Machines as teammates: A research agenda on AI in team collaboration

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ABSTRACT

What if artificial intelligence (AI) machines became teammates rather than tools? This paper reports on an international initiative by 65 collaboration scientists to develop a research agenda for exploring the potential risks and benefits of machines as teammates (MaT). They generated 819 research questions. A subteam of 12 converged them to a research agenda comprising three design areas – Machine artifact, Collaboration, and Institution – and 17 dualities – significant effects with the potential for benefit or harm. The MaT research agenda offers a structure and archetypal research questions to organize early thought and research in this new area of study.

1. Introduction

Imagine the following scenario: A typhoon has knocked out the infrastructure of a small nation. Hundreds of thousands of people in hard-to-reach places lack food, water, power, and medical care. The situation is complex – solutions that address one challenge create new ones. To find a workable solution, your emergency response team must balance hundreds of physical, social, political, emotional, and ethical considerations. It is mind-boggling to keep track of all the competing concerns. One teammate, though, seems to have a special talent for assessing the many implications of a proposed course of action. She remembers the legal limitations of the governor’s emergency powers, locations of key emergency supplies, and every step of the various emergency procedures for hospitals, schools, and zoos. Her insightful suggestions contribute to the team’s success in saving thousands of lives. But she is not human; she is a machine.

This scenario sketches a complex situation in which humans and a machine teammate need to quickly analyze a situation, communicate and cooperate with each other, coordinate emergency response efforts, and find reasonable solutions for emerging problems. In this context, collaboration between humans and the machine teammate plays a critical role for implementing effective emergency response efforts that can save thousands of lives. Although this scenario still remains hypothetical, recent progress in artificial intelligence (AI) capabilities suggests that collaboration technologies may soon be more than just tools to enhance team performance; machines may become teammates [1]. For machines to be effective teammates, they will need to be more capable than today’s chatbots, social robots, or digital assistants that support team collaboration. They will need to engage in at least some of the steps in a complex problem solving process, i.e., defining a problem, identifying root causes, proposing and evaluating solutions, choosing among options, making plans, taking actions, learning from past interactions, and participating in after-action reviews. Such machine partners would have the potential to considerably enhance team collaboration.
The major challenges to successful collaboration include poorly designed tasks, ineffective collaborative work practices, and inadequate information systems that are unable to facilitate teamwork [9]. Our understanding of the role of technology progressed swiftly with the intensive research on collaboration technology in general and Group Support Systems (GSS) in particular. Much of the early research was based on the understanding that GSS design features and a few relevant situational variables facilitate team processes and outcomes [10,11]. DeSanctis and Gallupe [10] proposed a multidimensional taxonomy of systems as an organizing research framework to study the effects of GSS. At its core, the organizing framework differed between three levels of GSS systems [10]. Level 1 systems support communication in the team with GSS features such as anonymity or parallelism. Level 2 systems support information processing with GSS features such as voting or categorizing. Level 3 systems support task performance with GSS features that automatically guide the behavior of humans, such as imposing communication patterns onto the group, asking clarification questions, giving recommendations, or providing feedback [10,12]. The framework considered initially three critical situational variables as influencing factors: group size, member proximity, and task type [10]. As research progressed, additional factors were identified, such as virtuality (face-to-face vs. blended vs. online team) [13], synchronicity (synchronous vs. asynchronous interaction), or group facilitation [12,14,15]. But still, findings on the effects of GSS were inconsistent. In response to that, a new model was developed based on a meta-review that suggested that GSS performance (e.g., numbers of ideas generated, satisfaction, decision quality, and time) was affected by the fit between the GSS features and the task as well as with appropriation support in the form of training, software restrictiveness, and facilitation [16]. Even though research could demonstrate the potential positive effects of GSS on team performance when considering fit and relevant situational factors, practice showed to be reluctant in adopting and sustaining GSS infrastructures (R. O. [17]). As it turned out, the expert facilitator, who provided direct interventions into the team process to encourage faithful appropriation, was the key bottleneck to the diffusion of GSS [16,17].

The “missing-expert-facilitator” challenge has been the focus of collaboration engineering (CE) research [18]. CE aims at packaging facilitation skills and GSS expertise in such a way that reusable and predictable collaboration work practices can be designed and executed for recurring, critical work situations [18]. To enable such reusable and predictable work practices, CE developed the concept of thinkLets, which are scripted facilitation techniques that trigger predictable effects and group dynamics among team members that work toward a common goal (R. O. [17]). Practitioners can be easily trained in these recurring work practices without becoming expert facilitators [17]. A main difference to previous GSS research is that CE research builds on the philosophy that design decisions have to be made on multiple levels spanning people, process, information, technology, and leadership [19]. Briggs et al. [20] translated this philosophy into the six-layer model of collaboration (SLMC). It functions as an organizing scheme for the concepts and methods of collaboration science that build the basis for the required design choices that have to be made. These layers comprise (1) collaboration goals, (2) group products, (3) group activities, (4) group procedures, (5) collaboration tools, and (5) collaborative behaviors. Similar to other layered models, layers in SLMC are interfaced with the ones that are above and/or below. Each layer attempts to make transparent the available design choices one has for the design of collaborative work practices based on relevant literature synthesized from different research streams [20]. This should help collaboration engineers, who design repeatable work practices, to make the necessary design decisions layer by layer to reduce cognitive load and increase performance [21].

The progress on the interplay between facilitation, collaboration technologies, and other influencing factors provides relevant insight into the effects of technology on team outcomes, such as improved knowledge sharing, task performance, satisfaction with process and outcomes, or shared understanding [22]. Despite these gained insights, effective IT-supported team collaboration remains a challenge because of multiple reasons. Collaboration engineers are expensive and rare...
which leaves practitioners that are usually domain experts but not professional facilitators, with the challenge to plan their meetings themselves and an increased potential to fail [18]. Additionally, the organizational context in which collaboration takes place changes tremendously in the time of digital transformation. Many organizations have adopted Open Innovation as a problem solving model to outsource their idea generation, convergence, and/or evaluation processes to the crowd [23,24]. Facilitating a crowd may differ considerably from teams because (1) individual crowd members are unlikely to interact with each other, (2) they may be anonymous to the sponsoring organization, and (3) crowd tasks are usually of short duration. Moreover, temporary impromptu and action teams, which refer to groups that form unexpectedly [25], are increasingly characteristic for novel collaboration settings. They differ from traditional teams as they may not follow pre-designed command structures, may not have a central authority, or may form only for a short duration. Finally, collaboration practice and research are about to face off with yet another disruptive force: the machine teammate entering AI into team collaboration that has the potential to alter and advance our understanding of collaboration as once GSS and CE did. The machine teammate is an autonomous, pro-active, and sophisticated technology that draws inferences from information, derives new insights from information, learns from past experiences, and provides predictions to unstructured problems, plus participates in cognitive decision making with human actors. Such a machine teammate may be an important technology to deal with in current designs and investigations of team collaboration. But what do we know today about intelligent machines in team collaboration?

2.2. AI joins the team

AI refers to the capability of a machine or computer to imitate intelligent human behavior or thought [26]. How this machine should behave or think, though, is disputed: should an AI be completely rational or incorporate social, emotional, or ethical considerations? Affective computing is a subdomain of AI, which investigates how AI learns to incorporate and understand emotional signals from humans, such as happiness, anger, or deception [27]. A rational AI, by contrast, would always base its decision-making on optimizing its objectives, rather than incorporating social or emotional factors.

AI has become more ubiquitous because of the increased accessibility of hardware and software that run large dense neural network training algorithms (also called Deep Learning), which mimic the neural architecture of the brain. These algorithms can be trained on unstructured data such as images, audio, or text, and have revolutionized the degree to which machines can learn to reason, classify, and understand. Currently, these algorithms are specific to narrow task domains, such as speech recognition, image classification, human emotion, and characteristic recognition. For example, the humanoid robot NAO can adjust its behavior based on the identified gender of its interaction partner [28].

Human–AI interaction requires more than just smart algorithms. It requires actual coordination of complex activities such as communication, joint action, and human-aware execution [8,29] to successfully complete a task, with potentially shifting goals, in varying environmental conditions mired in uncertainty.

With such rapid improvements to AI, ethical and moral challenges posed by AI are receiving greater attention as well. Answers to questions such as “what moral code should an AI follow?” [30] and “what unintended consequences could result from the technology that threaten human autonomy?” [26] are being examined. The optimal conditions for humans and truly intelligent AI to coexist and work together have not yet been adequately analyzed. For example, when expert polygraph examiners collaborated with an AI to detect deception, the human examiners did not improve their deception detection accuracy [31]. Instead of helping, the AI threatened the self-efficacy of the human experts by challenging their decisions, and as a result, the correct AI recommendations were disregarded. Similarly, the humanoid robot NAO has been found to influence acquiescence in children such that the children confirmed with the opinion of the robots instead of their own judgment [32].

These limited examples allow us to draw some inferences regarding the future of collaboration with machine teammates. As with the illustrations, mixed results can be expected with regard to the effects of machine teammates due to the diverse collaborative environments that AI will be used in. It is possible that machine teammates will be designed with different collaboration capabilities. Additionally, teams may develop different norms regarding the use of a machine as teammate or organizations might rely on different regulations for machine teammates. Hence, different implementations of a machine teammate in a team and an organization will most likely result in different effects. With this in mind, it appears meaningful to formulate a research agenda to structure future research efforts in our quest to generate cumulative knowledge on AI in team collaboration.

3. Method

We conducted a survey with 65 collaboration researchers to collect research questions on machine teammates. We used these research questions to develop a research agenda on the design and effects of AI machine teammates in team collaboration.

3.1. Survey design

The survey consisted of three parts. The first part aimed at getting participants into a creative thinking mode to envision a future where machines will be our teammates. We offered participants a fictional scenario, which aimed at describing a machine teammate in action:

A Category 5 Hurricane is sweeping over Florida. Jim, the severe weather technician, Mike - his boss, and Kate the AI Weather expert check the latest damage report of sensitive infrastructure to hospitals, main streets, and bridges. Jim is worried that the widening cracks in the concrete columns of the highway bridge, as reported from the sensor devices, may collapse. He wants to send one of the robots—smart ant-like robots—that can navigate in hurricane 5 winds and are equipped with a variety of tools. But, Kate is not convinced and explains: “The Bayside medical clinic has 30 critical care patients. The clinic’s power generator is down and the storm surge is expected to hit the clinic in 20 min. There is a 93% greater likelihood of loss of life if repair ants do not reach the facility in time. So, the repair-ant is needed first at the clinic.” Jim looks at Mike, “What do you think?” he asks. Mike looks thoughtful, “I had a repair-ant scheduled for maintenance tonight. It might just have enough 3D printing material left to produce gum for the most important cracks in the bridge” he says. “We might just be able to pull both the repairs off.”

To foster shared understanding, we defined machines as teammates (MaT) as “those technologies that draw inferences from information, derive new insights from information, find and provide relevant information to test assumptions, debate the validity of propositions offering evidence and arguments, propose solutions to unstructured problems, and participate in cognitive decision making processes with human actors”.

In the second part, we asked participants “What research questions (RQs) will the collaboration community have to answer to move from our current state-of-the-art to the future we envision with machines as teammates?” First, participants engaged in a free brainstorming [33] activity where they provided as many research questions as they could think of. When they moved to the next page, participants engaged in a
brainstorming activity with prompts. We adapted the brainstorming technique LeafHopper [34] using the following categories as prompts: affective, cognitive, communication, economic, ethical, organizational, physical, political, societal, technical, and other. An example prompt was “What technical research questions must we answer to have machines as teammates?” We selected the categories to cover a broad range of aspects of the socio-technical system of a machine teammate to stimulate researchers’ creative thinking. The variety of categories should ensure that researchers with diverse backgrounds, yet a shared interest in collaboration research, could contribute to the brainstorming task.

In the third part, we collected demographic information from participants (career level, expertise, gender, and country) and solicited additional qualitative feedback. Participants could also opt-in with their e-mail addresses to receive results from this study.

3.2. Sample

The survey was sent to collaboration researchers around the world. We had three subsamples: first, we invited authors of the HICSS 2018 conference through its mailing list. Second, we invited 96 collaboration researchers that we deemed to be domain experts in their areas of HCI, CSCW, or IS research. Third, also the authors could provide questions, as they are representative of the domain CE. The survey was accessible from February 28th to March 19th 2018. We received 65 responses (8 by co-authors, 42 by domain experts, and 15 by HICSS authors) that were later qualitatively analyzed within the authoring team. Respondents submitted a total of 819 ideas for research questions.

The idea frequency table (Table 1) shows the number of received contributions per category and per participant group. In the first step (FreeBrainstorm), we received 270 contributions. In the second step (LeafHopper), we received 549 additional contributions.

Demographic questions were not mandatory and therefore missing values were expected. Participants were primarily full professors (31%), male (45%), and from Europe (34%) (see Table 2).

3.3. Analysis procedure

We received a rich set of responses (N = 819). As expected, some of these ideas were redundant. Some ideas were on different levels of abstraction. Moreover, many ideas were not stated as open-ended or closed-ended questions but rather as statements and/or opinions. Therefore, we developed a multistep analysis procedure, which was in essence an iterative approach of qualitative content analysis consisting of content structuring and inductive theme analysis [35].

In step 1, three of the authors organized a subset of one hundred ideas into inductively derived categories to lower information overload. The preliminary categories were: machine artifact design, individual, social, organization, and society. Two of the co-authors and four additional graduate and PhD students used these categories and organized all remaining ideas using the collaboration system Think Tank. Then, all co-authors met virtually to discuss and explain the meaning of category labels. Subsequently, subteams of at least two co-authors were assigned to each category to evaluate the ideas in a category and determine whether they were a good fit for the category. If an idea was found to be a poor fit, that idea was moved into the category that was deemed to be most appropriate.

In step 2, each subteam categorized the ideas from their category pool into common themes. Themes were for example “appearance” in the category “machine artifact design,” “trust” in the category “group,” or “cost and benefit” in the category “organization.” The subteams also resolved differences in abstraction for their themes and selected the research questions for their category that were considered as representative for the themes. To further reduce information overload, the subteams removed redundant or merged highly similar ideas.

In step 3, the authors recognized a duality aspect inherent to many of the themes, e.g., benefit vs. threat, good vs. bad, and chance vs. risk. A duality refers to “an instance of opposition or contrast between two concepts or two aspects of something.” [36]. The coding continued with the analysis lens of dualities. Dualities were deduced from associated research questions that signaled ambivalence with respect to the direction with which MaTs affected theoretical concepts. Then, the authors selected the theoretical concepts that previous research had satisfactorily operationalized and that could be used in future empirical collaboration research to investigate the effects of MaTs. The following provides an example of the coding (Table 3):

Each duality expresses a paradoxical effect that arises from machines entering as partners into human team collaboration. The paradoxical effect could exist 1) within a theoretical concept with different manifestations (concept dichotomy) or 2) between two concepts (association dichotomy). An example of a concept dichotomy in human–machine collaboration is that a human could accept the technology (i.e., machine teammate) or reject it. In that sense, the theoretical concept is “technology acceptance” and the dualism exists in the notion that technology is “accepted” or “rejected.” An example of

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an association dichotomy in human–machine collaboration is a machine teammate that might receive acknowledgement for a job well done, which could lead to higher team expectations. In this case, “work acknowledgment” and “team expectation” represent associated theoretical concepts. The dichotomy describes that the associated concept changes as the base concept changes. Overall, the coding resulted in 17 identified dualities.

Only the categories machine artifact design, group, organization, and society remained with their themes. These themes did not address dichotomies but raised aspects of design for human–machine collaboration, e.g., the theme “sensing capability” within the category “machine artifact design.” We merged the categories “organization” and “society” into “institution.” Three categories (machine artifact design, collaboration, and institution) remained, which we refer to as design areas.

4. Design areas for AI human–machine collaboration

The first part of the results addresses the design areas for AI human–machine collaboration. The analysis revealed three design areas, which are machine artifact design, collaboration design, and institution design. Each of these design areas Shortly describes design challenges and provides exemplary research questions. Core topics from the original research questions are used to argue for the themes. In that sense, a core topic can be identified with an ID such as 236.3. The first three numbers refer to a randomly assigned user ID, and the last number is a running count of the user contribution. In this case, the original voice refers to user with ID 236 and his/her third submitted contribution. All collected contributions are provided in the appendix.

4.1. Machine artifact design

This design area is concerned with the diverse possibilities that exist to design a machine teammate. It consists of seven identified themes that, in turn, connect similar or closely related design choices of a machine teammate. Although the overall design will affect and will be affected by team collaboration, these consequences are not in the focus of the design areas. The potential consequences will be presented in Section 5.

Appearance. This theme addresses the question how a machine teammate should look like (178.3). Design choices need to be made to whether the machine teammate should have a gender and which (231.7), whether it should appear as a cartoon, avatar, or human-like (231.9, 256.1), whether it should have a personality (231.12), or whether humans should communicate via text or speech (168.1). These contributions are summarized in the following research question:

- How should a machine as teammate look like?

Sensing & awareness. This theme highlights what kind of sensory information, e.g., camera, heat, movement, heart rate (179.5), smell, or touch (272.3) a machine teammate should be equipped with. Moreover, research questions in this theme highlight to what extent machine teammates could infer emotions (221.6), interpret body language (221.2), and understand intention from text and interactions (220.2). We summarize this theme in the research question:

- How can machines as teammates sense their environment to become aware of their surroundings?

Learning and knowledge processing. This theme concerns how machine teammates should learn and share their learning with their human teammates (178.4). Besides building and maintaining a knowledge base (179.6), learning also addresses how machines can read body language (221.5), differentiate between serious requests and social chatter (220.3), set and attain goals (265.6), or have moral principles (235.5). Machine teammates could possess tremendous recording capacities (289.3) to remember the history of their interactions with different human teammates (235.4), and improve upon their experiences (268.4). It might also become important that they can forget (331.7). The corresponding research questions are:

- How can a machine as teammate select and acquire data that it can process?
- How can a machine as teammate learn to process and forget information?
- How can machines as teammates learn and how can they share their learning with their collaboration partners?

Conversation. One central capability of a machine teammate could be the ability to interact and socialize with their peers (256.2, 215.3, 168.3). This could concern the ability of turn-taking (179.7), understanding irony (220.4) or jargons (189.3), being polite (168.2, 185.9), or politically correct in their interactions (167.1). The summarizing research question is:

- How can we design the verbal and nonverbal communication from the machine, so that it fits the collaborative situation?

Architecture. This theme highlights the key architectural components for a functioning machine teammate (256.3). This might concern the questions on what kind of devices (231.13), e.g., distributed on-device deep learning architecture (189.4), the machine teammate will run, if it will be miniaturized (189.4), or if it will have an emergency “off/on” button (327.7). Moreover, the production and use of a machine teammate might create considerable demand for energy (220.6), which needs to be considered in its architecture. This is captured in the following research questions:

- What are key components of a machine as a teammate and how do they relate to one another?
- How can we design energy efficient machine teammates?

Visibility and reliability. To determine flawed behavior of a machine teammate, (203.3), designers could make deep-learning algorithms understandable for humans (237.2) so that they can explain their recommendations (256.4) and can be reviewed by humans at various stages (237.1). To ensure the reliability of a machine teammate, designers might need to find ways to determine when behaviors of the machine actor become flawed or when the machine actor develops undesirable intents (303.3). Alongside this, designers could also consider the need to transfer the machine teammate’s “personality” in case it breaks down (220.8). The derived research questions are:

- How can machines as teammates explain their actions?
- How can we build systems that are sufficiently reliable and make...
transparant how reliable they are for each suggestion they make?

4.2. Collaboration design

This design area is concerned with the design of the team, task, and collaboration process. Hence, the focus shifts from the machine team-mate to a team collaboration setting with human actors.

**Team design.** Future human–machine teams could be designed based on the core competencies brought in by humans and the core capabilities of machine teammates (181_7). Machine teammates might not only actively participate in problem solving (220_9), but eventually also adopt the role of a leader (264_8). Moreover, design choices might need to consider the size of the team (168_4, 231_16) and if the team is collocated or virtual (262_3). These research questions summarize this aspect:

- What is a good division of labor between machine teammates and human teammates?
- What is the ideal team size for machines as teammates for a specific task?

**Task design.** Human–machine teams could be designed based on the types of tasks that are most suitable for such mixed teams (168_5). Machines might possess general collaboration capabilities to actively engage in collaboration or capabilities for very specialized tasks (220_10). Some collaboration tasks might be more likely to become automated (181_5) while some tasks might be limited to humans only (256_6). Such aspects are reflected in these research questions:

- What are the criteria to decide whether a task can be executed by a machine, human, or through human–machine collaboration?
- How can we identify applications and problems that can benefit from the integration of human and machine knowledge?
- How can we decide between general purpose machine actors that can do anything and highly specialized machine actors built for a specialized role or task?

**Work practice design.** Machine teammates could be trained for specific collaboration processes, such as coordination, knowledge sharing, or evaluation (167_3), which might spark changes in creativity, groupthink, or problem solving (225_3). The mode of communication (voice or text) might influence the effectiveness of these collaboration processes greatly (231_20). When collaboration technology changes its role from tool to partner (171_3), it might become necessary to find new approaches to model and engineer the new collaboration and decision-making processes (171_2, 175_3). This is captured in the following research questions:

- How can we engage machine teammates in collaboration processes?
- How can we systematically design machines as teammates in a human-centric way?
- How ready are our tools and techniques for engineering collaborative processes for modeling future collaborative processes?

4.3. Institution design

This design area addresses questions related to the design of structures and rules for organizations and society.

**Responsibility and liability.** Machine teammates might perform actions (261_4) or make decisions (244_2) that cause problems (319_19). Organizations as well as federal governments might need to clarify, if the machine, the designer, or the human teammates are responsible and liable (261_5, 171_4). The rights and obligations of machine teammates and other stakeholders need to be clarified (178_13). Therefore, design choices relate to the definition of policies, regulations, and laws for machine teammates (327_10). These questions summarize this aspect:

- Who is accountable for the decisions of machines?
- What governance approaches are needed to set up a machine-as-collaborator work context?
- What rights and obligations do machine teammates have?

**Education and training.** When machine teammates join the team, humans will most likely need to adapt and change. Organizations could facilitate this change by training people in the required collaboration competences for collaborating with machines (178_10). On the societal level, we might see changes to education programs so that students become savvy in developing and working productively with machine teammates (175_5) and validating them (236_6). The associated research questions are:

- How can we change our education programs to develop student competencies for working with machine teammates?
- How should people be trained to collaborate with machine teammates?

Fig. 1 summarizes the three design areas: machine artifact design, collaboration design, and institution design, and lists the major design choices for each area.

5. Dualities in effects

The second part of the results addresses the dualities in the form of concept dichotomies or association dichotomies that could arise from AI human–machine collaboration. A concept dichotomy refers to the paradoxical effect that designed AI team collaboration has on a theoretical concept. An association dichotomy refers to the paradoxical association between two theoretical concepts in designed AI team collaboration.

5.1. Concept dichotomies

We found several potentially conflicting consequences for the use of machine teammates. Machine teammates might change the affect, knowledge, technology acceptance, trust, and group dynamics among teammates. Machine teammates might also change human health or job availability in organizations or within the society. We refer to these kinds of dual effect phenomena as conceptual dichotomies, which are described in more depth in the following.

5.1.1. Affect positive/negative

This dichotomy describes the positive and negative emotions that humans might feel when machine teammates join the team. In case machine teammates can understand and react to human emotions (179_10), they could build emotional bonds with humans (233_13) and show empathy or provide emotional support (264_14). Yet, there might be cases where humans feel inferior, feel a lack of belonging, or feel they lose status (220_34, 231_32). This might negatively affect their self-esteem (189_13), induce emotional stress (178_28), and increase...
anger and frustration (178,27).

- How do we deal with anger and frustration against machines as teammates?
- Under which conditions will people enjoy working with a machine teammate?

5.1.2. Team knowledge augmented / depleted

One of the intended effects of AI collaboration is to relieve human teammates from some of the mundane tasks that a machine can do better (e.g., calculations, information retrieval, and pattern recognition). Machine teammates will need to explain and visualize their suggestions (224,5) to augment human intelligence (227,5) and support the team in coming up with conclusions (207,19). Machines might even be able to fill structural holes (319,26). At the same time, there exists a risk that certain competences vanish (167,10, 189,14) or that humans become dependent on machines (227,5, 227,6). For example, with interfaces becoming voice enabled, we might see decreases in the human ability to read (225,11).

- How can artificial intelligence be used to support decision-making without depleting human knowledge?
- To what extent does (emotional) intelligence increase or decrease when machines join collaborative work?
- Under which conditions can and should machines augment humans’ cognition?

5.1.3. Technology accepted/rejected

We currently lack an understanding of the conditions under which humans accept machines as teammates, for example, whether they are more likely to accept a humorous or a serious machine teammate (167,11) or a machine teammate that supports coordination tasks or creative tasks (171,11). At the same time, we might see that humans reject technology because they do not take the machine teammate seriously (302,5), they do not want to obey to a machine that assigns tasks (347,9), or have technophobia in general (268,10). Additionally, a person’s cultural disposition might affect to what extent they accept or reject technology (175,18).

- To what extent will human collaborators accept the input from machine collaborators?
- To what extent do different styles of verbal and nonverbal communication affect the acceptance of the machine collaborator?
- Which machine-generated recommendations and solutions will individuals accept when they are the ones to carry out the work?

5.1.4. Trust built/lost

Trust could concern trust in the machine teammate (178,29), trust in its recommendations (256,20), or trust in its underlying algorithms (274,12). A machine teammate could change how we build trust with other humans (319,28) when we start to trust a machine recommendation more than a human recommendation (175,19). We might lose trust in the machine teammate when it contradicts a human (312,37) or when a human experiences certain emotions (312,38). We might lose trust in a machine’s recommendations when the associated decision is particularly difficult (e.g., life or death) (312,39).

- How much should we trust the machine teammate’s insights and recommendations?
- How does contradicting the human affect the human’s trust in the machine?

5.1.5. Group dynamics positive/negative

When machines join the team, they might be trained to identify certain group dynamics (167,12). They could help to foster team cohesion (347,11) but create negative group dynamics such as conflicts (178,30, 207,20).

- How do machine teammates influence group conflict?
- What group dynamics should the machines be able to assess to foster improved team performance?

5.1.6. Health enabler / risk

Machine teammates could contribute to the safety of humans, particularly in collaborative industrial teams (262,11) where they can use their physical strength (274,13) to protect humans. Equipped with sensors (274,13) and several safeguards (319,29), they could additionally foster the well-being and fitness of humans (189,15). At the same time, machine teammates could be a risk for humans as they might threaten the psychological health of humans (167,13) or leave dedicated areas (220,42) where they might harm humans.

- How can impact the psychological health of human co-workers?
- How can we insure the safety of humans in collaborative industrial teams with robots?

5.1.7. Jobs created / cut

When a machine becomes capable of performing certain tasks, organizations might require a smaller human labor force (175,21). This might be particularly true for highly repetitive tasks that require low skilled workers (267,15, 272,13). At the same time, new jobs might be created or humans could focus on certain more complex tasks in existing jobs (319,31). These jobs might be highly creative (267,14), require logic and rational thinking (272,13), or specialized skills (267,15).

- How can we deal with the reduced availability of low-skill jobs for humans that will result from increasingly capable machines?
- Do machines as teammates replace jobs or repurpose them?

5.2. Association dichotomies

The use of machine teammates should empower teams to achieve superior collaboration results. Machine teammates could become creative, efficient reasoners. They can also be human-like and adaptive. In addition, teams with a machine teammate might benefit from improved decision making, quicker task accomplishment, increased acknowledgement for their work, could receive more responsibility, and could have more transparent team processes. Organizations might benefit from machine teammates because they drive new value creation. Yet, once this is improved, new state of a theoretical concept is achieved, and a dark side of human–machine collaboration might emerge that is detrimental to another, associated theoretical concept.

5.2.1. Higher quality of decision making – reduced capability to criticize

Machines might be able to solve the problem of poor decision making in collaboration environments characterized by information overload. A machine teammate could improve information processing by mitigating negative cognitive biases (167,5) or effectively identifying reliable, accurate information (215,4). When contributions of a machine teammate are constantly useful and decisions are, in fact, improved (266,9), we might face a new problem, where humans become dependent on the automated machine algorithms and become passive information seekers (225,6).

- How can machine teammates be used to overcome human cognitive biases in decision making?
- How can a machine teammate determine how reliable, accurate, or truthful the information source is?
- How should humans interact with automated procedures without losing the ability to analyze and criticize?
5.2.2. Increased pace of work – increased cognitive overload

Machine teammates might increase the pace of collaborative efforts (167,6). They could be always “on” (221,9) and perform tasks while human teammates return to their private life. They might also be fast (256,12) because of their computation advantage over humans in certain tasks (235,8). Although it might be beneficial for a team to accelerate certain work tasks, e.g., information seeking, this could also spark an unintended challenge. Machine teammates might explain their reasoning insufficiently (178,20) for a human to understand, which might lead to misunderstandings between humans and machines (233,7) and increased demand on cognitive effort to sort out misunderstanding. Humans might need to rest while performing effortless tasks (269,15) and might need to adapt quickly to new tasks (236,9). This could be overwhelming for individuals as machine teammates are unable to deal with humans’ limited cognitive capacity (178,21).

- If MaT increase the pace of collaborative efforts, what positive or negative effects might such increased pace entail?
- How can we ensure transparency and speed of machines’ decision preparation processes to match human decision makers’ cognitive capacity?

5.2.3. Increased creativity – lack of serendipity

Machines might autonomously generate creative solutions (224,3). To do this, they need to gather insights that can be justified with data (201,1) or help highlighting disagreement among participants (215,5). Yet, many algorithms gain “insights” by assessing closeness and similarity of events, people, etc. This might create the problem of reinforcing existing views (225,7) decreasing the out-of-the-box thinking.

- As the relationship between machines and humans becomes more intertwined, how do we ensure that humans’ creativity does not become constrained?
- How should knowledge creation be dynamically shared between machines and humans?

5.2.4. More efficient reasoning – fewer human-driven decisions

A machine teammate might be able to draw inferences, give insights, and provide relevant information (256,14). If this is the case, they might become a more reliable source of information than experts or other people (221,11). They might become an integral part of our decision-making processes (244,4). When their proposal might be judged better than another human’s (289,10) because of, for example, calculated confidence intervals (312,24), their recommendations might become highly persuasive for humans. Humans might rely on machine teammates to such an extent that deskilling may set in, resulting in fewer human-driven decisions. Eventually, a machine teammate could often have the final say (312,23).

- How does a machine teammate determine if the information and insights he/she offers is relevant to the ongoing discussion with other teammates?
- What factors influence humans so that they rely on machine recommendations over time?

5.2.5. More work acknowledgement – higher expectations

We usually recognize and acknowledge good work completed by humans. However, also machines might provide important (intellectual) contributions to the team (201,3), which, according to this logic, would get recognized and rewarded (207,16). If so, employers might expect more from teams with a machine teammate and increase their workload (231,22). At the same time, machine inputs might be misappropriated, if proper credit is not given (302,4).

- How should machines be rewarded with their contribution to the projects?
- Will employers expect more from employees who are part of teams with machine teammates?

5.2.6. More anthropomorphism – more manipulation

When we collaborate with machine agents, e.g., in the form of avatars or robots, we tend to associate human-like characteristics to these nonhuman entities (called “anthropomorphizing”). This way, humans might start to like and accept the machine counterpart (231,23). Yet, other humans might exploit this kind of trust and manipulate or trick (231,24) other humans. Humans might manipulate others with the help of machine teammates (233,10) to strengthen their own position in a team (175,10). Hence, it might become important for machine teammates to have “certain characteristics that make them distinguishable as machines” (168,6). This might lower the likelihood that a machine “disguises” (171,7) itself as a human collaborator.

- How should human-like machine teammates appear or what characteristics should they have to be useful and likeable partners?
- Should machine collaborators be clearly identifiable as being machines or is it better to “disguise” them as being human collaborators?

5.2.7. More responsibility – loss of control

If machines are more helpful, process more information, and have better answers than humans (221,13, 256,15), employers might consider assigning machine teammates more authority (221,13) and responsibilities (237,7). This might create problems with control. If employers consider replacing a human teammate with a machine teammate due to good performance (256,15), humans might fear that machines take over (171,8). If people take the back seat and let machines perform tasks that until recently only humans were able to do, human teammates may feel inferior (267,4), have only nominal control (189,7), and may feel that an informal transfer of power and leadership may set in (189,8, 272,6).

- Should a machine get more authority if has better answers than humans, or if it can process more information?
- How can machines help individuals to have more power or influence in a team process?

5.2.8. More visibility – loss of privacy

To achieve effective collaboration and personalization (220,20), algorithms of machine teammates need to become transparent and controllable (225,8, 227,4). Data collected might comprise data from built-in cameras (185,15), about human teammates (225,8), but also confidential project information (207,17). With this increase in visibility, problems of privacy might emerge (175,11). Teammates might feel monitored and surveyed (175,12, 220,21) increasing the need for safe guards (175,11) and rules of confidentiality (207,17).

- How can we ensure data collected about a person and the inferences made based on them are transparent and controllable by the person?
- What safe guards need to be in place when organizations use machines that access confidential information?

5.2.9. Higher adaptiveness – more misbehavior

Machine teammates might require highly adaptive personalities to fit the individual preferences of their teammates (167,8) or a specific situation (235,13). Adaptiveness might refer to the emotional expressions (236,10), personality (171,9), use of communication channels (207,18), or bending the rules from time to time (220,28). When their learning algorithms are highly adaptive, machine teammates might also learn bad behavior from their human counterparts. They might express aggressive behavior (220,24), have prejudices (220,25), send nasty messages (231,28), or become biased (215,11).
• How can we allow machine teammates to learn from their perceptions without the fear that they learn bad behavior?
• How can machines build up something like a moral conscience?
• How can we teach machine teammates to “bend” the rules from time to time, without the fear that they will use it against us?

5.2.10. Higher value creation – extreme power shifts

Machines as teammates might affect humans beyond team boundaries. Machines might create organizational value, because they could improve an organization’s productivity (226,11), be commercialized (175,15), or rented (185,17). Some costs might occur, such as investment costs to acquire/build the technology (262,9), paying taxes (220,30), or retraining workers (262,9). However, it could be that these costs are considerably lower than the labor costs of the human workforce. This could trigger substantial power shifts among societies, organizations, and humans. Machine teammates could cause power differentials as they might improve the national strength (289,15) or help create more monetary or cognitive resources (225,10). Those who have machines (178,25) may become more powerful while those without a claim to ownership may lose power and prosperity.

• Should organizations develop machines in house or will we have COTS AI?
• How much does it cost to hire/build machine teammates vs. human teammates for the same task?
• How do societies react to the shifts in power between those who have machines as teammates and those who haven’t?

Fig. 2 provides an overview of the 17 dichotomies presented above.

6. Discussion and conclusion

6.1. Novelty of the research agenda

The goal of this paper was to develop a research agenda that supports collaboration researchers investigating socio-technical systems where machine teammates collaborate with human teammates to achieve a common goal. Based on a survey of 65 collaboration researchers, we discovered three design areas that guide attention toward the conditions under which the designed AI team collaboration affects either the positive or negative side of 17 dualities. We combine the three design areas and the 17 dualities in a MaT research agenda, which is depicted in Fig. 3.

Already during the last “AI hype” in the second half of the 1980s, researchers speculated that AI may significantly support group collaboration. We can now update their speculations with far advanced knowledge on AI and on collaboration [37]. We propose that AI will not (just) be the functionality of a tool but rather a machine teammate characterized by a high level of autonomy, based on superior knowledge processing capabilities, sensing capabilities, and natural language interaction with humans. This raises a whole new set of design issues ranging from HCI (MaT appearance and sensing/awareness), classical AI (learning and knowledge processing, visibility and reliability, and architecture), and computer linguistics (conversation). In doing so, we reconnect collaboration research to modern computer science and debates in other areas of modern IS research.

We anticipate that the decisions made in the three design areas with their 12 themes will define the composition of the machine teammate and its environment. The three areas, machine artifact, collaboration, and institution, complement each other. Design choices in one of these areas will influence design choices in the other two areas. The research agenda encourages to consider variations in AI-based human–machine collaboration depending on the design choices one makes with respect to the machine artifact, the collaboration, and the institutional environment in which the collaboration should take place.

The MaT research agenda also strives to catch and structure the most relevant consequences of designed AI team collaboration. It was striking to see so many research questions that linked to positive and negative anticipated consequences. This ambivalence in predicted effects is in line with the argument that AI is a dual-use technology; it can be used for both beneficial and harmful purposes [2]. The MaT research agenda incorporates this ambivalence in its dualities, which are organized into concept dichotomies and association dichotomies. Hence, the research agenda emphasizes the interdependence between design choices and consequences, which are a key to unravel the ambiguous theoretical predictions inherent to the dualities. It has long been established that system designs affect team collaboration for better or worse [10]. Progress in GSS and CE added knowledge of how non-technical variables, such as facilitation, need to be designed and put into practice for improved team collaboration [18]. The identified MaT dualities differ as they add variables, e.g., negative affect and team knowledge depletion. They highlight potential effects that collaboration researchers have not necessarily focused on; they emphasize the dark side of AI team collaboration. Furthermore, dualities such as “jobs created/lost” or “higher value creation – extreme power shifts” represent consequences outside the team context and refer to organizational and societal concerns. In this sense, the research agenda differs from previous emphases as it stresses the need to build and test AI in team collaboration for beneficial consequences, not just for teams but also for organizations and societies.

6.2. Research implications

The outlined dualities and design areas could help collaboration researchers from different domains, such as information systems, human–computer interaction, or organizational psychology to design research investigations into MaT in the following three ways:

First, the dualities could provide anchor points for exploratory research within organizations that already assimilated machine teammates into their organizational processes. For example, investigating the dualities through multiple case study research could help shed light on the relevance of these ambivalent effects in practice and the conditions under which they emerge. This empirical evidence is essential for understanding which of the dualities matter under what conditions and in what professional environments. Additionally, such insights allow future research to focus on the most relevant problems of AI in team collaboration.

Second, researchers could use the design areas to typify the machine

![Concept dichotomy](image)

![Association dichotomy](image)

Fig. 2. Concept and association dichotomies.
Designing AI in team collaboration

<table>
<thead>
<tr>
<th>Machine artefact design</th>
<th>Collaboration design</th>
<th>Institution design</th>
</tr>
</thead>
<tbody>
<tr>
<td>appearances, sensing &amp; awareness, learning &amp; knowledge processing, architecture, visibility &amp; reliability, design methodology</td>
<td>team, task, work practice</td>
<td>Responsibility &amp; liability, education &amp; training</td>
</tr>
</tbody>
</table>

the design of AI team collaboration leads to effects in collaborative work practices

the analysis of effects leads to design recommendations for AI team collaboration

### Dualities of effects

#### Concept dichotomy
- Affect positive / negative
- Technology accepted / rejected
- Group dynamics positive / negative
- Health enabler / risk
- Jobs created / lost

#### Association dichotomy
- Higher quality of decision making – reduced capability to criticize
- Increased pace of work – increased cognitive load
- Increased creativity – lack of serendipity
- More efficient reasoning – fewer human-driven decisions
- More work acknowledged – higher expectations
- More anthropomorphism – more manipulation
- More responsibility – loss of control
- More visibility – loss of privacy
- Higher adaptiveness – more misbehavior
- Higher value creation – extreme power shifts

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Fig. 3. MaT research agenda.

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The findings of this study could already be useful for managers that intend to adopt or have already adopted virtual assistants, conversational agents, or other AI collaboration technology into their workplaces. In these situations, managers could consider themselves as organizational designers who could influence, for example, the composition of teams, the distribution of tasks, or the extent of inclusion in collaborative work practices. Both types of dualities enable managers to become vigilant what effects the introduction of highly capable AI might entail in human–machine work environments.

Also, designers could benefit from the use of the MaT research agenda as it outlines several design factors that can be connected to one or more dualities. For example, when a designer intends to create a trustworthy machine teammate (see, trust built/lost), the research agenda also draws the attention to the design areas of collaboration and institution that might be relevant. The different aspects of the design areas, e.g., visibility and reliability in machine artifact design, could serve as further guidance to perform more comprehensive evaluation studies that focus on the effects on the human workforce.

### 6.3. Practical implications

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### 6.4. Limitations and future work

This exploratory study has several limitations that should be considered. First, the study discovered three design areas, i.e., machine artifact design, collaboration design, and institution design, and identified dualities as consequences of the design choices made in these areas. However, the resulting research agenda cannot be considered “complete”. Additional research questions could be formulated for each of the parts of the agenda. This is inherent in the fact that the research questions and associated research agenda are based on the collective input from a selection of the collaboration research community. In this sense, the research agenda is the beginning, not the end. It is meant to inspire and inform future studies, not limit this area of study. We trust that future research will further extend the research agenda.

Second, the research questions and statements were sourced from collaboration researchers and not practitioners. This was intentional because a machine teammate, as envisioned in this study, has not yet been sufficiently studied in the field. Hence, the contributions can be considered as qualified opinions from a group of informants that are trained to be open-minded, neutral, and knowledgeable about the domain of interest here. Our results, however, might be biased toward what researchers find relevant to study and do not necessarily fully capture professionals’ interests. Therefore, future research could acquire evidence for the (non) existence of dualities from organizations that are early adopters of predecessors of machine teammates, e.g., a chatbot or a digital assistant.

Third, the indicated relationships between association dichotomies are partly based on interpretations from content analysis and were not necessarily stated as such in any single research question. The construction of these associations was frequently built based on multiple research questions and statements that addressed these concepts and sometimes also on different levels of abstraction. Moreover, it is not our intention to suggest any kind of causality between the theoretical concepts as we do not yet possess sufficient understanding to argue for the directions of effects. For example, our association dichotomy “more visibility – loss of privacy” could also be argued that more need for privacy might lead to less visibility. Future research should, therefore, explore to what extent the suggested association dichotomies are well correlated and can explain the changes in collaboration practices and
outcomes when a machine teammate is present.

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Appendix

This section summarizes the received research questions and their association to either design areas or dualities. A total of 215 contributions were categorized as comments, too general, or out-of-scope contributions and are not listed here.

Design areas

Machine design

236_3 Provide machines with strategies for understanding metaphors and contextual sentences
235_1 How do human teammates behave socially toward their machine teammates in different team constellations, e.g., with or without other human teammates?
215_2 Is it useful enough and compact enough that a person will want to take it with them all the time.
appearance
178_3 What should maintenance of machines as teammates look like?
231_7 Does the apparent gender of the teammate matter? Do other physical characteristics matter?
231_8 Does it matter if the teammate is unseen, i.e., just a voice or just text?
231_9 If seen, does it matter whether the teammate is a cartoon/avatar or looks like a real person?
231_10 Should the teammate have a physical (as opposed to virtual) form, i.e., is a physical robot?
231_11 Should a physical robot look like a real person?
256_1 How should the machine teammate look like? Should he/she be human-like or just an invisible computer system?
168_1 How to shape and utilize interfaces between machines and humans (e.g., text-based, speech, or nonverbalized)?
231_12 Are there individual differences in how people respond to a teammate? Does it vary by age, gender, personality, cognitive ability, and familiarity with computers?
235_2 Which communication mode (speech based, chat based etc.) is suitable for which kind of interaction?
185_6 Comfort: e.g., fluffy texture of teammate? What are implications here?
175_2 How do we visualize or embody machines as teammates?
225_2 What is the effect of different human-machine interfaces (touch, visual, audio, brain-computer, ...) on the effectiveness of the whole human-machine system?
335_1 How should the interfaces look like through which we communicate with machines?
347_3 How will individuals react to machine if those display, or not, emotions.
264_5 Which types of interfaces are human workers most comfortable with? (e.g., regular computer terminal interface or humanoid-looking robot)
264_6 Do different cultures prefer different interfaces?
269_5 Do they have mimics and a face?
274_5 Can machines be sexually abused? Is it better to give machines an asexual appearance?
275_3 How do we design the interface of intelligent cognitive assistants to make the collaboration between humans and machines more enjoyable and effective?
289_2 Should machines as teammates have an eternal body?
Sensing and awareness
179_5 What sensors should the machine use (just plain camera, Heat, Movement, or heart rate...)?
220_2 Machines need to understand when people are talking to them independently from a certain keyword (derived from context)
221_2 How can machines infer emotion from humans?
235_3 Should machines act emotional, empathic,... and how can we implement this?
269_6 Should machines be emotional at all?
189_2 Enable machines to represent and process human emotions and states-of-mind
221_3 See first question, machines need to infer intentions from emotion, body language, etc. they should probably also be able to communicate emotions
319_8 Should we design teammates to be empathetic?
221_4 How can machines interpret messages from humans to understand intentions?
272_3 There is a lot of technical growth in this area, currently visual (audio/image/text) and speech are the main inputs to machines, how about smell, touch, and intuition?
274_6 Nonverbal communication: body contact, how close should they come, do humans like distance or being touched by the machines?
322_1 As agents can imitate and read human emotions “even micro expressions,” how will this alter our relationship with our autonomous agents?
274_7 How good is speech processing, so that humans aren’t reminded every time a machine does not understand, that it is not human?
302_1 Human abilities such as talking or humor may make communication with a machine entity more familiar.
312_10 What is the role of machine agent “personality” in collaboration?
Learning and knowledge processing
179_4 How should machines as teammates learn and how should they share their learning with their collaboration partners?
185_7 What type of memory is required for immediate interaction and what type of memory to learn from?
268_1 When a human makes decision, the decision is based on several knowledge areas and disciplines with complex relationships. How a machine can be programmed to contain knowledge of different disciplines? What disciplines should be included?
266_5 Where are we going to get the data? Or how are we going to mine the data?
269_7 Can they learn while we communicate?
268_2 Can machine’s behavior and attitude be affected by the human collaborator (as seen in human teams)? If so, how it should be incorporated in the design process?
329_2 How to draw inferences from information?
319_9 Design – Supervised or unsupervised AI?
312_11 Are there scenarios where a less conversationally capable machine teammate produces better outcomes than a more capable one?
179_6 How do we build up and maintain the knowledge base of the machine teammates? How can the system learn?
207_6 Should the machines be designed with the capacities such as human brain or unlimited resources?
235_4 How can machine teammates remember the history of their interaction with different team mates and distinguish different team members?
268_3 Machines need to make subjective decisions based on their experience like human teammates. How this experience is gained by a machine as opposed to the experience and knowledge a human teammate gains through years?
289_3 Should machines as teammates have eternal recording power?
331.7. Capacity to forget
331.8. Capacity to deal with nuance?
289.4. Can machines as teammates understand the nuances of words correctly?
207.4. How should the machines form a structured problem from unstructured problem?
266.6. How can we train the machine to see us as people rather than another variable?
266.7. How can we train a machine to respond emotionally to how their human team members treat it?
329.3. How to analyze unstructured problems as human do?
185.8. What influences the development of teammates such as censorship, morale principles?
315.5. Whose values are embedded in the machine algorithm?
319.10. Morality – how to design Good Samaritan machines?
235.5. Should machine team mates mimic human behavior and emotions?
335.2. How to keep up social aspects of collaboration when involving machines?
346.8. How will ethical trade-offs affect research design in human/machine research collaboration?
319.11. Can we program machines to learn from each other how to be good teammates? If so, how?
265.4. If machines have goals, how do they obtain these?
265.5. How does goal-setting work for machines – are they equals or subordinates?
265.6. How do machines as teammates help me/my team/my organization in achieving our goals?
289.5. Can machines as teammates properly understand problems to be solved and share goals with humans?
269.8. Do they understand many languages?
319.12. Language – what kinds of language should teammates machine use?
221.5. How can machines read body language from humans?
220.3. Machines need to differentiate between serious requests to action and social chatter.
302.1. Information must be structured and made available in a machine-readable format, i.e., if we use emails for collaborative teamwork, the machine agent must be equipped with proper tools to understand such communication and be able to participate.

Conversation

168.2. What code of conduct is required for machines collaborating in teams with humans? Do machines need to be polite?
185.9. What influences cultural aspects in developing teammates, such as what is perceived as “polite”?  
189.3. How to enable machine to be part of development and use of private languages, e.g., office or family jargons
167.1. Should machines as teammates be politically correct in their interaction with and about other co-workers?
220.4. Machines need to understand irony
256.2. How should the machine teammate interact with his/her peers?
215.3. Clearly your machine would have to be able to explain to me anything in your questions: What is RQs? (for example) One issue is designing the ability to socialize with the participants as well as transmitting social aspects such as the commitment level to a concept.
179.7. How can the machine learn how to interact with others (e.g., turn-taking? expected length of response? …)
168.3. When more than one machine collaborates together in a mixed team of machines and humans, should the machines be able to communicate among each other in a way that is incomprehensible by humans (machine language)?
274.8. Understanding humor, sarcasm, the context is still too difficult
312.12. Should interactions with machine teammates reinforce human-to-human communication norms (politeness, etc.)?
319.13. Tone – should teammate machines have a sense of humor?
233.3. Machines might not be intelligent enough to understand physical languages and other subtle expressions, how to promote collaboration in this case?
312.13. How does the machine teammates conversational capability influence perception and behavior?
265.2. Natural language processing and interaction with humans in the sense of interfaces (not interaction as in collaboration…)

Architecture

256.3. What are the key architectural components of a machine that can function as a “teammate”?
231.13. What kinds of devices will the teammate best run on?
189.4. Miniaturization and distribution of machine learning models, e.g., as part of distributed on-device deep-learning architectures.
207.8. Should the machines have emergency button?
171.1. Are there technical limitations that must be coded into the machines to avoid harmful outcomes?
327.7. How do humans control the “off” switch?
220.5. Will we build environments for robots or will we build robots for existing environments (wheels vs. legs)?
220.6. How can we produce enough clean energy and batteries for all the machines without destroying our environment?
220.7. How can we further reduce power consumption for processing power while at the same time increasing processing power?
231.14. How to structure organizations, and how to best deploy the machines. Will they be personal assistants for each person, or will they be shared?
264.7. Who is going to configure the machines, manage them etc.?  
268.4. What design elements should be considered to create socially flexible machines as teammates?

Transparency & reliability

237.1. How can we create algorithmic processing so it can be reviewed by humans at various stages
256.4. Can the machine teammate explain his/her recommendations? How could he/she do that?
237.2. How do we make deep-learning algorithms understandable to humans?
269.9. Do we still understand the algorithms they are based on?
322.2. Autonomous agent “Responsibility and Trust”: The machine learning models that underpin autonomous agents need to be as transparent as possible. Autonomous agents need to be able to explain their actions or behavior that we can understand.
203.3. Who is in charge of acquisition, programming, testing, and determining when behaviors are flaws or just favor one stakeholder over another?
220.8. How can we transfer “personality” of one robot into a successor, if the original one is broken?
346.9. How will machines as teammates weigh reliability vs. validity issues?
346.10. How will machines teammates’ evaluation of reliability and validity trade-offs in studies affect the quality of human/machine research collaboration?
268.5. Machines work perfectly until they break down. A minor technical issue may cause a significant failure and collaboration issue. How can we keep these issues at the minimum level?
272.4. What are the techniques to fall back, in case AI is shutdown unexpectedly?
319.14. Data – what kinds of data should we use for training and how often should we update to ensure accuracy?
322.3. Autonomous agent “reliability” and “predictability”: As Autonomous agents are designed-based deterministic and non-deterministic decision-making algorithms, new system verification methods should be researched/studies. Because these agents operate in partially unknown adversarial environments and acting upon ambiguous information, new verification techniques are required to confirm that a system does not have undesirable behaviors or intents.
322.4 Cyber Autonomy: As Autonomous agents are designed based on adaptive- and reinforcement-learning algorithms, new cyber security methods should be researched/studies to avoid traceless cyber attacks

**Design methodology**

178.5 How can we design machines as teammates in a human-centric way?

175.3 How can we model decision making or collaboration processes where some part is performed by machines? To what extent is this different from people’s activities?

171.2 How ready are our tools for engineering collaborative processes (e.g., facilitation process model) for modeling future collaborative processes?

181.2 What is needed to model human–machine collaboration in a structured and understandable way?

171.3 Do you need to adapt current collaboration engineering basics (e.g., the COPDA) to account for the changing role of technology (from tool to partner)?

181.3 How does a workflow of human–machine collaboration look like?

312.14 What processes do people use to evaluate machines as teammates?

**Collaboration design**

231.15 Are there cultural/national differences in response to teammate?

203.4 What is work? What is the difference between play and work? For what purposes will teams be drawn upon? What roles will humans have available to play in contrast to roles that machines will play? To what extent will physical and cyber realms remain distinct (they already are starting to blur at the edges)?

261.1 Under what conditions could we collaborate with teammates, determinants, and enablers and inhibitors?

**Team design**

168.4 What is the ideal team size for machines as teammates?

231.16 When introducing a teammate, does team size (number of humans) matter?

319.15 How many teammate machines should an organization have?

312.15 What is the optimal ratio of human to machines in a team?

231.17 How do teams of humans compare in performance with mixed teams (or dyads)?

231.18 Is there any advantage in having more than one teammate?

178.6 What types of relationships do humans build with machines as teammates?

207.9 What role should the machines have in the relationship with “its teammates?”

262.3 What challenges are there in using this technology in virtual teams? in collocated teams?

220.9 How can machines not only passively answer questions but actively participate in a collaborative problem solving process?

331.9 What would lead the meetings?

335.3 How should human–machine teams be composed to reach optimal outcomes?

347.4 Management of teams comprises of people and machines

264.8 Who’s the boss? The human (emotions) or the machine (data)?

265.7 Hierarchy between humans and machines

265.8 Is there a hierarchy between human and machine teammates – so, do I need to negotiate with the machine, or can I tell it that it needs to know that “A is B?”

267.1 What impact will machines as teammates have on an aging workforce and are there differences in outcomes between digital natives and digital immigrants?

269.10 Does it make a team more efficient to have bots as teammates?

302.2 How does the presence of machine teammates influence the conversation in terms of a subjectivity–objectivity spectrum? (i.e., if we test two groups: one with only humans and the other one mixed, would we find that human-only teams tend to discuss subjective qualities of teamwork more than the other group? how does this influence end-results of the team work?)

312.16 When should a machine teammate proactively provide information, compared to responding only to human queries (e.g., Microsoft Clippy)?

264.9 Diverse teams and cultural implications – the machines have to be suitable for workers with different cultural backgrounds

181.4 Can competence profiles build the basis for a matchmaking mechanism that helps to create groups of humans and machines to solve specific tasks?

312.17 How well do people handle being outnumbered by machines in a team?

**Task design**

168.5 What kinds of tasks are most suitable for human-only, machine-only, or mixed teams?

236.4 How to identify applications and problems that can benefit from the integration of human and machine knowledge?

230.2 How to identify applications and problems that can benefit from the integration of human and machine knowledge?

181.5 What are tasks that have the potential to become automated/ executed by a machine and what are tasks that need to be executed by humans?

207.10 Can the machines participate in any/just only parts/procedures it likes in the projects?

256.5 What kind of questions can we ask the machine teammate?

181.6 What are the foundations and demands to decide whether a task can be executed by a machine, human or human-machine collaboration?

256.6 What are the limitations of the machine teammate?

256.7 What are the things the machine teammate can bring to the table?

256.8 What are the problems we typically ask a teammate in group discussion or project? How many of those can we ask a machine teammate?

261.2 For which tasks machines could help?

167.2 In which domains will we see machines as teammates?

178.7 What collaboration infrastructure do we need to include machines as teammates into virtual/physical collaboration?

269.11 What are the most useful areas to use machines as team mates?

269.12 Are there areas where we should not use them?

319.16 Duties – what kinds of duties should machines have?

319.17 What areas do we want teammate machines to influence and how should we develop them to do so?

181.7 What are the core skills competences of AI? What are the core competences and skills of humans?

220.10 How can we find a good compromise between general purpose AI that can do anything and highly specialized machines built for a single purpose?

221.6 What tasks can or should they represent?

221.7 What tasks can a machine represent in a decision-making process?

236.5 How to organize decision-making procedures in presence of conflicting requirements?

227.2 How will the orchestration work in the way addressed in the RQ above, and how will people/machines/hybrid teams work together?

**Work practice design**

256.9 What are the organizational processes the machine teammates can be a part of?

233.4 We should also consider various degree of collaboration.

231.19 How does introducing a teammate affect team process?

178.8 What effects do machines as teammates have on collaboration processes?

167.3 For which communicative group processes (e.g.,
coordination, knowledge sharing, and evaluation) should machines be trained?

225_3 What is the effect on different group processes (creativity, group think, and problem solving) when intelligent agents are involved?

231_20 Does the mode of communication (spoken, written) affect how the real person relates to and works with the teammate?

233_5 In the case of joint projects, how to ensure smooth communication?

227_3 How can we orchestrate human robot teams to enhance cooperation?

261_3 How to coordinate tasks with machines?

185_10 Differences when working in organizational environment: hierarchy implemented in communication and behavior (e.g., CEO vs. employee)

268_6 Do machines learn the team process at the same pace as human teammates or they are already pre-programmed to know the team rules and norms?

Institution design

Education and training

175_4 What needs to change in our education programs to have students become savvy in working with AI machines?

175_5 What needs to change in our education programs to train students to develop productive AI?

225_4 How to make learning in educational institutions and beyond design oriented so that education becomes an enabler and shaper of digital transformation rather than a follower?

225_5 What are the skills and competencies that need to be acquired in the educational system, and how to best ensure these skills are acquired?

236_6 Evolving educational programs to include skills for designing, interacting with and validating intelligent artificial agents.

256_10 How to train people to collaborate with the machine teammates?

178_9 What collaboration capabilities do humans need to build to engage with machines as teammates?

178_10 How can we help humans to build such collaboration capabilities?

178_11 What second- and third-level learning effects can we expect from humans and from machines as teammates and how should we best address them?

178_12 What organizational capabilities do we need to build to include machines as teammates?

347_5 Training to working with these machines

267_2 How can we best implement training (acceptance of training and transfer of training) for working with non-human teammates?

275_4 Which skill set do human employees have to develop to maintain their employability?

319_18 Training – how should we train and how often?

322_5 Long-term training and education system redesign when agents can conduct mass decision making tasks in our society

262_4 What legislation can be passed to provide retraining of people who have been replaced by the technology?

265_9 What “educational” methods from the educational sciences need to be transferred to machine learning to teach robots what kinds of goals and approaches to living are “valid,” valuable, and will make them appreciated (is that even something that robots would aspire to?)

327_8 How do children’s abilities fully develop in a world where the cognitive/affective load for learning is born by the machine?

Responsibility and liability

233_6 Will machines be responsible for what he did/what he said?

261_4 To which extent machines are responsible for their acts, risks, and ethics?

261_5 Responsibility in case of problems – who is responsible: the machine or its designer?

262_5 Who has responsibility for systems/robots relying on AI. For example, if there is an accident involving a driverless car, is the manufacturer of the car to blame or the system designer for the system running the car? etc.

244_2 Who is responsible for the decisions of machines?

171_4 Will a human collaborator always be in charge and “responsible” for the result of the collaboration process or can this “responsibility” be transferred to an AI collaborator?

178_13 What rights and obligations do machines as teammates have?

331_10 Who should be punished for a wrong decision?

335_4 Who is held responsible for decisions made in human-machine collaboration?

268_7 Machines are not responsible for their deeds. How can be one responsible for a mistake made by a machine that happen to have significant negative social impact?

269_14 Who is responsible for the input or decisions?

319_19 Responsibility – who’s to blame when things go awry?

327_9 What is our responsibility toward vulnerable populations (children, the aged...)?

289_6 How should we deal with machines as teammates if rational but ethically inappropriate proposal?

266_8 How can we make sure that our new teammates see us as people rather than any kind of variable in their optimization problem?

220_11 Do we need social conventions for how to deal with robots (don’t treat it bad, don’t be mean to a robot)?

178_14 What effects do machines as teammates have on the professional norms and values of its collaboration partners?

221_8 What stakes should/could a machine represent ethically?

312_18 Trolley problem – how closely should the AI’s ethical decision making mimic human evaluation?

237_3 What governance approaches are needed to set up a machine-as-collaborator work context?

269_13 Do we need new laws in some areas?

185_11 Authentication with teammates: who and how can interact in what role with the teammates?

236_7 Which is the original root of legal/ethical liability of an agent?

235_6 Who is legally responsible for a machine teammate actions?

175_6 What are the legal consequences of using machines during decision-making tasks that may end up having negative outcomes, e.g., damages?

189_5 Without transfer of liability, how can we avoid the human being liable without holding effective power?

289_7 As a result of machines as teammates acting autonomously, what kind of law should judge them in case of harming humans?

302_3 Machines must legally bear the same responsibilities as humans, so that no one can use them to conduct illegal business practices.

327_10 We have systems and laws to regulate all forms of human activities (the environment, marriage, and family, education...). Do we need new systems for organizing this collaborative relationship?

203_5 Why would any behaviors by machines be permissible (or not) that are acceptable for humans? Given the likely speed of evolution of machine capabilities, how can ethical and legal constraints be administered in a timely manner?

312_19 What should be the legal ramifications for machine teammates in a military context?

Association dichotomies

Higher quality of decision-making – reduced capability to criticize

215_4 Can the machine determine how reliable, accurate, or truthful the information from a source is.

220_12 How can machines judge the reliability of information to use only valid ones as a basis for reasoning?

220_13 How can machines explicitly ignore facts they’ve learned to
answer “what if” questions for different scenarios?
215.6 Can the machine determine what is useful to a given individual?
262.6 How can we use technology to improve cognitive processing?
225.6 How can we educate people to be critical information seekers and users?
236.8 There is here a big challenge IMHO: how to interact with automated procedures without losing criticism
178.15 How do we cope with errors of machines as teammates?
256.11 If the decisions based on machine teammates’ recommendations turn out to be wrong, who to blame?
179.8 How do we handle wrong answers?
207.11 How should the machines act when “its teammates” are wrong?
262.7 To what extent should we be concerned about monitoring/controlling machines that use machine leaning to provide AI answers to work problems?
178.16 What effects do machines as teammates have on human decision making?
331.11 What is the difference between collaboration (with machines) and the concept of human augmentation?
347.6 Understanding how machines “think” may influence how their decisions about their own decision making and cognition
266.9 What if my team members are constantly improving in predicting choice (e.g., bargaining outcomes, risky choice, behavior in conflicts, etc.)
272.5 As almost all AI depends on available data, we need to always question the validity of data in this day and age. For instance, if say, data for housing model is based on say size of the lot. But in reality, we need other input such as no. of bedrooms, location from highway etc. If these new parameters are not available. Then one main question is can we generate new data with needed parameters for AI to learn
289.8 Can humans rectify the mistakes pointed out by machines as teammates without hesitation?
289.9 Is the proposal from machines as teammates useful as much as humans or more?
312.20 How can machine teammates be used to overcome human cognitive biases in decision making?
315.6 What are the impacts on our brain and cognition?
319.20 Are teammate machines likely to follow bounded rationality or be utility maximizers?
167.4 How will the accuracy of individual decision-making processes change?
167.5 How can machines as teammates recognize cognitive biases in collaborative decision-making and take countermeasures?
178.17 How can machines as teammates compensate for human cognitive limitations and biases?
178.18 What new decision heuristics emerge with machines as teammates?
178.19 How can we prevent/compensate for human cognitive biases?
331.12 What kind of cognitive biases will emerge in mixed groups?
346.11 How will machines as teammates recognize political bias in research?
346.12 How will machines as teammates respond to political bias in research?

Increased pace of work – increased cognitive load
167.6 Will machines as teammates increase the pace of collaborative efforts and with which positive or negative effects?
178.20 How do and should humans react in cases in which there is insufficient time for machines as teammates to fully explain their contributions?
220.14 How can we find a good compromise between long running calculation processes on a large body of data vs. a quick answer that is good enough?
Increased creativity – lack of serendipity

215,5 Be useful to some of the possible participants. Exposing disagreement is a very basic function that has to happen to generate creativity.

225,7 Many algorithms in use in the web today (information recommendation, filtering, ranking etc.) are based on social closeness and similarity (supposedly leading to filter bubbles). How can we create alternative algorithms that spark creativity in people rather than reinforcing existing views?

201,1 Can you machines have insights. Most great ideas come from insights that are then justified with data.

237,5 As the relationship between machines and humans becomes more intertwined, how do we ensure that humans' creativity does not become constrained?

237,6 How should knowledge creation be dynamically shared between machines and humans?

244,3 Not only generate suggestions but also be able to explain why suggestions have been generated.

175,8 Can we make machine behave creatively?

207,13 How should the machines and human go in the same original direction of solving a particular problem?

347,7 How can machine recognize good solutions for open and complex problems?

331,2 Capacity to generate win–win solutions.

More efficient reasoning – fewer human-driven decisions

264,10 Who is the “manager” and who is the “worker”? Should machines make data-driven decisions or should it still be done by humans?

312,22 How often does a machine have to be right before we decide to eliminate the human from the decision completely?

207,14 Should the machines be treated like a human when come to its opinion?

289,10 Can machines as teammates persuade others when their proposal is judged better than the proposal by others?

221,10 If a machine is a team mate, should it be/represent a stakeholder in a decision making process?

185,13 Teammates as “buddies”: how to what extent can and/or should a machine “behave” to get its current problem solved.

331,13 How to develop the mechanism of persuasion with mixed groups?

331,14 Will machines as teammates be able to compromise?

269,16 Can they decide something or just recommend?

312,23 Should the machine ever have the final say in a decision?

312,24 How can a machine teammate accurately assess its confidence in a decision or recommendation?

312,25 What factors influence decisions to rely on machine recommendations over time?

312,26 When, if ever, is it acceptable for the machine to override a human’s decision?

244,4 Will machines be allowed to make decisions?

215,9 Can it act for me in a given situation?!

312,27 Should the machine have the final say in a life-or-death decision?

256,13 How do the “knowledge” the machine teammate has should look like so that he/she can draw inferences, insights, and relevant information from?

256,14 How do the machine teammate determine if the information and insights he/she offers is relevant to the ongoing discussion with other teammates?

221,11 Who determines the ethics/values of machines, as they will become a more reliable source of information than people/experts to make decisions?

207,15 How should the machines classify the related information from unrelated information regarding a problem?

354,4 What level of decision making is humans comfortable with a machine making?

274,9 But, e.g., should machines decide on assisted suicide when they diagnose humans as terminally ill? At least their recommendation will have great impact on such decisions on turning off life-sustaining machines.

312,28 When, if ever, is it acceptable for a machine teammate to make a final life-or-death decision (e.g., medical or military context)?

221,12 If we have machines as ultimate reasoners, is there still room for negotiation on what people want?

312,29 How can information best be presented when it contradicts the assessment of the human?

231,22 Will the machine produce cognitive overload? Will it increase workloads. Will employers expect more of employees who have the machines?

215,10 It has to be a servant for everyone in the group that is using it as a teammate! to deal with a common concern.

201,2 How do you recognize the intellectual contribution of a machine?

207,16 Recognizing the contribution of the machine.

207,17 How does having machines as teammates lower organizational politics in the workplace. Is there a lower need for political skill (power, influence, and persuasion) in an environment where machines can’t be manipulated/biased in the same way that humans can?
More responsibility – loss of control

171.8 Will humans at some point fear that machines could take over?

189.7 People “taking the back seat” as supervisors of fast and complex machine activity (like in autonomous vehicles) can translate into unenforceable nominal control

189.8 Diverse proficiency levels in person–machine interaction may lead to informal transfer of power and leadership while organizational roles stay nominally unchanged. This may impair assessment of intellectual capital and perception of the organization’s capability

231.25 Assuming the human is in charge of the teammate, what sorts of leadership approaches will the human use?

231.26 How much control should the human have over the teammate?

178.22 How can we address issues such as dominance by machines as teammates?

261.6 Human control in case of the machine become more intelligent than humans

272.6 First question to ask is, in the power hierarchy where are AI teammates being deployed?

268.9 Human teammates may feel sometimes that the machines are superior, as they never forget what they have heard or learned in the past and they process the information fast and accurate.

221.13 If the machine has better answers than humans, if it can process more information, should it get more authority?

256.15 Will the boss replace human teammates with machine teammates if the machine teammates are more helpful than the human teammates?

178.23 To what extent and how are machines as teammates responsible and accountable for their contributions or for the consequences of decisions taken upon their input?

189.9 Novel organizational relations are needed to make such leadership visible, e.g., via new non-IT roles related to machine coordination

178.24 How can and should responsibility or accountability be shared with machines as teammates?

237.7 How should responsibility and control be assigned?

272.8 AIs allowed to grow in their position?

272.8 To what level of influence to the top of ladder are allowed to AI?

289.11 Are machines as teammates allowed to command humans?

289.12 Can humans recognize machines as teammates as leaders?

319.21 Should we allow teammate machines to have power and control in an organization?

319.22 Can we have a machine that is a teammate and a leader?

327.11 How do humans remain in control?

327.12 Where is the locus of control in the relationship between machine and human?

185.2 Differences when working in organizational environment: hierarchy implemented in communication and behavior (e.g., CEO vs. employee)

More transparency – loss of privacy

225.8 How can we ensure data collected about a person and the inferences taken on it is transparent, scrutable, and controllable by the person?

225.9 How can we make the decision-making process for decisions taken by humans in collaboration with machines transparent, inspectable, and scrutable?

227.4 Communication between humans and robots and transparency of what the machine does

220.20 How can we ensure all the data collected for personalization of the human machine communication is not abused?

179.9 How can we make the (unnatural) mixture of high competence and low competence of machines as teammates transparent to the users?

185.15 Teammates: usage of visual data from built-in cameras (also ethical aspect)

244.5 How to generate certainty percentages for AI-suggestions/evaluations?

185.16 Data privacy: what data have to be recorded and where is it located?

207.17 What is the rule for the confidentiality of the projects/information should be applied to the machines?

175.11 What safe guards need to be in place when organizations use machines that become privy to confidential information?

231.27 Privacy issues in terms of what people tell the machine and in terms of what the machine does for the individual.

175.12 Do teammates feel that machines also monitor them apart from participating in decision making and problem solving processes?

220.21 Potential of surveillance

189.10 Currently, machines are ethically neutral, with the possible exception of built-in obfuscations for privacy preservation.

264.11 If machines are to work as “real” teammates, they should store some info on their human counterparts. What kind of data can/should be saved/logged and for how long? When to use this data?

264.12 Human teammates relate to each other by talking about their experiences. They often store pieces of information about others and use these pieces later on in similar contexts. How can machines do it similarly without making humans feel uncomfortable as if they are being watched/recorded all the time?

264.13 Which data will be saved/logged? Who can access these data?

265.10 What do I/my team/my organization want machines to know about myself/my team/my organization?

267.5 Cybersecurity will become even more important as there is a move to having machines as teammates. How do organizations best prepare for possible data breaches, as the machine employees can be hacked with negative consequences for the organization and human workers?

267.6 Machine coworkers could have nearly unlimited storage space to record/monitor the workplace environment. This could cause privacy/ethics issues for human workers.

269.19 What kind of data should they process?

289.13 Can we use personal conversation records for learning machines as teammates? If we can use them, who is responsible for leakage of privacy?

237.8 What are the types of representation gaps that occur between machines and humans? How much visibility into the machine knowledge do humans need

Higher adaptiveness – more misbehavior

220.22 How can we allow robots to learn from their perceptions without the fear that they learn bad behavior?

189.11 As we empower machines for autonomous decision making, do we need to build them in such a way that ethical behavior is encouraged-preserved? (Asimov’s Robotics Laws)

220.23 How can machines build up something like a moral conscience?

220.24 Can we built machines with compassion but without aggression?

220.25 Machines learning about prejudice from humans and making them explicit

215.11 The same technology could be turned into a bias agent to sell things. Can the system be influenced by the users individually to be able to treat everyone the way they wanted with respect to the needs as perceived by the human the machine is dealing with.

231.28 The human asks the teammate to do something that would be unethical for a human to do, e.g., send nasty messages and trick someone.

220.26 How can we allow robots to learn from the internet without the fear to build a super A.I. that outsmarts humans?
167_8 Should machines as teammates have adaptive personalities to fit individual preferences?
235_12 How can machines be improved to adapt better to their human counterpart and the specific situation?
236_10 The emotional expressions provided by machines should be adaptive, for real
171_9 Should machines mimic a certain identity or stay neutral or even adapt their identity based on the identities of the human collaborators?
220_27 Machines need to understand that people change their mind from time to time
220_28 How can we teach robots to “bend” the rules from time to time, without the fear that they will use it against us?
207_18 How should the machines adjust its communicational level/channel to match with “its teammates?”
220_29 Will machines build emotions on their own without having them designed for this ability just because of their similarity to human brains?
235_13 Which displayed personality traits and emotional expressions foster desired behavior of the human team mates?
269_20 What if they are treated bad?
269_21 Can they have a sense for the upcoming of emotions and adapt their communication strategy?
289_14 Do humans decline or be corrupted due to machines as teammates?
312_30 Should machine agents’ personalities be changed depending on the situation, or who they are interacting with?
319_23 How can we teach machines to become good teammates?
319_24 What incorporates a bad teammate machine? What should we do to avoid building those?

**Higher value creation – extreme power shifts**

175_13 How do we demonstrate the value of machines as teammates?
266_11 How will machines as teammates affect the firm’s productivity?
175_14 How can we quantify the value that machines as teammates bring?
215_12 There has to be value for the individual humans to make use of this machine intelligence
265_11 Will machines be our slaves who work for us and we enjoy free time (think: old Greece)?
175_15 Should organizations develop machines in house or will we have COTS AI?
185_17 Business models for “booking teammates”
256_16 How much does it cost to hire/build machine teammates vs. human teammates for the same task?
233_11 How to control the cost of collaborating with machines?
220_30 If machines are doing “real labor,” are they getting paid so that there can be taxes on the wages?
168_7 How can work done by machines be taxed?
274_11 How much tax should employers of machines pay for using them? Unlike humans, they work for “free” at the moment.
262_8 What is the cost of retraining workers who have been displaced by the technology?
175_16 What is the ROI on machines as teammates?
262_9 Clearly the cost/benefit analyses need to be performed for the implementation of these new technologies. However, the costs of acquiring and implementing robots seem to be dropping radically and the benefits seem to be increasing. What about the costs to society in terms of people who are being replaced by machines.
189_12 Machines as workmates (as opposed to machines as tools) have new cost profiles that require novel micro and macroeconomic studies
220_31 What happens to traditional economical systems if labor can nearly 100% be replaced with money?
327_13 Will collaborative machines be a scaffold or a crutch?
234_3 How do we finance the state (welfare) in a context with fewer and fewer paid workers?
235_14 Should we pursue any technologically possible automation potentials, even at the expense of human teammates quality of work, life, or employability?
225_10 How can AI contribute to a more inclusive society, i.e., not benefit the ones that already have a lot of power, or the ones that have more resources (monetary, social, and cognitive) than others?
220_32 How can we ensure that robots will not stretch the discrepancy between a few super rich people and a large body of poor humans to a new all-time high?
220_33 How can we make sure that those in need benefit the most from robots and not mostly the rich?
231_29 As we become more automated, we will need new economic models because not everyone will be able to have a decent job. If we don’t change models, eventually a handful of people will own everything, as the rest will be starving on the street.
289_15 How does machines as teammates affect national strength?
327_14 Where does the power reside?
178_25 How do societies react to the shifts in power between those who have machines as teammates and those who haven’t?
265_12 Who will own the machines and make money from it - dystopia: rich people own machines, poor people have no work and no money
315_7 How to avoid the increase of the digital divide?
322_6 Fair trade policy as a result of access to autonomy and data
275_5 How do we establish governance structures to control machine to machine interaction?
231_30 Will people have to pay for the teammate? Will everyone have their own (like a cell phone) that can be used in a variety of settings
203_6 Who pays for the machines? Does the one paying for the machine determine its behaviors? Where benefits are created, how are they divided between human and machine teammates?
178_26 What value is created by machines as teammates and how is that value distributed among the collaboration partners?
267_7 How does additive manufacturing (e.g., 3D printing, etc.) through machines as workers and teammates impact organizational and national (GDP) outcomes?
315_8 What are the power imbalances/balances promoted by this approach to computing?
329_4 How these machines choose when there are conflicts between the benefits of the people they work for and the benefits of the people who build them?

**Concept dichotomies**

**Affect positive/negative**

185_18 Negative emotions and its priority of emotions (ranking) when dealing with human, e.g., frustration vs. ignorance
189_13 Humans “taking the back” seat may affect their self-esteem and perception of standing. Psychology studies are needed.
178_27 How do we deal with anger and frustration against machines as teammates?
312_31 How can we overcome an instinct to perceive machine teammates as job competition?
233_12 Collaborating with machines will cause a lack of belongingness. How to address this challenge?
220_34 Do we need courses for self-esteem so that humans don’t get feelings of inferiority?
231_31 People’s loss of self-esteem, status, and meaning as they get displaced.
267_8 What possible negative health and psychological well-being outcomes may occur as a result to the teammate? An example would be “does the worker have lower psychological well-being for fear of job
security (machines will replace their job too eventually)? How will these possible lower well-being outcomes affect the workforce?

178_28 How do humans deal with emotional stress due to machines as teammates?

231_32 How does introducing a teammate affect stress, i.e., will it be a stressor or will it buffer stress?

231_33 How much will people enjoy working with a teammate?

256_17 Should the machine teammate be empathetic to other teammates? Does he/she need to tell jokes?

312_32 What emotional factors influence continued use of machine teammates?

167_9 Will machines with humor improve team performance?

179_10 How can machine understand our emotions and appropriately react to them in a team setting?

272_9 How human teammates' emotional attachment to AIs influences their relations to other humans?

233_13 It's hard to build emotional bond with machines; however, emotional bond is important for team collaboration. How to address this challenge?

264_14 How do machine teammates influence the job-satisfaction of humans? Can machines also provide empathy and emotional support at the workplace?

269_22 How should they react on emotions?

185_19 RQ. Reactions to sentiments, emotions within a collaborative setting

256_18 If being a good teammate requires a person to be sensitive to the feelings of his/her peers, how could the machine teammate detect those feelings and respond in a sensible way?

168_8 How to motivate human teammates if the machine teammate always knows the answer?

264_15 Can these machines provide the emotional support and empathy that can be compared to human teammates?

264_16 Can machines provide the emotional support as teammates?

220_35 Are machines with emotions dangerous for humans or is it necessary to build machines with emotions for good cooperation between humans and machines?

266_12 How can we tackle the issue of perceived fairness in the tech–human interactions?

312_33 What emotional factors influence liking in machine teammates?

312_34 How can emotional factors be manipulated to increase trust, liking, and use?

312_35 Should emotional factors be manipulated to increase trust, liking, and use (ethical question)?

319_25 Should we design teammate machines to display any sort of emotions when we know that they are not capable of doing so? How are humans likely to respond to that?

185_2 Teammates: understanding emotion and sentiments

Team knowledge augmented/depleted

167_10 Will intelligence and emotional intelligence decrease when machines join collaborative work?

225_11 What is the effect on reading and literacy, if more and more interfaces turn to be voice enabled?

230_3 Can artificial intelligence support decision making without depleting human knowledge?

236_13 Can artificial intelligence support decision making without depleting human knowledge?

189_14 Understand better the permanent loss of cognitive abilities of humans. Machines as co-processors for the brain. The case of “Nintendo pilots”

267_9 Researchers have to consider the impact machines as teammates can have on transfer of training and lack of reliance on memory in general. Human workers/teammates may be apt to not rely upon their memory if there is a machine there with all the knowledge (similar to people not remembering phone numbers anymore because they are in the contacts list in a smartphone). How can we curb mental laziness in workers who depend on their machines as teammates?

227_5 How can we create human robot teams in a way that fosters human capabilities rather than making humans dependent on robots?

319_26 Can teammate machines fill structural holes inside a company and between organizations?

227_6 It will be about using human skills and complementing them rather than making humans slaves of machines.

244_6 How to explain/visualize the reasons for AI-decisions/suggestions to humans?

265_13 Explaining reasons for actions

207_19 Do the information/answers from the machines play a significant role in the team’s conclusion?

220_36 How can a machine explain its inferencing process, so that humans can retrace the logic behind?

Technology accepted/rejected

347_8 Acceptance by those impacted by the solution

167_11 Will machines with humor be more accepted by coworkers?

262_10 How should robots be designed to look more acceptable to their teammates?

256_19 How to convince people to accept and respect the machine teammates?

264_17 Is the human workforce going to accept machines as teammates?

269_23 How should we design bots that they will get accepted as teammates?

264_18 Is human labor force ready to accept machines as teammates?

319_27 Acceptance – do employees actually work or want to have machines as teammates?

269_24 Will people accept bots as team mates?

171_10 Will human collaborators accept the input from machine collaborators?

171_11 Are there certain tasks where input from machines is more likely to be accepted than other tasks (e.g., support in facilitation versus generation of ideas)?

175_17 How can we increase acceptance of recommendations from machines vs. people?

354_5 Acceptance of AI recommendations and the need to avoid discriminatory practices by AI.

354_6 We have in society some people who have techno-phobia and will resist the use of technology even when doing so prevents us from reducing human suffering. How much human suffering must we allow to accommodate superstition and unreasonable concern about machines?

347_9 How would individual feel about solutions generated by machines, acceptance by individuals that have to carry out the work and

302_5 Is machine input taken as seriously as that of humans in collaborative work? (i.e., is it easier to dismiss machines when you don’t like what they say?)

231_34 What are the DVs we care about? I can think of acceptance of the technology, preference for using it vs. a real person, resistance to using it, trust, how much people use it, performance with vs. without it, satisfaction with it, emotional response, sabotage of the teammate.

268_10 What design elements should be incorporated in the development of collaboration technology to adjust the needs of people with communication technology phobia?
There are individual differences in the acceptance of technology, which appears to be correlated with acceptance of miscommunication with technology (e.g., Siri misinterpreting a command/question) – some people ask the question with more enunciation and some just stop communicating with the technology and give up. This makes it important to consider both the technical aspect (better voice recognition, etc…), while also considering how to minimize or improve lack of acceptance of communication with technology.

Will machines as teammates be regarded differently in different cultures? Which cultures will be more likely to accept machines as teammates? Which cultures will be more likely to benefit from machines as teammates?

Do some religions have issues with robots? Will humans treat the teammate as if it is a real person. Will it talk nicely, chat with it, yell at it?

How can we facilitate trust in machines as teammates?

How much should we trust the machine teammate’s insights and recommendations?

How can we design machine teammates to be trustworthy and transparent in their behavior?

With the move to machines as teammates, one of the major research questions that should be addressed is how does trust between humans and machines as coworkers/teammates develop over time. Is the trust link between humans/machines more tenuous or volatile than trust between humans and how do we address the effects of different individual differences (e.g., technology acceptance) on how trust is built and maintained?

Do humans trust the algorithm of these machines?

What are the differences in trust with respect to recommendations from machines vs. people?

How can we build trust between humans and machine teammates?

How do humans develop trust of the teammate over time?

How to ensure trust between team members and machines?

How can we design machine teammates to be trustworthy and transparent in their behavior?

How do we develop trust and other emergent team properties?

Trust – are employees likely to trust their machine teammates more than human?

What conversational design factors influence trust in a machine teammate?

To what extent should the machines be trusted?

Are human teammates willing to trust their machine partners?

How does contradicting the human affect the human’s trust in the machine?

What emotional factors influence trust in machine teammates?

How does the weight of the decision (life or death, monetary value, job on the line) affect humans’ willingness to trust a machine?

How does AI influence group dynamics?

What group dynamics will be important to be learnt and read by machines to foster improved team performance?

How would that influence team cohesion and emotional contagion?

Does existence of a teammate in a group of humans affect inter-human conflict?

What is the defend mechanism to prevent the conflict between human and the machines?

How can we facilitate conflict management with machines as teammates?

How can disagreements between humans and machines be discussed and solved?

How would that impact human–machine relation in fitness and well-being?

Robots shall never harm humans

Robots need a lot of sensors to detect potential accidents early and prevent the worst

They are stronger, but must use their strength to protect humans and not to harm them

How to safeguard for the well-being of teammates machines?

How can we insure the safety of humans in collaborative industrial teams with robots?

Should be a board or consortium to ensure safety and secure usage of AI and research should also point in that need of it

Robots need a safe shell to protect humans from accidents with robots

Are they a threat for workers?

How can we prove that we have a water-proof network of laws to keep robots from becoming superhumans?

Are robots allowed to walk in public unrestrictedly such as humans?

What kinds of regulations must exist to ensure that machines won’t harm humans?

When machines become strong, how to address the social security issues?

How can we minimize machines unnerving humans due to following the rules 100%.

How will machines as teammates impact the psychological health of human co-workers?

What ethical guidelines should be developed to sanction the use of machines as teammates? (Like Asimov’s robot laws)

How safe are the AI teammates decisions?

How can we rethink social assistance in a jobless economy?

How to accommodate those humans who will inevitably be left out. Will there be universal income so that we can all benefit from machine workers? Will there be re-training/re-education programs for those left out, so that they can secure a job in other fields? Will there be generous severance packages that allow a person to regroup?

How does machines as teammates affect the human employment?
How do machines as teammates change our understanding of labor markets?

Will there be enough work for all humans? Will humans feel useful and unneeded? What can humans still contribute?

Are the various job markets would get affected?

The discussion about universal wages as a result of job loss.

Are we entering in a jobless society?

Taking people’s jobs.

Older and less-skilled workers may be replaced more frequently than younger/more skilled workers (e.g., creative creators). Is this fair to the worker?

Do machines as teammates replace jobs or repurpose them?

Though AI can potentially remove repetitive jobs, still there should be a human supervision over AI to prevent unexpected outcomes that defies logic and rational thinking.

What will be the impact of our new teammates on the job market?

How will the organization of paid work need to adapt to the shift in tasks, e.g., in terms of work hours or job profiles and qualification?

Similar to the ethical RQ above, the workforce is going to change a lot. It already is. But it will create a need for those who do specialized jobs that do not have a lot of monotony (those easily replaced by labour costs have a lower bound due to the Malthusian constraint of workers supporting their families. Minimum salary laws recognize this constraint.

What kind of research field will vanish? Maybe they can collect data themselves and do data analytics projects and publish them on MISQ, ISR… then a variety of research fields might not be needed to be done by humans anymore!

How can we deal with the reduction in low-skill jobs that will result from increasingly capable machines?

References


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