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More than a collaborator: the rise of human-machine symbiosis in service frontlines

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ABSTRACT

In the age of Artificial Intelligence (AI), serving customers together in human–machine teams is becoming more common, but optimizing this teamwork is new and increasingly complex. The traditional concepts of Machine Augmentation (MA) and Human-Machine Collaboration (HMC) do not fully realize the full potential of this new technology. This article introduces Human–Machine Symbiosis (HMS) as a dynamic adaptation process between employees and machines through ongoing service interactions with customers. We conceptualize this process as a higher-order system (including MA and HMS) that builds on co-specialization, co-acting, and is uniquely driven by co-learning – a process comprising three interdependent activities – knowledge sharing, assimilation, and calibration, that jointly shape human–machine team performance over time. This research identifies task decomposability and machine trustworthiness as key facilitators of the co-learning process. Additionally, HMS can also influence firm innovativeness in the long run. The framework offers guidance on how service organizations can benefit from HMS and effectively integrate AI into frontline work.

1. Introduction

The rapid digital transformation of service provision has enabled machines to become deeply integrated into multiple facets of service organizations (Danatzis et al., 2025). These technologies exhibit a high degree of agency in performing complex service-related tasks (Wirtz et al., 2018). Consequently, humans and machines coexist in the workplace (Döppner et al., 2019). For instance, autonomous service robots work with caregivers to jointly deliver care services (Shanks et al., 2025) or customer service employees work with AI agents in call centers (Luo et al., 2021b).In this research, the term machine refers to automated systems powered by AI and machine learning, including text-prediction software, data analytics tools, automated text-generation software, recommendation agents, physical robots, and chatbots (Azer & Alexander, 2025).

As machines take on increasingly complex and context-sensitive roles, human–machine interactions are evolving beyond simple, transactional exchanges at the individual level to deliver integrated services (Wirtz & Stock-Homburg, 2025). Prior research has emphasized complementarities in resources, roles, and tasks, alongside a deliberate division of labor in how humans and machines collaborate within service processes and in serving customers (Blaurock et al., 2025; De Keyser et al., 2019; Le et al., 2023; Wilson & Daugherty, 2018; Van Doorn et al., 2017). More recent studies have identified distinct interaction patterns, such as informative, experimenting, praising, and apprehensive forms of employee-machine interaction (Azer & Alexander, 2025), as well as new modes of collaboration, including employee-led, technology-led, and co-led synergies in which roles and decision authority shift dynamically between employees and machines (Danatzis et al., 2025). These frameworks underscore the transformative role of machines in service operations by capturing the nuances of how collaborative efforts between employees and machines can influence both the effectiveness and efficiency of service delivery.

Even though there has been progress in understanding how humans and machines work together in service, current models fail to capture how they continue to adapt to one another when working as a team.

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Most current research treats their teamwork as a one-time interaction (e.g., Le et al., 2023). What remains less examined is how human–machine teamwork unfolds over time, in which both agents influence and adjust to one another. For example, Stitch Fix uses algorithms to make first clothing suggestions based on customer profiles. Human stylists then improve these suggestions with their own ideas (Lake, 2018). Over time, as stylists modify suggestions and provide feedback, the system fine-tunes its recommendations. The algorithm improves by learning from expert human judgment, while stylists, in turn, draw on the system's evolving predictions to refine their curation strategies. In this setting, employee and machine capabilities are not merely complementary but co-adaptive, each reshaping and extending the other through iterative mutual learning. Current theoretical frameworks fail to capture this adaptive aspect of teamwork across repeated interactions. Framing such an interaction solely through complementarities highlights a fixed division of labor (e.g., Huang and Rust, 2018), which does not capture ongoing, reciprocal learning or fully show how machines can be integrated sustainably into frontline services (Kaartemo & Helkkula, 2025).

To address this conceptual gap in the literature, this research draws on the concept of symbiosis from biology. Symbiosis comes from "sym," meaning "together," and "biosis," meaning "living." It highlights how different organisms mutually benefit from one another by relying on and adapting to one another over time. For instance, in the symbiotic relationship between sea anemones and clownfish, both species continuously adjust their behaviors in response to one another – clownfish attract prey and remove parasites, while anemones provide protection (i.e., mutualism).

Extending this logic to human–machine interaction in service contexts, we conceptualize Human-Machine Symbiosis (HMS) as an interdependent, mutually beneficial adaptive process between employees and machines via repeated interactions in the service provision. Although symbiosis in nature can take many forms (e.g., commensalism, parasitism), this research deliberately focuses on mutualistic relationships, in which reciprocal adaptation and joint value creation are central (Döppner et al., 2019). The features and impact of HMS that we proposed emphasized the need to learn to adapt, making HMS especially pertinent in environments where interactions are continuous and unpredictable.

The service frontline is such an environment in which value is created through continuous interactions among employees, customers, and technologies (Bonetti et al., 2023). Services are inherently dynamic, shaped by evolving customer needs, contextual variability, and the iterative nature of problem-solving (Gwinner et al., 2005). In such environments, the mutual adaptation of employees and machines through ongoing learning enables the system to remain responsive and innovative amid shifting customer expectations. Using HMS to study this complex process helps us understand not just short-term improvements in service quality, but also long-term growth in innovation when both agents work together over a long time to serve customers.

This research advances the growing studies on human–machine interaction in service contexts (e.g., Azer & Alexander, 2025; Blaurock et al., 2025; Chan & Choi, 2025; Danatzis et al., 2025; Grewal et al., 2020; Simón et al., 2024; Van Doorn et al., 2017) in several ways. *First*, prior frameworks have tended to conceptualize augmentation and collaboration as discrete and static forms of interaction (e.g., De Keyser et al., 2019; Huang & Rust, 2022; Wirtz et al., 2018), overlooking the dynamic adaptation in human–machine relationships. We emphasize that HMS is not a standalone concept, but a higher-order system built on three components: co-specialization, rooted in the division and alignment of complementary capabilities as a foundation for machine augmentation; co-acting, grounded in coordinated actions as a foundation for human–machine collaboration; and co-learning, which is essential for understanding how human–machine relationships evolve and adapt over time. While these three pillars jointly constitute the architecture of HMS, this research uniquely positions co-learning as the main engine that gradually reshapes the other two pillars. Through repeated co-learning episodes, human and machine agents develop a deeper understanding of each other's capabilities and inform coordinated action in service processes. This integrative framing advances theoretical understanding of human–machine interaction on service frontlines by expanding the scope of analysis toward an adaptive-systems perspective that prior conceptualizations did not adequately capture.

Second, this research identifies three interdependent activities in co-learning episodes: knowledge sharing, assimilation, and calibration. While previous studies acknowledge learning interactions between humans and machines (e.g., Danatzis et al., 2025; Döppner et al., 2019; Jarrahi, 2018; Simón et al., 2024), none have delineated the underlying dynamics of the co-learning process as the core mechanism through which HMS emerges and evolves. We show how these activities jointly constitute an adaptive learning process in H-M teams, directly influencing their speed and accuracy. Clarifying these activities shows how they form the basic building blocks of HMS adaptation, highlighting their role in promoting ongoing improvement and mutual understanding. This research explains the micro-foundations of adaptation in HMS. Instead of viewing learning as just a side effect of interaction, we show how different, yet interconnected activities work together to improve the overall performance of the H-M team. We also identify two key facilitators of the co-learning process, task decomposability and machine trustworthiness. These contextual facilitators enable the HMS framework to incorporate contingent mechanisms that determine its effectiveness across different service conditions.

Third, this research distinguishes between two types of co-learning episodes in the H-M symbiotic journey: rapid and extended co-learning episodes, reflecting the duration of the individual learning episode. Prior research on human–machine interaction in service contexts has broadly adopted static or cross-sectional perspectives (e.g., De Keyser et al., 2019; Le et al., 2025), overlooking how learning depth and pace vary over time. Thus, this research shows how organizations can more effectively incorporate machines into their work processes by considering the rhythm and pace of co-learning episodes, thereby affecting long-term results in service settings. Finally, this research offers suggestions for service firms to foster HMS development. Beyond practical contributions, the research also highlights several avenues for future research.

2. A Hierarchy of concepts for developing Human-Machine Symbiosis

Integrating advanced AI and robotics into service workflows requires a clear understanding of how relationships between humans and machines develop over time (Noble et al., 2022). Prior research distinguishes two central paradigms – machine augmentation (MA), in which machines extend human capability (De Keyser et al., 2019; Grewal et al., 2020; Huang & Rust, 2018; Xiao & Kumar, 2021), and human–machine collaboration (HMC), in which machines function as active collaborators to human employees (Azer & Alexander, 2025; Blaurock et al., 2025; Danatzis et al., 2025; Wilson & Daugherty, 2018). We posit that both serve as stepping stones toward a more advanced form of interaction that we aim to delineate in this research – human–machine symbiosis.

Fig. 1 presents a hierarchical nature of related concepts. MA emphasizes co-specialization, which focuses on complementing one another's capabilities to perform tasks. In this paradigm, each agent possesses a unique skill set that augments others'. Employees provide social competence, while machines supply scale, precision, and speed (Huang & Rust, 2018; Wirtz et al., 2018; Garry & Harwood, 2019). Interdependence here is episodic and situational, activated when specialized resources need to be combined (Shrestha et al., 2019). In the MA paradigm, machines are considered as tools that help service workers do their jobs better, but such machines have limited agency (De Keyser et al., 2019). For example, employees could use smart earbuds for better communication with customers (Grewal et al., 2020). This

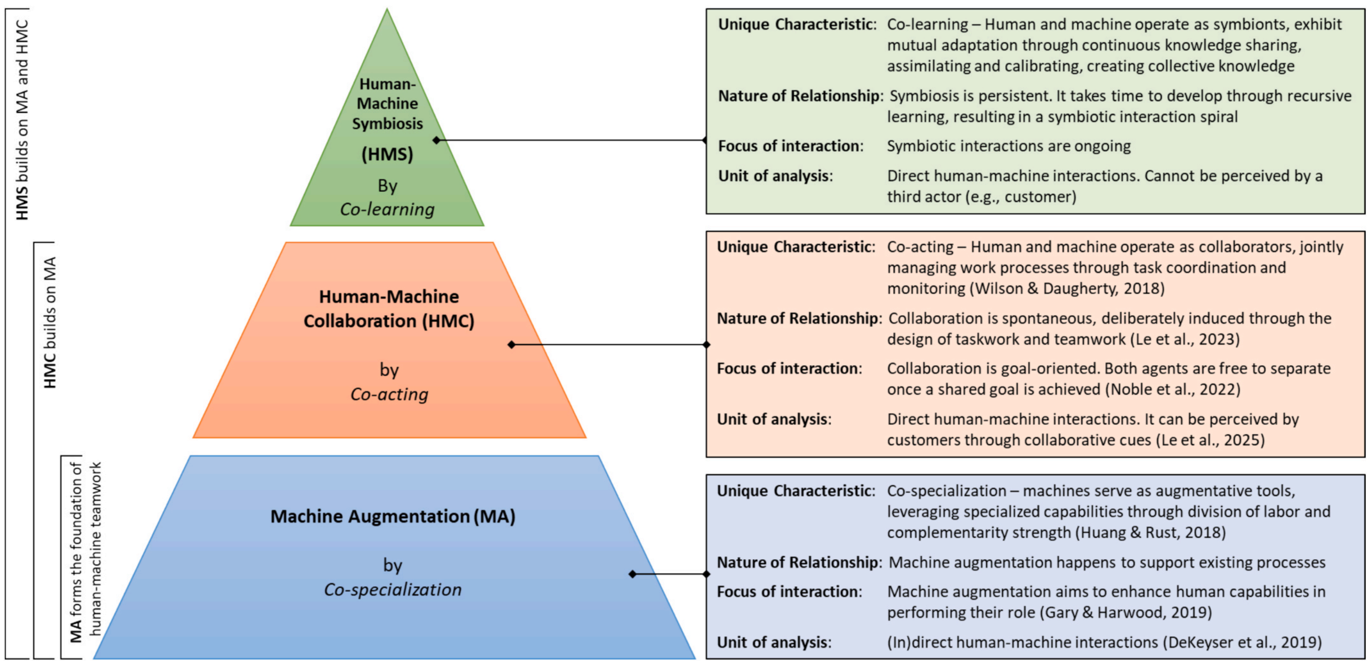

Fig. 1. A Hierarchical Nature of Human-Machine Symbiosis and Related Concepts.

paradigm is primarily analyzed at the role level, emphasizing resource complementarity through the division of labor and the respective strengths (Xiao & Kumar, 2021), thereby creating differentiated resources, such as knowledge or skill sets.

As machines become more sophisticated with the newer generation of technologies (e.g., Generative AI) and are integrated into service workflows, they evolve into collaborative agents, actively coordinating and contributing to shared goals alongside humans (Azer & Alexander, 2025; Blaurock et al., 2025; Wirtz and Stock-Homburg, 2025; Wilson & Daugherty, 2018). HMC is thus characterized by co-acting, with both agents engaging in shared, task-oriented activities informed by intentional taskwork process design (Gombolay et al., 2017; Le et al., 2023). The interactions between humans and machines in this context emphasize goal-oriented actions, with interdependence maintained through coordination and continuous monitoring of joint goals (Noble et al., 2022) to effectively combine differentiated knowledge. For example, assistive robots coordinate with caregivers to monitor patients' health (Čaić et al., 2018). Analyses within HMC contexts can occur at both the process and individual levels (Le et al., 2023). HMC allows evaluation through both employee experiences with robots (Blaurock et al., 2025) and customer experiences interacting with these hybrid teams (Le et al., 2023). Nonetheless, while HMC expands integration, it still operates within predefined service processes (e.g., script-based service interaction with chatbots – Le et al., 2025).

The MA paradigm emphasizes the establishment of differentiated and complementary expertise between humans and machines (De Keyser et al., 2019; Garry & Harwood, 2019; Huang & Rust, 2018). By allocating distinct domains of competence, MA creates heterogeneity within the human–machine knowledge pool, which serves as a necessary foundation for learning and adaptation in novel service situations. However, MA primarily specifies what resources are differentiated, rather than how they are combined in practice.

Building on this foundation, the HMC paradigm focuses on integrating these differentiated resources through coordinated action. Prior research highlights the role of resource integration mechanisms (Gombolay et al., 2017; Kunz et al., 2025; Seeber et al., 2020), including role alignment (Danatzis et al., 2025) and structured information flows (Le et al., 2025), that enable effective co-acting between humans and machines. Through such coordination, specialized knowledge can be exchanged and operationalized during service encounters. For example, in retail banking, AI systems contribute analytical expertise by processing credit histories and regulatory constraints, while human advisors contribute contextual judgment grounded in customer goals and situational cues. During customer interactions, coordinated actions allow the system's analysis and the advisor's judgment to be combined in real time. These interactions enable advisors to appropriate system-generated insights and allow systems to be refined through human input across repeated encounters.

Despite these complementarities, the core characterizations of MA and HMC (co-specialization and co-acting) remain insufficient to explain how human–machine relationships adapt over extended periods when serving customers. Neither paradigm explicitly theorizes the process of mutual adaptation that unfolds through sustained interaction. Instead, they function as enabling conditions that support the emergence of co-learning, which is the main feature of HMS that this research focuses on.

Our proposed HMS perspective (cf. Fig. 1) extends beyond simply integrating MA and HMC. Instead, HMS builds on these paradigms by transforming differentiated human and machine resources, enacted through coordinated taskwork, into a cumulative shared knowledge pool via an iterative process of co-learning. Consequently, HMS is irreducible to either MA or HMC and emerges only once both co-specialization and co-acting are established. Although early work on HMS dates back to Licklider (1960) and subsequent scholarship across disciplines has sought to conceptualize the phenomenon (e.g., Jarrahi, 2018; Lesh et al., 2004; Dellermann et al., 2019; Wilson & Daugherty, 2018), much of this literature emphasizes shared decision-making or resource complementarity – features more consistent with MA or HMC. In contrast, we conceptualize HMS as a recursive co-learning process through which co-acting and co-specialization are progressively reshaped, giving rise to deepening interdependence over extended interaction (Döppner et al., 2019). This interdependence persists beyond the achievement of immediate goals, as accumulated knowledge fuels ongoing cycles of refinement and improvement (Bonetti et al., 2023). Because these dynamics unfold over the long term through mutual adaptation, HMS can be meaningfully examined only at the team level.

3. A Human-Machine Symbiosis conceptualization

3.1. Theoretical foundation of HMS

Transactive Memory System (TMS) theory provides a well-established framework for understanding how teams organize and adapt knowledge through learning over time. It treats the team itself as the central unit of analysis (Brandon & Hollingshead, 2004). Initially developed in the context of team functioning, TMS emphasizes the collective knowledge system that emerges through a shared division of cognitive labor (Argote & Ren, 2012; Lewis & Herndon, 2011). This system enables teams to coordinate and learn from distributed expertise, thereby surpassing the sum of individual contributions when addressing complex tasks (Argote & Guo, 2016).

From a TMS perspective, team members develop an implicit understanding of responsibility allocation based on their shared knowledge of "who knows what," a phenomenon known as cognitive interdependence (Wegner, 1987). Hence, TMS rests on two primary premises: (1) an organized store of differentiated knowledge embedded within individual members that underpins the division of labor, and (2) a knowledge-accessing mechanism involving three interrelated activities – encoding, storing, and retrieving – which collectively constitute the TMS process (Hollingshead, 2001).

The success of adaptive team performance depends mainly on the formation and maintenance of this knowledge management process, in which differentiated expertise is effectively codified and made accessible to all members through learning (Wegner et al., 1991). During the encoding phase, team members exchange and convert task-relevant information into shared memories (Wegner, 1987). The storing phase involves integrating and aligning this knowledge with existing structures (Jackson & Klobas, 2008). The retrieval phase enables access either through direct recall or by consulting the recognized source, with the system continually refined through interaction (Lewis & Herndon, 2011).

3.2. Defining Human-Machine Symbiosis

Earlier, we emphasized that both co-specialization and co-acting must be embedded in human–machine teamwork as a necessary condition for HMS. Still, their combination alone does not define the unique aspect of HMS compared to HMC and MA. Instead, it is the emergence of a recursive learning mechanism that transforms complementary resources and joint coordination into collective knowledge, enabling adaptation. Therefore, we define Human-Machine Symbiosis (HMS) in the context of service provision as "*the interdependent, mutually beneficial adaptive process between employees and machines via repeated interactions in the service provision. This process is characterized by co-specialization, co-acting, and co-learning, with the last ultimately driving the adaptation of all aspects of symbiosis to improve the team's performance over time.*".

The components of this definition are best illustrated by the following stylized example. Consider a call center representative working with an AI assistant agent to resolve a billing dispute (e.g., Henkel et al., 2020; Luo et al., 2021b). The representative draws on intuitive judgment and experience to interpret the customer's tone of frustration, decide when empathy is needed, and determine whether escalation is appropriate. At the same time, the AI assistant quickly retrieves billing history, checks it against company policy, and generates resolution options (co-specialization). They then coordinate the interaction, with the representative managing the customer relationship and the GenAI system drafting potential responses that the representative reviews, refines, and finalizes before communicating with the customer (co-acting). Over time, this interaction evolves into an iterative cycle of mutual knowledge refinement. The representative enriches the system with contextual insights, which the AI incorporates into more personalized, policy-aligned solutions. In turn, the representative learns from the AI's generated options, improving their ability to handle similar cases in the future (co-learning). This ongoing cycle exemplifies how HMS emerges over time, with co-learning serving as the critical mechanism that sustains and deepens the symbiotic interaction.

Our proposed definition highlights that HMS is not an immediate state but an emergent process of continuous adaptation between frontline employees and machines through co-learning. Thus, achieving HMS requires time, during which both agents progressively align their capabilities, activities, and knowledge (Inga et al., 2023). Once realized, HMS combines their strengths in a way that neither could provide alone, making standalone human or machine performance less desirable (Huang & Rust, 2018). Prior research has primarily emphasized alignment in capabilities (co-specialization) and activities (co-acting) (cf. Fig. 1). What distinguishes our definition, however, is the centrality of the co-learning notion and the temporal unfolding of its activities, which together mark a departure from earlier views of human–machine interaction (e.g., Azer & Alexander, 2025; Danatzis et al., 2025; Huang & Rust, 2018; Xiao & Kumar, 2021) while still recognizing the foundation of co-specialization and co-acting on which HMS is built. To better understand this co-learning process, we draw on the TMS theory that we introduced before. TMS emphasizes the cognitive infrastructure necessary for accessing distributed knowledge, enabling team learning that transforms individual expertise into collective capability (Lewis & Herndon, 2011). Modern systems such as physical AI are increasingly agentic and will likely be able to perform complex service tasks (Wirtz & Stock-Homburg, 2025). Thus, although the principles of TMS are inherently for human actors, TMS can be utilized beyond human-only settings to include hybrid teams of human and non-human agents (Aggarwal et al., 2025). This theoretical framing aligns with current practice, in which employees increasingly work with machines to serve customers (Le et al., 2025).

3.3. The key components of co-learning

As described in our definition, co-learning is not a static activity but rather a dynamic process that occurs over time. Following TMS theory, this process can be characterized by three interdependent activities – knowledge sharing, assimilation, and calibration.

3.3.1. Knowledge sharing

We define *knowledge sharing* as the reciprocal transfer of task-specific information between humans and machines that enables mutual awareness of each side's reasoning and intent. For example, an AI system recommends room upgrades based on booking history and loyalty data, while the front-desk employee shares real-time cues about guest mood and expectations. This reciprocal transfer of information aligns the employee's understanding of the AI's rationale with the system's awareness of human judgment during the interaction. In service frontline contexts, this exchange is particularly critical because real-time alignment between employee judgment and AI outputs directly shapes customer experience (Le et al., 2023). Research shows that repeated exchanges of task-specific information create a shared knowledge pool that develops into an overarching awareness of each other's expertise and reasoning patterns (Danatzis et al., 2025), which enables the utilization of the team's collective knowledge resources (Wang & NOE, 2010). Without this reciprocal sharing, neither humans nor machines can anticipate actions to coordinate effectively or utilize collective knowledge. Thus, knowledge sharing serves as the first step in the co-learning process, through which the team's distributed expertise becomes usable for joint action.

Evidence also demonstrates that the quality of knowledge sharing directly shapes a human–machine team's performance. When AI systems fail to make their reasoning transparent or when employees neglect to articulate contextual intent, the result is misaligned actions and weakened collective performance (An et al., 2024; Hagemann et al., 2023). In contrast, when both agents communicate reasoning and context, they develop shared situational awareness, allowing humans to evaluate AI suggestions critically and enabling the system to adapt future recommendations more sensitively to human judgment (Le et al., 2025; Graef et al., 2021). In sum, knowledge sharing in H-M teams represents an initiation of a symbiotic journey by transforming specialized knowledge into collective intelligence.

3.3.2. Knowledge assimilation

We define *knowledge assimilation* as the process of integrating newly acquired knowledge into the existing collective knowledge system in human–machine teams. In frontline service contexts, where employees and AI agents must respond to diverse customer needs, this process is critical because every customer interaction generates new information that can enrich or reshape the team's collective understanding (Wirtz et al., 2018).

Knowledge assimilation extends beyond merely storing exchanged information; it involves continuously refining the shared knowledge base so that new insights enhance learning while existing knowledge is revised to reduce biases and inaccuracies (Wegner, 1987; Jarrahi et al., 2023). The logic here is that complementary knowledge resources cannot be effectively harnessed unless they are synthesized into a shared cognitive infrastructure accessible to both humans and machines (Döppner et al., 2019).

Evidence of this process in practice can be seen in Microsoft's Dynamics 365 platform, which uses a knowledge management agent to transform case files and conversational data into actionable insights (Microsoft, 2025). When a customer service case is closed, the platform synthesizes chat logs into new knowledge articles that are instantly accessible to employees and AI systems. This allows future problem-solving to draw upon prior cases, with each cycle of assimilation strengthening the shared cognitive infrastructure (Wirtz & Stock-Homburg, 2025). In short, knowledge assimilation functions as a continuous refinement process that integrates newly acquired and revised knowledge into a shared system, building capacity for new collective intelligence that sustains a co-learning process.

3.3.3. Knowledge calibration

We define *knowledge calibration* as the process by which a human–machine team generates novel, task-relevant solutions to customer queries by recombining and aligning the insights derived from the collective knowledge system. In this sense, calibration aligns assimilated knowledge across human and machine agents so that it becomes jointly actionable in novel situations and problems, thereby completing the co-learning cycle (Lewis & Herndon, 2011; Wegner, 1987). Thus, calibration bridges knowledge accumulation and real-world application, ensuring that shared intelligence is not only refined but also effectively enacted in service delivery (Danatzis et al., 2025), thereby likely creating new knowledge and learning for the team. In frontline service contexts, calibration is particularly critical because customers expect both accuracy and personalization, that is, the application of knowledge to the specific situation.

For example, consider a situation where a customer contacts a telecom provider to resolve an unexpected roaming charge. A GenAI agent integrated with the provider's policy database and past case archives retrieves relevant roaming regulations and prior dispute resolutions. The human service agent could work with the AI agent to recalibrate this knowledge into a tailored solution that is both responsive to the customer's specific circumstances and aligned with company policy. With each cycle of creating novel solutions for different customers, the AI becomes more specialized in synthesizing compliance-based solutions. In contrast, the service agent becomes more adept at handling similar disputes by learning from the AI's suggestions.

In this situation, calibration happens when the agent changes the AI's rules and examples. They do this by adjusting, rephrasing, or mixing them with details like customer travel habits or how long they have been with the company. This way, the final decision matches both the general policy and the specific service situation.

3.4. An overview of HMS and related concepts

Understanding the current research landscape of human–machine interaction is essential for justifying the advancement of HMS. As smart technologies increasingly become more common in service frontline environments, the nature of collaboration between humans and machines has shifted from simple task automation to dynamic, interdependent forms of joint problem-solving (Le et al., 2025). However, despite the rapid technological integration across industries, much of the extant literature remains emphasizing discrete aspects of HMS such as decision support (Azer & Alexander, 2025; Jarrahi, 2018), coordination (Danatzis et al., 2025), or capability enhancement (Garry & Harwood, 2019; Grewal et al., 2020; Henkel et al., 2020), without capturing the evolving nature of HMS. Table 1 provides an overview of related research in different contexts. We place HMS within the broader context of how humans and machines interact in frontline environments to show where current MA and HMC do not fully explain long-term relationships in human–machine teams.

As can be seen in Table 1, very few studies have explicitly addressed HMS beyond surface-level mentions, with most research mainly focusing on MA (e.g., Garry & Harwood, 2019; Huang & Rust, 2022) or HMC (e.g., Le et al., 2023; Noble et al., 2022) in the service frontline context. Although a small number of studies acknowledge learning-related dynamics (Danatzis et al., 2025; Döppner et al., 2019; Simón et al., 2024), none formally position co-learning as the central mechanism driving HMS and explicate its underlying activities. Instead, most prior work either ignores learning processes altogether or subsumes them within broader constructs such as coordination (Seeber et al., 2020) or capability enhancement (Grewal et al., 2020). Some studies have explored the roles of machines in supporting knowledge management (Jarrahi et al., 2023). Nevertheless, these efforts rarely capture the iterative and temporal nature of the learning process between humans and machines that underpins the essence of symbiotic interactions. For example, while Döppner et al. (2019) highlight improved decision-making effectiveness, the focus neither distinguishes nor integrates the activities of the co-learning process holistically, nor addresses how the co-learning process evolves.

By contrast, we advance the theory of HMS by identifying co-learning as its defining mechanism and integrating its three core activities – knowledge sharing, knowledge assimilation, and knowledge calibration – into a unified, temporal-based framework. This shift moves beyond static (De Keyser et al., 2019) or mechanistic (Huang & Rust, 2022) models of human–machine interaction toward an adaptation-oriented perspective (e.g., Inga et al., 2023), in which symbiosis unfolds through iterative and reciprocal knowledge exchange between humans and machines. Additionally, this framework makes explicit how variations in the tempo of co-learning shape distinct human–machine symbiotic journeys, an aspect largely overlooked in prior research (see Table 1). Addressing this gap, the current research delineates two co-learning episode tempos – rapid and extended – each reflecting a different pace of learning in human–machine teams. Recognizing these temporal dynamics is essential for advancing theory and practice in service frontline contexts, as different co-learning tempos can produce divergent outcomes in service speed, accuracy, and long-term firm innovativeness.

4. An Organizing temporal framework for HMS in service provision

The discussion thus far has centered on distinguishing HMS from related concepts and clarifying its essence through the notion of co-learning. In this section, we articulate the implications of HMS within the service frontline context. The conceptual framework is depicted in Fig. 2. We outline the premise for the propositions as follows.

As pointed out above, co-learning is an ongoing process rather than a one-time activity. Prior research suggests that team performance unfolds

Table 1
An Overview of Related Research on Human-Machine Interaction.

Author(s)	Context	Theoretical Focus			Dynamics of Co-learning Process			Emergence of Symbiotic Journeys		Facilitators of H-M Interaction	Focal Outcomes	Main Findings
		MA	HMC	HMS	KS	KA	KC	ET	RT			
This research	Service Operation			✓	✓	✓	✓	✓	✓	Task decomposability; Machine trustworthiness	– Short-term: H-M team performance – Long-term: Service innovation	– HMS is distinctive from other forms of interactions through co-learning episodes, a dynamic knowledge management process involving sharing, assimilation, and calibration – The H-M symbiotic journey evolves through repeated co-learning episodes, which can influence team performance and capability depending on the temporal rhythm of these episodes
Arora et al., (2025)	Marketing Strategy		✓		✓			×	×	N/A	Effectiveness and efficiency of the marketing research process	– A human-LLM hybrid approach enhances marketing research effectiveness and efficiency by leveraging complementary skills to jointly coordinate data exploration and analysis across qualitative and quantitative studies
Azer & Alexander (2025)	Service Operation		✓		✓			×	×	Competition pressure	Willingness to implement AI systems in services	– Four types of human–machine engagement with different intensity levels: Apprehensive; praising; informative; experimenting, and driven by emotional and cognitive factors
Blaurock et al., (2024)	Financial Service / Human Resource		✓		✓			×	×	N/A	Service improvement, outcome responsibility	– Collaborative intelligence (CI) systems operate across five dimensions: engagement, transparency, process control, outcome control, and reciprocal strength enhancement
Author(s)	Context	Theoretical Focus			Dynamics of Co-learning Process			Emergence of Symbiotic Journeys		Facilitators of H-M Interaction	Focal Outcomes	Main Findings
		MA	HMC	HMS	KS	KA	KC	ET	RT			
Cillo & Rubera (2024)	Marketing Strategy		✓		✓	✓		×	×	N/A	Innovation process	– GenAI can be involved in the innovation process through co-creating values with humans in different stages in the process – developing, testing, communicating, and engaging
Danatzis et al., (2025)	Organizational Frontlines		✓		✓			×	×	Employee readiness; Technological readiness	H-M team performance synergies	– Human-Technology synergies emerge through a three-stage process – existence, recognition, and enactment of complementarities
De Keyser et al., (2019)	Service Operation	✓			✓			×	×	N/A	N/A	– The conceptual research updates the role of frontline service technology along the replacement-augmentation continuum
Dellermann et al., (2019)	Organizational Frontlines		✓		✓			×	×	N/A	N/A	– Hybrid Intelligence combines human and artificial intelligence to solve complex problems more effectively than either alone
Döppner et al., (2019)	Air Cargo Operation			✓	✓	✓		×	×	N/A	H-M team performance effectiveness	– Before the intelligence system, decisions were manual. After implementation, employees and AI worked together, enhancing team decision effectiveness
Garry & Harwood (2019)	Service Operation	✓			✓			×	×	FLE roles in frontline service	Employee's capabilities	– Employees augmented by cyborg technologies could achieve an increase in performance efficiency and effectiveness when the technology 'melds' into employees and enhances their biological capabilities

(continued on next page)

Table 1 (*continued*)

Author(s)	Context	Theoretical Focus			Dynamics of Co-learning Process			Emergence of Symbiotic Journeys		Facilitators of H-M Interaction	Focal Outcomes	Main Findings
		MA	HMC	HMS	KS	KA	KC	ET	RT			
Gombolay et al., (2017)	Lab Experiment		✓		✓			×	×	Workflow preference	Human situation awareness	– Human situation awareness decreases when they cede their control of scheduling decisions to the robotic agent – Participants preferred robots that considered their workflow preferences in scheduling
Grewal et al., (2020)	Retail	✓			✓			×	×	HET usefulness framing	Employee's capabilities	– Employees' capabilities in performing physical, cognitive, and emotional tasks can be enhanced by Human Enhanced Technologies (HET). The employees gain increases in their productivity and performance quality
Henkel et al., (2020)	Service Operation	✓			✓			×	×	N/A	Interpersonal emotion regulation	– Augmenting service employees with AI significantly enhances their capability to moderate customer emotions
Huang & Rust (2022)	Retail	✓			✓			×	×	Machine Intelligence	Employee/ consumer's capabilities	– Human and AI can complement each other through optimized division of labor of the types of intelligence that each agent can utilize best
Inga et al., (2023)	Computer Science			✓	✓	✓		×	×	Task complexity	Human experiences (e.g., agency)	– The interaction in physically coupled systems is characterized by task, interaction, performance, and experience, offering a multivariate perspective framework
Jarrahi (2018)	Organizational Frontlines			✓		✓		×	×	N/A	H-M team performance effectiveness	– Machine should augment human decision-making, leveraging its analytical power for complexity, while humans apply intuition and holistic judgment to uncertain situations
Le et al., (2023)	Service Operation		✓		✓			×	×	Task complexity; task significance	Customer satisfaction; service quality	– The collaboration between employee and robotic system can be based on three aspects – joint workflow, decision-making authority, goal
Licklider (1960)	Computer Science			✓	✓			×	×	Computer hardware characteristics (e.g., memory capacity)	H-M team performance effectiveness	– By offloading formulative tasks to the computer, agents could focus on complex issues, leading to improved performance through shared workload and information exchange
Noble et al., (2022)	Retail		✓		✓			×	×	N/A	H-M team performance effectiveness	– Employees can form a 'service working alliance' with technology. It consists of three pillars – goal setting, task allocation, and bonding
Seeber et al., (2020)	Organizational Frontlines		✓		✓			×	×	N/A	H-M team performance effectiveness	– Both the human and AI systems can benefit from working together. This teamwork can be embedded in task design, machine artifact design, and institution design.
Simón et al., (2024)	Organizational Frontlines		✓				✓	×	×	N/A	H-M team performance effectiveness	– Three primary aspects of human-AI collaboration: establishing interoperability, fostering trust, and generating shared knowledge advancement.

MA = Machine Augmentation; HMC = Human-Machine Collaboration; HMS = Human-Machine Symbiosis; KS = Knowledge Sharing; KA = Knowledge Assimilation; KC = Knowledge Calibration; ET = Extended Tempo; RT = Rapid Tempo.

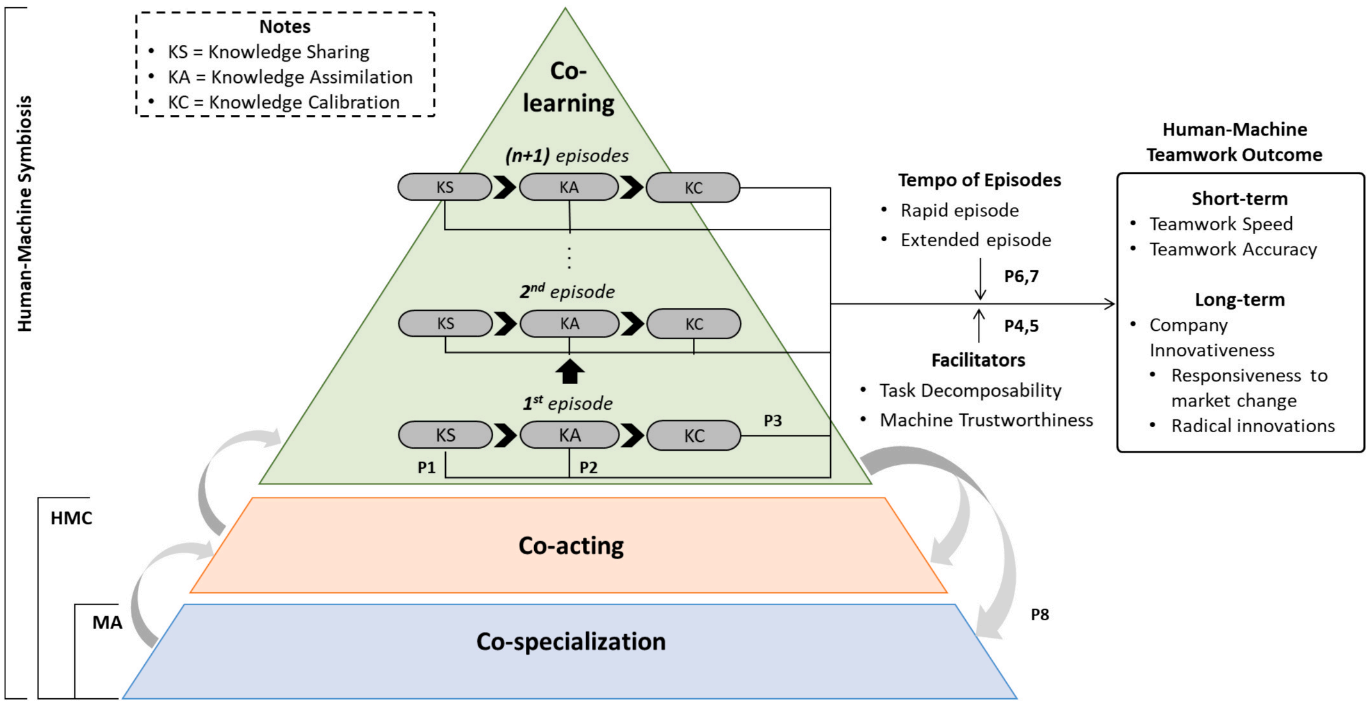

Fig. 2. An Organizing Framework of Human-Machine Symbiosis.

in bounded episodes of action and transition (Marks et al., 2001). Hence, this temporal characteristic makes episodes a natural unit for understanding how co-learning evolves in HMS. Episodes are "distinguishable periods of time over which performance accrues" (Mathieu & Button, 1992, p. 1759). Therefore, we propose that a co-learning process constitutes individual episodes as humans and machines learn to adapt to each other and the work environment (Döppner et al. 2019). Derived from the TMS theory, we see a co-learning episode in this H-M symbiotic journey as a discrete period during which knowledge is actively shared, assimilated, and calibrated within H-M teams when serving customers.

Viewing the co-learning process from an episodic perspective allows the distinction of two types of episodes based on their temporal dynamics – rapid and extended tempo. The rapid episodes denote a quick transition among knowledge sharing, assimilation, and calibration during a co-learning episode, given the limited time for each individual knowledge management activity. For example, customer service employees work with the Salesforce Einstein AI agent during live customer chats. The AI agent instantly retrieves relevant policy details, identifies sentiment cues, and suggests response options, while the employee quickly reviews and personalizes the final message before sending it.

Conversely, the extended episodes emphasize a slower transition between knowledge activities. For example, doctors and AI agents such as IBM Watson Health engage in prolonged knowledge exchange in diagnoses. This temporally oriented framework emphasizes that H-M symbiotic journeys are an evolving process of adaptation. While these two learning tempos are distinctive, they can co-occur in H-M symbiotic journeys, depending on how both agents engage in taskwork. Thus, we emphasize that co-learning episodes are not always rapid or extended; instead, they can alternate in an H-M symbiotic process.

The outcomes of these co-learning episodes influence H-M teamwork performance. We focus on speed and accuracy in the short term, as they have been recognized as key sources of competitive advantage in the service frontline and serve well as manifestations of service productivity and service quality (Marinova et al., 2008). H-M teamwork speed refers to the time required to perform a standard service. In contrast, the H-M teamwork accuracy indicates the degree of correctness of the service provider's execution to address a customer's request (Shrestha et al., 2019). When considering the long-term outcome of multiple co-learning episodes, we propose that a successful H-M symbiotic process will affect firm innovativeness – a firm's capability to develop novel service solutions (Kunz et al., 2011) by influencing the processes of value co-creation (Mahr et al., 2024; Kunz et al., 2025).

Finally, we propose that co-learning acts as the mechanism that transforms both co-specialization and co-acting within a human–machine symbiotic system. While MA and HMC offer the initial structural and procedural foundation, they remain static without the adaptive layer introduced by co-learning, as we argued previously. By enabling both exploitation, through incremental refinement of task execution, and exploration, through novel problem-solving in unfamiliar situations (March 1991), co-learning allows the H-M teams to evolve beyond their original design. Co-specialization, once shaped by preassigned roles, becomes dynamic as humans and machines continuously recalibrate responsibilities through mutual feedback and performance outcomes. Similarly, co-acting shifts from rule-based coordination to context-sensitive synchronization, as humans adjust to machine behavior and machines adapt to human cues. Hence, we posit that the presence of co-learning in H-M teams could influence the development of co-specialization and co-acting over time.

While we posit HMS holds strong potential to enhance service frontline performance, its effectiveness depends on how well organizations manage and facilitate the symbiotic interaction between frontline employees and machine systems. In practice, several challenges may influence how HMS unfolds. For instance, machines often update their models through rapid data-driven learning cycles, whereas human learning typically evolves through experience and reflection, which might have an implication on the rate of knowledge synthesis. Additionally, overreliance on machine outputs may shift decision influence (Banker & Khetani, 2019), requiring organizations to ensure that human judgment remains actively engaged. These issues highlight the need for structured interaction mechanisms that allow humans and machines to continuously align their expertise, decisions, and learning processes during service delivery. Nonetheless, such nuances do not negate the influence of HMS; rather, they underscore the value of our framework for managing these interactions.

4.1. The short-term implications of The co-learning process

In H-M service frontline teams, knowledge sharing represents the initial stage of symbiotic interaction in which human employees and machine agents exchange task-relevant information during service encounters with customers. For example, in restaurant settings where frontline employees work alongside service robots, they exchange information about order status, table needs, and robot task assignments to coordinate food delivery and maintain smooth service operations (Phillips et al., 2025). Information sharing enhances decision quality by reducing misinterpretation, particularly in interdependent and dynamic task environments (DeChurch & Mesmer-Magnus, 2010). Accordingly, the primary performance benefit of knowledge sharing in service frontline H-M teams lies in strengthening the informational foundation of decision-making rather than in accelerating task execution itself.

Consistent with this logic, we propose that relative to H-M teams without a co-learning process (i.e., only relying on either co-specialization or co-acting alone, which is enacted during service encounters – Le et al., 2023), the presence of knowledge sharing primarily improves short-term H-M team performance accuracy by enhancing the quality and completeness of information on which decisions are based. Knowledge sharing increases the diagnostic value of information by reducing ambiguity, thereby strengthening the informational basis of judgment. When humans and machines actively exchange information, it can incorporate current task conditions and updated inputs into their decisions, reducing errors caused by missing, outdated, or misaligned information (Döppner et al., 2019). Such an exchange allows frontline employees to integrate operational data and situational cues into their judgments when serving customers with robots, improving the accuracy of the service delivery (Wirtz et al., 2018). Although knowledge sharing can also facilitate faster coordination by increasing information availability, its effect on performance speed is likely weaker. Knowledge sharing alone does not incorporate the subsequent steps required to interpret, validate, and act on shared inputs. Consequently, while knowledge sharing prevents errors stemming from information gaps, it does not necessarily compress action cycles to the same extent that later stages of co-learning do.

Proposition 1. (*Relative to H-M teamwork without a co-learning process, the presence (vs. absence) of knowledge sharing enhances H-M teamwork performance, improving both speed and accuracy, with a stronger magnitude of effect on accuracy than on speed.*) *Knowledge assimilation represents the next stage of the co-learning process, building on prior knowledge sharing activity by enabling frontline employees and machine agents to incorporate shared information into their existing cognitive or computational memories. Whereas knowledge sharing focuses on making task-relevant information visible across agents, knowledge assimilation concerns how that information is internalized and used to guide action (*Jarrahi et al., 2023*). Through assimilation, both frontline employees and machine agents move beyond mere awareness of information to establish a working interpretation that can be immediately applied during service delivery.*

This process is particularly critical in frontline service contexts, where employees must quickly translate information about customer needs, service history, and situational cues into operational decisions during live customer interactions. Prior service research shows that frontline service encounters are characterized by the need for rapid response to customer requests or problems (Gwinner et al., 2005). In such environments, effective service performance depends not only on access to information but also on the ability to rapidly interpret and apply that information within the service encounter.

Consistent with research on dual-process cognition, rapid integration of information into existing representations supports efficient action (Evans & Stanovich, 2013). We propose that relative to H-M teams without a co-learning process, the presence of knowledge assimilation improves performance speed by allowing shared inputs to be smoothly translated into action (Döppner et al., 2019). When frontline employees and machine agents assimilate information into their operative representations, they reduce the need for repeated clarification or ad hoc interpretation during task execution. Such an action is increasingly common in hotel service environments where robots are deployed to perform functional tasks while human employees manage the overall service interaction and decision making (Belanche et al., 2021). This internalization streamlines decision processes and supports faster task progression (Marks et al., 2001).

Although knowledge assimilation can also contribute to accuracy by reducing bias and misalignment over time, its performance benefits are more strongly reflected in speed than accuracy. Assimilation focuses on incorporating and refining new information into existing knowledge structures so that it can be readily applied to the subsequent taskwork (Jarrahi et al., 2023). For example, many hotels deploy autonomous delivery robots to transport guest amenities, meals, or other items to guest rooms (Luo et al., 2021a). Frontline employees monitor the robot's delivery status and integrate these updates into their ongoing service workflow, enabling them to coordinate follow-up tasks or respond to additional guest requests without reassessing the service situation. This emphasis on immediate applicability means that knowledge assimilation prioritizes readiness for task execution rather than exhaustive validation within the same service episode. By aligning newly acquired information with existing task schemas and decision rules, assimilation creates a coherent action frame that enables humans and machines to respond without interrupting task flow.

Proposition 2. (*Relative to H-M teamwork without a co-learning process, the presence (vs. absence) of knowledge assimilation enhances H-M teamwork performance, improving both speed and accuracy, with a stronger magnitude of effect on speed than on accuracy.*) *Knowledge calibration represents the culminating stage of the co-learning process in which shared and assimilated knowledge is jointly recombined, aligned, and finalized to produce task-relevant solutions for customers (*Jarrahi et al., 2023*). Whereas knowledge sharing establishes mutual awareness and knowledge assimilation supports individual understanding, these activities alone do not ensure the effective creation of solutions for customers. In the absence of calibration, frontline employees and machine agents may operate with partially aligned interpretations, increasing the risk of inconsistency during service delivery. For example, in customer service situations where AI-based chatbots recommend responses during live interactions, the system may suggest a standard troubleshooting script based on keywords detected in the conversation, while the representative interprets the issue as a more complex case (*Le et al., 2025*). If the representative follows the AI recommendation without calibrating this difference when evaluating the assimilated information, the response may appear inconsistent with the customer's situation, leading to confusion or delays later in the interaction.*

Relative to H-M teams without a co-learning process, the presence of knowledge calibration enables agents to converge on a coherent and mutually endorsed representation of the service situation. Through calibration, humans and machines reconcile differences in interpretation, validate solution feasibility, and align on a course of action that integrates customer needs and potential contextual constraints. For instance, in customer service centers, employees need to reconcile multiple information sources, such as customer inputs, conversation transcripts, and AI-generated recommendations, before delivering a final response to the customer (Le et al., 2023). This convergence enhances short-term performance accuracy by ensuring that service responses are internally consistent and appropriately tailored to the task context, thereby reducing the likelihood of misapplication or the need for corrective intervention (Moliner-Tena et al., 2024). At the same time, knowledge calibration improves short-term performance speed by stabilizing decision pathways before execution. When human employees and machine agents share a calibrated solution frame, they can proceed with implementation without repeated validation or renegotiation during the encounter. This reduction in uncertainty and coordination friction minimizes rework, allowing service interactions to unfold more efficiently (Leiño Calleja et al., 2025).

Proposition 3. Relative to H-M teamwork without a co-learning process, the presence (vs. absence) of knowledge calibration enhances H-M teamwork performance, improving both speed and accuracy with equal magnitude of effect.

4.2. Facilitators of The Co-learning Process

The preceding discussion has outlined the mechanisms by which HMS alters the dynamics of H-M team performance, including speed and accuracy. This section extends the framework by examining how task and relational conditions shape the effectiveness of these co-learning activities. From a TMS perspective, the influence of co-learning activities could be influenced by task decomposability, the extent to which a task can be divided into interdependent subtasks distributed across human and machine agents (Lewis & Herndon, 2011). Complementing this structural dimension, the relational dynamic between humans and machines, particularly perceived machine trustworthiness, shapes how effectively shared knowledge is shared, assimilated, and calibrated over time (Glikson & Woolley, 2020). Together, task decomposability and relational trust define the boundary conditions of H-M symbiotic journeys and their trajectories.

4.2.1. Task decomposability

In service frontlines, many operational tasks, such as technical troubleshooting, are highly decomposable, enabling each agent to contribute their specialized capabilities in well-defined, complementary ways (Danatzis et al., 2025). For instance, in technical customer support environments, AI diagnostic tools often analyze system logs, error codes, or performance data to identify potential causes of technical failures, while human agents interact with customers to interpret contextual details and implement appropriate solutions (Kogents, 2026). We propose that when tasks are highly decomposable, the impacts of co-learning activities (i.e., knowledge sharing, assimilation, and calibration) on H-M teamwork performance are amplified. Decomposable tasks enable more precise role boundaries between frontline employees and machines, facilitating more effective knowledge sharing to target specific informational needs, knowledge assimilation to occur within well-defined task boundaries, and knowledge calibration to recombine insights into task-relevant solutions.

In contrast, other frontline service activities, such as consulting or complex service advisory interactions, are far less decomposable because problem definitions evolve during the interaction and cannot be fully specified in advance. In such contexts, frontline employees and machines must continuously interpret and adjust to emerging circumstances from serving the customers to jointly shape the service solution. Hence, although co-learning remains essential for such tasks, its influence is less immediately apparent because co-learning activities become entangled and occur iteratively or simultaneously rather than being mapped onto discrete subtasks.

Proposition 4. Decomposable (vs. non-decomposable) tasks amplify the effect of co-learning activities on H-M teamwork performance.

4.2.2. Machine Trustworthiness

Machine trustworthiness is a relational mechanism that shapes how employees engage with intelligent systems in the service frontline (Le et al., 2023). Defined as the perceived reliability and competence of machine agents (Wirtz et al., 2018), it determines the extent to which employees trust and rely on machine-generated outputs for subsequent taskwork (Glikson & Woolley, 2020). We propose that in H-M teams, perceived machine trustworthiness conditions the effectiveness with which co-learning activities are enacted and translated into speed and accuracy outcomes.

When perceived machine trustworthiness is high, frontline employees are more willing to engage fully in co-learning episodes with a machine. High trust encourages more open and timely knowledge sharing, as employees disclose additional contextual information beyond the necessary information with AI systems without excessive verification or withholding to generate more accurate responses (Döppner et al., 2019). This richer exchange subsequently provides higher-quality inputs for subsequent knowledge assimilation, enabling both humans and machines to internalize shared information with greater confidence. Trust further facilitates knowledge calibration by allowing employees to rely on machine-generated insights when recombining knowledge into task-relevant solutions, reducing hesitation and coordination friction during service execution. For example, in clinical settings where physicians work with AI diagnostic systems, it often generates recommendations based on medical imaging, patient records, or predictive risk models during patient consultations. When clinicians perceive the AI system as reliable and competent, they are more likely to incorporate its recommendations into their clinical decision-making, enabling faster and more effective diagnostic and treatment decisions (Tun et al., 2025). In contrast, when perceived machine trustworthiness is low, employees tend to intentionally limit information disclosure, resist reliance on machine outputs, or engage in defensive monitoring behaviors (Dietvorst et al., 2015). These behaviors disrupt the flow of knowledge sharing, weaken assimilation, and constrain calibration, thereby attenuating the influence of co-learning activities.

Proposition 5. Perceived machine trustworthiness amplifies the effect of co-learning activities on H-M teamwork performance.

4.3. The Long-term Implications of HMS

Firm innovativeness reflects a firm's capacity to stimulate a market and generate and implement new ideas that enhance service effectiveness and competitiveness over time (Kunz et al., 2011). Importantly, innovation does not manifest itself in a single form. On one end, innovativeness is expressed through responsiveness to market change – incremental, timely adjustments that enable firms to respond quickly to emerging customer needs, operational disruptions, or situational variability in service encounters (Hurley & Hult, 1998). On the other end, innovativeness also encompasses radical innovations that fundamentally reconfigure service processes, roles, or value propositions by recombining knowledge in novel ways (Jiménez-Jiménez & Sanz-Valle, 2011). These two forms of innovativeness differ in their underlying learning dynamics (Hurley & Hult, 1998) and temporal horizons. Recognizing this duality provides an important foundation for examining how different co-learning tempos in HMS may differentially foster long-term innovative capacity in service organizations.

4.3.1. Rapid co-learning episodes in H-M symbiotic journey

The rapid-dominance episodes represent a form of H-M symbiotic journey defined by high-tempo, tightly coupled co-learning episodes in which knowledge sharing, assimilation, and calibration are compressed in time. Within these short cycles, humans and machines continuously exchange task-relevant information, producing a rapidly refreshed shared knowledge base. Real-time AI retrieval and structuring capabilities synchronize with employees' contextual judgment, enabling immediate alignment on intent, priorities, and response logic. Such condensed learning cycles are increasingly visible in frontline service contexts such as call centers, where decision-making occurs "in the moment" rather than through back-stage review or batch processing (Henkel et al., 2020; Luo et al., 2021b). For example, in AI-assisted customer service platforms used in call centers, intelligent systems analyze incoming customer messages, retrieve relevant knowledge, and generate response suggestions while customer representatives simultaneously interpret the customer's situation and finalize the response (Le et al., 2025). Through tight cycles of interaction, human agents and AI systems continuously exchange and update information within the same service episode, enabling rapid alignment on customer intent and response strategies.

Compared to a symbiotic journey dominated by extended co-learning episodes, rapid-tempo co-learning episodes promote speed of adaptation over depth of integration. Frequent, short episodes of knowledge sharing, assimilation, and calibration allow both humans and machines to adapt rapidly, creating a near-synchronous learning rhythm that enhances information processing velocity (Göndöcs et al., 2025). Real-time decision support AI agents can help novice representatives respond to customer inquiries more quickly by retrieving relevant information and generating response suggestions during the interaction (Luo et al., 2021b). Consequently, high-velocity learning in H-M teams could augment the firm's responsiveness to emerging customer needs and competition. In practice, frontline AI systems such as Zendesk AI (https://www.zendesk.com/service/ai/) exemplify this pattern. During live customer interactions, the system rapidly ingests customer inputs, generates response recommendations, and adapts to agent selections in real time. Repeated interactions reinforce a rapid-tempo symbiotic journey in which agents become faster at deploying AI suggestions while the system fine-tunes its outputs based on short-cycle feedback. This configuration enhances responsiveness and consistency in handling customer inquiries but leaves agents with limited cognitive space to reflect on atypical cases or experiment with fundamentally different service approaches. Consequently, rapid-tempo symbiotic journeys support incremental, efficiency-oriented service innovation that responds to immediate problems and adjusts to shifting customer expectations and market conditions.

Proposition 6. H-M symbiotic journeys dominated by rapid (vs. extended) co-learning episodes are likely to enhance firms' responsiveness to market change.

4.3.2. Extended Co-learning Episodes in H-M Symbiotic Journeys

H-M symbiotic journeys that feature an extended tempo in co-learning episodes unfold across a longer temporal horizon, enabling deeper integration of insights into the shared knowledge base and more deliberate refinement of task-relevant solutions (Nixdorf et al., 2025). In service frontline contexts, this form of co-learning episode becomes particularly salient when employees and AI systems confront ill-structured or high-stakes customer problems that cannot be resolved through standardized scripts or small deviations from the dominant design (Graef et al., 2021). For example, in insurance claims assessment, AI systems increasingly analyze large volumes of claim data, such as photos, documents, and historical records, to generate preliminary fraud risk signals. The employee then reviews these AI-generated insights and integrates them with contextual information such as policy terms, accident circumstances, and regulatory constraints before making the final claims decision (Bhattacharya et al., 2025). Because this joint work unfolds through repeated rounds of interpretation and verification rather than a single real-time interaction, the human and AI gradually align their assessments before the final resolution is implemented.

Compared with symbiotic journeys dominated by rapid episodes, journeys dominated by extended co-learning episodes tend to facilitate opportunities for reflection on learning. Deep engagement in sharing, assimilating, and calibrating knowledge enables greater validation of new information and supports the co-construction of higher-order solutions prior to execution, thereby increasing correctness (Döppner et al., 2019; Lewis & Herndon, 2011). Prior research indicates that transformative service innovations could emerge from the gradual integration and recombination of knowledge that redefines roles, processes, and resource linkages across the service ecosystem (Sklyar et al., 2019). Through prolonged cycles of sharing, assimilation, and calibration, H-M teams can accumulate higher-order insights that enable the reconfiguration of service architectures rather than incremental efficiency gains. Such a deliberate learning process enables the emergence of entirely new service protocols or ideas that go beyond efficiency improvement toward systemic innovation (Snyder et al., 2016). Consequently, extended learning tempo in symbiotic journeys enhances the potential for radical innovation in service provision by supporting deep, system-level learning and reorientation. For instance, in financial advisory services, relationship managers collaborating with AI-driven portfolio management systems, such as Swiss investment bank UBS's AI advisory agents, engage in extended feedback loops in which the AI generates investment scenarios and risk projections, which advisors then refine using contextual insights about clients' preferences and market conditions. This process takes time, but when done multiple times, it can lead to completely new investment products beyond the established strategies (Cordeira, 2025).

Proposition 7. H-M symbiotic journeys dominated by extended (vs. rapid) co-learning episodes are likely to enhance a firm's potential for breakthrough service innovations.

4.3.3. The Transformative Role of Co-learning in HMS

We argue that effective co-learning functions as a generative mechanism that strengthens both co-specialization and co-acting in H-M teams over time. Co-learning episodes provide the temporal mechanism through which human and machine agents progressively adapt to one another across repeated service interactions. For example, in retail banking, relationship managers increasingly work with AI-based credit assessment systems when evaluating loan applications. Through repeated interactions across multiple cases, bankers learn when to rely on AI analytics and when to apply additional judgment, while the system improves with new data, gradually strengthening role differentiation and coordination between human expertise and machine analysis.

Sustained cycles of effective co-learning episodes enable agents to develop increasingly accurate awareness of differentiated expertise and stable expectations regarding "who knows what" and "who does what" (Wegner, 1987; Lewis, 2003; Argote & Ren, 2012). This evolving cognitive infrastructure deepens co-specialization by clarifying role boundaries between humans and machines and allowing differentiated capabilities to be refined through experience. At the same time, co-learning reinforces co-acting by stabilizing coordinated action patterns. Through repeated learning interactions, human and machine agents become more sensitive to each other's informational cues, which supports tighter synchronization and smoother coordination across service episodes (Lewis, 2003; Seeber et al., 2020). As co-learning unfolds over time, this accumulated mutual understanding strengthens agents' ability to anticipate, sequence, and adjust their actions in relation to one another, thereby enhancing coordinated task execution. Such learning-driven reinforcement enables co-acting to evolve beyond ad hoc coordination toward more reliable and coherent joint action, even as task demands and service contexts vary.

By contrast, when co-learning is absent across repeated interactions over time, H-M interactions remain locked into static task allocations and rule-based coordination. Although such arrangements may enable basic task execution, they restrict the development of deeper complementarities between human expertise and machine capabilities. In service settings, this lack of adaptive learning can result in rigid workflows where employees either over-rely on or disregard system outputs, leading to inefficient coordination and underutilization of AI capabilities over time.

Proposition 8. Relative to H-M teams without a co-learning process, the presence (vs. absence) of co-learning strengthens co-specialization and co-acting over time.

5. General discussion

5.1. Theoretical implications

Building on the metaphor of interspecies symbiosis in nature, this research advances the discourse on human–machine interaction in service contexts by moving beyond traditional paradigms of augmentation and collaboration (De Keyser et al., 2019; Huang & Rust, 2018; Noble et al., 2022; Wirtz et al., 2018; Van Doorn et al., 2017; Xiao & Kumar, 2021). Unlike recent studies that predominantly focus on the conceptualization of collaborative intelligence (Azer & Alexander, 2025; Danatzis et al., 2025; Inga et al., 2023; Jarrahi, 2018; Simón et al., 2024; Wilson & Daugherty, 2018), this research centers on symbiosis between humans and machines through the lens of co-learning, which we conceptualized through three core knowledge management activities drawing on TMS theory (Lewis & Herndon, 2011; Wegner, 1987). These processes are not merely transactional but evolve dynamically, with both short- and long-term implications for the service frontline, reflecting the adaptive interdependence between human and machine agents. Additionally, this research highlights the temporal influences of co-learning episodes, which have been largely overlooked in similar conceptualizations (e.g., Inga et al., 2023; Jarrahi, 2018). This long-term perspective offers a more granular understanding of how human and machine capabilities co-evolve, enabling more profound insight into the impact of machine adoption on service provision (Wirtz et al., 2018).

Moreover, while recent studies have examined how interactions with robotic systems shape user experience (Blaurock et al., 2025; Le & Cayrat, 2025), this research goes further by unpacking the impact of HMS on joint human–machine performance. It shows that team speed and accuracy rely on effective management of the co-learning process. This highlights the need to design good co-learning mechanisms to facilitate a beneficial H-M symbiotic journey. Beyond immediate performance outcomes, the research also identified the long-term service implications of HMS, such as the company's responsiveness to market change and its potential for radical innovation. In doing so, it responds directly to recent calls for deeper investigation into machine integration at the service firm level (e.g., Cillo & Rubera, 2024).

Finally, this research complements and extends prior work (Azer & Alexander, 2025; Danatzis et al., 2025) by integrating task- and relationship-oriented moderators, specifically task decomposability and machine trustworthiness, into the theorization of HMS. This insight not only enriches the theoretical framework of HMS but also offers practical guidance for frontline service operations with hybrid H-M teams.

5.2. *Managerial implications*

A recent report highlights that many firms continue to struggle with realizing the full benefits of integrating machines, particularly AI technologies, into their operations (McKinsey & Company, 2024). The HMS framework developed in this research highlights that its benefit does not emerge automatically from the introduction of machines into service operations. Instead, firms need to actively design and develop how employees and machines exchange knowledge, internalize information, calibrate solutions, and coordinate task execution over repeated interactions.

To foster a beneficial H-M symbiotic interaction, we present the following recommendations, summarized in Fig. 3. Additionally, to illustrate how the recommendations can be operationalized in practice, we showcase its applicability in two contrasting service environments – high-velocity services (e.g., customer support) and high-expertise services (e.g., healthcare). These environments were selected because they differ fundamentally in interaction tempo, decision structure, and knowledge intensity. High-velocity environment represents service sectors that involve rapid, repetitive customer interactions where decisions must be made in real time and efficiency is paramount. In contrast, high-expertise environments represent service sectors that involve complex problem solving, high stakes, and deliberative decision processes where professional judgment dominates. By applying the HMS framework across these contrasting sectors, we demonstrate its flexibility in guiding managerial strategies.

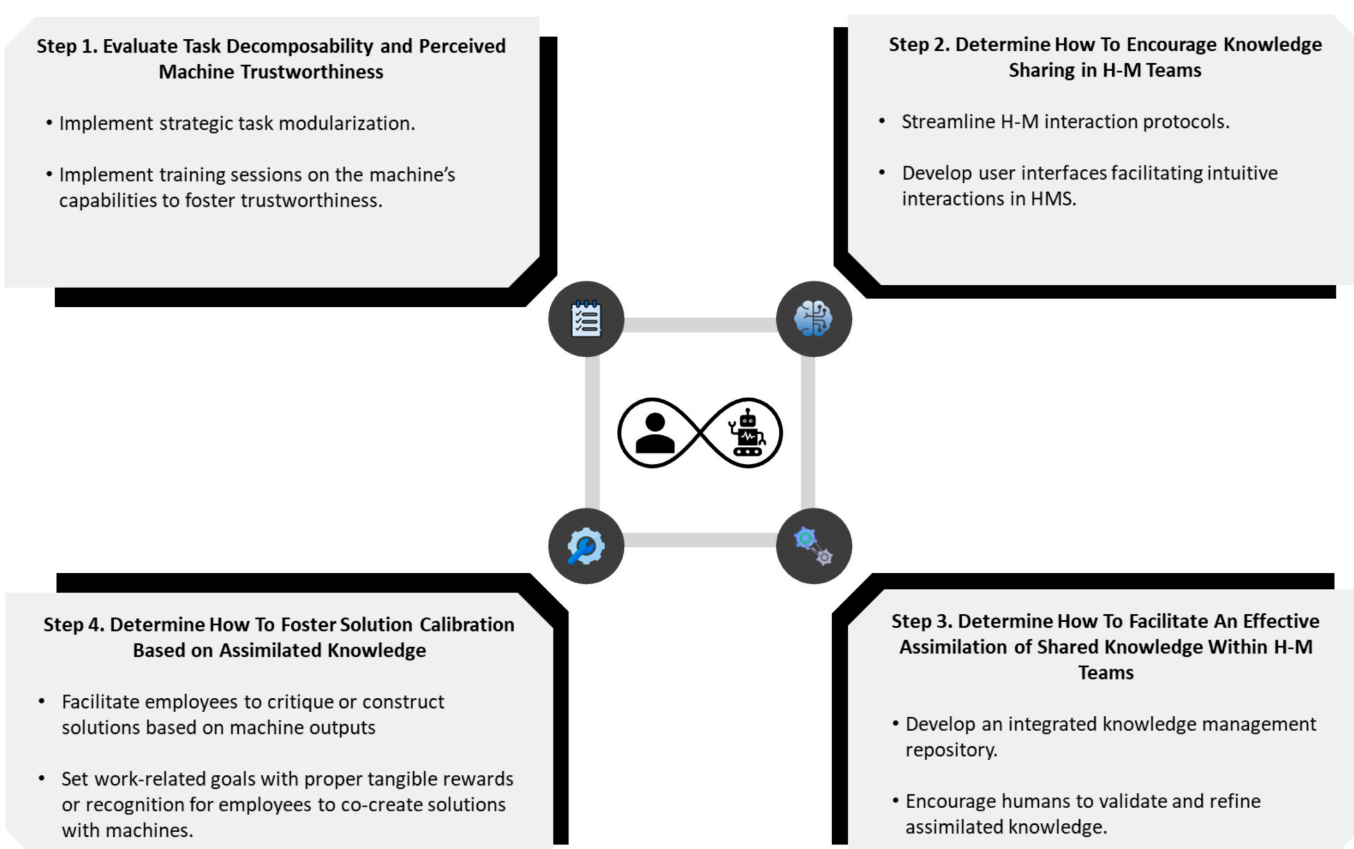

Fig. 3. A Summary of Managerial Implications.

Our recommendation begins with shared-task design, particularly through modularization that allocates decomposable tasks to humans and machines, ensuring complementarity. Further, organizations could align user expectations with machine capabilities through targeted training that builds informed confidence and trustworthiness, avoiding both over-reliance and resistance. Once task design and expectation calibration have been implemented, firms can focus on fostering the co-learning process in H-M symbiotic interactions. For managing knowledge sharing activity, firms could introduce standardized interaction protocols and intuitive interfaces that reduce ambiguity and enable real-time, high-quality exchanges. In terms of managing knowledge assimilation activity, centralized knowledge repositories could be deployed to ensure both actors operate from a consistent and continuously updated knowledge base. Further, to maintain knowledge assimilation integrity, firms should embed ongoing validation mechanisms, including human-in-the-loop checkpoints, to refine and align assimilated insights. Finally, for managing knowledge calibration activity, firms should actively cultivate divergent thinking within H-M teams, thereby expanding the solution space and enabling innovation. This cognitive orientation can be further reinforced through clear goal structures and incentive systems that reward active engagement and co-learning with AI. Next, we illustrate our recommendations with the two contrasting service environments.

5.2.1. High-velocity service environment

High-velocity service environments such as customer support centers present a distinct operational context for HMS. Service interactions with customers are often rapid and standardized, meaning that symbiotic interactions between employees and machines typically rely on swift interpretation and application of machine-generated insights.

Task Design & H-M Relationship: The first step in fostering a beneficial HMS is to consider task modularization and evaluate employees' attitudes toward machine trustworthiness. In high-velocity environments such as call centers, AI can perform technical-oriented functions such as speech transcription, sentiment detection (e.g., Henkel et al., 2020), while human agents focus on interpreting customer needs and delivering responses. Such a division allows machines to process information rapidly while employees retain control of interaction with customers. Further, complacency due to seemingly logical outputs, although it contains errors, may lead to blind acceptance of machine recommendations (Le & Kunz, 2026), whereas under-trust can produce redundant verification and inefficiencies. Hence, training programs that explain AI capabilities and limitations can help employees develop balanced reliance on AI tools and support an effective co-learning process.

Knowledge Sharing: The second step is to encourage knowledge sharing between employees and machines. In high-velocity service environments, the speed of information exchange is critical. Customer service call centers represent such an environment. Firms should therefore streamline human–machine interaction protocols that reduce ambiguity and streamline communication during service encounters. One approach is to integrate conversational interfaces that allow employees to interact with machines using natural language. For example, United Airlines implemented a standardized human–machine interaction protocol that integrated real-time data and enabled seamless handoffs. This overhaul boosted customer satisfaction to over 82% during peak demand (Conway, 2025). Furthermore, developing an intuitive user interface to facilitate interactions between humans and machines could enhance the quality of knowledge sharing. For example, Verizon deployed Google's Contact Center AI to assist customer support representatives in real-time. When employees interact with the system via voice or text, it uses natural language processing and backend system integration to provide support, significantly reducing training time and improving knowledge access during live calls (Cai, 2025).

Knowledge Assimilation: The third step is to facilitate knowledge assimilation. To do this, firms could implement centralized knowledge repositories that allow both employees and machines to access updated organizational knowledge. Such systems ensure that employees and machines operate using consistent and current information. Ultimately, it would facilitate rapid knowledge assimilation. For example, Zendesk AI integrates knowledge management systems directly into customer support platforms, allowing their AI systems to retrieve information from company knowledge bases and recommend responses to representatives during customer interactions. This integration allows frontline employees to quickly assimilate relevant knowledge into their responses without manually searching internal documentation. Further, firms should encourage continuous validation and refinement of assimilated knowledge to ensure its quality. This helps both human and AI agents align with current insights, thereby preventing actions based on outdated or erroneous information. For example, Amazon's Bedrock Agents includes built-in human-in-the-loop workflows such as user confirmation triggers. In a scenario when an internal HR system processes an employee's time-off request, human reviewers can validate or override the AI's suggestions before finalization (Perrot et al., 2025).

Knowledge Calibration: The fourth step is to facilitate meaningful solution building based on assimilated knowledge. Knowledge calibration in high-velocity service environments occurs through short feedback cycles during live customer interactions. Rather than relying on AI recommendations alone, firms should encourage frontline employees to compare and refine multiple system-generated response options before executing service actions. Many customer service platforms now provide agents with several suggested responses that can be edited or combined before being delivered to customers. For example, Bank of America's virtual assistant Erica supports customer service agents by providing recommended responses and financial insights during live interactions. The employee reviews these suggestions and adapts them based on the customer's specific situation before delivering the final response. Additionally, organizations could embed performance structures that reinforce active cognitive engagement with machine outputs. Tangible rewards and recognition mechanisms can then be aligned with these behaviors to incentivize deliberate refinement.

5.2.2. High-expertise service environment

High-expertise service environments, such as healthcare, present a distinct operational context for HMS. Clinical decisions are complex, high-stakes, and often uncertain, meaning that symbiotic interactions between clinicians and AI systems typically unfold more slowly and require deeper engagement with machine-generated insights.

Task Design & H-M Relationship: For the first step of creating a beneficial symbiotic interaction in H-M teams in high-expertise service settings such as healthcare, AI systems can be assigned to data-intensive functions, such as analyzing medical images or identifying patterns in patient records, while clinicians concentrate on contextual interpretation and patient communication. This division fosters complementary specialization, which facilitates symbiotic interactions. Further, training programs that clarify how diagnostic algorithms function, including their advantages and limitations, enable clinicians to critically evaluate AI-generated insights. This supports balanced reliance, ensuring that AI augments rather than displaces professional judgment in complex clinical decisions.

Knowledge Sharing: The second step is to enable effective knowledge sharing between clinicians and AI systems. Healthcare organizations could standardize the interaction protocols when communicating patient records or diagnostic outputs through structured diagnostic dashboards that integrate AI-generated results with patient data in a unified interface, allowing clinicians to interpret outputs within the clinical context (Xu et al., 2023). Furthermore, designing intuitive clinical decision-support systems that present explanations alongside recommendations can improve transparency and facilitate more accurate knowledge sharing during diagnosis and treatment decisions (Sadeghi et al., 2024).

Knowledge Assimilation: The third step is to facilitate knowledge assimilation. Centralized clinical knowledge repositories that integrate validated medical guidelines, patient records, and prior case insights could be deployed. Such repositories ensure that machine-generated recommendations are grounded in contextually relevant knowledge, enabling clinicians to interpret outputs in light of evidence and patient-specific data. Further, encouraging clinicians to critically evaluate AI recommendations and feed outcomes back into the system to refine both the knowledge repository and system performance could also be used to support effective assimilation. Such mechanisms prevent overreliance on automation. For example, clinical workflows often include physician sign-off on AI-assisted interpretations, ensuring that final decisions remain anchored in expert judgment while leveraging repository-supported and machine-augmented insights (Olawade et al., 2026).

Knowledge Calibration: The fourth step is to support knowledge calibration. In high-expertise service environments, calibration unfolds through deliberate clinical decision processes. Rather than accepting algorithmic outputs at face value, healthcare organizations could introduce review protocols, such as multidisciplinary case discussions that explicitly facilitate divergent thinking to foster multiple competing diagnoses and treatment pathways, including those that contradict AI recommendations, and systematically compare these alternatives before reaching a final decision. This would ultimately facilitate beneficial symbiotic interactions in H-M teams. Additionally, organizations should align professional goals and recognition systems to reinforce active cognitive engagement with AI agents. Such incentives reinforce a learning environment in which clinicians critically evaluate algorithmic recommendations and refine decisions through co-learning episodes.

Table 2
Future Research Avenues.

Research Avenue 1: Components of Individuals Co-learning Episodes in HMS	
Knowledge Sharing	**KS1.** What are the factors and under what circumstances influence the employees' willingness to disclose information and train AI systems? **KS2.** Under what conditions does asymmetric knowledge sharing (e.g., when machines share more than humans or vice versa) affect the formation of a shared knowledge system in H-M teams? **KS3.** How do differences in service context (e.g., high-touch vs. high-tech) affect the knowledge sharing between humans and machines?
Knowledge Assimilating	**KA1.** What mechanisms best support continual assimilation of new knowledge in dynamic service environments where both human and machine learning rates differ? **KA2.** How does the interaction frequency between humans and machines impact the quality of the shared knowledge base? **KA3.** How does the cognitive load on human agents influence the effectiveness of knowledge assimilation?
Knowledge Calibrating	**KC1.** How does the integration of learning practices affect the long-term skill development of employees working with machines? **KC2.** How do different levels of machine autonomy impact the process of knowledge calibration in creative problem-solving scenarios? **KC3.** What factors determine the boundary conditions under which knowledge calibration leads to emergent service innovation (e.g., operation efficiency, service excellence, new service product development)?
Research Avenue 2: H-M Symbiotic Journeys	
H-M Symbiotic Journeys	**SJ1.** How do firms sustain the rapid and/or extended tempo of co-learning episodes in H-M symbiotic journeys across service ecosystems that demand both personalization and scale (e.g., digital banking)? **SJ2.** What triggers the transition between the rapid and extended tempo in symbiotic journeys within human–machine teams, and how do these shifts influence the balance between short-term and long-term outcomes? **SJ3.** How do the rapid and extended tempos of co-learning episodes in H-M symbiotic journeys reshape customer expectations for service quality, responsiveness, and perceived effectiveness of such a hybrid team over time?
Research Avenue 3: Shared Task Design and H-M Relational Characteristics	
Task Decomposability	**TD1.** In what ways does task decomposability shape knowledge transfer between humans and machines in frontline service in both rapid and extended tempo of co-learning episodes in symbiotic journeys? **TD2.** How do different levels of task decomposability influence the rhythm, duration, and effectiveness of activities in co-learning episodes over time? **TD3.** In what ways does task decomposability influence the depth and breadth of knowledge integration in H-M teams when serving customers?
Machine Trustworthiness	**MT1.** How do fluctuations in machine trust over time shape the interplay among knowledge sharing, assimilation, and calibration during co-learning episodes, and how does this process contribute to the gradual emergence of H-M symbiotic journeys? **MT2.** How does power structure in H-M teams shape the development of trust and, in turn, influence the processes of knowledge sharing, assimilation, and calibration in co-learning episodes?

6. Future Outlook

This research advances the understanding of how humans and machines can co-exist in service systems, moving beyond the dominant frames of augmentation and collaboration toward a symbiotic relationship. We conceptualize HMS uniquely through the lens of co-learning, grounded in TMS theory, to capture how humans and machines continually evolve through mutual learning. To support continued inquiries into the opportunities and challenges of HMS, Table 2 summarizes the potential future research avenues.

Research Avenue 1 focuses on the micro-dynamics of co-learning episodes to uncover how humans and machines develop shared understanding over time. Future research could investigate the conditions under which employees willingly disclose knowledge, how asymmetries in human–machine information exchange shape the emergence of shared knowledge systems, and how differing service contexts (e.g., high-touch vs. high-tech) alter these dynamics (KS1-3). By addressing these questions, it would further reinforce understanding around the cognitive and relational mechanisms in H-M teams that enable effective knowledge sharing, thereby providing a deeper insight into how co-learning can be better initiated in frontline service. Knowledge assimilation is the next critical aspect in the H-M symbiotic journey. Future studies could explore how different learning mechanisms, interaction frequencies, and cognitive demands shape the depth and speed of assimilation in H-M teams (KA1-3). Understanding these aspects would be vital for designing systems that foster a positive learning environment. Finally, future research on knowledge calibration could investigate how human employees develop new skills (e.g., prompting) when working with machine agents through emergent learning practices (e.g., Bonetti et al., 2023). Further, future research could explore how varying levels of machine autonomy influence the calibration of human and machine knowledge in creative problem-solving contexts. Addressing this challenge would inform the design of symbiotic systems that leverage machine autonomy to expand employees' creative problem-solving capability (KC1-3).

Research Avenue 2 extends the focus to macro-level H-M symbiotic journeys. Scholars could investigate how firms sustain both the rapid and extended tempo of co-learning episodes in symbiotic journeys across service ecosystems that must reconcile personalization with scalability (SJ1). Further studies might explore the mechanisms and contextual triggers that prompt transitions between these two modes of symbiotic journeys and assess how such shifts alter the balance between short-term team performance and long-term service innovation (SJ2). In addition, future work could examine how these evolving symbiotic journeys reshape customer expectations for service quality and responsiveness, as well as perceptions of hybrid team effectiveness (SJ3). Pursuing these directions would link episodic co-learning processes to the broader temporal and systemic evolution of HMS, emphasizing the need for dynamic, ongoing management of symbiotic trajectories in service.

Research Avenue 3 highlights research direction on the implications of task decomposability and machine trustworthiness in H-M symbiotic journeys. Future research could examine how varying degrees of task decomposability influence the flow of knowledge transfer between humans and machines (TD1). Further studies might investigate how decomposability influences the rhythm, duration, and effectiveness of activities within co-learning episodes over time (TD2) and how decomposability affects the depth and breadth of knowledge integration within frontline H-M teams (TD3). Additionally, future research might investigate how fluctuations in trust across repeated co-learning episodes shape the dynamic interplay among knowledge sharing, assimilation, and calibration (MT1), thereby influencing the continuity and maturation of H-M symbiotic journeys. Similarly, the role of power structures within H-M teams warrants deeper examination (MT2).

CRediT authorship contribution statement

Khanh B.Q. Le: .Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Laszlo Sajtos:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization. **Werner H. Kunz:** Writing – review & editing, Writing – original draft, Visualization, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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