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REVIEW ARTICLE

Reciprocal learning in human–machine collaboration: a systematic literature review and implications for production and logistics

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ABSTRACT
The integration of automation technologies and artificial intelligence into production and logistics is transforming work organisation for human and machine agents. Beyond the scope of classical collaborative task allocation problems, studies on social aspects, especially the mutual learning of humans and intelligent machines during interactions, remain scarce. By enhancing cyber-physical production and logistics systems to become intelligent, learnable, and social, human–machine symbiosis can be fostered to enhance their complementary strengths. Despite studies addressing the potential of this bidirectional learning process in the form of reciprocal human–machine learning (RHML), this concept remains ambiguous and lacks a comprehensive knowledge base in production and logistics. Therefore, in this study, a systematic literature review was conducted to gather and categorise the existing knowledge on RHML in different disciplines. Further, efforts were made to (i) consolidate existing design components of RHML into a taxonomy; (ii) describe current design patterns of RHML with classified RHML archetypes; and (iii) apply the resulting taxonomy and archetypes to discuss the potential of RHML concepts in production and logistics. This interdisciplinary approach aims to extend the existing design concepts in cyber-physical production and logistics systems. In addition, initial discussions on the future research agenda are provided.

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Hybrid intelligence; Industry 4.0; human–machine interaction; assistance system; reciprocal human–machine learning

SUSTAINABLE DEVELOPMENT GOALS
SDG4: Quality education; SDG8: Decent work and economic growth; SDG9: Industry, innovation and infrastructure

1. Introduction

Recent technological advancements in automation technologies and artificial intelligence (AI) have attracted attention for (re)designing production and logistics systems. The inclusion of technologies in originally manually operated systems has led to different forms of interactions (Hentout et al. 2019): (i) coexistence: sharing a workspace without common tasks; (ii) cooperation: sharing the same working purpose while fulfilling time and space requirements; and (iii) collaboration: performing complex tasks with direct interactions. Based on these system settings, as confirmed by various literature review studies (e.g. Sauer, Burggräf, and Steinberg 2025b; Simões et al. 2022), cognitive and social processes remain largely unaddressed at present. In particular, the learning process, which stems from psychology (Gross 2012), is yet to be studied further in the industrial context.

Notably, based on the existing literature focusing on (human or machine) learning in the industry, efforts have been made to enable knowledge sharing and transfer between humans and machines to achieve tight, close, and harmonious relationships between human and machine agents (human–machine symbiosis; see Pacaux-Lemoine and Trentesaux 2019; Wang et al. 2019). For instance, a recent literature review (Zheng et al. 2024) discussed the feasibility and potential benefits of AI-driven assistance, with a focus on knowledge transfer in production and maintenance procedure training. In fact, such unidirectional knowledge transfer has been conceptualised and adopted in recent studies in production and logistics. In particular, human learning assisted by intelligent tutoring or learning assistance systems is referred to as computer-in-the-loop (CITL) learning (Shneiderman 2020), whereas human-in-the-loop (HITL) machine learning (ML) focuses on optimising ML by leveraging human feedback (Wenskovitch and North 2020). The preliminary adoption of these concepts has created new research opportunities and practical benefits in terms of both human-centricity and system efficiency (e.g. HITL: Cimini et al. 2020; CITL: Zheng et al. 2024).

Therefore, an industrial system involving human and machine agents to link HITL and CITL could be designed to create mutual benefits by fostering social behaviour based on various forms of human–machine interaction

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(HMI), as mentioned above. The key is to enable a bidirectional learning process between these two agents to form reciprocal human–machine learning (RHML). Several former studies have already discussed similar issues, a brief description of which follows. An initial definition of RHML can be found in the conceptual work of Ansari et al. (2018b), who also summarised the potential benefits of RHML in modern smart factories, e.g. efficient task conduction (short-term), optimal task assignments (mid-term), and an improved understanding of the manufacturing process (long-term). The authors pointed out that a bidirectional learning process between human and machine agents is a key feature of RHML, as opposed to the unidirectional learning processes in HITL and CITL. The first use cases were envisioned by Ansari, Erol, and Sihn (2018a). An illustrative example of RHML in inhouse transportation processes was provided by Ansari, Erol, and Sihn (2018a), who suggested that knowledge transfer between human workers and autonomous vehicles can leverage the strengths of both parties and contribute to continuous routing optimisation. For instance, whereas humans can inform vehicles about changes in infrastructure layouts, the vehicles can map real-time traffic conditions and detect unplanned obstacles using laser arrays. Another example can be found in assembly processes involving both humans and robotic arms. In this case, humans can teach specific movements to robots through sensory input, while the robots can analyse human activities to identify; for example, more efficient task sequences, thereby enabling bidirectional learning between human and machine agents. To provide an overview of the RHML concepts in production and logistics, Nixdorf, Ansari, and Schlund (2022a; 2022b) reviewed the literature on small sample sizes and contributed to the development of the conceptual understanding. Nevertheless, reviews of the current state of the art remain limited, particularly for applications in production and logistics. Moreover, comprehensive definitions of RHML, instantiations of RHML in practice, and descriptive design knowledge are limited. Therefore, considering industry technological readiness and advancements in AI and learnable technologies, the feasibility of RHML in industrial practice remains underexplored. Consequently, identifying potential pilot study fields is crucial for determining the technological and non-technological RHML requirements in production and logistics.

Inspired by the aforementioned motivation, the current study intends to take a further step towards providing a comprehensive RHML framework that describes various potential application scenarios in production and logistics involving the bidirectional learning process. To achieve this, the following research questions (RQ1–3) are presented:

- RQ1: What design knowledge on reciprocal human–machine learning exists across academic disciplines?
- RQ2: How can this interdisciplinary reciprocal human–machine learning knowledge be structured and conceptualised?
- RQ3: What are the potential benefits of applying reciprocal human–machine learning in production and logistics, and what avenues for future research can be identified?

The formulation of the research questions (particularly RQ1) is based on the fact that RHML is yet to be conceptualised in production and logistics, whereas numerous initial empirical case studies have been conducted in other disciplines. These studies and their proposed design knowledge are yet to be examined in terms of their applicability in production and logistics. Thus, our approach to answering RQ1 is to conduct a systematic literature review (SLR) without restricting the discipline to gather RHML design knowledge. The rationale behind this approach is to identify the existing explicit knowledge (Kalpič and Bernus 2006), which is formal, systematic, and objective, while the current stage of RHML discussion in production and logistics remains tacit knowledge, and hence, not comprehensive (see Section 2). To leverage interdisciplinary knowledge transfer, the 'codification' of knowledge (Dickhaut et al. 2022), as gathered from the SLR, is realised by the development of an RHML taxonomy and the identification of common RHML archetypes (RQ2). In particular, design components were derived from the sampled studies and classified into four categories: system, interaction, task, and learning. Based on this classification, an RHML taxonomy was developed (see Section 4 and Appendix D). A combination of design components in the taxonomy was further summarised to build four archetypes (see Section 5.1), revealing state-of-the-art RHML design patterns. Finally, RQ3 provides a forward-looking perspective on how to apply the RHML design knowledge in production and logistics (see Section 5.2), based on which a future research agenda is systematically developed (see Section 5.3).

The remainder of this paper is organised as follows: Section 2 discusses the relevant terminologies, outlining the step-by-step conceptual development of RHML, which mainly includes human and machine learning, CITL, and HITL. An SLR was conducted to answer RQ1, the methodology of which is described in Section 3. Section 4 presents the results of the SLR structured by the

Table 1. Core concepts of RHML.

Core concept	Working definition	References
Human learning	Permanent change in behaviour	Thorndike (1932)
Machine learning	Improving performance over time	Russell and Norvig (2021)
HITL learning	Human supervises machine learning	Monarch (2021)
CITL learning	Machine assists human learning	Shneiderman (2020)
Hybrid intelligence	Integration of HITL and CITL	Dellermann et al. (2019b)

four descriptive principles of RHML, as listed in Table 1. Common characteristics of RHML design in the sample are identified and summarised into a taxonomy (see Appendix D). Section 5 presents a reconceptualization of RHML, defining four RHML archetypes of common design patterns resulting from the sampled papers in the SLR (RQ2). This outlines the systematic derivation of potential RHML applications and the future research agenda in production and logistics (RQ3). Section 6 concludes the paper, conceptualising RHML and the knowledge transfer of RHML system design across disciplines to production and logistics.

2. Background and terminologies

2.1. Human and machine learning in interaction

Learning is a natural behaviour of human intelligence. However, the scholarly understanding of this behaviour is captured in various descriptive theories that lack a uniform understanding of the biochemical, psychological, and social processes involved. Human learning is understood as a permanent change in human behaviour resulting from experience (Thorndike 1932), irrespective of external stimuli (i.e. behaviourism), internal cognitive processes (i.e. cognitivism), or individual differences.

Humans learn individually by interacting with their environment. In social interactions with humans, e.g. by sharing information or through imitation actions, learning is described according to the social learning theory (Bandura and Walters 1977). Based on this theory, Vygotsky suggested that a 'spiral of development' can be recognised in social learning behaviour (Vygotsky 1981). Bidirectional learning has been described in various instances, such as 'reciprocal teaching' and 'reciprocal learning' (Carrington 2004; Jörg 2004; Noël et al. 2013).

ML itself is not 'natural' to AI, as only some AI can learn, i.e. by replicating aspects of human learning capabilities (Russell and Norvig 2021). ML is typically specified as a set of methods, which rely on (1) training data with different levels of supervision (supervised ML), (2) iterative improvements in reward metrics (reinforcement learning; RL), and (3) the reduction of dataset labels (unsupervised learning). Overall, ML can be understood as the ability of machines to improve their performance over time based on experience (Russell and Norvig 2021). Similar to human social learning, learning between AI systems in multi-agent systems is possible, with differences in the methods used (Qiu et al. 2022; Zhang, Yang, and Başar 2021). Therefore, learning in human–machine systems is typically one sided.

First, humans can take over the role of the supervisor in the learning process of the machine, i.e. HITL learning, typically in tasks in which human capabilities are required, such as intuition, judgment, expertise, and awareness; e.g. in decision-making and problem-solving (Kumar et al. 2024). The following approaches can be identified under HITL (Monarch 2021): (1) active learning, in which the system retains control of the learning process; however, human experts solely provide feedback for the learning process (Ren et al. 2021) and label selected data; (2) machine teaching, in which human experts control the learning process (Mosqueira-Rey, Alonso-Ríos, and Baamonde-Lozano 2021) by providing, revising, and annotating datasets and then iteratively transferring their domain knowledge into ML models (Khodaee, Viktor, and Michalowski 2024); and (3) interactive ML, in which control of the learning process is shared between humans and machines (Mosqueira-Rey et al. 2023), and human feedback is provided in a corrective manner after viewing the ML output (Gómez-Carmona et al. 2024).

In contrast, bringing the machine into the loop of human learning (Shneiderman 2020) focuses on supporting human learning (Auernhammer 2020; Xu 2019). The terms CITL and 'machine-in-the-loop' exist synonymously. CITL tools are designed to assist humans and are widely adopted in production and logistics (e.g. Sauer, Burggräf, and Steinberg 2025a; Zheng et al. 2024). In general, learning from machine assistance is possible and based on the type of information provided by the machine agent, such as suggestions and feedback. CITL tools can function as learning assistance to enable and teach humans.

Both HITL and CITL are unidirectional. The integration of human intelligence and AI has been proposed through various terminologies. Hybrid intelligence (Peeters et al. 2021) was propagated to characterise a human–machine system that forms a complementary combination of artificial and human intelligence. According to Akata et al. (2020), combined human and machine intelligence augments human intellect and capabilities instead of replacing them, achieving goals that are unreachable by either humans or machines. Thus, hybrid intelligence suggests continuous improvement through hybrid and interdependent agents learning from one another (Sherson et al. 2023). Its core concept includes learning as improvements in the individual capabilities of agents over time (Dellermann et al. 2019b), highlighting the nature of hybrid intelligence as a combination of HITL and CITL (Wiethof and Bittner 2021).

2.2. Conceptual foundation of RHML

RHML is bidirectional learning between humans and machines, which is enabled by hybrid intelligence. Ansari, Erol, and Sihn (2018a) defined RHML as follows:

> […] a bidirectional process involving reciprocal exchange, dependence, action or influence within human and machine collaboration on performing shared tasks, which results in creating a new meaning or concept, enriching the existing ones or improving skills and abilities in (symmetric or asymmetric) associated with each group of learners.

Table 2. Descriptive principles of RHML.

Principles of RHML	Description
P1 – System	Multiplicity of agents encompassing a hybrid composition (human and machine)
P2 – Interaction	Interaction through the exchange of information (communication) for improvement (feedback)
P3 – Task	Shared task environment with respective agents involved in the same task and partially shared task goals
P4 – Learning	Learning effects on both sides related to the task or context of the task that enhance the task performance. A learning effect directed towards the interaction, such as learning about the other agent to improve communication, does not qualify

Zagalsky et al. (2021) and Te'eni et al. (2023) coined an extension to the term, suggesting that RHML systems '[…] *are conceptual systems consisting of humans and machines that interactively leverage their intelligence for learning to solve problems, analyze, explain, and judge.*'

RHML originates from the hybridisation of labour-specific task sharing between humans and intelligent machines in smart factories (Ansari, Erol, and Sihn 2018a). Humans and machines form complementary relationships because of the divergent capabilities of each type of agent. Such complementarity enables task participation and dependency owing to interaction (Ansari 2019).

Several descriptive principles can be derived based on the earliest understanding of RHML, as outlined in Table 2. For details of the descriptive principles, we refer to the conceptualisation and laboratory validation experiments conducted by Nixdorf (2024).

Figure 1 depicts unidirectional learning, such as in CITL and HITL learning, and bidirectional learning, which occurs between humans, between machines, and in hybrid teams (i.e. RHML).

Table 3 presents the introduced concepts distinguished by the degree to which the principles of RHML are met, as indicated in Table 2. These principles serve as a comprehensive definition of RHML. However, knowledge regarding the current state of research on RHML, including its practical implementations across disciplines, remains limited. Therefore, this review aims to analyse the existing body of literature on RHML across all disciplines to determine its current state of the art.

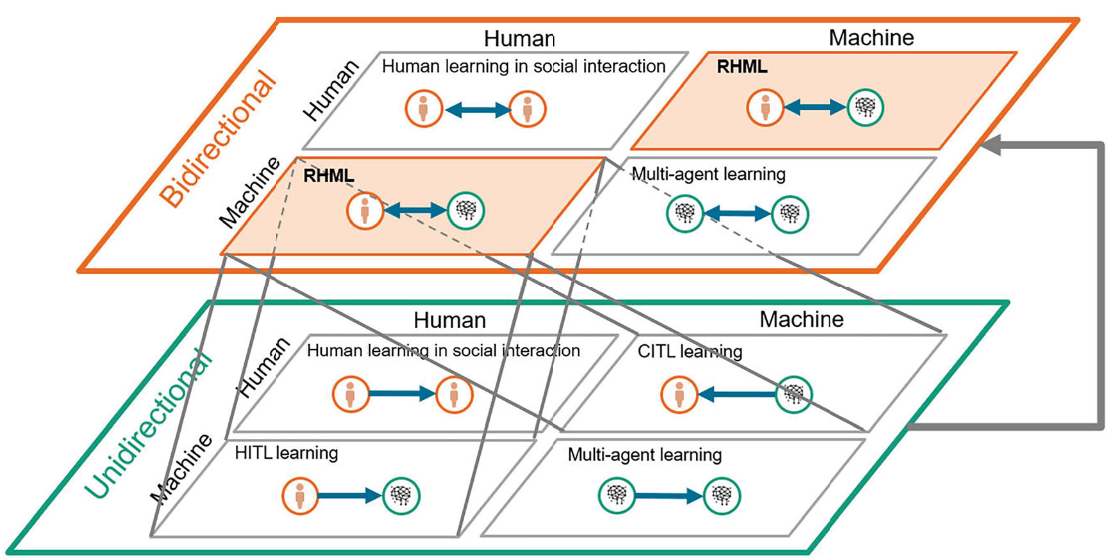

Figure 1. RHML classified into unidirectional and bidirectional learning.

Table 3. Classification of concepts according to principles of RHML (P1–P4).

Concept	P1 – System	P2 – Interaction	P3 – Task	P4 – Learning
RHML	•	•	•	•
Hybrid intelligence	•	•	•	○
HITL learning	•	•	○	○
CITL learning	•	•	○	○
Human learning	/	/	/	○
ML	/	/	/	○

Legend: • full ○ partial / none

Building on the conceptual foundations and key principles outlined in Section 2, the study takes a further step by conducting an SLR to identify current design knowledge of RHML, which is to be applied in production and logistics, and to formulate a future research agenda, as illustrated in the framework presented in Figure 2.

3. Methodology

We performed an SLR to identify and summarise the current knowledge of RHML following a structured framework (a six-step approach, as suggested by Sauer and Seuring (2023)). Steps 1 and 2 (defining research questions and determining the required characteristics of the sampled studies) have already been described in Sections 1 and 2. This section is dedicated to explaining the sample search (step 3) and selection (step 4) processes. Following the key decisions in SLR studies suggested by Sauer and Seuring (2023), our approach consists of 9 phases (see Appendix B) that are described in the following, while step 5 (synthesising the literature) and step 6 (reporting the results) are detailed in Sections 4 and 5, respectively.

The literature search process included an exhaustive keyword search, backward and forward searches, and an evaluation of the relevance of the extracted literature. Scopus, which is a leading database with comprehensive research coverage across various fields, such as technology, social sciences, arts, and humanities, was considered as the primary source of academic papers (Pranckutė 2021). A preliminary compilation of keywords was applied and justified by the conceptual background introduced in Section 2. Hence, a search string (see Appendix A) emerged, encompassing the following components based on the design principles of RHML: (1) human agent, (2) intelligent/machine, (3) the reciprocal characteristic of interaction, and (4) learning.

This search string resulted in 118,543 hits on Scopus (25.12.2024). These results were refined by the following inclusion criteria: (i) publications from the past six years (from 2018) were included, as recent advances were considered most relevant to this review, (ii) only conference papers and journal articles were included, (iii) only publications available in English were included, and (iv) duplicates were omitted from the sample.

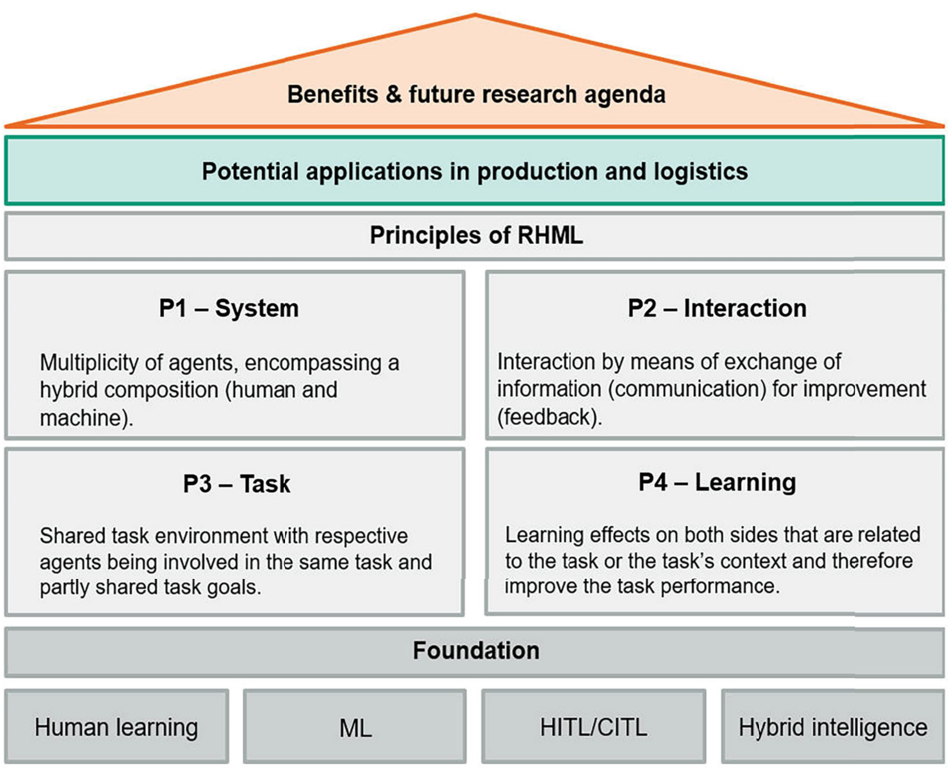

Figure 2. Framework of SLR.

Table 4. Relevance criteria for inclusion of publications.

#	Relevance criterion and description
1	Human agent involved in the system (P1)
2	Machine agent involved in the system (P1)
3	Interaction between both types of agents (P2)
4	Shared task environment (P3)
5	Machine agent exhibits a capability to learn by means of changing its behaviour (P4)
6	Human agent exhibits learning (P4)

Owing to the numerous studies, two additional refinement steps were implemented. First, 'index terms' assigned by Scopus were excluded from the dataset, resulting in the exclusion of 40% of the sample, highlighting inaccuracies introduced by cross-indexing. Second, most studies in the sample still lacked emphasis on the human agent as a learner and were merely concerned with ML methods, e.g. humans as a source of data, involved in pre-processing, or as users of the model (see principle P4 in Table 2 and the corresponding criteria in Table 4). Therefore, to justify principle P1, the term frequency (TF) criterion (Chen and Xiao 2016) was used to warrant consideration of the human agent. The TF of the term 'human' in the title and abstract was formulated to increase the relevance of the sample (TF(*human*) > 0.01). Consequently, 6,322 publications (approximately 10%) were retained. To minimise false negative results, an iterative forward–backward scheme was deployed following screening.

A set of six criteria was employed to assess the relevance of each publication to comply with the principles of RHML, as shown in Table 4. Each query was related to a core principle of RHML. However, P4 was only partially applied because the task-related learning objective was not queried. Consequently, the publications that provided positive results for all queries were considered as relevant. Publications were assessed based on the number of relevance criteria met, and only 56 met the criteria.

Owing to the screening process, particularly the heuristic limitation of the original sample, a forward–backward search approach was used to ensure exhaustiveness and include studies that may have been overlooked (as described in Vom Brocke et al. (2009)). The forward–backward search had general limitations on the publication date to ensure that the maximum number of relevant publications was achieved in this step. The references to the 56 publications from the SLR were reviewed in the backward phase. Conversely, the forward phase consisted of searching for articles that cited any of the 56 publications. All publications considered in the forward–backward search were assessed using the same set of six criteria (see Table 4). The forward–backward search was carried out in two steps, with publications from the first forward–backward search considered for the second step. The forward–backward search yielded a total of 16 additional publications. Consequently, 72 publications were considered relevant to RHML. Notably, almost half of the sampled publications (35) focused on the preliminary conceptualisation of RHML, whereas 37 publications presented use cases or illustrative examples to characterise its design. The processes discussed in this section are depicted in Appendix B, and a brief descriptive analysis of the number of sampled publications per year is provided in Appendix C.

4. Results of the literature review on RHML (all disciplines)

Our SLR sample included 14 studies in the domain of production and two studies in logistics, with the majority of studies (56) originating from various other academic disciplines. This section presents the results of the thematic analysis conducted on the sampled studies, with the objective of codifying the interdisciplinary design knowledge into a coherent taxonomy. The coding process was carried out by two authors, each of whom independently reviewed all publications. Their individual results were subsequently consolidated through discussion with all co-authors. Specifically, the analysis focused on the following key characteristics of RHML in each paper: P1 – System: Assessed based on the number and type of agents (referring to human and machine agents). P2 – Interaction: Examined in terms of the type of information communication and feedback mechanisms. P3 – Task: Analyzed for task type, task allocation, and sequencing. P4 – Learning: Investigated in terms of the learning objectives of agents, learning methods used by machine agents, and learning outcomes for human agents.

Accordingly, this section is structured around the four fundamental RHML design principles (P1–P4), presenting the current design components identified in the literature. This structure supports the development of the RHML taxonomy (see Appendix D), which is applied in the context of production and logistics in Section 5, following the interdisciplinary knowledge codification approach proposed by Dickhaut et al. (2022).

4.1. P1 – system

The system is composed of human and machine agents. Both contribute to hybrid intelligence (cf. Akata et al. (2020), Hanika et al. (2019), and Dellermann et al. (2019b)). Most publications do not specify the composition of these systems and merely refer to a 'hybrid' of agents (cf. Holstein, Aleven, and Rummel (2020), Järvelä, Nguyen, and Hadwin (2023), and Sherson et al. (2023)), 'teaming' (cf. Dominguez-Péry and Vuddaraju (2020), Haimson et al. (2019)), 'tandems' (cf. Hromada (2022)), 'meta-human' systems (cf. Lyytinen, Nickerson, and King (2021)), 'human–machine interaction' (cf. Gweon, Fan, and Kim (2023)), and 'human–machine collaboration' (cf. Süße, Kobert, and Kries (2021) and Van Zoelen, Van Den Bosch, and Neerincx (2021b)). Humans and machines participate in a multiplicity, indicating the participation of *a single* or *multiple* agent(s) in the respective teams. Thus, most systems are dyadic, often related to a lower complexity, such as those of Abdel-Karim et al. (2020), Shafti et al. (2020), and Van Zoelen, Van Den Bosch, and Neerincx (2021a). Others facilitate the involvement of multiple human agents, such as those of Patel et al. (2019) and Wellsandt et al. (2022). However, a multi-agent system consisting of multiple machines for interacting with a single human, such as a crowd or network of agents, was not found in the literature. Although Bannan et al. (2020), Hwang and Nurtantyana (2022), and Ogiso et al. (2015) reported multiples on both sides, no representatives of systems with single human agents but multiple machines were identified. This suggests a primarily integratory approach for the design of the AI agent to ease complexity and focus on the human agent, including their interaction.

Despite all humans being assumed to exhibit cognitive and physical capabilities, machine agents can be distinctly categorised as *cognitive* (e.g. conversational agents and algorithms) or *physical* (e.g. robots and vehicles). Earlier publications on RHML refer to cyber-physical–social interactions between cyber-physical production systems and humans (Ansari 2019; Ansari et al. 2018b; Ansari et al. 2018c; Ansari, Erol, and Sihn 2018a; Ansari, Hold, and Khobreh 2020). Thus, the machine agent technology is cast within the broad scope of the cyber-physical production system. Numerous studies have discussed cognitive machines by referring to cognitive agents (Azevedo, Raizer, and Souza 2017) or AI technologies (Akata et al. 2020). Overall, AI-based systems incorporate cognitive technologies, while a large body of literature also includes a significant physical dimension, e.g. robots. For instance, Blanchet et al. (2020) used cobots to guide humans towards skill improvement. Tabrez, Agrawal, and Hayes (2019) and Wang et al. (2015) supported task learning through guidance. Ikemoto et al. (2012) and Shafti et al. (2020) reported a highly interactive environment in which humans and robots learn to collaborate. All of the above learning processes are based on different levels of interaction, ranging from sequential to collaborative interaction.

4.2. P2 – interaction

Because of the mixed group of agents, the interaction between agents is essential for RHML to understand the intent and foster collaboration for communication, as shown in Table 5 (Akata et al. 2020). Therefore, the interaction between learning agents is an established core principle for RHML (cf. P2), manifesting in the reciprocity of agents (Ansari 2019). Numerous studies have examined RHML in the context of socialisation, such as socio-technical interaction (Nixdorf, Ansari, and Schlund 2022a), cyber-physical–social interaction (Romero et al. 2019), social interaction (Gweon, Fan, and Kim 2023), and social learning (Järvelä, Nguyen, and

Table 5. Communication types.

Communication type		
Human to machine	Haptic (19)	Abdel-Karim et al. (2020), Battistoni et al. (2021), Brereton et al. (2023), Blanchet et al. (2020), Bourahmoune, Ishac, and Carmichael (2024), Chan et al. (2019), Döppner, Derckx, and Schoder (2019), Ikemoto et al. (2012), Mosqueira-Rey et al. (2023), Ogiso et al. (2015), Patel et al. (2019), Patil et al. (2022), Shafti et al. (2020), Trojan et al. (2024), Van Zoelen, Van Den Bosch, and Neerincx (2021a), Van Zoelen, Van Den Bosch, and Neerincx (2021b), Wang et al. (2015), Wenskovitch and North (2020), Yin, Billard, and Paiva (2015)
	Visual (1)	Tabrez, Agrawal, and Hayes (2019)
	Auditory	–
	Natural language (12)	Damacharla et al. (2020), Dubey et al. (2020), Hromada and Kim (2023), Hwang and Nurtantyana (2022), Liu et al. (2019), Lu et al. (2024), Moussalli and Cardoso (2020), Qian and Qian (2020), Schoonderwoerd et al. (2022), Te'eni et al. (2023), Wellsandt et al. (2022), Zagalsky et al. (2021)
	Multimodal (1)	Bannan et al. (2020)
Machine to human	Haptic (5)	Bourahmoune, Ishac, and Carmichael (2024), Chan et al. (2019), Shafti et al. (2020), Wang et al. (2015), Yin, Billard, and Paiva (2015)
	Visual (19)	Abdel-Karim et al. (2020), Bannan et al. (2020), Battistoni et al. (2021), Brereton et al. (2023), Döppner, Derckx, and Schoder (2019), Hromada and Kim (2023), Ikemoto et al. (2012), Lu et al. (2024), Mosqueira-Rey et al. (2023), Ogiso et al. (2015), Patel et al. (2019), Patil et al. (2022), Schoonderwoerd et al. (2022), Te'eni et al. (2023), Trojan et al. (2024), Van Zoelen, Van Den Bosch, and Neerincx (2021a), Van Zoelen, Van Den Bosch, and Neerincx (2021b), Wenskovitch and North (2020), Zagalsky et al. (2021)
	Auditory	–
	Natural language (9)	Blanchet et al. (2020), Damacharla et al. (2020), Dubey et al. (2020), Hwang and Nurtantyana (2022), Liu et al. (2019), Moussalli and Cardoso (2020), Qian and Qian (2020), Tabrez, Agrawal, and Hayes (2019), Wellsandt et al. (2022)
	Multimodal	–

Hadwin 2023). Thus, synergetic relationships and symbioses (Nixdorf, Ansari, and Schlund 2022a) are formed, similar to those of learners and teachers in human-only settings. In addition, some ML models rely on human interaction to optimise the learning behaviour, thereby highlighting dependency (Wiethof and Bittner 2021).

The interaction activity of humans and machines is *proactive* or *reactive*. When it is proactive, it suggests solutions, asks for feedback, or acts on the task. When it is reactive, it reviews the suggestions or solutions of others. In this manner, interaction is typically structured, while parallel task execution can also require proactivity in both agents, resulting in higher independence, as discussed by Schoonderwoerd et al. (2022), Shafti et al. (2020), and Abdel-Karim et al. (2020).

Van Den Bosch et al. (2019) highlighted communication as a source for acquiring implicit and explicit knowledge. In addition, communication depends on the direction from humans to machines, or vice versa, as distinguished for *implicit* or *explicit* communication. Explicit communication is a form of communication in which there is a clear associated intent for the transmitted information to be received by another agent or system over an established channel. In contrast, implicit communication is an action or behaviour that represents information rather than a deliberate message that is conveyed through language or codified gestures. For instance, machine agents that can react to human actions based on observations through sensors commonly implicitly infer information from human actions (Chan et al. 2019). Moreover, they engage in implicit communication. Others exchange information through direct channels by providing feedback via text or speech (Hromada and Kim 2023).

More precisely, we distinguish among *auditory*, *haptic*, *visual*, and *gesture-based* communication, each of which was identified as a possible communication channel in smart manufacturing systems by Peruzzini, Prati, and Pellicciari (2024). We further distinguish communication in *natural language*. A combination of haptic (human-to-machine) and visual (machine-to-human) communication is prevalent across the literature in the form of manual controllers (buttons), visualisations (on screens) (cf. Abdel-Karim et al. (2020) and Döppner, Derckx, and Schoder (2019)), or augmented reality (AR)/virtual reality (VR) devices (cf. Zhang and Wang (2020)), as shown in Table 5. In physical interactions, machine communication can simultaneously be haptic and visual, and thus, multimodal (cf. Shafti et al. (2020) and Ikemoto et al. (2012)).

Bannan et al. (2020) described *multimodal* communication, suggesting that multimodal data sources, such as audio, video, and wearables, are analysed to derive feedback. Numerous studies have highlighted the significant benefits of communication in natural language in terms of explainability (Akata et al. 2020; Azevedo, Raizer, and Souza 2017). *Natural language* has a significant effect in the form of either textual or voice-based communication in several publications (Damacharla et al. 2020; Dubey et al. 2020; Qian and Qian 2020). Communication is crucial in RHML as a means for achieving mutual understanding (Gweon, Fan, and Kim 2023). Understanding other agents, tasks, and results enables adaptation and learning (Holstein, Aleven, and Rummel 2020).

Specific means of interaction and communication between agents culminate in the question of how feedback is exchanged to facilitate RHML. The types of feedback that are provided by machine agents are limited (Holstein, Aleven, and Rummel 2020). Feedback refers to information that is fed back to the agent, which affects the learning process. However, *verifying*, *corrective*, *explanatory,* and *informative* feedback are distinct. Most feedback is explicit communication, such as agents providing corrective feedback to one another, for example, by overwriting solutions (Ogiso et al. 2015; Qian and Qian 2020) or verifying solutions by labelling them as right or wrong (Abdel-Karim et al. 2020; Battistoni et al. 2021; Hromada and Kim 2023). Humans are asked to label machine outputs in a binary manner (right or wrong, i.e. verifying) or to correct them by returning a corrected version of the output (i.e. corrective). Humans primarily receive informative feedback, such as actions, facts, and suggestions, from machines. Examples of corrective feedback include machine responses to human suggestions. In some instances, machine agents provide explanations based on natural language (Tabrez, Agrawal, and Hayes 2019; Zagalsky et al. 2021).

4.3. P3 – task

Dependency on a shared task, which is sharing based on task assignments and goals, is essential for RHML. Moreover, tasks must be divided between humans and machines according to their respective advantages (Peeters et al. 2021). Thus, machines take over routine tasks, whereas humans contribute towards non-routine elements, such as creativity or dexterity (Süße, Kobert, and Kries 2021). Human and machine agents may pursue different sub-goals in static task allocation. However, they always contribute to a common task goal. The current literature demonstrates diverse types of tasks, although many papers do not specify particular tasks, but rather, task environments.

Inspired by Dellermann et al. (2019b), we distinguish the task goals *recognition*, *prediction*, and *coordinated action*. Object instances, such as those described by Dubey et al. (2020), Patel et al. (2019), and Yin,

Table 6. Task types in RHML literature.

Type of task	Reference
Decision-making (16 publications)	Abdel-Karim et al. (2020), Brereton et al. (2023), Chan et al. (2019), Dellermann et al. (2019a), Dominguez-Péry and Vuddaraju (2020), Döppner, Derckx, and Schoder (2019), Gupta et al. (2023), Gweon, Fan, and Kim (2023), Lu et al. (2024), Mosqueira-Rey et al. (2023), Ogiso et al. (2015), Patel et al. (2019), Qian and Qian (2020), Tabrez, Agrawal, and Hayes (2019), Te'eni et al. (2023), Zagalsky et al. (2021)
Problem-solving (10 publications)	Ansari, Erol, and Sihn (2018a), Ansari et al. (2018c), Ansari (2019), Ansari, Hold, and Khobreh (2020), Dubey et al. (2020), Trojan et al. (2024), Van Zoelen, Van Den Bosch, and Neerincx (2021a), Van Zoelen, Van Den Bosch, and Neerincx (2021b), Wellsandt et al. (2022), Wenskovitch and North (2020)
Training (11 publications)	Bannan et al. (2020), Blanchet et al. (2020), Damacharla et al. (2020), Çil et al. (2020), Hromada (2022), Hromada and Kim (2023), Hwang and Nurtantyana (2022), Järvelä, Nguyen, and Hadwin (2023), Liu et al. (2019), Moussalli and Cardoso (2020), Yin, Billard, and Paiva (2015)
Coordination (7publications)	Battistoni et al. (2021), Bourahmoune, Ishac, and Carmichael (2024), Ikemoto et al. (2012), Patil et al. (2022), Shafti et al. (2020), Takata and Takeuchi (2019), Wang et al. (2015)

Billard, and Paiva (2015), must be identified for recognition. These tasks are correlated with decision-making tasks in which collaborative recognition is the foundation for decision-making, as indicated earlier for image-based diagnostics (Patel et al. 2019). Prediction is also crucial for decision-making. Prediction refers to decisions regarding the steering of future events. Döppner, Derckx, and Schoder (2019) presented a prediction of optimal routing for air cargo. In action-related tasks, coordination is required for both agents to be effective. According to Van Zoelen, Van Den Bosch, and Neerincx (2021a) and Patil et al. (2022), learning can enhance coordination.

Table 6 outlines the distinguished overarching task types. Decision-making and problem-solving are the most prevalent. Ansari et al. (2018c), Dubey et al. (2020), and Wellsandt et al. (2022) discussed RHML in troubleshooting and problem-solving (mostly cognitive). Both agents contribute their strengths towards identifying issues, suggesting solutions, and guiding implementation. Decision-making is manifold. Abdel-Karim et al. (2020) and Patel et al. (2019) investigated the improved capabilities of image-based diagnosis using RHML. In decision-making, both agents contribute to the decision by either comparing decisions ex-post (Abdel-Karim et al. 2020), suggesting decisions ex-ante (Döppner, Derckx, and Schoder 2019; Qian and Qian 2020), or providing specific information to reach a collective decision, as discussed by Dellermann et al. (2019a). Typical performance measures include the decision accuracy and error rate. Moreover, numerous studies on RHML feature training. These works are primarily concerned with leveraging RHML for the education and training of humans, such as learning a new language (Liu et al. 2019), emergency care training (Damacharla et al. 2020), or handwriting (Yin, Billard, and Paiva 2015). In addition, coordination tasks, stemming from coordinated task goal action, constitute the final distinct task type that is evident in the literature. The task is significantly intertwined with the interactions between the two agents. Shafti et al. (2020) described a physical balancing task that was performed collaboratively. Ikemoto et al. (2012) and Wang et al. (2015) demonstrated highly interdependent physical tasks in which humans and robots must coordinate their actions.

Table 7. Task allocation.

Task allocation	References
Dynamic (9)	Ansari et al. (2018b), Bourahmoune, Ishac, and Carmichael (2024), Ikemoto et al. (2012), Patil et al. (2022), Schoonderwoerd et al. (2022), Shafti et al. (2020), Van Zoelen, Van Den Bosch, and Neerincx (2021a), Van Zoelen, Van Den Bosch, and Neerincx (2021b), Wang et al. (2015)
Static (26)	Abdel-Karim et al. (2020), Bannan et al. (2020), Battistoni et al. (2021), Brereton et al. (2023), Blanchet et al. (2020), Chan et al. (2019), Damacharla et al. (2020), Döppner, Derckx, and Schoder (2019), Dubey et al. (2020), Hromada and Kim (2023), Hwang and Nurtantyana (2022), Liu et al. (2019), Lu et al. (2024), Mosqueira-Rey et al. (2023), Moussalli and Cardoso (2020), Ogiso et al. (2015), Patel et al. (2019), Qian and Qian (2020), Tabrez, Agrawal, and Hayes (2019), Takata and Takeuchi (2019), Te'eni et al. (2023), Trojan et al. (2024), Wellsandt et al. (2022), Wenskovitch and North (2020), Yin, Billard, and Paiva (2015), Zagalsky et al. (2021)

The allocation between agents to perform a shared task successfully is another crucial dimension of tasks. Table 7 outlines general task allocation between humans and machines, as discussed by Ansari et al. (2018c). The specific allocation depends on the actual task. However, the literature makes distinctions based on the complementarity of agents and the distribution of sub-tasks based on capability, availability, and efficiency. A uniform approach to task allocation is either *dynamic* or *static*. Static task allocation acknowledges the specific strengths and weaknesses of agents. Hence, task allocation between humans and machines is usually static to account for the different capabilities of the agents. Te'eni et al. (2023) and Zagalsky et al. (2021) applied ML algorithms based on inputs from human experts to analyse large datasets. Döppner, Derckx, and Schoder (2019) facilitated workers by providing recommendations generated via AI-based optimisation. Hromada and Kim (2023) discussed a tutoring system for vocabulary training. In dynamic task allocation, humans and machines share some capabilities that are required to perform specific tasks. Therefore, the allocation is based on other factors, such as the availability of agents or efficiency of carrying out the task. Dynamic task allocation enables the close collaboration of agents (Schoonderwoerd et al. 2022; Van Zoelen, Van Den Bosch, and Neerincx 2021a). Ikemoto et al. (2012), Shafti et al. (2020), and Wang et al. (2015) investigated the dynamic allocation of physical collaborative tasks. In addition, dynamic task allocation enables *parallel* task sequencing. However, Abdel-Karim et al. (2020) discussed the application of parallel execution, advocating for static task allocation. *Sequential* task sequences typically result in idle time for at least one of the involved agents, similar to that described in an action–reaction scenario (Wellsandt et al. 2022; Zagalsky et al. 2021).

4.4. P4 – learning

Learning can manifest on various scales, including (1) adaptive behaviour for seamless collaboration; (2) enhanced task execution; and (3) the development of knowledge, skills, and competencies that can be applied across diverse contexts and tasks. As discussed in Section 2.2, RHML fosters the learning of both agents. However, learning is manifested in fundamentally different manners in the two types of agents, encompassing different parameters, methods, and processes. To distinguish the learning of different agents in this review, the publications are discussed based on the learning objectives of both agents, the methods and timing for machine agents, and the learning outcomes and didactic methods for human agents.

4.4.1. Learning objectives

The reviewed literature revealed two primary learning objectives: improving the task or interaction. This simple distinction between learning objectives is universally applicable to human and machine agents. Learning objectives define what learning is about, via (1) a task: learning about the task and its context to improve the task performance, or (2) an interaction: learning about other agents or oneself to improve interactions. RHML is a primarily task-centric phenomenon, as discussed in Section 2.6, and its concept revolves around collaborative task performance, for example, in production and logistics (Nixdorf et al. 2022b). The paper at hand seeks to distinguish between learning objectives in the sample literature. Both types of agents can learn about the task or interact with it. Hence, four general combinations of learning objectives exist, as shown in Figure 3, and can be divided into three types of symmetry and asymmetry: (1) Type I, task-focused symmetry: learning objectives are symmetrical as both agents learn about the task, enhancing the joint task performance. (2) Type II, asymmetry: learning objectives are asymmetrical as one agent learns about the task and the other learns about the interaction or the other agent only. (3) Type III, interaction-focused symmetry: learning objectives are symmetrical as both agents learn about the interaction or the other agent to improve the interaction.

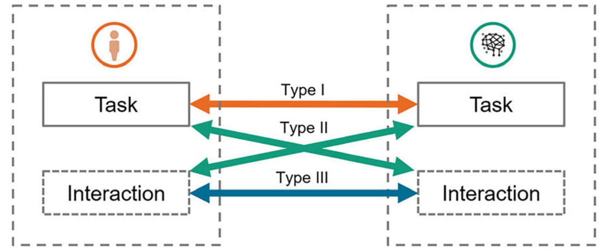

Figure 3. Symmetry of learning objectives.

In cases in which publications could be assigned to more than one type because of a vast scope of objectives, they were assigned to either Type I or Type II, as this characterisation maintains the focus on task-based learning. Figure 3 depicts the structure of the following discussion.

First, we discuss learning about the task for both agents, i.e. Type I, which resembles our understanding of RHML. An individual description of the learning objectives of each publication is provided.

Decision-support systems in image-based diagnosis use RHML to improve the diagnostic performance of both agents (Abdel-Karim et al. 2020; Patel et al. 2019), and task performance in managing unit load devices is improved (Döppner, Derckx, and Schoder 2019). Ogiso et al. (2015) reported on a machine agent that was informed about the decision-making process of human crowds, thereby learning from human supervision. An individual receives feedback from an agent to reflect on their earlier decisions. Thus, both agents enhance their task performance sequentially. Te'eni et al. (2023) and Zagalsky et al. (2021) demonstrated improved text classification accuracy. Machine agents generate feedback, outcomes, and explanations, from which the domain expert can learn and the classification knowledge can be enhanced (Zagalsky et al. 2021), providing the machine agent with a refined knowledge base. Qian and Qian (2020) combined the strengths of humans and machines for masked language tasks. Humans can enhance their accuracy in the long term by considering machine suggestions (Qian and Qian 2020). Patil et al. (2022) used deep RL to enhance task performance in a collaborative task with human agents. Van Zoelen, Van Den Bosch, and Neerincx (2021a, 2021b) shared perspectives on the continuous co-adaptation of agents based on interactive problem-solving. Agents adjust their behaviour based on their theory of mind and knowledge of others' abilities. Shafti et al. (2020) confirmed that both agents adapted to the actions of the other in a balancing game. Wang et al. (2015) reported adaptations in which both agents adjusted their physical movements (Tai Chi Chuan) to the movements of the other agent and predicted their intentions. In these publications, improved task performance is the primary objective for both types of agents. Ansari et al. (2018b) discussed the benefits of work-based training. In addition, recommending task sequences in human–robot collaborative assembly or adapting to the routing of automated guided vehicles may enhance task performance and collaboration simultaneously (Ansari, Erol, and Sihn 2018a). Learning from the predictions and actual results of problem-solving tasks during maintenance can increase the flexibility and capacity of agents in human–machine systems. In the study of Wellsandt et al. (2022), maintenance workers were continuously augmented to enhance the accuracy of their predictions. Learning increases the complementarity of agents, thereby improving collaborative problem-solving (Ansari et al. 2018c). Ansari (2019) aimed to enhance productivity through effective learning for both 'knowledge actors.' Ansari et al. (2018b) found that, owing to challenges raised by the need for workforce training in production and logistics, *short-term* (i.e. optimisation), *mid-term* (i.e. division of labour), and *long-term* (i.e. innovation) learning goals were relevant to manufacturing. Dubey et al. (2020) focused on intelligent agents that learned to solve specific tasks by observing human experts and could teach from opposite directions. Similarly, robot agents learned from human demonstrations to teach students (Yin, Billard, and Paiva 2015). However, these instances of transfer learning have not yet been extensively studied.

Second, we discuss asymmetric learning objectives (Type II). In some studies, the adaptive capabilities of agents have been used to provide tailored feedback to learners. Therefore, humans learn to enhance task performance. However, the machine agent utilises its intelligence to analyse human behaviour (Bannan et al. 2020), provide tailored feedback (Blanchet et al. 2020; Damacharla et al. 2020), or adapt to preferences or behaviour (Ikemoto et al. 2012). The primary objective of machine agents is to assist humans in the learning process (Hromada and Kim 2023; Hwang and Nurtantyana 2022; Liu et al. 2019). Moussalli and Cardoso (2020) used dialogue systems for foreign-language learning. Tabrez, Agrawal, and Hayes (2019) demonstrated that human learning outcomes can be achieved more efficiently with explanation-based feedback. In a collaborative puzzle task, a robot learned to understand the hidden policy of a human to interrupt and provide corrective feedback (Tabrez, Agrawal, and Hayes 2019).

Third, numerous studies have highlighted the significance of learning to co-adapt (Type III) and learning about interactions (Van Zoelen, Van Den Bosch, and Neerincx 2021a). More effective interactions between different agents are promoted through adaptation. However, specific tasks and their contexts are secondary, which cannot be considered RHML despite their existence in the sample.

4.4.2. Learning of machine agent

The learning behaviour of the machine agent can be described according to the method and timing employed. Machines learn in *supervised*, *semi-supervised*, or *unsupervised* manners. In addition, RL is regularly deployed.

In all cases, humans are involved in the learning process. Hence, learning occurs continuously in *real time* or after a task through *pre-trained* models. In pre-trained models, humans interact with a static algorithm that does not learn during the interaction. However, it can be adjusted after the operation based on the gathered data and feedback from the human user. Döppner, Derckx, and Schoder (2019) presented a pre-trained model that can be trained on previous optimal solutions and augmented by incorporating additional human-based solutions. Bannan et al. (2020) implemented an intelligent tool for training monitoring that can scaffold, provide advice, and be updated after each training run based on new data in an unsupervised manner. Hromada and Kim (2023), Jiang, Liu, and Chen (2019), and Moussalli and Cardoso (2020) implemented language training, in which the machine agent can adjust to understand the human accent during each interaction via supervised learning. Blanchet et al. (2020) used RL to adjust human feedback based on rewards. Hence, machine agents learn based on interactions, such as their mistakes (Battistoni et al. 2021). Learning about human behaviour (preferences) can be achieved using inverse RL (Tabrez, Agrawal, and Hayes 2019). Hwang and Nurtantyana (2022) employed external AI in real time to complete foreign-language tasks and enhance its knowledge, such as answering questions if human feedback indicates unsatisfactory conditions. Shafti et al. (2020) and Wang et al. (2015) pursued improved real-time coordination between agents for physical tasks based on RL. However, the rewards were based on the success of the task. Van Zoelen, Van Den Bosch, and Neerincx (2021a) demonstrated adaptive interactions between robots and humans in a simple collaborative task setting. Rewards were based on human feedback and performance to adapt to behaviour in real time. Despite most studies implementing learning in real time, influential publications on RHML exist that do

Table 8. Learning outcomes.

Learning outcome	References
Knowledge (3)	Hromada and Kim (2023), Hwang and Nurtantyana (2022), Yin, Billard, and Paiva (2015)
Comprehension (7)	Battistoni et al. (2021), Bourahmoune, Ishac, and Carmichael (2024), Chan et al. (2019), Ikemoto et al. (2012), Shafti et al. (2020), Takata and Takeuchi (2019), Wang et al. (2015)
Application (9)	Bannan et al. (2020), Blanchet et al. (2020), Damacharla et al. (2020), Liu et al. (2019), Moussalli and Cardoso (2020), Patil et al. (2022), Schoonderwoerd et al. (2022), Van Zoelen, Van Den Bosch, and Neerincx (2021a), Van Zoelen, Van Den Bosch, and Neerincx (2021b)
Analysis (14)	Abdel-Karim et al. (2020), Brereton et al. (2023), Döppner, Derckx, and Schoder (2019), Lu et al. (2024), Mosqueira-Rey et al. (2023), Ogiso et al. (2015), Patel et al. (2019), Qian and Qian (2020), Tabrez, Agrawal, and Hayes (2019), Te'eni et al. (2023), Trojan et al. (2024), Wellsandt et al. (2022), Wenskovitch and North (2020), Zagalsky et al. (2021)
Evaluation	–
Synthesis	–

not take this approach. Abdel-Karim et al. (2020), Te'eni et al. (2023), Zagalsky et al. (2021), and Schoonderwoerd et al. (2022) combined supervised ML methods with pre-trained models. Others combined pre-trained models with RL. Van Zoelen, Van Den Bosch, and Neerincx (2021a) relied on reward-based learning after each iteration. The maturity of technical implementation in these works is low. In addition, the required number of iterations for RL was not achievable in a reasonable time. A distinction between pre-training (or post-training) and learning in real time cannot always be made seamlessly because of the latent learning effects based on the responsiveness of individual algorithms at runtime and the duration of the interactions. Thus, a clear differentiation of RHML regarding the timing of ML is not always feasible, but it can still significantly affect the user experience with RHML.

4.4.3. Learning of human agent

To define the levels of human learning in the literature, we used Bloom's (1976) taxonomy of learning outcomes, which often resembles a pyramid: *knowledge/remembering*, *comprehension/understanding*, *application*, *analysis*, *synthesis (creating)*, and *evaluation* (see Table 8).

However, not all publications specify learning outcomes, either implicitly or explicitly. The current literature on RHML does not indicate learning at higher levels of Bloom's taxonomy. In addition, none of the reviewed publications focuses on fostering learning towards 'synthesis' or 'evaluation.' The lowest level of learning, 'knowledge' (Bloom 1976), which is the recall of facts, methods, and patterns, is featured in three publications. Hromada and Kim (2023) enabled humans to practice foreign language vocabulary training with machine assistance. Yin, Billard, and Paiva (2015) suggested the recall of the handwriting of specific letters by RHML. Hwang and Nurtantyana (2022) established conversation-based learning of object characteristics and functions and overall language learning.

Learning on the level of 'comprehension' is reported in seven publications. Human operators were supported in understanding their preferences for optimising multi-armed bandit tasks (Chan et al. 2019). Battistoni et al. (2021) discussed how a human user adjusts expectations and fosters the alignment of agents based on mutual understanding. Other studies have incorporated physical skills that resemble the psychomotor domain of learning outcomes (Krathwohl 2002). Ikemoto et al. (2012) described the human understanding limitations of robotics and adjusting towards guided psychomotor responses. Shafti et al. (2020) and Wang et al. (2015) featured the coordination of agents, leading to a guided response based on mutual understanding. Takata and Takeuchi (2019) simulated a similar task environment.

Application-related learning is reported in nine publications, which constitute the largest proportion in the literature on RHML. Patil et al. (2022) pursued learning by applying simple methods and fostering practices in simulations. Application-oriented learning was performed on realistic tasks (Damacharla et al. 2020). Schoonderwoerd et al. (2022) and Van Zoelen, Van Den Bosch, and Neerincx (2021a, 2021b) used RHML to foster the mutual understanding of agents. This understanding led to the development of skills towards highly collaborative tasks. The related learning outcomes were linked to 'application,' including the learning outcomes of the lower hierarchies. Ansari et al. (2018b) described learning specific tasks and applying new methods and practices in a human–robot production process. Blanchet et al. (2020) demonstrated skill improvement in a simple physical human–robot task. Liu et al. (2019) and Moussalli and Cardoso (2020) enabled humans to practice foreign languages by listening and speaking.

Analytical tasks and learning outcomes related to 'analysis' are common, and aligned with the focus on decision-making and problem-solving in the literature. A total of 14 publications were assigned to this level, which is the highest level of Bloom's taxonomy. Tabrez, Agrawal, and Hayes (2019) taught humans how to complete a Sudoku-like game successfully by learning to make correct decisions. Abdel-Karim et al. (2020) enabled humans to learn image-based diagnoses. Patil et al. (2022) propagated similar learning outcomes through the facilitation of human experts. Ogiso et al. (2015) enabled human experts to learn from crowd-based feedback and enhanced their decision-making. Qian and Qian (2020), Te'eni et al. (2023), Zagalsky et al. (2021), and Wenskovitch and North (2020) discussed language tasks in which humans learned to decide on the correct phrase to complete a sentence (Qian and Qian 2020) or analyse the elements and relationships of texts to refine keyword sets (Te'eni et al. 2023; Wenskovitch and North 2020; Zagalsky et al. 2021). Others assisted humans in learning problem-solving and decision-making in logistics (Döppner, Derckx, and Schoder 2019), maintenance (Wellsandt et al. 2022), and service call centres (Dubey et al. 2020).

Human learning has a deep theoretical foundation, accompanied by a methodological approach that can also be described as didactic. Didactics promotes the learning process to enable humans to learn more effectively. Such didactical methods have been infrequently reported in the literature. Bannan et al. (2020) opted to model their learning processes according to Kolb's concept of experiential learning (Kolb 1984). Numerous studies have adopted a similar approach; however, this concept is rarely explicitly considered in the publications. Te'eni et al. (2023) and Zagalsky et al. (2021) were oriented towards the Jörg (2004) theory of reciprocal learning (in humans). Methods for transferring reciprocal learning in humans have frequently been presented. Ansari, Erol, and Sihn (2018a) based their RHML process entirely on reciprocal classroom teaching (cf. Hacker and Tenent (2002)).

In terms of the RHML timeframe, the literature supports mainly short-term and mid-term goals. According to the definitions by Van Zoelen, Van Den Bosch, and Neerincx (2021a), *short-term* learning goals aim for optimisation in short timeframes without significant persistence, resulting in enhanced performance. However, *mid-term* learning goals aim for learning in medium timeframes with significant persistence, resulting in sustainable behaviour changes. *Long-term* learning goals aim for evolution and long timeframes with persistence and transferability across contexts, resulting in continuous development. RHML to enable mid- and long-term learning has yielded results in the continuous beneficiary cycle of RHML.

This section has described the different characteristics of RHML systems based on the sampled papers. These characteristics were grouped into different dimensions under the four design principles, forming an initial RHML taxonomy to present more comprehensive design knowledge under the RHML concept (see Appendix D). This serves as the preliminary result of the SLR. To test the descriptive validity of the taxonomy, we applied it to the set of studies identified in the literature review. Each study was consistently classifiable across all dimensions, supporting the utility of the taxonomy.

Despite these dimensions or characteristics indirectly highlighting the potential RHML applications in various planning situations, different RHML design patterns, particularly in production and logistics, remain limited. Thus, in the following section, RHML is (re)conceptualised, with a focus on production and logistics.

5. Discussion: (Re)conceptualisation of RHML in production and logistics

The application-oriented reconceptualization of RHML is based on the conceptual foundation discussed in Section 2.2 and the general patterns that emerged from the results of the SLR and have been presented in different contexts of RHML in Section 4. As suggested by Dickhaut et al. (2022), interdisciplinary knowledge transfer requires codification of knowledge to enable seamless application. Thus, efforts were made to identify repeated general patterns based on use/illustrative cases in the sampled papers and to form descriptive archetypes of RHML (see Section 5.1). The archetypes derived from interdisciplinary instantiations could provide insights into the current landscape of RHML for developing specific solutions, specifying quality metrics, defining assessment metrics, and deriving design principles, in alignment with the visionary paper of Ansari, Erol, and Sihn (2018a) in production and logistics. Therefore, Section 5.2 describes potential RHML applications based on the defined archetypes to demonstrate the benefits of the concept. Section 5.3 presents a critical reflection of this study and discusses the methodological limitations. Finally, RHML design studies are receiving increasing attention, and the knowledge base is continuously being updated. Based on the current challenges in production and logistics studies, we attempt to discuss possible refinement and development of the RHML archetypes, which could be beneficial in future system design and control in the industrial context (discipline-specific future research agenda of RHML; see Section 5.4). An overview of the reconceptualization process is presented in Figure 4.

5.1. *Basic design patterns of RHML (archetypes)*

We selected one dimension to describe the distinguishing characteristics of the archetypes for the design principles defined in Section 4 and to demonstrate the inductive definition process (based on instantiations from sampled papers), which was carried out in two iterations. The dimensions must:

1) be suitable for both humans and machines,

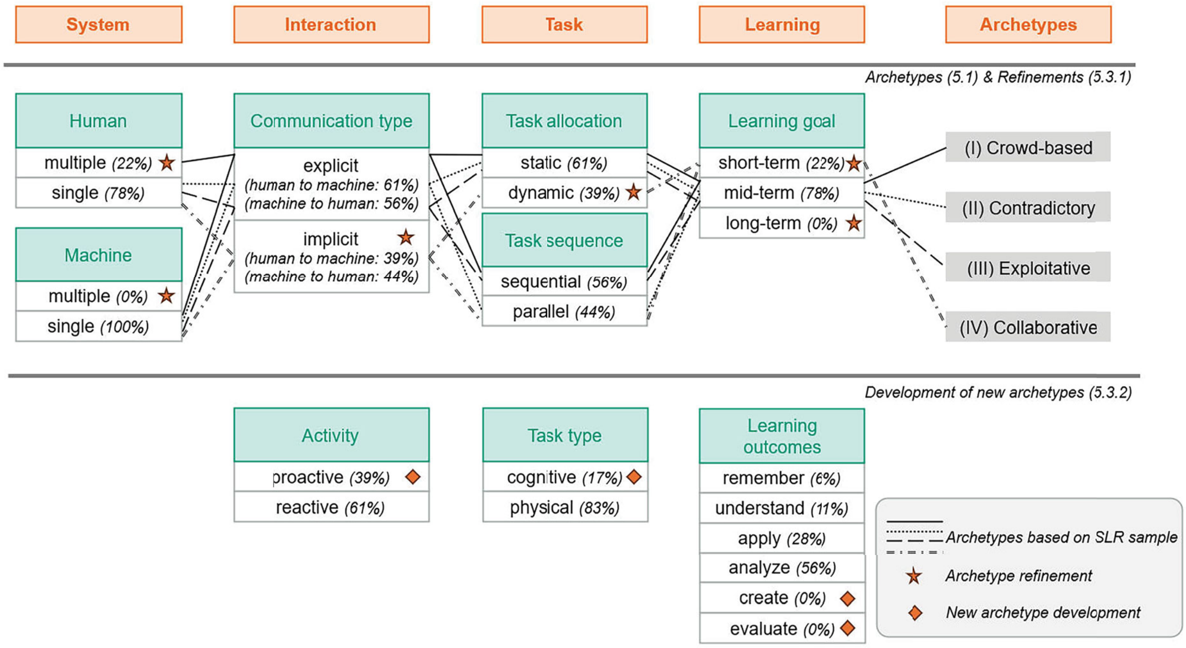

Figure 4. Overview of RHML archetypes.

Table 9. Descriptive archetypes of RHML based on selected dimensions.

	P1 – System		P2 – Interaction	P3 – Task		P4 – Learning
Archetype	Human	Machine	Communication type	Allocation	Sequence	Learning goal
(I) Crowd-based	Multiple	Single	Explicit	Static	Sequential	Mid-term
(II) Contradictory	Single	Single	Explicit	Static	Parallel	Mid-term
(III) Exploitative	Single	Single	Explicit	Static	Sequential	Mid-term
(IV) Collaborative	Single	Single	Implicit	Dynamic	Parallel	Short-term

2) contain mutually exclusive characteristics (without overlaps between them), and
3) represent key characteristics of the four principles.

As a result, according to the selected dimensions, each archetype of RHML was:

1) facilitated and bounded by the agents' *multiplicity* at the system level (P1),
2) enabled by explicit/implicit *communication* between agents (P2),
3) based on tasks (P3) with various combinations of static/dynamic *allocation* over time and a sequential/parallel task *sequence* by different agents,
4) aimed at short-/mid-/long-term *learning goals* (P4).

Hence, the SLR sample provided four state-of-the-art RHML design patterns, which could be distinguished and differentiated by the dimensions selected above (see Table 9).

Among the four archetypes, *crowd-based RHML (I)* is the only one that requires a multiple-human team (combined with a single-machine agent). This team configuration at the system level is based on the basic mechanism that different solutions to the same task are proposed by a human crowd, with diverse perspectives and expertise merged by the machine agent. This merging process includes identifying common solution patterns and innovation based on discrepancies in the solutions. The solution that is merged by the machine is returned to the human crowd. Thus, the RHML process is characterised by static task allocation and a sequential task sequence between humans and machines. The learning goal, which is defined as a mid-term goal, suggests that the knowledge base that is updated by merging solutions could be applied to similar tasks in the future (persistence). However, it is not always transferable across contexts.

Compared with archetype (I), *contradictory RHML (II)* can be characterised by a parallel task conduction process between the human and machine team. Hence, each task is assigned to these agents to create knowledge via disagreement and the divergence of multiple solutions. Therefore, the learning process requires one human and machine agent. The explicit communication on contrasting results triggers the reassessment, adjustment, and improvement of knowledge. The contextual sensitivity of the human and bias-free algorithmic power of the machine are combined to enhance the performance of similar tasks in the mid term.

The archetype *exploitative RHML (III)* assumes asymmetric capabilities of humans and machines. Based on the minimal team size of one human and machine agent, one agent assumes an expert role, leveraging its superior skills in a particular domain and sharing its knowledge with novices. Moreover, the expert agent creates new knowledge during the teaching process by specialising and refining the existing approach, while interacting with others with different skill and experience levels. Compared with archetypes (I) and (II), this explicit knowledge transfer based on static task allocation and a sequential task sequence will extend beyond the short-term optimisation of one specific task and pursue mid-term persistent behavioural changes in similar tasks.

Finally, the archetype *collaborative RHML (IV)* is directly rooted in human–machine collaboration. Based on a minimal single-human–single-machine team, collaboration with dynamic task allocation in a shared workspace fulfils the fluid demands of tasks. The instantiations in our sample demonstrate a preference for applying collaborative RHML for complex tasks, such as urban search and rescue and manufacturing assembly. Therefore, the tasks are conducted in parallel, forming an implicit HMI via a learning process that is deeply embedded in the collaboration. The resulting continuous improvements in coordination are enabled by learning about the capabilities and limitations of other agents and adjusting the activities accordingly. Thus, compared with the other three archetypes, collaborative RHML demonstrates learning effects in a short-term timeframe by optimising the performance of specific tasks with higher complexity and a repetitive nature.

5.2. Application of RHML in production and logistics

With the development of automation technology and AI, involving humans and machines in the same industrial process results in various interactions between agents and raises the question of the optimal design of hybrid intelligence (Sauer and Burggräf 2024). The distinction between cooperative and collaborative HMI is based on the task level, with cooperative interactions involving static allocation and a sequential sequence, and collaborative interactions involving dynamic allocation and a parallel sequence. Therefore, when designing a process with diverse agents (humans and machines), the task allocation and sequence must be considered in the foreground based on the task characteristics (complexity or repetition). On this basis, the learning process has been discussed and integrated into industrial processes in recent years. We first refer to several literature review studies for an overview of human learning (Glock et al. 2019) and ML (Bertolini et al. 2021) in this context. As discussed in Section 2, HITL and CITL are two concepts based on which unidirectional learning between humans and machines is enabled, which can be considered as one initial step of combining human learning and ML in system planning and control. For illustrative purposes, several representative studies of these concepts in production and logistics are described in the following. As explained by Turner et al. (2021), HITL can be utilised to provide human knowledge to enhance the decision-making of machines, e.g. via ML algorithms or digital twin technologies. In particular, the cognitive capabilities of humans are leveraged to build socio-technical industrial systems (Emmanouilidis et al. 2019). In contrast, CITL, with the core concept of transferring the knowledge of machines to leverage human learning, has been realised in studies on assistance systems in most cases (e.g. Hinrichsen, Riediger, and Unrau (2016)). A recent study (Zheng et al. 2024) discussed the knowledge transfer process via digital assistants with several illustrative cases that are aligned with the CITL concept. The brief discussion above confirms that the learning process (human learning, ML, HITL, and CITL) has drawn attention in the production and logistics community, highlighting the need for conceptualisation effort, which could help to clarify and categorise various learning possibilities in the industrial context. Hence, RHML, which enables the human–machine bidirectional learning process, is a further step based on HITL and CITL. The novelty and applicability of the RHML concept is discussed further using potential scenarios in the following.

Based on the categorisation of HMI, two of the four RHML archetypes demonstrate similar characteristics on the task level: *exploitative RHML* with static task allocation and a sequential task sequence (similar to cooperation) and *collaborative RHML* with dynamic task allocation and a parallel task sequence (similar to collaboration). Therefore, potential RHML systems could be formed by enabling bidirectional learning effects based on the original process.

Consider the order-picking process in logistics as an example. Manual picking tasks include (1) navigating the storage area, (2) searching for/identifying the items to be collected, and (3) transporting the collected items for delivery. Therefore, the process exhibits significant repetition with less challenging task contents. Grosse and Glock (2015) first discussed the possibility of considering the human learning curve in order picking, identifying possible human learning effects. This process can be enhanced by assistive systems, such as pick-by-light or augmented devices (Glock et al. 2021). Therefore, the speed of human learning increases as the error rate decreases. Further, empirical studies (De Vries, De Koster, and Stam 2016) have already shown that human order picking may vary based on different personalities in the context of applying assistive technologies. This highlights a future research need and the potential improvement of such technologies through assisting different humans.

In addition, assistive devices can learn to provide better guidance for each human picker (the archetype *collaborative RHML*), e.g. collaborative RHML in order picking (Ansari, Erol, and Sihn 2018a). In an automated guided-vehicle-assisted order-picking system, the routes that are optimised by collaborative RHML must provide solutions other than the typical routing solutions that focus solely on minimising the total travel distance (Ansari, Erol, and Sihn 2018a). According to Franzke et al. (2017), this technology can potentially resolve and reduce human–robot blocking situations during collaboration. The empirical results of Pasparakis, De Vries, and De Koster (2023) suggest that human cognitive aspects must be considered when designing collaborative RHML to ensure that the RHML can be beneficial. The RHML concept could be integrated into the system design to improve the efficiency of human–robot collaboration, especially with larger human and robot team sizes, as reported by Koreis et al. (2025). In this case, the learning process is built directly on the collaborative process.

The assembly process (formulated as an assembly line balancing problem), which is a production process, exhibits different task characteristics. First, each assembly task is a result. Second, following the decomposition of the process and definition of tasks as minimum work units, each single task cannot be divided further. The robotic assembly station exhibits strength in conducting simple and repetitive tasks at higher rates, whereas complex tasks are suitable for human workers (Çil et al. 2020). Recent empirical studies have explored the possibility of applying cognitive assistive technologies (VR/AR) to leverage the human learning process while reducing the cognitive workload in the assembly process, which shows the potential of knowledge transfer from machines to humans. Moreover, preliminary laboratory experiments have explored the benefits of implementing collaborative robots to teach humans in assembly processes to improve the quality (Gervasi et al. 2024). Liu and Wang (2017) designed an assembly line by focusing on collaborative robots learning human motion during the process, which represents the closest approach to knowledge transfer from human to machine agents. As a further step, the RHML concept could provide further learning possibilities, from which both humans and machines could benefit. In particular, a collaborative assembly station that aims to conduct human–robot collaborative tasks directly provides possibilities for learning from one another (the archetype *collaborative RHML*). Despite the tasks that must be performed collaboratively, deliberately switching to sequential task conduction in the assembly station enables robot assemblers to learn from human workers, and vice versa (the archetype *exploitative RHML*). Studies on diverse human teams and human learning curves in assembly could deliver insights into RHML applications (Cohen et al. 2022). In knowledge-based tasks, such as problem-solving in maintenance, *exploitative RHML* supports the building of knowledge documentation by human experts and successful maintenance cases, and teaches humans based on documentation.

The archetypes *contradictive* and *crowd-based RHML* suggest that tasks exhibit high levels of complexity. Thus, conventional systems based on cooperative/collaborative HMI must be reformed to leverage the learning process, generating a new knowledge base. Crowd-based RHML utilises machine agents to combine multiple types of human intelligence. Despite the static task allocation and sequential task sequence, the machine is responsible for merging diverse solutions, thereby differentiating crowd-based RHML from typical cooperative HMI. Similarly, contradictive RHML combines intelligence from different agents, particularly the intelligence from humans and machines, through the contradicting processes between them. This indicates static task allocation and a parallel task sequence. The RHML process from the archetypes compares and concludes multiple solutions, which requires each single (complex) task to be conducted more than once.

Machines often assist humans in performing repetitive tasks for quality assurance in the production process, in which *contradictive* RHML could be integrated to enhance process accuracy and consistency. The visual inspection of components can be performed using ML (Ravikumar, Ramachandran, and Sugumaran 2011). Previous studies (e.g. Weiher et al. 2023) have already incorporated HITL to enhance the performance of such automatic visual inspection, indicating the possibility of machine agents benefiting from contradiction in terms of reducing errors and optimising algorithms. Resolving contradictions between human and machine results could also teach humans to improve long-term accuracy.

Another case involving complex tasks in the maintenance process was identified. In this case, *crowd-based* RHML assisted by machine intelligence can help to define an optimised procedure for problems for which the standard procedure is yet to be defined. This process relies on the knowledge base of human experts. Moreover, *contradictory RHML* enables knowledge transfer between humans and machines while updating the maintenance knowledge base. In these cases, an optimised solution for certain maintenance tasks is yet to be defined owing to the complexity of the tasks. The prediction and identification of such tasks represent the next level of RHML application in the decision-making process. In addition, predictive maintenance powered by digital twin models or ML algorithms leverages historical data and domain knowledge, proactively predicting machine failures (Zonta et al. 2020). The predictive and data-based nature of these methods generates a suitable context in which *crowd-based* and *contradictory RHML* can find potential applications. In these scenarios, human workers must communicate with machine algorithms. Moreover, generative AI (Badini et al. 2023) could aid in constructing suitable human–machine interfaces.

5.3. Limitations

This review has several limitations. The literature search strategy and derived conceptual model focus on sociotechnical systems, primarily human–machine collaboration, thereby potentially overlooking sociological and psychological dimensions that could be relevant to this study. Nonetheless, the breadth of the literature survey was intended to allow the inclusion of manifold interdisciplinary research under clear criteria. Given the novelty of the RHML concept and its emergence within a rapidly expanding research landscape, it was necessary to adopt such a broad literature search strategy to capture potentially relevant studies. A rigorous and conceptually grounded set of inclusion criteria, aligned with the core principles of RHML (see Table 2), was developed and applied to identify a focused set of pertinent publications within this wider body of work. Although the selected methodological approach could have been extended, it was purposefully designed to ensure depth, contextual sensitivity, and alignment with the exploratory objectives of the study.

Although the novelty of the research topic is a strength, it also means that only a small pool of relevant studies was available, in particular in the field of production and logistics. This limited dataset reduced the robustness that is typically afforded by inductive sampling, particularly in terms of thematic diversity. While this research offers a valuable first step toward understanding the topic, it remains an early-stage contribution. As scholarly interest grows and more empirical evidence becomes available, this work can be a valuable starting point for future research in this area. However, a reassessment and expansion of this work may be necessary in the future, as discussed in Section 5.4.

5.4. Future research agenda for RHML in production and logistics

The current RHML taxonomy forms the basis for identifying the four archetypes with potential applications in production and logistics. Furthermore, following the footprints of technology development and the dynamics of system design challenges, the current taxonomy and archetypes must be re-evaluated and innovated. To achieve this long-term goal, we analysed the frequency of occurrence of several characteristics in our taxonomy. The results serve as a basis for the possible formulation of new RHML archetypes by clarifying characteristics and dimensions that are less frequently (or not) applied in the current SLR sample. In particular, Section 5.4.1 analyses the possible refinements of RHML archetypes by analysing dimensions that were formerly selected for the current archetypes, and hence, by altering characteristics in the selected dimensions. Section 5.4.2 discusses the possibilities of including new dimensions for developing further RHML archetypes. Therefore, this section provides insights into future research agendas with a focus on RHML design and applications in production and logistics. By analysing instantiations from the current SLR, the discussion mirrors the state of the current RHML system design, guaranteeing a systematic view of research gaps.

5.4.1. Refining RHML archetypes

P1 – System (benefiting from multi-machine intelligence): Human and machine teams are the key components of RHML systems that involve single or multiple agents. The potential for employing multiple-agent teams is yet to be explored. In our sample, only 22% of the instantiations applied to multiple human teams, whereas RHML systems including multiple machine teams were undetected. Therefore, on the system level, only crowd-based RHML considered the possible knowledge transfer between multiple humans with the aid of a single machine. In multi-agent systems beyond the scope of RHML, a multiple-machine team is considered a basic premise of the system design. The current RHML paradigm is being extended by considering how machine teams interact with and learn from humans.

P2 – Interaction (enabling multimodal knowledge transfer): Among the four RHML archetypes, explicit communication assumed a leading role (in 61% and 56% of the cases for humans and machines, respectively), indicating that information is directly conveyed, such as sharing results or suggestions for review, or responding to inquiries with concrete solutions. Implicit communication requires other agents to observe during the process. Thus, information is transferred within the interaction (with the archetype collaborative RHML). Future works could further explore the potential of combining these two communication types to facilitate the RHML process during task fulfilment (implicit) and after solving a particular task (mostly explicit) via multimodal communication, for which empirical laboratory studies are required to test the effectiveness and feasibility of different communication channels (e.g. auditory, haptic, visual, and gesture-based communication).

P3 – Task (pursuing real-time dynamic task allocation): On the task level, the four current archetypes exhibit a pre-defined combination of characteristics in the dimensions of the task allocation (static or dynamic) and task sequence (sequential or parallel). Static allocation (61%) and a sequential sequence (56%) (crowd-based and exploitative RHML) was the most common combination, which shows similarity with the commonly adopted definition for human–machine cooperation. Dynamic task allocation is only adopted by collaborative RHML. Therefore, a refinement of the current RHML archetypes should focus on assigning tasks dynamically to diverse agents, with special consideration for their learning progress. This dynamic human–machine ecosystem requires precise estimation of the human and machine capabilities, enabling real-time adjustment of the expert role. Moreover, the combination of dynamic allocation and a sequential sequence is lacking in the sampled instantiations. The possible human–ML process is yet to be defined accordingly.

P4 – Learning (exploring short- and long-term learning goals): Our sampled studies in the SLR (37) pursued mid-term goals (78%), with significant persistence in medium timeframes, resulting in a sustainable behaviour change. Thus, long-term learning goals, particularly learning progress with transferability across contexts, must be facilitated in the future. Conversely, the short-term learning goals detected in 22% of the sampled instantiations must also be examined because they yield instantaneous performance optimisation with lower operating costs, which ensures their wide adoption in particular contexts.

5.4.2. Developing new RHML archetypes

According to the sampled instantiations, the current RHML archetypes depend on the current state of technology. Therefore, several dimensions in the taxonomy were undifferentiable in the use/illustrative cases. This section discusses various dimensions that were excluded in the development of the archetypes and their potential integration for developing new archetypes.

First, the activity dimension describes how each agent acts in the task conduction process on the system level, and defines which agent takes initiative in the RHML process on the interaction level. In the sampled instantiations, these cases exhibit opposing characteristics between humans and machines, indicating the proactive human and reactive machine, and vice versa. However, the instantiations show highly parallelised activity and independence of the agents. Therefore, several instantiations (39%) featured proactive humans and proactive machines. This aspect of future RHML design could result in a further step in defining different mechanisms of interactions between diverse agents, based on which the RHML process could be specified. Second, the task type on the task level differentiates primary cognitive and physical tasks, with most cases (83%) only involving cognitive tasks. Therefore, RHML is involved in the decision-making process, ignoring the need to coordinate humans and machines physically with RHML. Thus, solutions for coordinated actions must be further examined. Third, in the taxonomy, the human learning outcomes were categorised as 'remember,' 'understand,' 'apply,' and 'analyze.' However, the outcomes 'evaluate' and 'create' were not detected, limiting the application situations for RHML. However, a similar categorisation was not adopted for machine agents owing to their current capabilities. In the future, additional RHML archetypes could be developed for humans and machines to enhance the learning outcomes and extend the learning context. Finally, the archetypes only include examples of using current learning methods and theories to enable human learning and ML (e.g. supervised ML and RL). As a next step, these methods can be extended to develop a learning process that is designed for RHML based on serious games (Liu, Huang, and Zhang 2018).

6. Conclusions

This paper has described a conceptual framework for RHML, with potential applications in production and logistics. First, we reemphasized the RHML concept and its differences from the relevant terminologies (human learning and ML). Second, we enhanced the RHML characteristics (taxonomy) with an SLR across all disciplines. Third, we formed the RHML design patterns (archetypes: contradictory, crowd-based, collaborative, and exploitative RHML), enabling its direct application in production and logistics. Fourth, we discussed the future research agenda based on the RHML archetypes. This paper provides a comprehensive overview of current RHML development and serves as a tool for future research and application of RHML in production and logistics management. We highlighted the advantages of combining human learning and ML processes that surpass the current mainstream research topics for researchers, focusing on the learning process within a homogeneous agent group. In addition, our archetypes, which were defined based on a thorough SLR, are suitable for practitioners in various industrial contexts. Based on the demand for specific production and logistics processes, the RHML taxonomy further delivers insights into defining process design details in various aspects.

The knowledge base of RHML, including the taxonomy and archetypes, remains in the conceptual stage and is highly dependent on the current state of technology, which is a limitation of this research. In the future, empirical studies based on various scenarios are essential to investigate the potential RHML concepts for industrial applications and to evaluate its influence on system performance. Moreover, further refinement of the archetypes and exploration of different characteristic combinations based on our taxonomy are required. When designing these studies, task characteristics, human/machine capabilities, and desired learning outcomes that formulate hypotheses based on suitable RHML archetypes must be considered. Furthermore, the lack of research on RHML from a social science perspective in particular further highlights the demand of future RHML conceptualisation based on knowledge updates from social science. The current RHML concept stems from the existing learning paradigms of humans and machines. This paper enables the formulation of a (human–machine) bidirectional learning process for industrial applications, further exploring RHML concepts. Therefore, learning techniques for humans and machines must be refined and developed based on RHML paradigms. A specially designed interface between humans and machines can enhance the process efficiency and learning outcomes owing to the nature of bidirectional learning. In conclusion, this study addresses a critical gap at the intersection of human–machine collaboration and industrial systems. Contemporary manufacturing environments are increasingly evolving into symbiotic systems, where human agency and learning are dynamically complemented by machine- and AI-driven intelligence. This evolution signifies a shift from unidirectional learning – where humans learn from machines – to bidirectional or reciprocal learning, in which humans and machines continuously learn from and adapt to one another. Such a transformation holds significant implications for knowledge management within production and logistics systems. By highlighting this emerging paradigm, the present work provides valuable insights into the pivotal role of reciprocal human–machine learning in shaping future research directions and practical applications in industrial contexts.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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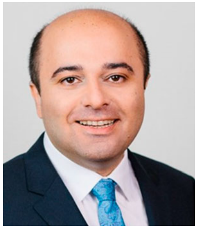

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Data availability statement

Data is available on request from the authors.

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Appendices

Appendix A (SLR search string)

Search string:

TITLE-ABS-KEY (human AND (*agent* OR *machine* OR *ai* OR *artificial intelligence* OR *algorithm* OR *computer*) AND (*reciprocal*∗ OR *mutual*∗ OR *collective*∗ OR *bilateral*∗ OR *bidirectional*∗ OR *cooperative*∗ OR *collaborative*∗ OR *hybrid* OR *interaction* OR *teaming* OR *symbiosis*) AND (*learn*∗ OR *train*∗ OR *teach*∗))

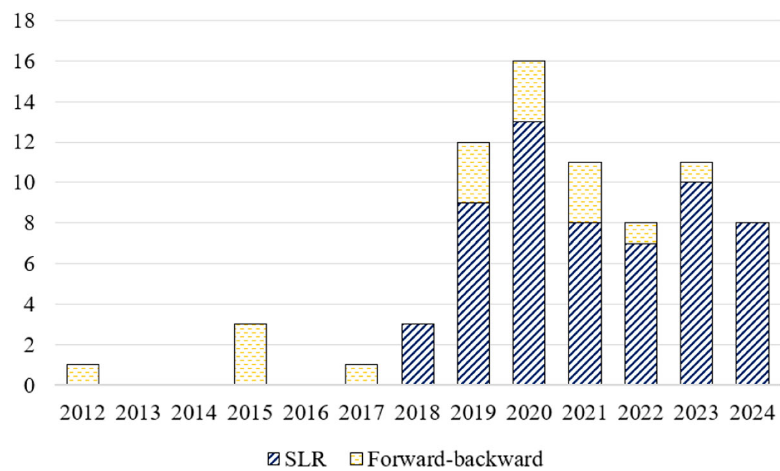
Appendix B (SLR process)

Descriptions of literature search and selection process

Phase	Description	Number of works
1	**Definition of search string**: Reviewing previous work on RHML	–
2	**Refinement of search string**: Iterative adjustment of search terms and Boolean operators; exclusion of terms that do not address the research field directly	–
3	**Search**: Search title, abstract, and keywords in Scopus with search string (25.12.2024)	118,543
4	**Inclusion criteria**: Time, type of publication, language	41,508
	- Time span: 2018–2024 (6 years)	(72,024)
	- Types of publication: conference papers and journal articles only	(63,191)
	- Language: English only	(61,958)
	- Omit duplicates	(61,736)
5	**Refinement to exclude index keywords:** Scopus assigns various 'index' keywords to each of the listed publications, which misleads to irrelevant hits	31,583
6	**Term frequency**: Refine by frequency of *human* in body title-abstract-author keywords ($>$ 0.01) to exclude papers with minimal or no focus on human agents	6,322
7	**Relevance appraisal:** Scan abstracts for evaluation according to six criteria (see Table 4) for relevance of publications (exclude work that is not relevant)	56
8–1	**Forward–backward search**: Inclusion of cited publications (forward and backward) that pass relevance appraisal	13
8–2	**Second forward–backward search**: Repetition of step 8 to ensure exhaustive results	3
9	**In-depth review** of all accessible publications	72

Appendix C (Number of publications per year)

Years of publication of sampled papers:



Appendix D (RHML taxonomy)

Level	Dimension	Exclusivity∗	Characteristics
P1 – System	Multiplicity	ME	Single; Multiple
	Agent type	NE	Cognitive; Physical
P2 – Interaction	Activity	ME	Proactive; Reactive
	Communication type	ME	Explicit; Implicit
	Communication mode	NE	Haptic; Visual; Auditory; Natural language; Multimodal
	Feedback type	NE	Informative; Verifying; Corrective; Explanatory
P3 – Task	Task type	ME	Cognitive; Physical
	Task goal	ME	Recognition; Prediction; Coordinated action
	Task allocation	ME	Dynamic; Static
	Task sequence	ME	Sequential; Parallel
P4 – Learning	Learning timing	ME	Pre-/Post-trained; Real time
	Learning method	ME	Supervised; Reinforcement
	Learning outcome	NE	Remember; Understand; Apply; Analyze; Create; Evaluate
	Learning goal	ME	Short-/Mid-/Long-term

∗Mutually exclusive (ME): Characteristics in this dimension are exclusive.
Non-exclusive (NE): Characteristics in this dimension can coexist with overlaps.