rules, roles, norms, and beliefs, collectively termed the institutional arrangements that guide resource integration and service exchange (Vargo & Lusch, 2016; Vink et al., 2021). These institutional norms and social rules provide a broader context that shapes how

value co-creation occurs by influencing and structuring the interactions between actors (Orlikowski, 1992; Walshaw & Han, 1991). Moreover, Lusch and Nambisan (2015) emphasize that all actors, including inanimate (i.e., material or artificial) agents, recreate and alternate these institutional arrangements through their actions. Table 2 summarizes the fundamental concepts of S-D logic and provides definitions, which are applied as a theoretical lens for our own conceptualization of HISE.

Recent research has increasingly examined how technology, particularly AI, functions in service ecosystems (Kaarntemo & Helkkula, 2024; Manser Payne et al., 2021; Neuhofer et al., 2021). AI-driven technologies are typically viewed as operand resources that can be integrated with human capabilities to facilitate value co-creation on higher levels (e.g., Breidbach & Brodie, 2017). They also enable complex interactions among networks of human and non-human actors, expanding opportunities for value creation (Storbacka et al., 2016). Furthermore, emerging regulations such as the EU AI Act (European Union, 2024) are implemented to form new institutional arrangements that shape contemporary service ecosystems. While Vargo and Lusch (2017) anticipated the growing importance of cognitive computing and AI-powered smart service within service ecosystems, they largely maintained a traditional view of technology as an operand resource or even black boxes any technological aspects. In contrast, within the given context of HISE, we consider technology an active participant in the service ecosystem—an approach explored in more depth below.

Agency in information systems research

The IS discipline has traditionally been subject to the primacy of human agency dominance (Grashoff & Recker, 2023), where technological artifacts are often viewed solely as passively used tools (Baird & Maruping, 2021) and thus as operand resources from an S-D logic perspective. However, with the advent of advanced AI technologies, there is a growing recognition of the agentic capabilities of AI systems, leading to a reexamination of their role within IS research and beyond.

Various literature streams, such as actor-network theory (e.g., Braa & Sahay, 2004; Chiasson & Davidson, 2005; Hanseth et al., 2006; Lamb & Kling, 2003; Scott & Wagner, 2003), sociomateriality (e.g., Cecez-Kecmanovic et al., 2014; Leonardi, 2011), and agent-based computing (e.g., Brenner et al., 1998; Miller & Parasuraman, 2007; Russell, 2019), posit that human agents are in mutual relationships with agentic information technology (IT) artifacts. These relationships form constantly (re-)emerging structures with themselves and their context in practice (Orlikowski, 2000). In this context, AI systems are

Table 2 Fundamental concepts of S-D logic

S-D logic concept	Definitions and relevant axioms of S-D logic	Citation
Service	Service is the “application of operant resources (skills and knowledge)” for another party (i.e., actor). “Service is exchanged for service.” “Service provision implies the ongoing combination of resources, through integration, and their application, driven by operant resources — the activities of actors.” “Service is the fundamental basis of exchange.” (Axiom 1)	Vargo and Lusch (2008), p. 6 f Vargo and Lusch (2011), p. 184 Vargo and Lusch (2016), p. 18
Actor	“All social and economic actors are resource integrators.” “Actors need to be viewed not only as humans, but also as machines/technologies, or collections of humans and machines/technologies, including organizations.” “[...] structures connect [multiple] actors and provide their context and become actors themselves. [...] In the service-science framework, they are service systems.”	Vargo and Lusch (2008), p. 6 Storbacka et al. (2016), p. 3010 Vargo and Lusch (2011, p. 186)
Service ecosystem	“A service ecosystem is a spontaneously sensing and responding spatial and temporal structure of largely loosely coupled, value-proposing social and economic actors interacting through institutions, technology, and language to (1) co-produce service offerings, (2) engage in mutual service provision, and (3) co-create value.” “[A] relatively self-contained, self-adjusting system of resource-integrating actors connected by shared institutional arrangements and mutual value creation through service exchange”	Vargo and Lusch (2011), p. 185 Vargo and Lusch (2016), pp. 10 f
Operand resources	Resources “that require some action to be performed on them to have value (e.g. natural resources).”	Vargo and Lusch (2011), p. 184
Operant resources	Resources “that can be used to act (e.g. human skills and knowledge).”	Vargo and Lusch (2011), p. 184
Value co-creation	“The processes and activities that underlie resource integration and incorporate different actor roles in the service ecosystem.” “Value is cocreated by multiple actors, always including the beneficiary.” (Axiom 2)	Lusch and Nambisan (2015), p. 162 Vargo and Lusch (2016), p. 18
Value	Value is an “emergent, positively or negatively valenced change in the well-being or viability of a particular system/actor.” Value “is viewed as an improvement in a system as determined by the system or by the system’s ability to adapt to an environment. In other words, value can be conceptualized as improved system viability.” “[...] value occurs when the offering is useful to the customer or beneficiary (value-in-use), and this is always in a particular context.” “Value is always uniquely and phenomenologically determined by the beneficiary.” (Axiom 4)	Vargo and Lusch, (2018), p. 740 Wieland et al. (2012), p. 17 Lusch and Nambisan (2015), p. 159 Vargo and Lusch (2016), p. 18
Institutions and institutional arrangements	Institutions are “humanly devised rules, norms, and beliefs that enable and constrain action and make social life predictable and meaningful.” Institutional arrangements are “sets of interrelated institutions (sometimes referred to as ‘institutional logics’).” “Value co-creation is coordinated through actor-generated institutions and institutional arrangements.” (Axiom 5)	Vargo and Lusch (2016), p. 6 Vargo and Lusch (2016), p. 11 Vargo and Lusch (2016), p. 18

increasingly viewed as possessing agency—the capacity to act autonomously and influence outcomes—thereby becoming active participants in organizational processes.

Baird and Maruping (2021) call for a theoretical delegation framework that stresses the importance of how rights, responsibilities, and coordination occur between human and machine agents and how this relationship evolves (e.g., Akinola et al., 2018; Klein et al., 2006; Leana, 1986; Ribes et al., 2013). This shift towards acknowledging that IT artifacts, particularly AI systems, have agency leads to a broadened view on theorizing the relationship between technology and humans. By recognizing the oscillating nature of interactions between agentic IT artifacts and humans, new

structures arise, each depending on constituting factors of either human or IT artifact attributes.

Baird and Maruping (2021) conceptualize three main attributes of both human agents and agentic IT artifacts: *endowments*, *preferences*, and *roles*, which provide a conceptual basis for understanding the recent shift from traditional agency conceptualization towards a dynamic delegation-oriented perspective. Interestingly, all three agency-relevant attributes are highly cohesive with S-D logic.

From an S-D logic perspective, *endowments* are the actors’ operand (e.g., data) and operant resources (e.g., knowledge and thinking capabilities). The skills and knowledge attributed to human-artifact dyads require a certain

level of shared knowledge and capabilities. For example, an artificial agent might be able to access or analyze data, and the human agent is aware of its meaningfulness and usefulness. In addition to this shared basis, the same dyad requires substantial differences to justify the cost of delegation from human agents to artificial agents and potentially vice versa (Baird & Maruping, 2021; Lane & Lubatkin, 1998).

Preferences are motivations that capture the goals of agents shifting their agency between the aforementioned dyads (Bandura, 2006; Enfield & Kockelman, 2017; Schanze, 1987; Shapiro, 2005), which can be separated into decision models and goals (Baird & Maruping, 2021). Decision models are representations of how and why decisions are ranked, whereas goals are a “cognitive representation of a desired end point” (Fishbach & Ferguson, 2007, p. 491). These preferences define the reason for how and why agents engage in delegation dyads (Baird & Maruping, 2021).

Roles are constituted by a set of rights and responsibilities that agents either have or transfer to one another. This perspective aligns with Leonardi’s sociomateriality-related concept of imbrication, which describes how human and artificial agents interact within dyads but still exist as separate entities (Leonardi, 2011). This means that even though humans and AI collaborate and form hybrid ensembles, they still exist as single entities and might act independently in specific cases.

The theoretical foundations of agency in human-AI collaboration underscore the importance of understanding how tasks and responsibilities can and should be allocated between human and AI agencies. Agency in this context refers to the ability of an agent (human or AI) to act in a given environment and influence outcomes (Leonardi, 2011). Related to that, we understand actors as entities capable of *exercising agency*. Bridging from actors to agency, we see that AI systems, when endowed with agency, might also be considered actors within service ecosystems. This view enhances the traditional understanding of actors and includes not only humans and organizations. It implies that AI artifacts can act autonomously and contribute to value co-creation processes.

Research on human-AI collaboration outlines that the effective configuration of agency is critical for achieving optimal task performance. Dellermann et al. (2019) emphasize that hybrid intelligence leverages the strengths of both human and AI agents, creating a socio-technical ensemble that enhances decision-making and problem-solving capabilities. Examples of configured agency in practice demonstrate micro-level interactions where human and AI agents complement each other’s capabilities, resulting in superior service performance (Storbacka et al., 2016; Vargo & Lusch, 2017). For example, in healthcare, AI systems assist radiologists by pre-analyzing medical images and highlighting areas of concern, which

radiologists then review and interpret using their expertise (Topol, 2019). In finance, AI algorithms analyze market trends and provide investment recommendations, which are evaluated and acted upon by human analysts (Davenport & Kirby, 2016).

Research method

We pursued a conceptual research approach to explore and describe HISE. Conceptual research aims to integrate different streams of existing theory to develop an agreed-upon meaning (van der Waldt, 2020) about real-world phenomena (Meredith, 1993). Through logical argumentation, relationships are established between currently disintegrated research streams within and across domains (Gilson & Goldberg, 2015; Mora et al., 2008), resulting in theoretical contributions that advance our understanding of a phenomenon (Jaakkola, 2020; Mora et al., 2008). In conceptual work, data are used, if at all, only to confirm or falsify testable propositions that have been developed through argumentation (Jaakkola, 2020).

We implemented a five-step conceptual research process inspired by Mora et al. (2008) to synthesize and integrate theory (Jaakkola, 2020) through the exploration and description of hybrid intelligence in value co-creation processes of service ecosystems (see Fig. 1). As a first step, we identified the existing research gap regarding HISE, which stems from the currently disintegrated research streams on (1) hybrid intelligence and human-AI collaboration, (2) service ecosystems, and (3) agency in IS research. Second, our team of eight researchers decided to adopt a conceptual research approach to address the gap. We selected the S-D logic as a suitable theoretical lens for our conceptualization, assuming that it provides concepts and constructs that can be borrowed and integrated with the existing knowledge base on hybrid intelligence and the conceptualization of agency in the IS literature. In the third step, we identified and integrated concepts and constructs from each research stream to conceptualize a framework for HISE. In step four, we discuss scenarios that demonstrate how the framework of HISE can be applied to explore and describe value co-creation. We deliberately chose a diverse set of domains and use cases to demonstrate the validity of the conceptual framework by testing its consistency with real-world phenomena. The scenarios include semi-autonomous driving, elderly care, sustainable coding, precision agriculture, and IT customer support. In the final step, we formulate five propositions to explain the theoretical underpinnings of the HISE elements and their interrelations and develop pathways for future research.

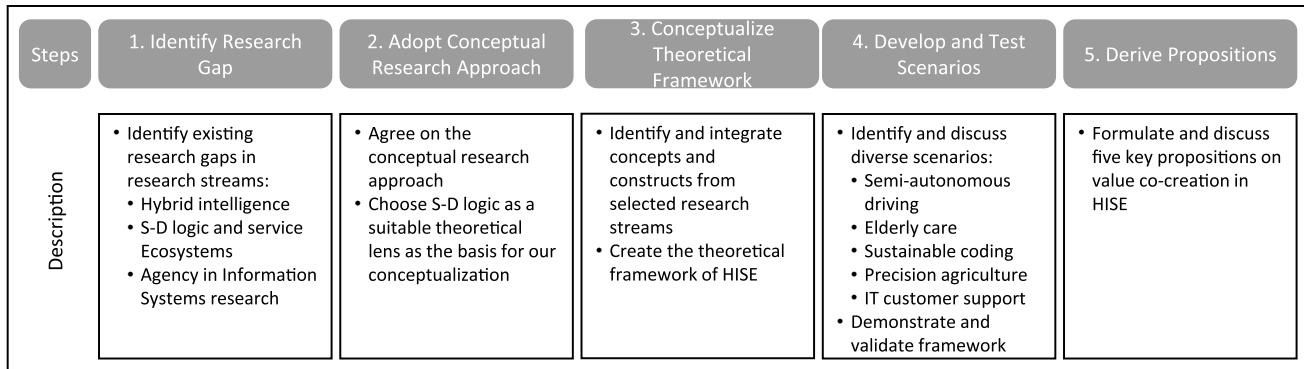


Fig. 1 Conceptual research process

Conceptualizing hybrid intelligent service ecosystems

We define HISE as service ecosystems that leverage human and artificial intelligence to configure human and AI agency as human-AI hybrids. Based on the S-D logic's definition of a service ecosystem, a HISE is a dynamic network of interconnected actors—humans, AIs, and human-AI hybrids—along with their resources and overarching institutional arrangements that enable value co-creation through hybrid intelligent service. In a HISE, human-AI hybrids seamlessly collaborate by configuring human and AI agencies to perform tasks more effectively, generating value-in-use for the involved actors. The hybrids co-create value through resource integration with other hybrid actors, human actors, or AI actors, engaging in what we term *hybrid intelligent service*, while institutional arrangements guide and shape this value co-creation process in the service ecosystem. Reflecting on the concept of generic actors, all actors in a HISE can be both service providers and recipients (or benefactors and beneficiaries, respectively). Human-AI hybrids can appear on either side of a service interaction, such as a doctor using AI tools (service provider) or a patient employing AI to evaluate medical results (service recipient).

Figure 2 provides an overview of our conceptual framework, illustrating the key components and their interactions within a HISE. The framework depicts the dynamic network of human-AI hybrids, humans, and AIs, along with their resources and the institutional arrangements that collectively enable value co-creation through hybrid intelligent service. This visual representation helps convey the complex interdependencies and mechanisms that drive the integration and optimization of human and AI capabilities within service ecosystems.

The primary objective of HISE is to leverage the complementary strengths of humans and AI to facilitate resource integration and service exchange, ultimately resulting in superior value-in-use for diverse actors. By leveraging the

potential of human-AI hybrids to integrate resources in hybrid intelligent service, organizations can address challenges and inefficiencies associated with solely human or machine-based value co-creation. AI offers unique capabilities such as data processing, pattern recognition, and predictive analytics that can significantly improve decision-making and operational efficiency. In contrast, humans excel in creativity, empathy, and contextual understanding, aspects often beyond the reach of current AI systems. By strategically assigning tasks to human or AI agencies based on situational needs, individuals, teams, and organizations can achieve results that surpass the capabilities of either party alone.

In a HISE, agency configuration processes take place constantly. Human-AI hybrids continuously negotiate the configuration of human and artificial agencies for optimized task performance in each instance of an interaction. This perspective aligns with Baird and Maruping's (2021) extension of the dyadic delegation model to a multi-agent perspective. Task allocation depends on factors such as the availability and maturity of AI technologies and situational constraints that lead to the imbrication of human and material (i.e., AI) agencies (Leonardi, 2011). The agency configuration of human-AI hybrids can range from no or minimal reliance on artificial agency to full reliance, depending on the task and context (Dellermann et al., 2019). This situational *configured agency* (see Fig. 2) of human-AI hybrids emphasizes that individual interactions and agency configurations determine immediate task performance and, thus, service outcomes.

The proposed framework, as depicted in Fig. 2, comprises four key components of HISE:

- 1) *Actors*: In a HISE, we identify three types of actors: human-AI hybrids, AI actors, and human actors. *Human-AI hybrids* are actors—which could also be conceptualized as service systems at the micro level—that configure human and artificial agencies to perform tasks more effectively. They leverage the complementary strengths of both human and AI agencies and can adapt

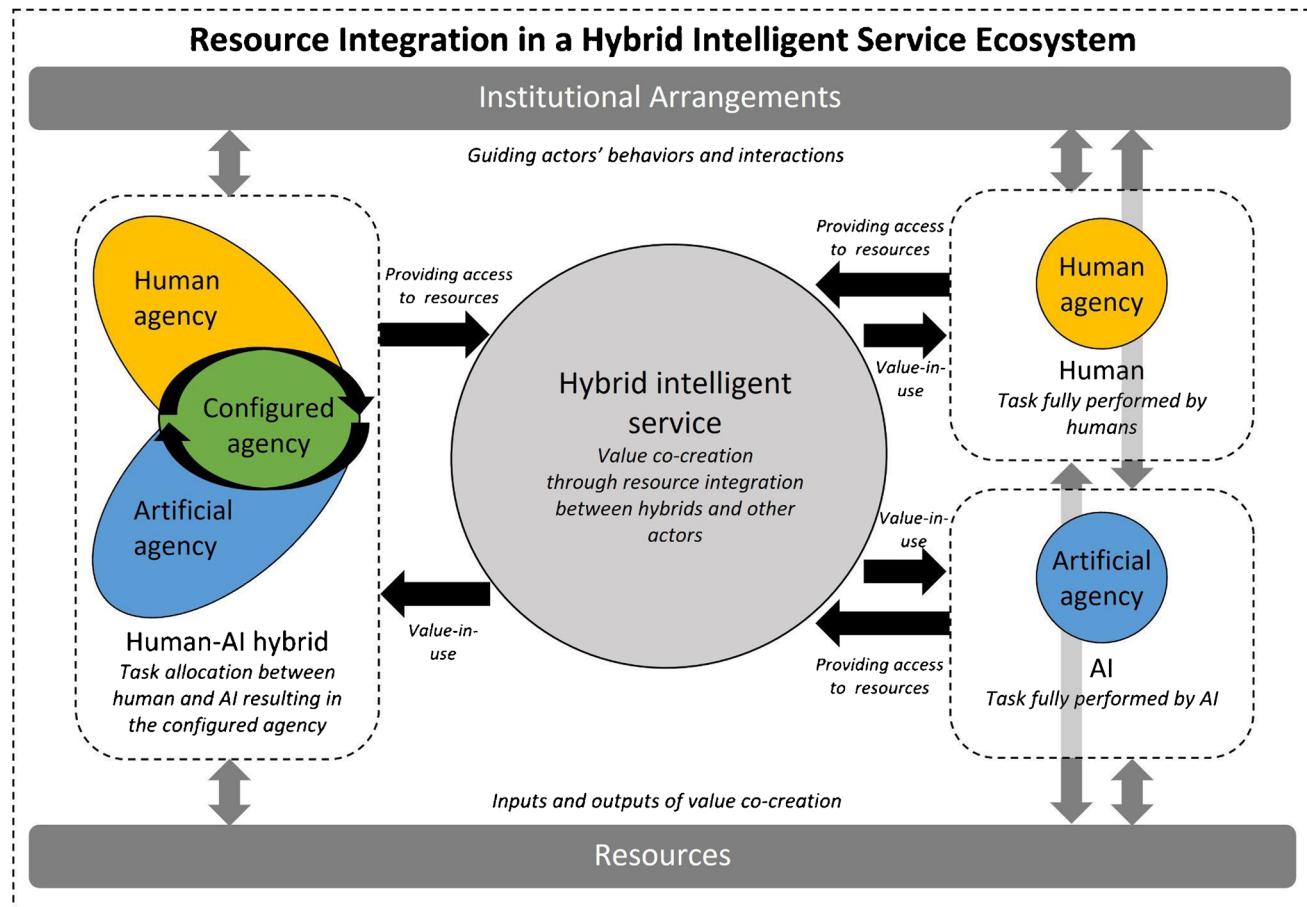


Fig. 2 Resource integration in a hybrid intelligent service ecosystem

their configured agency in every instance of service provision to co-create value by integrating resources with other human-AI hybrids, human actors, or AI actors. In contrast, *human actors* are those actors who rely solely on human agency, thus performing tasks and engaging in service exchanges without the direct assistance of AI. *AI actors* are actors operating based on AI agency alone. While fully autonomous AI actors are not yet prevalent, we anticipate their emergence in the near future, reflecting advancements toward strong AI with increasing levels of autonomy and self-awareness within boundary conditions. Including AI actors in our conceptualization prepares the framework for future developments.

2) *Hybrid intelligent service*: Hybrid intelligent service refers to the collaborative processes by which different types of actors, including at least one human-AI hybrid, integrate their unique capabilities and resources to co-create value within the ecosystem. By integrating human creativity and contextual understanding with AI's data processing and analytical capabilities within the configured agency of human-AI hybrids, hybrid intelligent service enables enhanced decision-making and service

delivery that neither humans nor AI could achieve independently.

3) *Resources*: Resources encompass both operant and operand resources that all or some actors within the ecosystem mobilize, configure, and integrate. These sets of resources are dynamic and can partially be updated and enhanced by all types of actors in the ecosystem. Operant resources are active resources such as human skills, knowledge, and competencies, but also advanced AI systems, while operand resources are passive resources like traditional technological assets, infrastructure, and data. These resources provide the foundation for resource integration and value co-creation in the service ecosystem. Actors can selectively deploy different combinations of resources depending on the specific requirements of a service interaction, thereby optimizing joint value creation. For example, in a telemedicine scenario, resources that actors can access might include the IT systems for internet telephony (operand), the knowledge of the medical personnel (operant), wearables of the patient (operand), patient health data (operand), and advanced AI diagnostic systems (operant).

4) *Institutional arrangements*: Institutional arrangements consist of formal regulations (e.g., laws, policies), informal norms (e.g., cultural expectations), and practices that guide the behaviors and interactions of actors within the ecosystem. Institutional arrangements influence and constrain how human-AI hybrids configure their agency, ensuring that service delivery processes align with ethical standards and the overarching “rules of the game” of the ecosystem. They reflect the institutional logic of service ecosystems (Lusch & Nambisan, 2015; Storbacka et al., 2016). For instance, data privacy laws may constrain the use of certain AI technologies, affecting how actors in HISE integrate resources.

Table 3 provides the definitions of these core concepts of HISE.

The HISE framework adopts an ecosystem perspective to examine how interactions among actors facilitate value co-creation. While Fig. 2 depicts a simplified model of a triadic service ecosystem with three actors, modern service ecosystems typically involve complex “actor-to-actor networks” (Lusch & Nambisan, 2015), where multiple actors directly or indirectly integrate resources in value co-creation processes. As demonstrated in our application scenarios, these networks are dynamic and multifaceted.

Accordingly, Fig. 3 outlines the various interaction possibilities within a service ecosystem, which becomes a HISE when at least one of the actors involved in the resource integration process is a human-AI hybrid, leading to interactions such as human-AI hybrid → human-AI hybrid; human-AI hybrid → human; human-AI hybrid → AI; or vice versa. The introduction of human-AI hybrids significantly expands the interaction possibilities within the ecosystem, effectively doubling the potential types of interaction relationships. This expansion increases both the complexity and richness of

the value co-creation processes, providing a more nuanced understanding of how value is generated and exchanged in modern service ecosystems that constitute HISE.

HISE can be nested within larger organizational structures that bring together human actors, AI actors, and human-AI hybrids. The classification of an actor as a human-AI hybrid, human actor, or AI actor, therefore, depends on the level of aggregation. At the micro level of atomic actors, a human-AI hybrid represents an individual collaborating with AI; a human actor represents a single individual, and an AI actor represents an autonomously acting AI system. For example, if a client company uses an AI system to handle service provider requests with minimal human intervention due to embedded algorithmic oversight, the AI system functions as an AI actor at the individual level. Conversely, suppose the company itself is considered an actor within the HISE. In that case, it may be classified as a human-AI hybrid, comprising human employees collaborating with AI systems, including those setting the boundaries for the artificial agency. In line with Storbacka et al. (2016), higher-order sets of actors, their resources, and resource integration patterns represent the meso level of HISE, while the overall HISE with its institutional arrangements represents the macro-level perspective.

The presence of human-AI hybrids during resource integration activities can also be “hidden” for other actors, for example, if humans conceal their interaction with AI technologies or vice versa. This information asymmetry creates unique dynamics and raises important questions about institutional arrangements, such as transparency obligations and ethical considerations. The fact that human-AI hybrids are not always identifiable by their counterparts in the HISE underscores the critical role of mutual trust between actors and their confidence that institutional arrangements effectively guide the use of AI for resource integration. Trust becomes a fundamental component in the adoption and

Table 3 Definitions of core concepts of hybrid intelligent service ecosystems

Concept	Definition
Hybrid intelligent service ecosystem (HISE)	A service ecosystem containing human and artificial intelligence that configures human and AI agencies as <i>human-AI hybrids</i>
Hybrid intelligent service	A service characterized by the involvement of human-AI hybrids who integrate resources with other human-AI hybrids, human actors, or AI actors to co-create value
Human/artificial agency Actors:	The capacity of humans or AI systems to exercise decision-making, control, and action in a given context
• Human-AI hybrids	• Actors that configure human and artificial agencies to perform tasks more effectively within the ecosystem
• Human	• Actors who rely solely on human agency within the ecosystem
• AI	• Actors who operate based on AI agency alone within the ecosystem
Resources	The supply of operant (active, intangible) and operand (passive, tangible) resources employed for interaction, action, and value co-creation
Institutional arrangements	Interdependent assemblages of formal, informal, and semi-formal rules, norms, and practices that guide actors' behaviors and interactions within the HISE

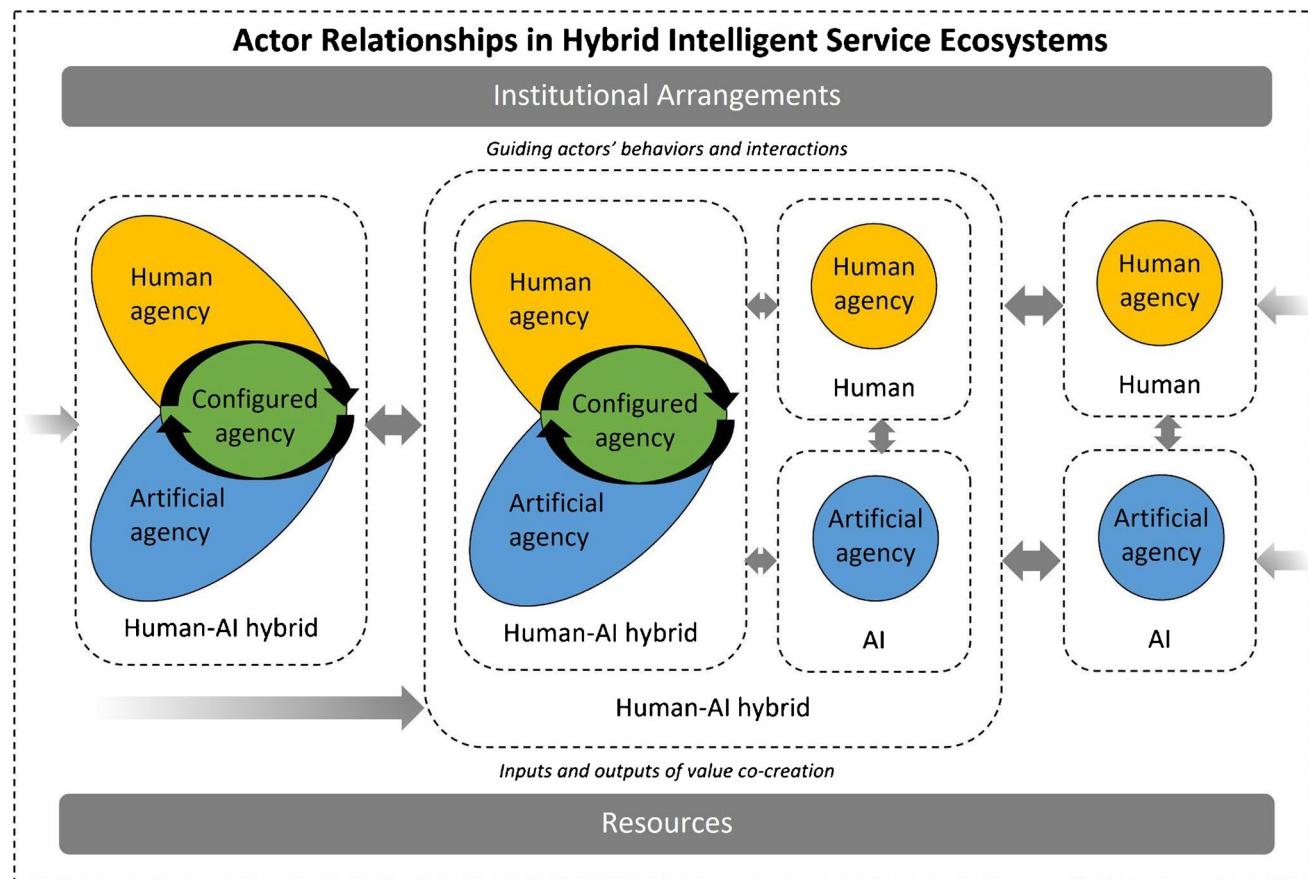


Fig. 3 Actor relationships in hybrid intelligent service ecosystems

success of hybrid intelligent service exchange, influencing how actors engage with one another and how value is co-created within the ecosystem.

Application scenarios of the HISE framework

The proposed HISE framework integrates human-AI hybrids with human and AI actors in service ecosystems, highlighting the configuration of human and artificial agencies, the dynamic nature of resources, and the guiding role of institutional arrangements to co-create value in hybrid intelligent services. The dynamic nature of resources is evident in their continuous evolution and adaptation as actors mobilize and integrate operant and operand resources in response to changing circumstances and needs within the ecosystem. The framework elucidates the interplay between these components and provides concepts to describe how hybrid intelligence can transform and enhance value co-creation processes, playing an active role in redefining service interactions and outcomes.

In this section, we demonstrate the applicability of our conceptual framework for HISE in five distinct service

contexts: semi-autonomous driving, elderly care, sustainable coding, precision agriculture, and IT customer support. These scenarios were chosen because they represent industries where human-AI collaboration addresses complex, high-impact challenges, providing strong examples of how human-AI hybrids can improve efficiency, decision-making, personalization, and sustainability of service interactions. Sectors like healthcare, transportation, and agriculture were selected for their advanced integration of AI systems, offering clear and diverse illustrations of how a HISE reaches across different service environments. In the last case, IT customer support is a typical knowledge-intensive service that has showcased the potential of hybrid intelligent services from an operational and ecosystem perspective. We provide a comprehensive understanding of the dynamic interplay between human and artificial agencies, institutional arrangements, and resources in these application scenarios, addressing key aspects of the HISE framework—namely, the agency configuration process of human-AI hybrids, the hybrid intelligent service, resources, and institutional arrangements—summarized in Table 4.

Table 4 Summary of application scenarios

Scenario A: Semi-autonomous driving	Scenario B: Elderly care
<ul style="list-style-type: none"> • <i>Hybrid intelligent service:</i> AI-assisted semi-autonomous driving • <i>Directly involved actors:</i> <ul style="list-style-type: none"> <i>Human-AI hybrids:</i> Drivers using advanced driver assistance systems (ADAS) <i>Human actors:</i> Passengers, pedestrians, and drivers without AI assistance <i>AI actors:</i> Fully autonomous vehicles • <i>Actors in the broader service ecosystem:</i> <ul style="list-style-type: none"> Car manufacturers, telecommunications and other infrastructure providers, insurance companies, regulators, traffic authorities, etc 	<ul style="list-style-type: none"> • <i>Hybrid intelligent service:</i> AI-augmented elderly care • <i>Directly involved actors:</i> <ul style="list-style-type: none"> <i>Human-AI hybrids:</i> Caregivers and care coordinators using AI-based health and facility management systems <i>Human actors:</i> Patients, family members <i>AI actors:</i> Automated conversational assistants for caregivers, care coordinators, and patients • <i>Actors in the broader service ecosystem:</i> <ul style="list-style-type: none"> Healthcare providers, pharmaceutical companies, medical device manufacturers, social workers and community services, policymakers, regulators, etc
<ul style="list-style-type: none"> • <i>Human agency in hybrid:</i> Driver's decision-making and situational awareness • <i>Artificial agency in hybrid:</i> ADAS for adaptive cruise control, lane-keeping, collision avoidance • <i>Resources:</i> Physical road infrastructure (roads, signs, gas stations, etc.), sensor data, mapping information, AI algorithms, vehicle communication systems, etc • <i>Institutional arrangements:</i> Road traffic laws, government regulations, safety standards, data-sharing agreements, etc 	<ul style="list-style-type: none"> • <i>Human agency in hybrid:</i> Caregiver's empathy and compassion, care coordinator's care management expertise and flexibility • <i>Artificial agency in hybrid:</i> AI system for personalized care plans, health monitoring, predictive analytics • <i>Resources:</i> Wearable devices, health monitoring sensors, patient records, AI algorithms, communication platforms, etc • <i>Institutional arrangements:</i> Privacy regulations, professional guidelines, quality management processes, etc
Scenario C: Sustainable coding	Scenario D: Precision agriculture
<ul style="list-style-type: none"> • <i>Hybrid intelligent service:</i> Carbon-friendly software development • <i>Directly involved actors:</i> <ul style="list-style-type: none"> <i>Human-AI hybrids:</i> Software engineers with AI-based systems (e.g., ChatGPT, GitHub Copilot) <i>Human actors:</i> Software engineers without AI assistance in the same project <i>AI actors:</i> Automated AI-based code quality and compliance systems (e.g., on the client side) • <i>Actors in the broader ecosystem:</i> <ul style="list-style-type: none"> Software companies, cloud providers, energy companies, environmental organizations, standards bodies, regulators, educational institutions, end-users, etc 	<ul style="list-style-type: none"> • <i>Hybrid intelligent service:</i> AI-driven precision agriculture • <i>Directly involved actors:</i> <ul style="list-style-type: none"> <i>Human-AI hybrids:</i> Farmers and agronomists using AI-based decision support systems <i>Human actors:</i> Field workers, consumers buying agricultural products <i>AI actors:</i> Automated inventory management and demand forecasting and procurement systems for agricultural products • <i>Actors in the broader ecosystem:</i> <ul style="list-style-type: none"> Agrochemical companies, equipment manufacturers, data analysis firms, food distribution and retail chains, environmental agencies, end customers, etc
<ul style="list-style-type: none"> • <i>Human agency in hybrid:</i> Software engineer's creativity, problem-solving and programming expertise • <i>Artificial agency in hybrid:</i> AI system for carbon-friendly code generation and optimization • <i>Resources:</i> Programming languages, development environments, source code repositories, APIs, etc • <i>Institutional arrangements:</i> Software industry standards, cybersecurity frameworks, environmental regulations, intellectual property laws, etc 	<ul style="list-style-type: none"> • <i>Human agency in hybrid:</i> Farmer's local knowledge, agronomist's crop management expertise • <i>Artificial agency in hybrid:</i> AI for optimizing irrigation, fertilization, pest management, etc • <i>Resources:</i> IoT devices, remote sensing data, foundational models, AI algorithms, agricultural machinery, etc • <i>Institutional arrangements:</i> Government subsidies, industry standards, environmental regulations, data-sharing protocols, agricultural policies, etc
Scenario E: IT customer support	
<ul style="list-style-type: none"> • <i>Hybrid intelligent service:</i> AI-augmented IT customer support • <i>Directly involved actors:</i> <ul style="list-style-type: none"> <i>Human-AI hybrids:</i> IT service agents collaborating with AI-driven decision support systems and chatbots <i>Human actors:</i> End users submitting IT service requests, IT managers overseeing support operations <i>AI actors:</i> Automated ticket classification, virtual assistants, AI-powered troubleshooting models • <i>Actors in the broader ecosystem:</i> <ul style="list-style-type: none"> IT service providers, enterprise IT departments, cloud service providers, cybersecurity firms, software vendors, regulatory bodies, compliance officers 	
<ul style="list-style-type: none"> • <i>Human agency in hybrid:</i> IT support agents validating, refining, and enhancing AI-generated service recommendations • <i>Artificial agency in hybrid:</i> AI-driven ticket classification, real-time issue resolution recommendations, adaptive learning from human feedback • <i>Resources:</i> IT service logs, historical issue-resolution data, knowledge bases, cybersecurity insights, AI-driven monitoring systems, chatbots, etc • <i>Institutional arrangements:</i> IT governance policies, SLAs, cybersecurity frameworks, data privacy regulations (e.g., GDPR), industry compliance standards (e.g., ISO 27001), AI ethics guidelines 	

Semi-autonomous driving

Given the rapid advancement of AI technologies in the automotive industry, semi-autonomous driving serves as a compelling application of the HISE framework. The integration of AI into the mobility landscape demonstrates the dynamic nature of resources, as data sources, sensor technologies, and AI algorithms continuously evolve and adapt to new conditions. This integration transforms value co-creation by enhancing safety, increasing driving efficiency, and enriching the overall driving experience. Multiple actors within the ecosystem of semi-autonomous driving collaborate to co-create, implement, and refine hybrid intelligent services that enable safer and more efficient transportation.

In this scenario, a driver operates a semi-autonomous vehicle equipped with AI-powered advanced driver assistance systems (ADAS), including features such as adaptive cruise control, lane-keeping assistance, and collision avoidance. The driver, as a *human-AI hybrid*, contributes human expertise in situational awareness, decision-making, and overall vehicle control, particularly in rare events—so-called “edge cases.” Simultaneously, the AI system provides real-time data analysis and decision support by processing information from sensors, cameras, and external data sources such as mapping, traffic, and weather updates.

The *dynamic interplay between human and artificial agency* is evident: for example, while the AI system manages routine tasks such as lane-keeping and adaptive cruise control, the driver retains control during critical or unexpected traffic conditions. The driver relies on expertise to navigate complex environments and makes high-level decisions, such as interpreting ambiguous road signs or responding to unforeseen situations. Meanwhile, the AI system assists with real-time adjustments, like maintaining a safe distance from other vehicles, adhering to lanes, or applying automatic braking to avoid collisions. In extreme situations, the AI system might alert the human driver to take over control, or conversely, it may execute emergency maneuvers autonomously. This continuous negotiation and reconfiguration of agency between the human driver and the AI-powered ADAS exemplifies the concept of *configured agency* in human-AI hybrids, while it can be assumed that the continuum on which humans allocate tasks to the ADAS varies according to individual preferences and the specific context.

An interesting aspect of this scenario is that actual driving can be understood as a “self-service,” where a human actor both provides and benefits from the service of controlling the vehicle, while passive actors (passengers) are beneficiaries of the mobility service. This highlights the dual role of the driver as both a service provider (operating the vehicle) and a beneficiary (gaining mobility), underscoring the complexity of service interactions within the HISE, where roles can overlap and shift depending on the context.

Moreover, the interactions between actors within the HISE extend beyond the driver and the vehicle’s AI systems. The driver and vehicle interact with other *human-AI hybrids* (drivers using ADAS), *human actors* (passengers, pedestrians, drivers without AI assistance), and potentially *AI actors* (fully autonomous vehicles). For example, the vehicle may communicate with nearby autonomous vehicles to coordinate movements and optimize traffic flow. This necessitates integrating resources such as shared road infrastructure, communication protocols, and data exchange mechanisms.

Resources in this scenario are dynamic and modular, including physical infrastructure (roads, traffic signs, gas stations), sensor data, mapping information, and AI algorithms. The continuous updating of mapping data, traffic information, and software updates for AI systems exemplifies the dynamic nature of resources, which typically adhere to defined structures (e.g., specified data formats, APIs, access rights to in-vehicle data, etc.) that facilitate seamless interoperability. Actors within the ecosystem can selectively deploy different combinations of these resources depending on situational needs, optimizing joint value creation. For instance, the vehicle’s operating system consolidates data from sensors and external sources to assess the driving environment, anticipate potential hazards, and optimize driving performance. Additionally, data marketplaces may enable third parties, such as insurance companies or maintenance providers, to contribute additional services, enhancing the ecosystem’s overall value. Overall, the prevailing resource structure empowers actors to utilize resources to make well-informed decisions, adapt to evolving conditions, and achieve superior outcomes in terms of safety, efficiency, and well-being. The dynamic nature of resources is further recognized through the continuous advancements in AI technologies, sensor capabilities, and communication infrastructures. For example, new algorithms for better object recognition or improved decision-making in complex traffic scenarios may be developed and integrated into the ADAS. Similarly, updates to mapping information or traffic data systems reflect changes in road conditions, construction, or traffic patterns, requiring the human-AI hybrid to adapt accordingly.

Institutional arrangements play a crucial role in shaping the behaviors and interactions of actors within this HISE scenario. Government regulations, industry standards, and safety guidelines—such as the SAE levels of driving automation (Society of Automotive Engineers, 2021) and associated safety standards—govern the development and deployment of AI-driven capabilities, ensuring safety while promoting innovation. For example, regulations may specify the required safety features for ADAS or set standards concerning data privacy and cybersecurity in connected vehicles. Data-sharing agreements and protocols enable smooth data integration from diverse sources, fostering effective

collaboration among actors while reflecting data sovereignty principles. Informal networks and collaborations between manufacturers, technology providers, and service providers contribute to knowledge sharing and the evolution of best practices within the ecosystem.

The interplay between individual behaviors, organizational responses, and regulatory actions exemplifies how different levels within the HISE influence each other. For instance, incidents, where drivers of semi-autonomous vehicles misused the technology by engaging in activities like sleeping while driving, have prompted regulatory bodies to scrutinize and demand changes from manufacturers. This has led to adjustments in the design and functionality of ADAS to limit inappropriate use and enforce safer agency configurations. Tesla, for example, has been required to implement driver monitoring systems that detect inattentiveness and issue alerts or even disable autonomous features if necessary. Such dynamics illustrate how actors across different levels of the HISE interact to enforce institutional arrangements, ensuring that human responsibility is appropriately maintained within agency configurations. These regulatory interventions represent a self-regulating effect of the ecosystem, where macro-level authorities enforce institutional rules that necessitate actors to adjust their technologies, ultimately influencing micro-level behaviors.

Elderly care

Elderly care represents another illustrative case for applying the HISE framework, as integrating AI technologies into the human care service sector can significantly enhance the quality of life for older adults. By blending human expertise with AI capabilities, AI-augmented elderly care services improve value-in-use through personalized care plans, efficient monitoring, and, ultimately, better well-being outcomes. Multiple actors within the elderly care service ecosystem collaborate to design, implement, and refine hybrid intelligent service offerings that promote optimal care and support.

In this scenario, a *caregiver* and a *care coordinator* collaborate with an *AI-based health and facility management system* to provide comprehensive care to an older adult, the primary beneficiary. The caregiver and care coordinator are considered *human-AI hybrids* because they actively configure and integrate both human and artificial agencies in their roles. The caregiver contributes human empathy, compassion, and tailored care, while the care coordinator offers expertise in care management and coordination of support services. The AI system assists by gathering and analyzing data from various sources, including wearables, smart home devices, and health records, generating personalized recommendations for daily routines, medication management, early detection of potential health issues, and improving

the efficiency of care management processes in the facility. In domains such as elderly care, which face shortages of highly skilled workers, this frees up time for the staff to focus on their core competencies in human interaction with the beneficiaries instead of tedious tasks such as reporting medicine intake.

The dynamic interplay between human and artificial agencies is evident as the caregiver and care coordinator negotiate the configuration of agencies for optimized task performance. For example, the caregiver may rely on their human expertise to provide emotional support and recognize subtle changes in the patient's behavior that require attention. Simultaneously, the AI system monitors health indicators in real time, analyzes patterns in the data, and provides alerts or suggestions, enabling proactive interventions. This collaboration enhances the quality and responsiveness of care, illustrating the configured agency within the human-AI hybrid.

Patients within the elderly care service ecosystem can be described as *human actors* who do not necessarily become hybrids. While they interact with AI systems indirectly through the services provided, they typically do not actively configure agency between themselves and AI systems. However, they do *integrate resources* by using wearable devices and health monitoring sensors, which collect data essential for the AI system's functioning. This participation is crucial for resource integration within the HISE, although the patients themselves do not configure agency with AI systems. This enables the other actors to utilize resources to make informed decisions effectively, adapt to changing needs, and achieve better outcomes in elderly care and support than could be achieved without the involvement of AI. The service ecosystem could also include resources that allow for integration with adjacent service ecosystems, such as an electronic health record that enables sharing of health-related data with third-party health professionals.

Resources in this scenario include operant resources like the caregiver's skills and knowledge, and operand resources like wearable devices, health monitoring sensors, AI algorithms, and communication platforms. These resources are *dynamic*, continuously adapting to new technologies, patient needs, and medical advancements. For example, new wearable devices may offer additional health metrics, or AI algorithms may be updated based on the latest medical research, requiring actors to adapt and integrate these evolving resources into the care process.

In this scenario involving vulnerable actors, the macro-level *institutional arrangements* play a significant role in shaping the behavior and interactions of actors within the HISE. Regulations and standards for privacy and security govern the handling of sensitive personal health information, ensuring compliance with laws such as HIPAA in the USA or GDPR in Europe. In addition, professional guidelines,

quality management processes, and certification requirements for caregivers and care coordinators maintain high standards of care and service quality. For instance, there may be protocols for responding to specific health alerts generated by the AI system, ensuring ethical and effective interventions. Informal knowledge-sharing networks, such as online forums, community groups, and workshops among caregivers, healthcare professionals, and service providers, can also shape the ecosystem around elderly care services. These networks foster the sharing of best practices, innovations, and experiences, which drive further advances in the field and improve the quality of care for older adults across human agency, artificial agency, and agency configuration.

Sustainable coding

The software industry is responsible for approximately 1.8% to 2.8% of global greenhouse gas emissions (Freitag et al., 2021). Therefore, addressing sustainability in software engineering has become critical, with various initiatives aiming to reduce emissions and promote environmentally friendly practices (Ma et al., 2022; Naumann et al., 2011). For example, minimizing the carbon footprint of software can be achieved by reducing data storage, database requests, and API calls when developing software. *Carbon-friendly programming* represents a scenario of hybrid intelligent service where software engineers collaborate with AI systems to develop sustainable software, thereby reducing the carbon footprint associated with software applications. This scenario illustrates how hybrid intelligence can transform and enhance value co-creation processes by enabling the development of environmentally sustainable software solutions.

In this context, a *human-AI hybrid* is formed by a *software engineer* working alongside an *AI-based coding assistant*, such as an instance of ChatGPT or GitHub Copilot specifically trained for developing carbon-friendly code for client applications. The software engineer contributes human agency through creativity, requirements engineering, and programming expertise. They understand the software's concept, user requirements, and design specifications, bringing critical thinking and problem-solving skills to the development process. Meanwhile, the AI system provides artificial agency by generating carbon-friendly code, optimizing algorithms for energy efficiency, and identifying patterns that contribute to unnecessary emissions.

The configuration of human and artificial agency is evident as tasks are allocated based on situational needs and expertise. For instance, the software engineer may write initial code structures and algorithms, leveraging their creativity and understanding of the software's intended functionality. Simultaneously, the AI system analyzes the code for potential inefficiencies, suggests alternative coding practices that reduce computational resource usage, and optimizes the

code for sustainability without compromising performance or security. Whether the AI system contributes in a sequential, parallelized, or iterative process can be configured flexibly, accounting for project-specific goals, preferences, and resource availabilities.

For example, during the development process, the software engineer might design a data processing module that handles large datasets. The AI assistant could proactively analyze the expected load and data access patterns and, therefore, recommend more efficient data structures or algorithms that require fewer computational resources, thereby reducing energy consumption. The AI system might also autonomously switch the application from a traditional relational database to a more efficient NoSQL database like MongoDB that offers better performance and lower energy consumption for the given application's unstructured data needs—thus aligning the software infrastructure with sustainability goals. In a hybrid intelligent service in software development, the human-AI hybrid will interact with other hybrid or human actors in the software development process, and the beneficiary (client) might also use human, hybrid, or even AI actors, for example, to perform a quality evaluation on the developed code.

Resources in this scenario include operant resources such as the software engineer's skills, knowledge, and competencies, and operand resources like programming languages, development environments, source code editors, and access rights. Moreover, the AI system utilizes extensive, growing datasets of coding practices and sustainability metrics to provide real-time feedback and optimization suggestions. These resources are *dynamic*, constantly evolving with technological advances and changing industry standards, as well as with experience in providing this hybrid intelligent service. For example, by receiving feedback from the AI system on sustainable software development practices, the software engineer may gain knowledge for future projects that allow them to adopt these practices by themselves or improve their workflow in collaboration with the AI system. Additional resource structures support this co-creation process by enabling a fluid exchange and integration of resources. Standardized programming languages, code repositories, and development tools facilitate collaboration between human engineers and AI systems. For instance, GitHub Copilot integrates seamlessly into Visual Studio Code, creating a symbiotic development environment where both human engineers and AI systems can access and collaborate on software source code in real time, moving beyond the traditional role of AI systems as a tool by enacting their own agency.

Institutional arrangements guide behaviors and interactions within the sustainable coding HISE. Macro-level software industry standards, cybersecurity, and data security frameworks ensure that code meets quality and security requirements. Environmental regulations and organizational

policies may mandate sustainability practices, influencing software development approaches. Intellectual property laws and licensing agreements affect the use of AI-generated code, ensuring compliance and ethical considerations in the collaboration of human and AI actors. Data security is also paramount; sensitive client data appearing in specifications must be protected and explicitly excluded from further training of AI models to comply with privacy regulations.

Precision agriculture

Precision agriculture serves as an illustrative case of HISE, demonstrating the value of hybrid intelligence in transforming traditional farming practices through the integration of AI technologies. The agricultural sector has been a relatively early adopter of AI technologies compared to other domains. By utilizing data-driven insights and advanced analytics, precision agriculture enhances value co-creation, e.g., by optimizing resource utilization, improving crop yields, and promoting sustainable farming practices. The various actors in the precision agriculture HISE work together to deliver high-quality agricultural products, leveraging hybrid intelligent service offerings that facilitate effective shared decision-making and resource allocation between these actors.

In this scenario, *human-AI hybrids* are formed by a *farmer* and an *agronomist*, respectively, collaborating with AI-based decision support systems to manage a field of crops. The farmer provides human agency through local knowledge of the land, understanding of crop history, and practical farming experience. The agronomist contributes expertise in crop management, soil science, and pest control strategies. The AI systems offer artificial agency by integrating data from multiple sources—such as soil sensors, weather history and forecasts, drone imagery, and historical crop data—to generate real-time recommendations for optimal irrigation schedules, fertilizer application rates, or pest management interventions. Both of these human-AI hybrids not only interact with each other but also with other human (e.g., consumers, field workers), hybrid (e.g., semi-autonomously operated field machinery), or AI actors (e.g., automated inventory management and procurement systems) within the HISE. For instance, a distribution center for agricultural products with an AI-based inventory management and demand forecasting system could connect the hybrid farmer with the shops for consumers. This AI system autonomously orders agricultural products based on real-time data, ensuring a seamless supply chain. Thus, it assumes the role of an AI actor minimizing waste and ensuring consumers' access to fresh products. Human consumers, the end-users of agricultural products, benefit from the high-quality, sustainably produced goods resulting from this hybrid intelligent service.

The configuration of human and artificial agencies is evident as tasks are dynamically allocated based on expertise,

situational demands, and levels of granularity. For example, the farmer or agronomist may use their judgment based on their human expertise to interpret AI-generated insights to determine the appropriate crop rotation plan and soil treatment within the context of their specific environment, making strategic decisions that consider factors beyond the analysis of the data available, such as market conditions or community practices. Similarly, the AI system might suggest an optimal irrigation schedule as a real-time recommendation based on soil moisture data and weather forecasts, but the farmer may adjust this recommendation based on knowledge of local water availability or irrigation equipment constraints.

Resources integrated by the actors in the precision agriculture HISE include operant resources like the knowledge and expertise of the farmer and agronomist, and operand resources such as agricultural machinery, IoT devices, remote sensing data, and AI algorithms. The modular structure of these resources facilitates effective resource integration by standardizing, e.g., data formats, communication protocols, and authorization systems. For example, an integrated platform might combine soil moisture sensors, satellite imagery, and AI-based models to monitor crop health, predict yield, and optimize resource use. This standardized structure allows utilizing resources effectively, making informed decisions, adapting to changing conditions, and achieving better outcomes in terms of productivity and sustainability. Furthermore, these resources are dynamic, adapting to continuous advancements in sensor technologies, AI algorithms, and data analytics. For example, new sensor technologies may provide more accurate soil moisture readings, or AI algorithms may improve in predicting pest infestations. As new data sources become available and algorithms improve, human-AI hybrids must adapt their practices to incorporate these developments, ensuring that farming remains responsive to environmental conditions and technological innovations.

Institutional arrangements play a critical role in guiding the behaviors and interactions of actors within the precision agriculture HISE. For example, government subsidies and agricultural policies (on the macro level) may encourage the adoption of sustainable farming practices and AI technologies such as variable rate fertilization, promoting environmental stewardship and resource conservation by individual actors (on the micro level). Industry standards for data sharing and interoperability foster collaboration among diverse actors in the service ecosystem, ensuring that data from different devices and IT systems can be integrated effectively. Environmental regulations influence resource utilization, pest management practices, and the use of fertilizers and pesticides, shaping the decisions made by human-AI hybrids. For example, compliance with environmental regulations may require the farmer and agronomist to limit the

use of certain chemicals. The AI system can assist by suggesting alternative pest management strategies or optimizing the application of fertilizer to meet regulatory requirements while maintaining crop health.

IT customer support

As IT service management (ITSM) grows in complexity, organizations increasingly struggle with handling support requests efficiently. The rising volume of service requests, the fragmentation of knowledge across distributed teams, and workforce turnover make it difficult to maintain high service quality. AI-powered automation offers potential solutions by enhancing decision-making and optimizing ticket resolution, yet its isolated deployment often lacks adaptability, explainability, and trust among IT service employees. Research analyzing over 17,000 IT support tickets has shown that AI often misclassifies cases in edge scenarios, requiring human intervention to ensure accuracy and continuous learning (Li et al., 2024). This underscores the need for a structured framework that conceptualizes how hybrid intelligence should be designed and managed in service ecosystems. The HISE framework provides this foundation by defining how human actors, AI actors, and human-AI hybrids interact in dynamic, co-evolving service environments, enabling seamless value co-creation through hybrid intelligent service. The HISE framework conceptualizes service ecosystems as dynamic networks where human, AI, and human-AI hybrid actors collaborate to optimize task performance. The hybrid intelligent service support (HISS) model (Reinhard et al., 2023) instantiates the HISE framework by demonstrating how hybrid intelligence enhances operational scalability, adaptability, and knowledge retention in IT customer support. Unlike traditional automation models, HISE's situationally configured agency enables IT service agents to continuously negotiate task allocation with AI-driven decision support systems. Depending on the complexity and urgency of a ticket, AI may take the lead in automated issue classification, while human agents intervene for high-stakes decision-making. For example, human-AI hybrids in ITSM negotiate agency configurations continuously, determining the optimal mix of AI automation and human expertise for each service instance.

A key contribution of HISE to IT service management is its structured view of *agency configurations*. ITSM involves various types of service interactions, ranging from simple, repeatable tasks that can be fully automated to complex, high-stakes decisions that require human expertise. The HISE framework provides a conceptual lens for understanding how agency is dynamically distributed across human and AI actors. In the HISS scenario, routine service requests—such as password resets or basic troubleshooting—can be handled by AI actors through chatbots and automated ticket

classification. More complex issues—such as diagnosing a previously unseen network outage or resolving multi-system integration failures—require human expertise, where human agents take the lead. However, HISE emphasizes that many service interactions fall between these extremes, requiring human-AI hybrid agency. In HISS, human agents collaborate with AI-powered decision-support systems that recommend solutions, retrieve knowledge from past incidents, and highlight potentially relevant troubleshooting steps. By leveraging the HISE framework's triadic interaction model, HISS actors dynamically shift between human, AI, and hybrid roles to optimize service efficiency.

Beyond structuring agency configurations, HISE clarifies *how resources are integrated and mobilized* in hybrid intelligence environments. IT service management relies on various forms of data resources, including historical ticket logs, service knowledge bases, system monitoring data, and real-time user feedback. AI models in HISS process this data to classify issues, predict resolution pathways, and suggest solutions based on prior cases. However, HISE highlights that data alone is not enough—resource integration in hybrid intelligence environments requires continuous knowledge validation, refinement, and adaptation by human actors. IT customer support applies this principle by incorporating structured feedback loops, where service agents review AI-generated recommendations, correct errors, and flag knowledge gaps that require human-driven updates. Over time, this co-creation process shapes a shared knowledge base, improving AI predictions while reinforcing human expertise. This ensures that AI models evolve in alignment with organizational best practices and service-specific contexts. For example, a multi-armed bandit reinforcement learning model applied in ITSM has demonstrated how AI can dynamically adjust ticket classifications based on human agent feedback, ensuring that automated suggestions remain contextually relevant and continuously improving over time (Li et al., 2024). HISE's structured approach to resource mobilization ensures that operant resources, such as human skills and AI analytics, are continuously optimized through iterative co-creation processes. Thus, as knowledge evolves, AI dynamically adjusts its models to improve accuracy and adaptability over time, ensuring that human-AI hybrids can integrate relevant resources effectively for enhanced decision-making.

HISE also provides a governance framework for structuring *institutional arrangements* in hybrid intelligent service ecosystems. In HISS, AI-driven service recommendations must comply with service-level agreements (SLAs), regulatory standards (such as GDPR for user data protection), and organizational policies on AI governance. The institutional layer of HISE ensures that hybrid intelligence does not operate in a regulatory vacuum; instead, it aligns with clear governance mechanisms that define accountability for AI-driven recommendations, compliance with

regulatory standards, and mechanisms for bias mitigation and explainability. Institutional arrangements also influence the adaptation of AI-based decision-making tools over time, ensuring that models evolve in alignment with ethical considerations, industry standards, and regulatory requirements. These governance mechanisms are shaped not only by predefined rules but also by continuous interaction between IT managers, AI system designers, regulatory bodies, and service desk employees, who negotiate standards, refine best practices, and respond to emerging AI-driven risks in real-world environments. Hence, AI-driven service recommendations may need to adapt dynamically to comply with emerging cybersecurity frameworks, privacy regulations, and evolving ITSM standards, ensuring that hybrid intelligence remains ethically and legally aligned.

The value of the HISE framework becomes particularly evident when considering the long-term impact of hybrid intelligence on scalability, adaptability, and resilience in ITSM. HISS illustrates how a well-structured hybrid intelligence service model enables IT organizations to reduce the cognitive load on service agents, improve ticket resolution accuracy, and ensure continuity of knowledge despite workforce changes (Reinhard et al., 2023). By following HISE's principles, organizations can adapt their service operations dynamically, scaling AI involvement up or down as needed without compromising service quality. Moreover, by systematically integrating hybrid agency, resource mobilization, and institutional governance, HISE ensures that AI-driven service enhancements are sustainable, ethical, and aligned with human expertise. This structured approach positions HISE as a fundamental framework for understanding, designing, and managing hybrid intelligent service ecosystems, with HISS serving as a concrete instantiation of its principles in IT service management.

HISS exemplifies the transformative potential of HISE by showcasing how hybrid intelligence enables IT customer support to become more adaptive, knowledge-driven, and operationally resilient. Rather than treating AI as a simple efficiency tool, HISE reveals how IT service organizations can strategically configure hybrid intelligence to enhance decision-making, optimize service workflows, and maintain high-quality user experiences. As ITSM landscapes continue to evolve, future research should explore how the HISE framework can guide the development of more advanced hybrid intelligence models, ensuring that AI-driven service support remains transparent, explainable, and aligned with human expertise. By conceptualizing IT service management as a hybrid intelligent service ecosystem, HISE provides a structured, theoretically grounded approach to designing AI-augmented service environments, offering both researchers and practitioners a blueprint for the next generation of intelligent IT customer support.

Propositions for future research

After presenting and illustrating our conceptualization of HISE, we now discuss the implications for researchers and practitioners raised by our conceptual research. For this purpose, we highlight the effects of deliberate configurations of human and artificial agencies in service ecosystems by introducing five propositions as a foundation for future investigation.

Our framework integrates existing theoretical concepts and constructs to propose and describe a distinct set of concepts and their relationships within HISE. We adopt widely discussed and agreed-upon concepts related to the S-D logic, such as actors, resources, resource integration, institutional arrangements, value co-creation, and service ecosystems. To distinguish HISE from related yet conceptually different service (eco-)system conceptualizations (e.g., smart service systems; Beverungen et al., 2019), our conceptual framework prominently includes the incorporation of artificial agents as a subtype of material agency (Leonardi, 2011). We integrate current discussions about hybrid intelligence from the field of human-AI collaboration, emphasizing that the appropriate combination and configuration of human and artificial agencies can enable superior task performance and, thus, value co-creation through hybrid intelligent service.

The application scenarios presented in the previous section indicate the significant impact of AI adoption on service ecosystems and how these AI systems affect the agency configuration by actors, their resource integration activities, their dynamically evolving resource structures, and the overarching institutional arrangements. Consequently, we postulate that future research should further explore the respective role of these elements in HISE, building on the five propositions presented below. Our propositions offer potential avenues for future research to investigate the complex interplay between human and artificial agencies, resources, institutional arrangements, and the evolution of HISE, ultimately contributing to a deeper understanding of how to design and manage these ecosystems effectively.

The accelerated pace of change within HISE presents both opportunities for rapid innovation and challenges for adaptation. AI integration enables more efficient and responsive service delivery, personalized experiences, and the emergence of innovative service offerings. However, it also poses challenges for actors within HISE to adapt to rapid technological advancements, evolving institutional arrangements, and changing customer expectations. Organizations may need to become more agile and adopt continuous learning approaches to remain competitive within these rapidly evolving service ecosystems.

Proposition 1: Actors

Proposition 1: In HISE, the configuration of human and artificial agencies of human-AI hybrids is dynamic and context-dependent.

Drawing upon the conceptualization of hybrid intelligence (Dellermann et al., 2019), our framework provides a detailed view of the role and interplay of human and material agencies for technology-enabled value co-creation in service ecosystems (Bartelheimer, 2020). While traditional conceptualizations in marketing and IS position IT and AI as mere “tools” (i.e., operand resources) for humans, we follow recent calls from research on human-AI collaboration in IS research and adjacent IT-related disciplines (e.g., human-computer interaction, computer science) to acknowledge the growing importance of IT and especially AI technologies in many application contexts, manifested in material agency that is increasingly equal to human agency (Demetis & Lee, 2018).

This proposition emphasizes that the balance between human and AI agencies of human-AI hybrids is not fixed, but it is continuously negotiated based on the context of the service interaction. Factors influencing this configuration include task complexity, individual skills and preferences, the perceived usefulness of AI functions, and (the ability to receive) real-time feedback during service delivery. For example, in the semi-autonomous driving scenario, the driver’s reliance on AI systems may vary depending on driving conditions, personal comfort with technology, and the capabilities of the AI assistant. Generally, leveraging AI agencies enables more efficient and responsive service delivery, personalized experiences, and the emergence of new service offerings. However, it also poses challenges for actors within HISE to adapt to rapid technological advancements, evolving institutional arrangements, and changing customer expectations. Understanding the dynamic configuration of agencies is crucial for designing HISE that support value co-creation, subject to future behavioral and design-oriented research.

Proposition 2: Resources

Proposition 2: In HISE, human-AI hybrids and AI actors often have different access to resources compared to human-only actors, leading to new resource integration patterns based on AI’s ability to process and analyze large datasets.

From a resource perspective, the ongoing digitalization of service ecosystems promotes the decoupling and (re-)combination of data. The agency of AI—and the types of tasks that AI systems can perform—is subject to the availability of data, which is constantly increasing due to

resource liquefaction and resource density (Lusch & Nambisan, 2015). Service ecosystems enable all actors to exploit the virtually limitless availability of data, but AI actors or human-AI hybrids can integrate, configure, and create resources in ways that human-only actors cannot. For instance, in the precision agriculture scenario, a farmer utilizing the AI-driven analysis of soil conditions and weather patterns might gain a significant advantage over a farmer who relies solely on traditional farming based on experience, as the AI system’s ability to process vast amounts of data enables more precise decision-making, optimizing resource consumption and increasing yields.

This proposition highlights the potential disproportion between resource usage of hybrids and AI systems compared to human actors within HISE. AI’s ability to gather, process, and learn from extensive datasets can provide hybrid and AI actors with significant advantages in areas like market prediction, risk assessment, or operational efficiency. This advantage might create power imbalances within ecosystems, potentially disadvantaging actors who (can) rely solely on human capabilities and can only capitalize on a limited subset of the available resources. Over time, this phenomenon may intensify, as hybrid and AI actors contribute additional resources to the ecosystem that they can mobilize, but human-only actors may find it challenging to use due to complexity, opacity, and lack of access. Addressing these power imbalances is essential to the sustainable long-term success of HISE.

Proposition 3: Information asymmetries

Proposition 3: In HISE, uncertainty about whether an actor is a human-AI hybrid, a human actor, or an AI actor results in information asymmetries in service exchange.

Depending on how tasks have been allocated along the continuum between fully AI-based and fully human-based allocation, resource integration activities might be performed by humans first, machines first, or synchronously (Recker et al., 2023). Transparency regarding agency configurations can foster trust and facilitate collaboration; however, strategic ambiguity can offer competitive advantages in certain situations. For example, organizations might deliberately obscure the extent of AI involvement in their value propositions and offerings to maintain a competitive advantage. The resulting ambiguity about whether resources are being integrated with a human-only actor, an AI-only actor, or a human-AI hybrid often leads to distortions of trust among actors. In healthcare scenarios, patients may be hesitant if they are uncertain whether their care is being managed by humans or AI systems. Conversely, in competitive industries like financial trading, firms may prefer to keep their use of AI confidential.

This proposition acknowledges that the lack of clarity about which actors utilize AI and to what extent this impacts interactions introduces information asymmetries within HISE. Envisioning that these asymmetries will increase and become more complex with higher autonomy of AI actors in the future, as well as the nested structures that actors can form, balancing transparency and strategic interests is a critical challenge of HISE. Ensuring appropriate levels of transparency can build trust and promote effective value co-creation in HISE, while excessive opacity may lead to mistrust, reduced cooperation, and potential ethical concerns.

Proposition 4: Institutional arrangements

Proposition 4: In HISE, the development of higher-order institutions and governance mechanisms is essential to effectively address the unique challenges posed by integrating human-AI hybrids and AI actors.

Institutional arrangements play a decisive role in shaping any ecosystem (Orlikowski & Baroudi, 1991), including HISE, by enabling and constraining value co-creation activities. Understanding their role and impact on human and AI agencies and how they are configured is crucial. Following Ostrom (2009, 2011), we argue that two types of institutional arrangements need to be studied in the context of HISE: formal institutional arrangements and informal institutional arrangements.

Formal, i.e., legally binding institutional arrangements include laws and regulations that enable and constrain the configuration of agency and value co-creation. For example, data privacy laws determine which resources (e.g., personal data) can be used by which configurations of agencies to perform a particular task. The recently passed EU AI Act regulates the use of AI technologies in different high-risk service contexts, ensuring ethical and responsible usage (European Union, 2024). Informal institutional arrangements refer to social norms, cultural contexts, and industry practices that affect actors' willingness to engage in certain resource integration activities. Cultural differences may influence how comfortable individuals are with AI involvement in service provision. Understanding these nuances is essential when designing HISE and configuring agencies to ensure acceptance and effective collaboration among actors.

This proposition emphasizes the need for robust institutional frameworks to guide the development, management, and evolution of HISE. Existing regulations and ethical guidelines may need to be adapted or expanded to consider the specific challenges and potential risks associated with AI integration. Issues like algorithmic bias, data privacy, ethical use of AI, and the possible displacement of human workers require careful consideration and the development

of appropriate governance mechanisms to ensure that HISE benefit all actors. The EU AI Act exemplifies the emerging regulatory efforts to address these challenges (European Union, 2024). However, it is still unknown how the introduction of such regulatory instruments will affect the design and management of HISE over time.

Moreover, we anticipate future adaptations of institutional arrangements as we observe a shift in the predominant "dogma" of AI use. Currently, humans can independently decide whether or not to collaborate with an AI (e.g., in healthcare), but this might change. For example, patients are becoming aware of the higher accuracy (at least on average) of diagnosis when AI is involved. Hence, we expect in parts to see a shift towards the mandatory use of AI (i.e., configuring agencies as human-AI hybrids) in at least some application domains due to shifting customer demands and regulatory requirements.

Proposition 5: Ecosystem evolution

Proposition 5: In HISE, AI's capabilities accelerate the pace of ecosystem evolution, creating both opportunities and challenges for how these ecosystems develop over time.

Within service ecosystems, actors and their underlying agency configurations can have far-reaching impacts on the success and evolution of service offerings (Mele et al., 2018; Nenonen et al., 2018; Vink et al., 2021). In HISE, human-AI hybrids and AI actors can be expected to adapt more rapidly to environmental changes, given their ability to sense and respond faster than human-only actors (Vargo & Lusch, 2011).

This proposition highlights that rapid adaptation in HISE may demand and drive swift adjustments in institutional arrangements, resources, and co-creation processes—leading to both opportunities and challenges concerning the evolution of HISE. Considering the emergence in service ecosystems (Vargo et al., 2023), the AI-driven adaptation of HISE can be viewed as a multi-layer process in which AI actors, human-AI hybrids, and human actors recursively shape institutions, resources, and co-creation processes. The interplay between emergence and institutionalization suggests that AI-driven innovations typically appear first as novel outcomes, become embedded as recurring patterns in service exchange, and eventually become institutionalized through regulatory frameworks (Vargo et al., 2023). This accelerated evolution adds complexity to human-led processes and requires service ecosystems to continually adjust to new developments in the configuration of human and artificial agency.

On the one hand, hybrid and AI actors facilitate the rapid rollout of incremental changes. Service ecosystems, in turn,

can be comprehensively and sustainably (re-)designed in agile, iterative ways thanks to flexible task allocations between human and AI agencies. On the other hand, this speed and complexity introduce significant uncertainty about future states. Vargo et al. (2023) emphasize that such uncertainty stems from intensified, recursive interactions AI actors introduce as they engage with human actors and institutions—yielding both intended and unintended consequences. The accelerated pace may surpass human and institutional capacities to adapt, potentially causing systemic risks. To manage these risks, deliberate strategies are necessary to balance continuous innovation with ecosystem stability, ensuring that overall evolution remains aligned with the individual and collective interests of the actors involved.

In the semi-autonomous driving application scenario, ADAS progressively take on tasks like adaptive cruise control and collision avoidance, shifting decision-making authority from human drivers to AI. As a result, institutional arrangements (e.g., road safety laws, liability frameworks) must evolve accordingly. These AI-driven advancements also reshape resource configuration by integrating sensor data, real-time navigation based on data exchange between vehicles, and predictive analytics for vehicle control. In turn, these changes illustrate a dynamic feedback loop in which regulatory measures and technological progress continually influence each other—reinforcing or constraining possible future evolution paths (Vargo et al., 2023). As AI becomes more central, service ecosystems remain in constant flux, with evolving co-creation processes and regulations both propelled by and shaping AI's growing agency.

Conclusion, limitations, and outlook

This paper provides a conceptualization of HISE, a dynamic network of interconnected human-AI hybrids, human-only, and AI-only actors, dynamically evolving resources, and overarching institutional arrangements that collectively enable value co-creation through the development, deployment, operation, and adaptation of hybrid intelligent service. Hybrid intelligent service refers to value co-creation processes that involve at least one human-AI hybrid, potentially resulting in superior mutual value-in-use by allocating tasks to human and AI agencies. We propose that our HISE framework provides a theoretically sound basis for better understanding, designing, and managing these complex service ecosystems. For example, it may help to understand that the task allocation of hybrid actors (e.g., individuals, teams, organizations) is often not transparent for other actors, which can result in a lack of trust among actors and might finally lead to unrealized value potentials within HISE.

We contribute to the academic body of knowledge by integrating previously distinct streams of research on

(1) hybrid intelligence and human-AI collaboration, (2) S-D logic and service ecosystems, and (3) socio-material agency. We provide an integrated perspective for understanding the growing generative potentials and mechanisms of AI systems in relation to existing social and institutional arrangements at multiple levels—individuals, teams, organizations, and societies—which is central to the IS discipline. Additionally, we present five propositions that call for high-impact future research on HISE, offering potential avenues for further investigation.

Beyond these theoretical implications, our conceptual insights provide guidance for practitioners and policymakers, who can employ the HISE framework to analyze and understand the increasing importance of AI in service ecosystems and to reflect on how artificial agencies may affect resource integration activities and institutional arrangements. This implies that managers need to monitor their own and other actors' progress in adopting AI systems and recognize new opportunities to reconfigure human and artificial agencies for superior value co-creation. That is, actors within service ecosystems should deliberately seek new patterns of resource integration facilitated by the advancing capabilities and use of AI systems, whether within their own organizations or through access to other actors' AI-related resources at the ecosystem level. At the micro level, the framework can guide managers in effectively allocating tasks to human and artificial agencies.

This study is naturally subject to limitations that provide impetus for future research at the same time. Given the scope and conceptual nature of this work, our research represents only a first step toward exploring the consequences of the deep integration of human-AI collaboration in value co-creation processes from a service perspective. While the selected scenarios provide valuable insights into the applicability of the HISE framework, other relevant domains were not included. This limitation stems from our focus on industries where human-AI collaboration is more elaborated already. Future research should investigate other promising areas to further broaden and validate the HISE framework's applicability in diverse service ecosystems.

In addition to the conceptual framework, future design-oriented, qualitative, and quantitative empirical research should develop and study different scenarios (e.g., those presented in this paper) to contribute to further developing the HISE framework as an adaptation and extension of the S-D logic directed at understanding and explaining socio-technical phenomena. Empirical studies can build on our propositions to investigate the processes of configuring hybrid agencies in HISE, as well as the processes by which these agency configurations are shaped and also shape institutional arrangements, i.e., the evolution of HISE in the long term.

Similar to S-D logic and the service ecosystem concept, the HISE framework motivates zooming out to understand

how a multitude of diverse actors interact on different levels of complex ecosystems. This approach offers a promising direction for future research on hybrid intelligence and human-AI collaboration by conducting multi-level (micro, meso, macro) analyses of human-AI interactions. The HISE framework acknowledges that hybrid agency configurations can exist at all of these levels, providing a potentially fruitful lens for revealing and explaining multi-level dependencies between social and material agency.

Studying agency configurations in HISE is an essential future research path for IS scholars. In this regard, the HISE framework can be employed as a kernel theory for future design-oriented research. For example, researchers can utilize the HISE framework to design AI-enabled healthcare platforms that optimally allocate diagnostic tasks between medical professionals and AI systems. By applying the principles of agency configuration, resource integration, and adherence to institutional arrangements outlined in the framework, designers can develop systems that enhance diagnostic accuracy and efficiency while respecting patient privacy and complying with medical regulations. This illustrates how the HISE framework can inform the creation of AI agents and service platforms embedded within service ecosystems, leading to improved value co-creation. We posit that it is an essential task for IS researchers to develop prescriptive design knowledge that supports the development of efficient and useful AI agents for specific tasks and contexts, considering their embedding in service ecosystems as described in the HISE framework.

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Competing interests The authors declare no competing interests.

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References

Adam, M., Wessel, M., & Benlian, A. (2021). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets*, 31(2), 427–445. <https://doi.org/10.1007/s12525-020-00414-7>

Akinola, M., Martin, A. E., & Phillips, K. W. (2018). To delegate or not to delegate: Gender differences in affective associations and behavioral responses to delegation. *Academy of Management Journal*, 61(4), 1467–1491. <https://doi.org/10.5465/amj.2016.0662>

Anthony, C., Bechky, B. A., & Fayard, A. -L. (2023). “Collaborating” with AI: Taking a system view to explore the future of work. *Organization Science*, Article orsc.2022.1651. Advance online publication. <https://doi.org/10.1287/orsc.2022.1651>

Arrieta, A. B., Díaz-Rodríguez, N., Del Ser, J., Bennetot, A., Tabik, S., Barbado, A., García, S., Gil-López, S., Molina, D., Benjamins, R., Chatila, R., & Herrera, F. (2019). *Explainable artificial intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI*. <https://doi.org/10.48550/arXiv.1910.10045>

Baird, A., & Maruping, L. M. (2021). The next generation of research on IS use: A theoretical framework of delegation to and from agentic IS artifacts. *MIS Quarterly*, 45(1), 315–341. <https://doi.org/10.25300/MISQ/2021/15882>

Bandura, A. (2006). Toward a psychology of human agency. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, 1(2), 164–180. <https://doi.org/10.1111/j.1745-6916.2006.00011.x>

Barile, S., Lusch, R., Reynoso, J., Saviano, M., & Spohrer, J. (2016). Systems, networks, and ecosystems in service research. *Journal of Service Management*, 27(4), 652–674. <https://doi.org/10.1108/JOSM-09-2015-0268>

Bartelheimer, C. (2020). Conceptualizing task-technology fit for technology-pervaded value co-creation. *Proceedings of the 28th European conference on information systems*. https://aisel.aisnet.org/ecis2020_rp/49

Beverungen, D., Müller, O., Matzner, M., Mendling, J., & vom Brocke, J. (2019). Conceptualizing smart service systems. *Electronic Markets*, 29(1), 7–18. <https://doi.org/10.1007/s12525-017-0270-5>

Braa, M., & Sahay, (2004). Networks of action: Sustainable health information systems across developing countries. *MIS Quarterly*, 28(3), 337–362. <https://doi.org/10.2307/25148643>

Breidbach, C. F., & Brodie, R. J. (2017). Engagement platforms in the sharing economy. *Journal of Service Theory and Practice*, 27(4), 761–777. <https://doi.org/10.1108/JSTP-04-2016-0071>

Brenner, W., Zarnekow, R., spampsps Wittig, H. (1998). *Intelligent software agents: Foundations and applications*. Springer Berlin Heidelberg. <https://doi.org/10.1007/978-3-642-80484-7>

Brozović, D., & Tregua, M. (2022). The evolution of service systems to service ecosystems: A literature review. *International Journal of Management Reviews*, 24(4), 459–479. <https://doi.org/10.1111/ijmr.12287>

Brynjolfsson, E., & McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Caliskan, A., Bryson, J. J., & Narayanan, A. (2017). Semantics derived automatically from language corpora contain human-like biases. *Science*, 356(6334), 183–186. <https://doi.org/10.1126/science.aal4230>

Cecez-Kecmanovic, D., Galliers, R. D., Henfridsson, O., Newell, S., & Vidgen, R. (2014). The sociomateriality of information systems: Current status, future directions. *MIS Quarterly*, 38(3), 809–830. <https://doi.org/10.25300/MISQ/2014/38:3.3>

Chandler, J. D., & Lusch, R. F. (2015). Service systems. *Journal of Service Research*, 18(1), 6–22. <https://doi.org/10.1177/1094670514537709>

Chandler, J. D., & Vargo, S. L. (2011). Contextualization and value-in-context: How context frames exchange. *Marketing Theory*, 11(1), 35–49. <https://doi.org/10.1177/1470593110393713>

Chiasson, & Davidson (2005). Taking industry seriously in information systems research. *MIS Quarterly*, 29(4), 591. <https://doi.org/10.2307/25148701>

Clough, D. R., & Wu, A. (2022). Artificial intelligence, data-driven learning, and the decentralized structure of platform ecosystems. *Academy of Management Review*, 47(1), 184–189. <https://doi.org/10.5465/amr.2020.0222>

Constantin, J. A., & Lusch, R. F. (1994). *Understanding resource management: How to deploy your people, products, and processes for maximum productivity*.

Davenport, T. H., & Kirby, J. (2016). Just how smart are smart machines? *MIT Sloan Management Review*, 57(3), 20–25.

Dellermann, D., Ebel, P., Söllner, M., & Leimeister, J. M. (2019). Hybrid intelligence. *Business & Information Systems Engineering*, 61(5), 637–643. <https://doi.org/10.1007/s12599-019-00595-2>

Demetis, D. S., & Lee, A. S. (2018). When humans using the IT artifact becomes IT using the human artifact. *Journal of the Association for Information Systems*, 19(10), 929–952. <https://doi.org/10.17705/1jais.00514>

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., Koohang, A., Raghavan, V., Ahuja, M., Albanna, H., Albashrawi, M. A., Al-Busaidi, A. S., Balakrishnan, J., Barlette, Y., Basu, S., Bose, I., Brooks, L., Buhalis, D., Carter, L., Chowdhury, S., Crick, T., Cunningham, S. W., Davies, G. H., Davison, R. M., Dé, R., Dennehy, D., Duan, Y., Dubey, R., Dwivedi, R., Edwards, J. S., Flavián, C., Gauld, R., Grover, V., Hu, M.-C., Janssen, M., Jones, P., Junglas, I., Khorana, S., Kraus, S., Larsen, K. R., Latreille, P., Laumer, S., Malik, F. T., Mardani, A., Mariani, M., Mithas, S., Mogaji, E., Nord, J. H., O'Connor, S., Okumus, Fevzi, Pagani, M., Pandey, N., Papagiannidis, S., Pappas, I. O., Pathak, N., Pries-Heje, J., Raman, R., Rana, N. P., Rehm, S.-V., Ribeiro-Navarrete, S., Richter, A., Rowe, F., Sarker, S., Stahl, B. C., Tiwari, M. K., Aalst, W. V. D., Venkatesh, V., Viglia, G., Wade, M., Walton, P., Wirtz, J., & Wright, R. (2023). “So what if ChatGPT wrote it?” Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management*, 71. <https://doi.org/10.1016/j.ijinfomgt.2023.102642>

Ekman, P., Raggio, R. D., & Thompson, S. M. (2016). Service network value co-creation: Defining the roles of the generic actor. *Industrial Marketing Management*, 56, 51–62. <https://doi.org/10.1016/j.indmarman.2016.03.002>

Enfield, N. J., & Kockelman, P. (2017). *Distributed agency*. Oxford University Press. <https://doi.org/10.1093/acprof:oso/9780190457204.001.0001>

European Union. (2024). Regulation (EU) 2024/1689 of the European parliament and of the council (Artificial Intelligence Act). In *Official journal of the European union*. <https://eur-lex.europa.eu/eli/reg/2024/1689/oj>. Last accessed: 2024-10-29.

Fabri, L., Häckel, B., Oberländer, A. M., Rieg, M., & Stohr, A. (2023). Disentangling human-AI hybrids: Conceptualizing the interworking of humans and AI-enabled systems. *Business & Information Systems Engineering*, 65(6), 623–641.

Fishbach, A., & Ferguson, M. J. (2007). The goal construct in social psychology. In A. W. Kruglanski & T. E. Higgins (Eds.), *Social psychology: Handbook of basic principles* (pp. 490–515). Guilford Press.

Freitag, C., Berners-Lee, M., Widdicks, K., Knowles, B., Blair, G. S., & Friday, A. (2021). The real climate and transformative impact of ICT: A critique of estimates, trends, and regulations. *Patterns*, 2(9), 1–18. <https://doi.org/10.1016/j.patter.2021.100340>

Fügner, A., Grahl, J., Gupta, A., & Ketter, W. (2022). Cognitive challenges in human–artificial intelligence collaboration: Investigating the path toward productive delegation. *Information Systems Research*, 33(2), 678–696. <https://doi.org/10.1287/isre.2021.1079>

Gilson, L. L., & Goldberg, C. B. (2015). Editors' comment. *Group & Organization Management*, 40(2), 127–130. <https://doi.org/10.1177/1059601115576425>

Ginko, L., & Elbanna, A. (2023). The appropriation of conversational AI in the workplace: A taxonomy of AI chatbot users. *International Journal of Information Management*, 69, 102568. <https://doi.org/10.1016/j.ijinfomgt.2022.102568>

Grashoff, I., & Recker, J. (2023). Design, development, and implementation of artificial intelligence technology: A scoping review. *Proceedings of the 31st European conference on information systems*. https://aisel.aisnet.org/ecis2023_rp/305

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT press.

González-Mendes, S., González-Sánchez, R., & Alonso-Muñoz, S. (2024). Exploring the influence of artificial intelligence on the management of hospitality and tourism sectors: A bibliometric overview. In . Sing, R., Kha S., Kumar, A., Kumar, V. (Eds.), *Artificial intelligence enabled management: An emerging economy perspective (Chapter 14)*, de Gruyter. <https://doi.org/10.1515/9783111172408>

Gregory, R. W., Henfridsson, O., Kaganer, E., & Kyriakou, H. (2022). Data network effects: Key conditions, shared data, and the data value duality. *Academy of Management Review*, 47(1), 189–192. <https://doi.org/10.5465/amr.2021.0111>

Hanseth, O., Jacucci, E., Grisot, M., & Aanestad, M. (2006). Reflexive standardization: Side effects and complexity in standard making. *MIS Quarterly*, 30(3), 563–581. <https://doi.org/10.2307/25148773>

Hemmer, P., Westphal, M., Schemmer, M., Vetter, S., Vössing, M., & Satzger, G. (2023). Human-AI collaboration: The effect of AI delegation on human task performance and task satisfaction. *Proceedings of the 28th International Conference on Intelligent User Interfaces* (pp. 453–46). <https://doi.org/10.1145/3581641.3584052>

Hernandez L. (2022). AI watch – Artificial intelligence in public services | Overview of the use and impact of AI in public services in the EU. URL <https://joinup.ec.europa.eu/collection/elise-european-location-interoperability-solutions-e-government/document/report-ai-watch-artificial-intelligence-public-services-overview-use-and-impact-ai-public-services>. Last accessed: 2024-04-29.

Hildebrand, C., & Bergner, A. (2021). Conversational robo advisors as surrogates of trust: Onboarding experience, firm perception, and consumer financial decision making. *Journal of the Academy of Marketing Science*, 49(4), 659–676. <https://doi.org/10.1007/s11747-020-00753-z>

Hönigsberg, S., & Dinter, B. (2024). Facilitating value co-creation through inter-organizational information systems. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, 55(3), 70–107. <https://doi.org/10.1145/3685235.3685240>

Huang, M. H., & Rust, R. T. (2018). Artificial intelligence in service. *Journal of Service Research*, 21(2), 155–172. <https://doi.org/10.1177/10946705177752>

Hunt, S. D. (2004). On the service-centered dominant logic for marketing. *Journal of Marketing*, 68(1), 21–22.

Jaakkola, E. (2020). Designing conceptual articles: Four approaches. *AMS Review*, 10(1–2), 18–26. <https://doi.org/10.1007/s13162-020-00161-0>

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons*, 61(4), 577–586. <https://doi.org/10.1016/j.bushor.2018.03.007>

Jia, N., Luo, X., Fang, Z., & Liao, C. (2023). When and how artificial intelligence augments employee creativity. *Academy of Management Journal*. Advance online publication. <https://doi.org/10.5465/amj.2022.0426>

Kaartemo, V. and Helkkula, A. (2024). Human–AI resource relations in value cocreation in service ecosystems. *Journal of Service Management*, Vol. ahead-of-print No. ahead-of-print. <https://doi.org/10.1108/JOSM-03-2023-0104>

Klein, K. J., Ziegert, J. C., Knight, A. P., & Xiao, Y. (2006). Dynamic delegation: Shared, hierarchical, and deindividualized leadership in extreme action teams. *Administrative Science Quarterly*, 51(4), 590–621. <https://doi.org/10.2189/asqu.51.4.590>

Knote, R., Janson, A., Söllner, M., & Leimeister, J. M. (2021). Value co-creation in smart services: A functional affordances perspective on smart personal assistants. *Journal of the Association for Information Systems*, 22(2), 418–458. <https://doi.org/10.17705/1jais.00667>

Lamb, & Kling. (2003). Reconceptualizing users as social actors in information systems research. *MIS Quarterly*, 27(2), 197. <https://doi.org/10.2307/30036529>

Lane, P. J., & Lubatkin, M. (1998). Relative absorptive capacity and interorganizational learning. *Strategic Management Journal*, 19(5), 461–477. [https://doi.org/10.1002/\(SICI\)1097-0266\(199805\)19:5<461::AID-SMJ953>3e3.0.CO;2-L](https://doi.org/10.1002/(SICI)1097-0266(199805)19:5<461::AID-SMJ953>3e3.0.CO;2-L)

Leana, C. R. (1986). Predictors and consequences of delegation. *Academy of Management Journal*, 29(4), 754–774. <https://doi.org/10.5465/255943>

LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444. <https://doi.org/10.1038/nature14539>

Leonardi, P. M. (2011). When flexible routines meet flexible technologies: Affordance, constraint, and the imbrication of human and material agencies. *MIS Quarterly*, 35(1), 147–167. <https://doi.org/10.2307/23043493>

Li, M. M., Reinhard, P., Peters, C., Oeste-Reiss, S., & Leimeister, J. M. (2024). A value co-creation perspective on data labeling in hybrid intelligence systems: A design study. *Information Systems*, 120, 102311. <https://doi.org/10.1016/j.is.2023.102311>

Lusch, R. F., & Nambisan, S. (2015). Service innovation: A service-dominant logic perspective. *MIS Quarterly*, 39(1), 155–175. <https://doi.org/10.25300/MISQ/2015/39.1.07>

Lusch, R. F., Vargo, S. L., & Gustafsson, A. (2016). Fostering a trans-disciplinary perspectives of service ecosystems. *Journal of Business Research*, 69(8), 2957–2963. <https://doi.org/10.1016/j.jbusres.2016.02.028>

Lusch, R. F., & Vargo, S. L. (2006). Service-dominant logic: Reactions, reflections and refinements. *Marketing Theory*, 6(3), 281–288. <https://doi.org/10.1177/1470593106066781>

Ma, Q., Tariq, M., Mahmood, H., & Khan, Z. (2022). The nexus between digital economy and carbon dioxide emissions in China: The moderating role of investments in research and development. *Technology in Society*, 68, 101910. <https://doi.org/10.1016/j.techsoc.2022.101910>

Maglio, P. P., & Spohrer, J. (2008). Fundamentals of service science. *Journal of the Academy of Marketing Science*, 36, 18–20. <https://doi.org/10.1007/s11747-007-0058-9>

Malone, T. W. (2018). How human-computer ‘superminds’ are redefining the future of work. *MIT Sloan Management Review*, 59(4), 34–41.

Manser Payne, E. H., Dahl, A. J., & Peltier, J. (2021). Digital servitization value co-creation framework for AI services: A research agenda for digital transformation in financial service ecosystems. *Journal of Research in Interactive Marketing*, 15(2), 200–222. <https://doi.org/10.1108/JRIM-12-2020-0252>

Meynhardt, T., Chandler, J. D., & Strathoff, P. (2016). Systemic principles of value co-creation: Synergetics of value and service ecosystems. *Journal of Business Research*, 69(8), 2981–3298. <https://doi.org/10.1016/j.jbusres.2016.02.031>

Mele, C., Nenonen, S., Pels, J., Storbacka, K., Nariswari, A., & Kaartemo, V. (2018). Shaping service ecosystems: Exploring the dark side of agency. *Journal of Service Management*, 29(4), 521–545. <https://doi.org/10.1108/JOSM-02-2017-0026>

Meredith, J. (1993). Theory building through conceptual methods. *International Journal of Operations & Production Management*, 13(5), 3–11. <https://doi.org/10.1108/01443579310028120>

Miller, C. A., & Parasuraman, R. (2007). Designing for flexible interaction between humans and automation: Delegation interfaces for supervisory control. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 49(1), 57–75. <https://doi.org/10.1518/001872007779598037>

Mora, M., Gelman, O., Paradice, D., & Cervantes, F. (2008). The case for conceptual research in information systems. In *CONFIRM Proceedings 2008* (Paper 52). <http://aisel.aisnet.org/confirm2008/52>

Mordor Intelligence. (2024). Artificial intelligence as a service market size & share analysis - growth trends & forecasts (2024 - 2029). url:<https://www.mordorintelligence.com/industry-reports/artificial-intelligence-as-a-service-market>. Last accessed: 2024-04-29

Naumann, S., Dick, M., Kern, E., & Johann, T. (2011). The GREENSOFT model: A reference model for green and sustainable software and its engineering. *Sustainable Computing: Informatics and Systems*, 1(4), 294–304. <https://doi.org/10.1016/j.suscom.2011.06.004>

Nenonen, S., Gummerus, J., & Sklyar, A. (2018). Game-changers: Dynamic capabilities' influence on service ecosystems. *Journal of Service Management*, 29(4), 569–592. <https://doi.org/10.1108/JOSM-02-2017-0025>

Neuhofner, B., Magnus, B., & Celuch, K. (2021). The impact of artificial intelligence on event experiences: A scenario technique approach. *Electronic Markets*, 31(3), 601–617. <https://doi.org/10.1007/s12525-020-00433-4>

Newlands, G. (2021). Lifting the curtain: Strategic visibility of human labour in AI-as-a-service. *Big Data & Society*, 8(1). <https://doi.org/10.1177/20539517211016026>

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science*, 3(3), 398–427. <https://doi.org/10.1287/orsc.3.3.398>

Orlikowski, W. J. (2000). Using technology and constituting structures: A practice lens for studying technology in organizations. *Organization Science*, 11(4), 404–428.

Orlikowski, W. J., & Baroudi, J. J. (1991). Studying information technology in organizations: Research approaches and assumptions. *Information Systems Research*, 2(1), 1–28. <https://doi.org/10.1287/isre.2.1.1>

Ostrom, E. (2009). *Understanding institutional diversity*. Princeton University Press. <https://doi.org/10.1515/9781400831739>

Ostrom, E. (2011). *Governing the commons: The evolution of institutions for collective action* (29 Ed.). *Political economy of institutions and decisions*. Cambridge Univ. Press.

Poepelbuss, J., Ebel, M., & Anke, J. (2022). Iterative uncertainty reduction in multi-actor smart service innovation. *Electron Markets*, 32, 599–627. <https://doi.org/10.1007/s12525-021-00500-4>

Polese, F., Payne, A., Frow, P., Sarno, D., & Nenonen, S. (2021). Emergence and phase transitions in service ecosystems. *Journal of Business Research*, 127, 25–34. <https://doi.org/10.1016/j.jbusres.2020.11.067>

Recker, J., von Briel, F., Yoo, Y., Nagaraj, V., & McManus, M. (2023). Orchestrating human-machine designer ensembles during product innovation. *California Management Review*, 65(3), 27–47. <https://doi.org/10.1177/00081256231170028>

Reinhard, P., Wischer, D., Verlande, L., Neis, N., & Li, M. M. (2023). Towards designing an AI-based conversational agent for on-the-job training of customer support novices. *International Conference on Design Science Research (DESRIST)*.

Ribes, D., Jackson, S., Geiger, S., Burton, M., & Finholt, T. (2013). Artifacts that organize: Delegation in the distributed organization. *Information and Organization*, 23(1), 1–14. <https://doi.org/10.1016/j.infoandorg.2012.08.001>

Russell, S. J. (2019). *Human compatible: Artificial intelligence and the problem of control*. Pearson Global Edition.

Russell, S. J., & Norvig, P. (2021). *Artificial intelligence: A modern approach* (Fourth Edition). Pearson Series in artificial intelligence. Pearson.

Sarno, D., Enquist, B., Polese, F., Sebastiani, R., Petros Sebhatu, S., & Viljakainen, A. M. (2024). A processual view on sustainability transitions in service ecosystems. *Journal of Service Management*, ahead-of-print. <https://doi.org/10.1108/JOSM-03-2023-0094>

Schanze, E. (1987). Contract, agency, and the delegation of decision making. In Bamberg, G. spampsps Spremann, K. (Eds.), *Agency theory, information, and incentives* (pp. 461–471). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-75060-1_23

Schuetz, S., & Venkatesh, V. (2020). The rise of human machines: How cognitive computing systems challenge assumptions of user-system interaction. *Journal of the Association for Information Systems*, 21(2), 460–482.

Scott, S. V., & Wagner, E. L. (2003). Networks, negotiations, and new times: The implementation of enterprise resource planning into an academic administration. *Information and Organization*, 13(4), 285–313. [https://doi.org/10.1016/S1471-7727\(03\)00012-5](https://doi.org/10.1016/S1471-7727(03)00012-5)

Shapiro, S. P. (2005). Agency theory. *Annual Review of Sociology*, 31(1), 263–284. <https://doi.org/10.1146/annurev.soc.31.041304.122159>

Siemon, D., Strohmann, T., & Michalke, S. (2022). Creative potential through artificial intelligence: Recommendations for improving corporate and entrepreneurial innovation activities. *Communications of the Association for Information Systems*, 50, 241–260. <https://doi.org/10.17705/1CAIS.05009>

Society of Automotive Engineers. (2021). Taxonomy and definitions for terms related to driving automation systems for on-road motor vehicles. *SAE International*, 4790(724), 1–5.

Spohrer, J., Vargo, S. L., Caswell, N., & Maglio, P. P. (2008). The service system is the basic abstraction of service science. In *Proceedings of the 41st Hawaii international conference on system sciences* (HICSS 2008) (pp. 104–104). IEEE. <https://doi.org/10.1109/HICSS.2008.451>

Stahl, B. C. (2022). Responsible innovation ecosystems: Ethical implications of the application of the ecosystem concept to artificial intelligence. *International Journal of Information Management*, 62, 102441. <https://doi.org/10.1016/j.ijinfomgt.2021.102441>

Storbacka, K., Brodie, R. J., Böhmann, T., Maglio, P. P., & Nenonen, S. (2016). Actor engagement as a microfoundation for value co-creation. *Journal of Business Research*, 69(8), 3008–3017. <https://doi.org/10.1016/j.jbusres.2016.02.034>

van der Waldt, G. (2020). Constructing conceptual frameworks in social science research. *The Journal for Transdisciplinary Research in Southern Africa*, 16(1), 1–9.

Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, 25(1), 44–56.

Vargo, S. L., & Akaka, M. A. (2012). Value cocreation and service systems (re)formation: A service ecosystems view. *Service Science*, 4(3), 207–217. <https://doi.org/10.1287/serv.1120.0019>

Vargo, S. L., & Lusch, R. F. (2004). Evolving to a new dominant logic for marketing. *Journal of Marketing*, 68(1), 1–17. <https://doi.org/10.1509/jmkg.68.1.1.24036>

Vargo, S. L., & Lusch, R. F. (2008). Service-dominant logic: Continuing the evolution. *Journal of the Academy of Marketing Science*, 36(1), 1–10. <https://doi.org/10.1007/s11747-007-0069-6>

Vargo, S. L., & Lusch, R. F. (2011). It's all B2B...and beyond: Toward a systems perspective of the market. *Industrial Marketing Management*, 40(2), 181–187. <https://doi.org/10.1016/j.indmarman.2010.06.026>

Vargo, S. L., & Lusch, R. F. (2016). Institutions and axioms: An extension and update of service-dominant logic. *Journal of the Academy of Marketing Science*, 44(1), 5–23. <https://doi.org/10.1007/s11747-015-0456-3>

Vargo, S. L., & Lusch, R. F. (2017). Service-dominant logic 2025. *International Journal of Research in Marketing*, 34(1), 46–67. <https://doi.org/10.1016/j.ijresmar.2016.11.001>

Vargo, S. L., Robert F. L. (2018). *The SAGE handbook of service-dominant logic*. SAGE.

Vargo, S. L., Peters, L., Kjellberg, H., Koskela-Huotari, K., Nenonen, S., Polese, F., Sarno, D., & Vaughan, C. (2023). Emergence in marketing: An institutional and ecosystem framework. *Journal of the Academy of Marketing Science*, 51(1), 2–22. <https://doi.org/10.1007/s11747-022-00849-8>

Vink, J., Koskela-Huotari, K., Tronvoll, B., Edvardsson, B., & Wetter-Edman, K. (2021). Service ecosystem design: Propositions, process model, and future research agenda. *Journal of Service Research*, 24(2), 168–186. <https://doi.org/10.1177/1094670520952537>

Walsham, G., & Han, C.-K. (1991). Structuration theory and information systems research. *Journal of Applied Systems Analysis*, 18, 77–85.

Wedel, M., & Kannan, P. K. (2016). Marketing analytics for data-rich environments. *Journal of Marketing*, 80(6), 97–121. <https://doi.org/10.1509/jm.15.0413>

Wieland, H., Polese, F., Vargo, S. L., & Lusch, R. F. (2012). Toward a service (eco) systems perspective on value creation. *International Journal of Service Science, Management, Engineering, and Technology (IJSSMET)*, 3(3), 12–25. <https://doi.org/10.4018/jssmet.2012070102>

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: Service robots in the frontline. *Journal of Service Management*, 29(5), 907–931. <https://doi.org/10.1108/JOSM-04-2018-0119>

Woolley, A. W., Chabris, C. F., Pentland, A., Hashmi, N., & Malone, T. W. (2010). Evidence for a collective intelligence factor in the performance of human groups. *Science*, 330(6004), 686–688. <https://doi.org/10.1126/science.1193147>