Reciprocal Learning in Human-Machine Collaboration: A Multi-Agent System Framework in Industry 5.0

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1. Introduction

Recently, the European Commission introduced the term Industry 5.0. Its concept is entirely based on Industry 4.0, while Industry 5.0 provides a vision beyond productivity and efficiency as the sole goals, and reinforces the role and contribution of research and innovation to society (European Commission 2021). The well-being of the worker is put at the center of the production process in order to provide sustainable prosperity beyond jobs and growth. The European Commission defines three main elements of Industry 5.0: i) human-centricity, ii) sustainability, and iii) resilience (European Commission 2021). Human-centric approaches in manufacturing industry explore what the technology can do for the worker than the other way around. In this way, humanistic perspectives and investment in human capital, which is an important factor for economic growth (Goldin 2016), are respected. Thus, human-centric manufacturing emphasizes that novel production systems adapt to worker's individual needs, e.g., guide, assist, and train the workforce (European Commission 2021).

Fostering learning opportunities for human workers directly contributes to the vision of human-centricity (European Commission 2021), specifically by providing skilling and upskilling to increase human capital (Smith 1776). Due to fast evolving technologies, training is a cornerstone of Industry 5.0, because demand of new skills is high, skill gaps are glaring, and unlearning matters. Moreover, industrial practice lacks behind in adoption of novel technologies due to skill gaps in companies' workforces. A study about skills and key technologies pointed out, that skill imbalances significantly diminish growth in technology and employment (CEDEFOP 2019). Therefore, investigating learning opportunities in the process of work may significantly impact the competitiveness of European enterprises.

Where humans and machines collaborate, the term Reciprocal Learning has been coined to describe learning between both agents, i.e., the human and machine. Reciprocal Learning has been inspired by reciprocal teaching (Rosenshine and Meister 1994) and reciprocal altruism (Trivers 1971). Both terms are originating from observing human behavior in human-human symbiosis. Reciprocal Learning has first been introduced by Ansari et al. (2018), motivated by collaboration of learnable technological agents and human agents to form reciprocating learner-teacher interactions.

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Complementing human-centric manufacturing, transformation towards human-automation symbiosis is envisioned (Wang et al. 2019). Human and intelligent agents (machines) will share workplaces and solve complex tasks by combining their complementary competences, i.e., human-machine collaboration. Symbiotic relationship foresees mutual benefits for both agents, such as learning. In this way, the concept of Reciprocal Learning, which describes learning as a bidirectional process between intelligent agents, namely humans and machines, contributes to the notion of human-machine symbiosis. To the best of our knowledge, however, there is neither work that discusses Reciprocal Learning to consolidate its concept comprehensively nor to make it tangible. A first step is taken in this paper, by presenting a work in progress. Therefore, we present a consolidation of a heuristic literature review from various scientific disciplines, e.g., psychology on learning of human(s), computer science on learning of machine(s), as well as human-machine collaboration to form the context of Reciprocal Learning. Thereby, a framework of Reciprocal Learning is provided to outline what it is and what it is not by taking its characteristics, stemming from the human agent, the machine agent, the task, and their collaboration as well as learning processes, into account.

Therefore, the context of human-machine collaboration and human-machine symbiosis is discussed (Section 2, followed by fundamentals of learning and intelligence in humans and machines (Section 3). Further, agent learning divided by single-agent learning (human learning, single-AI agent learning) and multi-agent learning (collaborative human learning, multi-AI agent learning) is discussed (Section 4). In Section 5 the concept of Reciprocal Learning is defined and supported by a framework of Reciprocal Learning in human-machine collaboration, including definitions of characteristics of agents, both human and technology, as well as task and processes of collaboration and learning. Finally, future research objectives are discussed (Section 6).

2. Human-machine partnership in manufacturing

The latest advances in AI technologies and especially collaborative robotics open new horizons for cooperative or collaborative work forms between human and machines as an extension to fully automated production processes. Research on human-machine interaction firstly concentrated on socio-technical systems that contain social (human-related) and technical (non-human) aspects which will interact to pursue a common goal (Avis 2018). Moreover, human and machine components are often referred to as agents in socio-technical systems, i.e., social agent (human), artificial agent (machine). Agents are capable to act independently with an own agenda, i.e., decision-making (Zafari 2020). Throughout this paper, the term "agent" refers to either human or machine actors, if not further indicated.

2.1. Human-machine collaboration

With the development of highly complex and dynamic human-machine systems, comprising of enhanced connectivity, increased autonomy and automation, as well as intelligence, adaptive mechanisms, are emerging. These enable forming independent (active) machine agents for the application in dynamic and uncertain environments to support and assist human workers (Krupitzer et al. 2020), which are, despite the technological enhancement, a significant factor in design of manufacturing systems. Assistance systems aim to compensate human worker's shortcomings in cognitive, physical, or even sensorial capabilities. Besides acting as a mere assistant for human operators, machine entities can actively collaborate with humans on joint activities, sharing and dividing tasks according to the respective strengths and capabilities. Thus, human-machine collaboration is a system of agents which cannot be considered in isolation, but as a team that is formed in order to perform tasks collaboratively. Characterization of human–machine collaboration can be done by the nature of the collaboration, i.e., the distribution of tasks between agents according to their abilities and capacities. In this way, we follow definitions of the fundamental characteristics of human-machine collaboration by Simmler and Frischknecht (2021):

- automation, defining the allocation of situational executive control, ranging from independent human decision-making to fully automated machine decision making and
- autonomy of the machine agent, defining interdependence in completing an assigned task, ranging from deterministic systems to open systems.

Autonomy of the technical system can be assessed by its transparency (i.e., traceability of input/output relations), determination (i.e., same inputs leading to the same outputs), adaptability (i.e., learning from experience), and openness (i.e., expanding input through cooperation with other systems). Openness is considered to be the highest level of autonomy, because the machine is neither limited to specific inputs nor to its own experience. However, input/output relations of open systems become non-transparent. In contrast, autonomy of the human in human-machine collaboration is in general considered superior to the machine's (Simmler and Frischknecht 2021). Still, competence levels of human, such as, novice, competent, proficient, expert, and mastery can be distinguished, which have similar meaning to humans as automation and autonomy for machines (Ansari et al. 2020). E.g., a human at mastery level corresponds to a fully autonomous machine. Multiplicity is distinguished as another characteristic of human-machine collaboration based on the number of agents in a given scenario, i.e., single (human-machine), multiple (multiple of either or both), and team (multiples act coordinated and in consent) (Wang et al. 2017). These three characteristics, namely, autonomy, automation, and multiplicity highlight differences among human–machine collaborations. Competence levels, multiplicity, autonomy and automation, are gradual dimensions that capture a more differentiated understanding of human-machine collaboration in task environments.

2.2. Human-machine symbiosis (HMS)

Symbiotic relationships between human and machine are discussed in human-machine collaboration (Lu et al. 2021; Wang et al. 2019; Wang et al. 2017; Gerber et al. 2020). It defines mutual benefits for both actors (Wang et al. 2019). The symbiotic partnership may also facilitate depth of collaboration, in which both agents are pursuing similar goals, benefit mutually, and become smarter (Jarrahi 2018). Human-machine symbiosis (HMS) has been described in context to manufacturing work environments (Lu et al. 2021; Wang et al. 2019), to achieve previously unattainable goals by merging capabilities and overcoming individual agent's restrictions (Gerber et al. 2020). They form a partnership of agents which is capable of solving problems the individual members alone would not be able to tackle (Wang et al. 2019). Requirements of HMS systems are shortly described in the following, based on Lu et al. (2021), Gerber et al. (2020), and Wang et al. (2019):

- Balanced **autonomy**, all agents are inherently autonomous, i.e., in equal position, they form together a team or group which is responsible for the successful and efficient performance of a set of tasks. Roles of leadership change dynamically, as the actual situation and the task requires.
- Accurate **context-awareness**, all agents are context-aware, i.e., their actions and decisions are grounded on the actual physical and cognitive circumstances. The shared physical work environment tracks and traces the objects, to enable interaction and manipulation in the real world.
- Transparent **representation**, all agents apply at least partially shared representations of the environment to formulate common goals, take roles, execute plans, and solve tasks. The shared virtual representations or mental models are dynamically adjusted in real-time.
- Effective **communication**, all agents continuously engage with each other. Multimodal and bidirectional communication by means of, e.g., voice, physical inputs/outputs, gesture, pose, brainwaves, augmented reality, video, image, text. Communication and exchange of information adapts to content, context, and identity.
- Dynamic **adaptability**, the performance of a symbiotic system improves over time, by adapting to new situations, changing conditions, and learn from failures and successes based on feedback of the environment.
- Natural **human-centricity**, the ability to focus on the human's needs (e.g., safety)
- **Social wellness**, the ability to detect and respond to human distress or fatigue in physical and mental performance to assure well-being.

In conclusion, HMS systems possess the capability of perception, learning, communication, and decision making for context-aware human-machine collaboration. In this way, HMS is a significant extension to the notion of human-machine collaboration for which Reciprocal Learning can be a significant contribution as the core idea of mutual benefit is respected in both concepts.

3. Fundamentals of intelligence and learning from human and machine perspectives and its relevance for manufacturing

Intelligence and learning alike lack consensus and clear definitions. This especially holds true since artificial intelligence (AI) has been emerging and developers pursue their vision to embed intelligence in machines that replicate human's intelligence. Gottfredson (1997) defines **human intelligence** as

> "… a very general mental capability that, among other things, involves the ability to reason, plan, solve problems, think abstractly, comprehend complex ideas, learn quickly and learn from experience."

Thus, human intelligence and learning are closely connected. Human learning has been the subject of various disciplines in human science, inter alia, psychology, pedagogy, didactics, sociology, philosophy, and biology. This is reflected by a wide variety of different definitions of learning. Psychology puts the human individual in the focus of research and has been exploring and examining cognitive processes of humans intensively. However, human cognition is hardly observable. Therefore, theories and hypotheses about learning have been constructed to explain and investigate learning in humans. This notion is fully reflected in behaviorism, a theory which investigates input-output relations of human behavior, neglecting any internal processes (Skinner 1938). In this way, learning is described as changes in human behavior based on conditioning. Contrary, cognitivism is a learning theory focusing on receiving, organizing, storing, and retrieving information, i.e., knowledge (Lefrançois 2015). Another theory, constructivism, is closely related to cognitivism. While cognitivism is limited by the available and provided information, constructivism describes self-directed learning and construction of knowledge from problem-based contexts (Kelly 2003), often enacted in social processes of interaction (Kadam and Vaidya 2021). The learner actively constructs new ideas and concepts based on existing and new knowledge by constructing connections. Additionally, individuals' subjective perception and interpretation of their environment significantly influences their reality, recognition of problems, and behavior (Ertmer and Newby 2013). Notably, the body of knowledge represents several other learning theories, while behaviorism, cognitivism, and constructivism are the most respected. In order to combine the theories mentioned and provide a comprehensive definition of learning, the authors choose to follow Ertmer and Newby (2013) with "learning is a change in behavior, or in the capacity to behave in a given fashion, which results from practice or other forms of experience". However, changes in behavior can also result from processes or be influenced by factors that are not considered learning, e.g., maturation, sensitization, adaptation, and fatigue. All of these are excluded from consideration. Further, it should be noted, that cognitive learning, i.e., changes in learner's knowledge (cf. cognitivism), is inferred from learner's behavior too, thus inherent.

Machine intelligence and AI are used interchangeably. A clear and consensus definition of AI is lacking (Russell and Norvig 2021). In contrast to Russell and Norvig (2021), who propose AI to be an imitation of human intelligence or system of rationality, Wang (2008) defines it as:

> "… the capacity of a system to adapt to its environment while operating with insufficient knowledge and resources."

Machine learning (ML) is a subset of AI, i.e. a method for modeling the ability of human learning and reproduction of human skills by artificial models and computational algorithms (Russell and Norvig 2021). ML is a promising area of computer science that evolved from pattern recognition, and which consists of a manifold range of applicable algorithms and learning strategies.

Both agents' intelligence differs substantially, in terms of definition, application, and measurement. Learning, however, can be described similarly by adopting the aforementioned notion of learning to be a change of behavior, based on practice or experience. This common ground will be needed to establish Reciprocal Learning.

Manufacturing education relies on work-based learning (WBL) as a promising approach for closing skill gaps. WBL defines learning in the context of work, with respect to process-orientation, experiential learning and the combination of informal, non-formal and formal learning that are increasingly prevalent in digitalized work processes (Dehnbostel and Schröder 2017). For manufacturing practice, learning of humans is the cornerstone of competence development of workforces. Due to transformative skill gaps, learning for production, i.e., training of workers for meeting workplace requirements, and learning in production, i.e., work-based learning (WBL), are increasingly important (Abele et al. 2015). Digitalization enables the creation of work environments with new opportunities for workers to learn performing new tasks and enable the creation of innovative learning approaches at the workplace for skilling, reskilling, and upskilling of workforces. High volumes of real-time information from process production data as well as intelligent assistance and production information systems enable WBL. Considering the differences in employee's education, experience, and skill sets, WBL may close skill gaps efficiently, especially if learning is integrated into the actual workplace. Transforming work organization in order to foster (lifelong) learning and implementing training strategies at the workplace conforms the human-centric notion of modern manufacturing. However, innovative approaches to WBL, such as approaches that are integrated at the workplace remain rare (Nixdorf et al. 2021). Investigating learning from perspective of production engineering to integrate learning processes into human-machine collaboration in manufacturing is necessary to enable efficient training opportunities of tomorrow's workforce. Reciprocal Learning as a type of innovative work-integrated learning, may contribute significantly to the continuous training of human capital.

4. Agent learning

This section discusses learning of human and machine individually, starting with single-agent scenarios, i.e., individual agents without any interactions with any other agents, namely human learning (cf. Section 4.1) and single-agent learning (cf. Section 4.2). Furthermore, learning in multi-agent scenarios (cf. Section 4.3 and 4.4), i.e., humans learning from each other (collaborative learning) and machines learning from each other (multi-agent learning) are discussed. As pointed out above, psychology and computer science have similar definitions for learning. Descriptions of learning in multi-agent scenarios is, however, different. Hence, the following section synthesizes commonalities and describes the components of agent learning and multi-agent learning.

4.1. Human learning

Human learning consists of a wide range of subtypes, mostly conceptualized in behaviorism, cognitivism, or constructivism. While the cognitive process of learning itself remains ambiguous, types of learning are characterized by either their inputs (e.g., instruction, observation, etc.) or outputs (e.g., association, representation), regardless of the theory applied. Hence, in the following, the focus lies on the components and characteristics of learning.

Evidently, human individuals have characteristics, which affect learning, that are independent of the task or situation at hand, i.e., motoric capabilities, cognitive capabilities, knowledge, skills, and competences. In other words, these characteristics vary in individuals, affect the individual's behavior in certain task situations and affect limitations of potential changes in behavior from gathered information. E.g., cognitive capabilities affect the interpretation and processing of information, which is provided to the human. Further, task specific and situational characteristics can be identified, e.g., attention, emotion, motivation, goal, and behavior. Attention is a situational characteristic of a human, which limits quality of gathered information and thereby the potential learning (from experience). Similarly, individual's emotion can negatively affect learning due to, inter alia, lack of confidence, fear of failure, previous negative experiences, and the learner’s emotional state (Bierema 2008). Motivation of human affects the behavior as well as the definition of a goal. An individual's goal in a specific task can be divided in a performance goal, i.e., aiming at finishing the task, and learning goal, i.e., aiming at effective learning (Hauer et al. 2014). Generally, goal setting affects the behavior of humans.

The task is typically characterized by its complexity, uncertainty, difficulty, predictability, and novelty, which all influence the required capabilities and thus its outcome. In this way, adequate selection and design of tasks can facilitate learning (Hauer et al. 2014). Furthermore, learning scenarios contain information flows, namely, information available before the task, e.g., instructions (cf. instructional learning), feedback to human during the task, e.g., trial-and-error learning, associative learning.

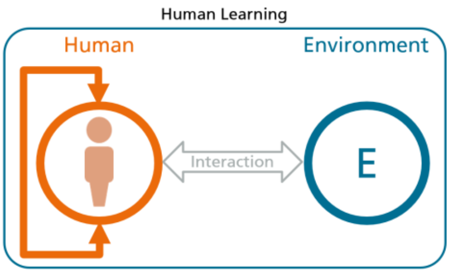

Figure 1: Human learning as a single-agent

The human processes and interprets provided information, which can either be done passively (any information is considered, e.g., associative learning, instructional learning, etc.) or actively, which allows self-directed selection of information to be considered. As depicted in Figure, the human learning scenario contains one human who learns from interaction with the environment, i.e., performing a task and changing its behavior.

4.2. Single-AI agent learning

In AI, an intelligent agent is referred to an entity that is capable of taking decisions from an environment (Russell and Norvig 2021). Weiß and Dillenbourg (1999) define agency, as a matter of distributed AI, to be composed of the following basic components:

- sensors and actuators, which both enable the agent to interact with the environment, e.g., carry out actions or exchange data,
- knowledge base, which contains information about the environment, e.g., regularities, rules, and activities of other agents (in multi-agent systems),
- inference engine, which allows to perform tasks like inferring, planning, and learning, e.g., by deducing information, generating behavioral sequences, increasing efficiency of environmental interaction.

An AI agent is meant to improve its individual skills, irrespective of the domain in which it is embedded (Alonso et al. 2001). Generally, technological agents are distinguished into weak and strong notions. The weak agents are usually independent, i.e., operate on their own without or limited human guidance while imitating human-like intelligence. Pro-activeness and reactivity are both elements of weak agents (Nwana and Ndumu 1998). Strong agents are considered to have mental attitudes, namely, information state (e.g., belief, knowledge, etc.), deliberative state (e.g., intention, commitment, etc.), and motivational states (e.g., desire, goals) (Weiß and Dillenbourg 1999), which is an intelligence considered to be actually human-like. In this way, strong agents do have more commonalities with human beings than weak agents and come closest to resembling them. However, strong agents are not making significant developmental progress. Learning capabilities of agents are necessary to cope with novel situations, which have not been foreseen in the design process, and adapt to the environment (Alonso et al. 2001). Learning of AI agents is subject of ML research, currently encompassing a wide range of learning algorithms, inter alia, (semi-/un-) supervised learning, reinforcement learning, active learning, or deep learning (Russell and Norvig, 2021). Most of ML research has focused on single agents. Machines need to interact with the environment, as depicted in Figure .

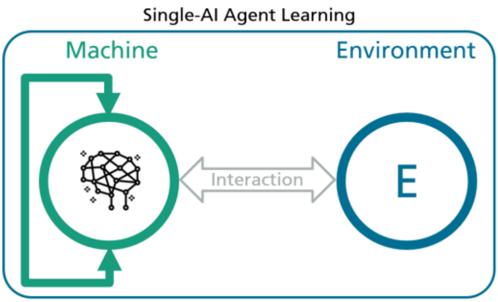

Figure 2: Single-AI agent learning

4.3. Collaborative human learning

Trial-and-error is one of the most fundamental learning techniques humans use. Interestingly, humans can learn by observing trial-and-error learning of other humans without the risk associated with the error. This type of learning is called observational learning (Csibra and Gergely 2009). In social learning, which is often modelled as a learner-teacher (supervision) scenario, the observation is supplemented with active teaching, whose communication allows transmission of knowledge and skills between humans (Csibra and Gergely 2009). Most social learning mechanisms involve some form of observational learning in which behavior is imitated or emulated. Imitation is the repetition of previous actions, while emulation is inferring goals, beliefs, and intentions of the other human. Research suggests that supervision learning, between teacher (supervisor) and learner (supervisee), could be seen as a bidirectional learning process, since the supervisor also learns (i.e., supervision has potential benefits for supervisors and supervisees) (Carrington 2004). In fact, "reciprocal learning" has been mentioned occasionally to describe iterative learning effects between humans (Noël et al. 2013; Carrington 2004; Patrick et al. 2010). It suggests that teaching-learning distribution between humans can dynamically adapt. Importantly, learning results are heavily influenced by the social relationship of the humans and their mutual trust. In group learning situations, observational learning is weighted towards the most skilled individuals of a group. However, information gained from own experience is still considered the most reliable. Supervision learning typically revolves around an unequal relationship between supervisor and supervisee, e.g., one being more knowledgeable than the other, and influence not being mutual (O'Donnell and Hmelo-Silver 2013). Cooperative learning and collaborative learning lean one step further, by introducing learning between humans in equal settings, i.e., groups of equally knowledgeable humans, e.g., a group of students (Davidson and Major 2014). Both concepts originate from education and teaching, occur when (equal) human individuals solve a problem together. In particular, a common shared task, interdependence (i.e., need to rely on each other to achieve goals), individual accountability (i.e., all participants are held accountable for share of work), equal participation (i.e., balanced knowledgeable roles), and simultaneous interaction (e.g., providing feedback, challenging conclusions) are needed (Laal and Laal 2012; Davidson and Major 2014).

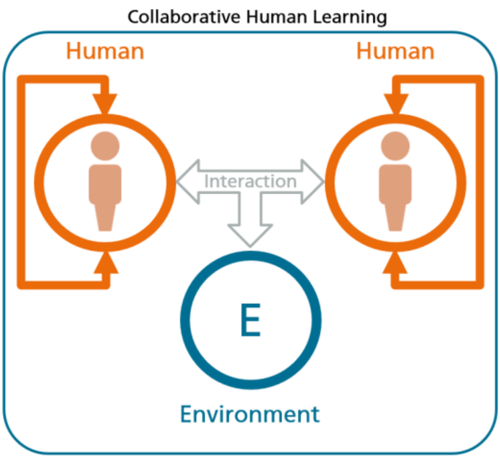

Figure 3: Collaborative human learning

In contrast to cooperative learning, according to Davidson and Major (2014), collaborative learning is open-ended by design, i.e., not limited to only one true approach or response. Additionally, Laal and Laal (2012) highlight adaptability of collaborative learning by pointing to self-assessment of achievements, goals and identification of potential changes to function more effectively as a group. As collaborative learning also qualifies as a type of social learning, it requires trust, leadership, decision-making, communication and conflict management (Davidson and Major 2014).

4.4. Multi-AI agent learning

While AI research mainly concentrates on learning techniques in single-agent environments, distributed AI research concentrates on multi-agent systems (MAS). MAS consists of several interacting agents which are limited and differ in their actuators, sensors, cognitive capabilities, and knowledge about the environment, while their communication, and interaction, i.e., cooperation and collaboration, are relevant to the solution of the task (Weiß and Dillenbourg 1999; Vlassis 2007). MAS can be distinguished by their design (identical or heterogenous agents), environment (dynamic or static), perception (i.e., information and interpretation of the environment), control (e.g., centralized/decentralized decision-making), knowledge of and about other agents (e.g., their actions, perception, knowledge), and communication (e.g., sending and receiving information) (Vlassis 2007). Many MAS implement reinforcement learning algorithms as they enable agents to learn from interacting with the environment (Vlassis 2007), similarly to associative learning (cf. Section 4.1). MAS in some cases aim to maximize a global reward function (e.g., in collaborative reinforcement learning) or own reward functions to find equilibrium (Lin et al. 2021). Design of learning in MAS is a complex matter. Each of the participating agents may learn (i.e., change behavior), thus change the environment and, thereby, affect learning of each agent. Agents need representations of their agent counterparts to reason about them. However, even if an agent is not explicitly aware of other agents, it perceives them as part of the environment and their behavior still affects the agent (Alonso et al. 2001). In this way, learning and teaching in context of MAS cannot be separated (Shoham and Leyton-Brown 2012). In addition, there are three classes of mechanisms that distinguish single-agent learning from learning in MAS, namely multiplication, division, and interaction. Multiplication refers to independent learners in the MAS, where learning processes are isolated, agents may use different learning algorithms and pursue their own goals. In division of multi-agent learning, single tasks or algorithms are divided among agents, which may be due to functional aspects or the data to be processed. Weiß and Dillenbourg (1999) suggest divided multi-agent learning for manufacturing processes, in which each agent concentrates on another step. In interactive learning the interaction is a dynamic activity that concerns the intermediate steps of the learning process. Interaction enables a truly cooperative search for a solution of the task.

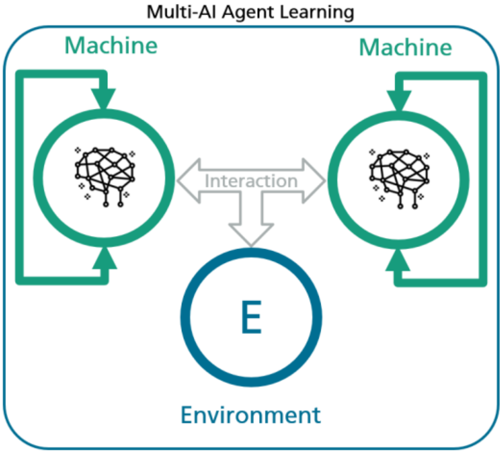

Figure 4: Multi-AI agent learning

Agents involved in interactive learning influence the learning path and synthesize conflicts along the learning process. Imitation learning attempts to train agents to learn from expert demonstrations by means of supervised learning (Lin et al. 2021). Employed learning algorithms to MAS have shown promising results in learning cooperative behavior (e.g., Zhang et al. (2021), Tan (1993)) and have adopted observational learning to MAS (Borsa et al. 2017).

5. Framework of Reciprocal Learning in human-machine collaboration

In the previous section, single-agent and multi-agent learning have been investigated, for humans and machines, comparably. Evidently, interaction of agents in learning scenarios can support achieving agent-specific learning goals. Similarly, collaboration between agents supports achieving mutual learning goals, maximize global payoffs. In the following, findings of Section 4 are consolidated to describe Reciprocal Learning, comprising of characteristics of agents, the task, collaboration, and learning. Based on the definition of Reciprocal Learning, a framework is presented.

Reciprocal Learning between human and machine in the context of human-machine collaboration in manufacturing has been defined by Ansari et al. (2018) as:

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

The concept of Reciprocal Learning has been inspired by reciprocal altruism, in which human behavior is beneficial to others (West et al. 2007) and reciprocal teaching, in which humans learn from each other by switching between trainee and trainer (Rosenshine and Meister 1994). Reciprocal Learning exploits the complementarity and reciprocity of human and machine to achieve mutual benefits.

Any human and any intelligent machine agent, regardless of type of interaction (if any) or task, comprise of basic characteristics that affect learning (cf. Table), namely, a knowledge base (e.g., previous experience, knowledge about the environment, skills, and competence), actuators (e.g., ways to act and interact) , sensors (e.g., ways to receive feedback and information), the general ability to adapt or learn (e.g., change own behavior), a perception of the environment (e.g., interpretation of reality), and autonomous cognition or inference engine (e.g., reasoning, problem-solving), respectively. The characteristics affect the behavior of the agent and are required to learn. Additionally, each agent comprises of situational characteristics that affect learning. These change regardless of any learning effects that may occur in the meantime, e.g., due to fatigue, emotions, or the task environment. Situational characteristics are attention (or data pre-processing), information (or data) selection, motivation, and goals. In Table , human's and machine's characteristics are evenly aligned, however, the underlying morphologies of these characteristics are substantially different, e.g., human's actuators are entirely different to machine's.

A task has several characteristics that affect learning, such as its complexity, difficulty, uncertainty, predictability, and novelty. Moreover, information of required skills is needed to evaluate the task's impact on collaboration and learning processes. Task design, namely defining the characteristics above, can have an impact on learning by choosing design conducive to learn.

	Human	Machine
Basic characteristics	Cognition	Inference engine
	Knowledge base	Knowledge base
	Actuators	Actuators
	Sensors	Sensors
	Adaptability (learning)	Adaptability (learning)
	Perception	Perception
Situational characteristics	Attention	Data pre-processing
	Information selection	Data selection
	Motivation	Motivation
	Goals	Goals

Table 1: Characteristics of human and machine relevant for learning

Human, machine, and task characteristics serve as inputs to human-machine collaboration in order to facilitate Reciprocal Learning. Accordingly, Reciprocal Learning requires multiplicity of agents, i.e., at least one human and one machine agent. Hence, each agent has to deal with a dynamic environment, i.e., changing over time, by mere presence of the other agent(s) (Vlassis 2007). In a MAS environment, organization of the task either by multiplication or division is required for Reciprocal Learning. Further, it foresees collaboration between human and machine in order to gain mutual benefits, similar to HMS. However, HMS goes beyond the concept of Reciprocal Learning. Hence, another level of Reciprocal Learning can be defined, i.e., Symbiotic Reciprocal Learning, satisfying all requirements of HMS, in particular, context-awareness, representation, human-centricity, and social wellness. In the following, these requirements are discussed in Table . Characteristics of multi-agent learning (human and machine agents) also affects Reciprocal Learning, as detailed in Table . Notably, Weiß and Dillenbourg (1999) suggest that humans excel at establishing mutual and shared understanding, by, inter alia, conflict resolution, and explanations. MAS, however, are designed to avoid misunderstandings of any kind, while collaborative human learning is facilitated by resolution of conflict. In particular, humans will likely reach states of disagreement in their collaboration (i.e., conflict), whose resolution can further enhance learning, as also explanations are constructed iteratively.

Collaboration characteristics	For Reciprocal Learning
Autonomy/Competence	Autonomy and competence levels
Automation	Action independence
Multiplicity	Multiples (at least one type of agent each), teams
Communication	Continuous, multidirectional and multimodal
Adaptability	Dynamic change of behavior for improvement
Trust	Mutual trust
Task sharing	Flexible task division or multiplication
	Symbiotic Reciprocal Learning
Context-awareness	Accurate perception
Representation	Adjustable and shared mental models
Human-centricity	Focus on human's condition
Social wellness	Detect and respond to human's condition

Table 2: Characteristics of HMS in context of Reciprocal Learning

Learning characteristics	For Reciprocal Learning
Interdepence	Mutual influence on results
Accountability	Individual accountable for own share of work
Participation	Balanced roles, low skill difference
Conflict management	Understandable explanations
Leadership	Changing teacher-learner

Table 3: Characteristics of learning in context of Reciprocal Learning

A framework of Reciprocal Learning is established (cf. Figure), taking all inputs (i.e., human, machine, and task characteristics) and processes (i.e., collaboration and learning) into account. Hence, Reciprocal Learning is the output of this framework, which is characterized by its inputs' characteristics, characteristics of processes, namely collaboration and learning. Depending on requirements regarding HMS, Symbiotic Reciprocal Learning is characterized as an extension of Reciprocal Learning. In this way, characteristics of both agents are respected. Both agents are defined by a range of basic characteristics that define their states regardless of any given task and situational characteristics (cf. Table). Reciprocal Learning is defined by the agents' characteristics, as well as characteristics of collaboration and learning, as described above. The interaction is characterized by the collaboration of human and machine, as well as the learning process. In addition to the aforementioned characteristics, Reciprocal Learning is distinguished by quality of mutual effects (cf. Table). Learning, i.e., change/adaptation of behavior, needs to be realized in both type of agents in order to label learning to be reciprocal. Additionally, benefits must be mutual, i.e., improved performance, skills, ergonomics may not be imposed on only one of the agents, but both of them. However, the benefits do not need to match in their respective qualities, which allows asymmetrical benefits. In this way, Reciprocal Learning is not present if only one individual agent changes its behavior, or only one single agent benefits from the learning, regardless of the encountered learning mechanism. These may include learning mechanisms, such as: Trial-and-error learning, observational learning, social learning, supervision learning, imitation learning, and collaborative learning.

Benefit	Change of behavior	
	Individual	Mutual
Individual	**No** Reciprocal Learning	**No** Reciprocal Learning
Mutual	**No** Reciprocal Learning	**Reciprocal Learning**

Table 4: Reciprocal Learning defined by mutual change of behavior and mutual benefit

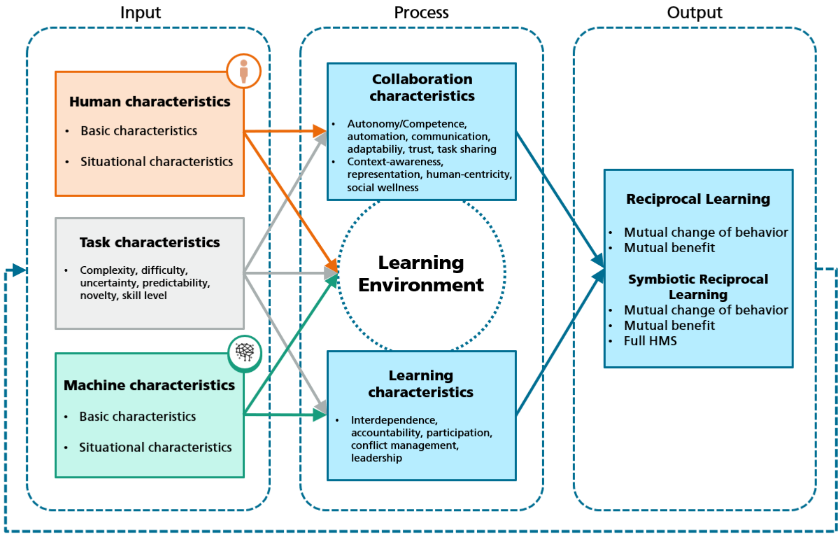

Figure 5: Framework of Reciprocal Learning in human-machine collaboration

6. Conclusion and future research in Reciprocal Learning in human-machine collaboration

In conclusion, human intelligence and AI have ambiguous definitions and are conceptually evolving due to substantial efforts in psychology and computer science. The vision of Reciprocal Learning has been gaining interest due to its innovative approach to WBL. However, the concept has not been clearly defined. Hence, this paper offers intermediate results of a work in progress on Reciprocal Learning by means of outlining inputs, processes, and outputs to characterize Reciprocal Learning.

In future research, characteristics of Reciprocal Learning need to be defined comprehensively, in order to define qualitative and quantitative requirements for Reciprocal Learning. Moreover, research is encouraged to investigate technology readiness to deploy Reciprocal Learning to MAS in manufacturing. Therefore, use-cases and applications need to be investigated in order to leverage potentials of Reciprocal Learning in enhancing WBL and enable empirical research.

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