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The New Dream Team? A Review of Human-AI Collaboration Research From a Human Teamwork Perspective

Marvin Braun
University of Goettingen, marvin.braun@uni-goettingen.de

Maike Greve
University of Goettingen, maike.greve@uni-goettingen.de

Ulrich Gnewuch
Karlsruhe Institute of Technology (KIT), ulrich.gnewuch@kit.edu

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Marvin Braun
University of Göttingen
Göttingen, Germany
marvin.braun@uni-goettingen.de

Maike Greve
University of Göttingen
Göttingen, Germany
maike.greve@uni-goettingen.de

Ulrich Gnewuch
Karlsruhe Institute of Technology (KIT)
Karlsruhe, Germany
ulrich.gnewuch@kit.edu

Abstract

A new generation of information systems based on artificial intelligence (AI) transforms the way we work. However, existing research on human-AI collaboration is scattered across disciplines, highlighting the need for more transparency about the design of human-AI collaboration in organizational contexts. This paper addresses this gap by reviewing the literature on human-AI collaboration through the lens of human teamwork. Our results provide insights into how emerging topics of human-AI collaboration are connected and influence each other. In particular, the review indicates that, with the increasing complexity of organizational settings, human-AI collaboration needs to be designed differently, and team maintenance activities become more important due to increased communicational requirements of humans. Our main contribution is a novel framework of temporal phases in human-AI collaboration, identifying the mechanisms that need to be considered when designing them for organizational contexts. Additionally, we use our framework to derive a future research agenda.

Keywords: Human-AI collaboration, teamwork, literature review

Introduction

Artificial intelligence (AI) is becoming a crucial technology for advancing information systems (IS) by equipping machines with unprecedented capabilities in information processing (Berente et al., 2021). AI has taken a big leap to achieve human-level sensory, cognitive, execution, and adaptive capabilities (Xu et al., 2021). A recent example of the novel emerging capabilities are large language models, such as ChatGPT, which are capable of conducting complex tasks such as debugging software code and writing sophisticated speeches (OpenAI, 2022). Furthermore, AI revolutionizes computationally intensive processes, such as drug development, not only in terms of time but also in quality. For example, while human drug development often enhances existing drugs through minor changes, AI is able to create substantially new compositions of drugs and also reduces the development time by a factor of 100 (Lou & Wu, 2021). Hence, it is projected that AI will continue to revolutionize the workplace at an increasing pace, effectively changing processes and job roles for humans (Eloundou et al., 2023) by transiting from tools to complementary digital assistants and partners (Seeber, Waizenegger, et al., 2020; Xu et al., 2021).

This shifting role of machines has great implications for the interaction between humans and AI in organizational contexts (i.e., contexts where AI is an integral part of work processes and routines) (Grønsund & Aanestad, 2020). AI-based information systems (IS) exhibit higher agency compared to traditional IS and take on more active roles (Baird & Maruping, 2021). Furthermore, Vössing et al. (2022) emphasize that with the increasingly opaque design that comes with AI, novel ways are needed to understand the design of AI in organizational contexts, and "established assumptions on how humans interact with technologies need to be reevaluated" (Vössing et al., 2022, p. 879). IS research has started to address this need by investigating individual facets of human-AI collaboration such as task delegation toward AI (Fügener et al., 2021a; Baird and Maruping, 2021), human-AI team performance (Fügener et al., 2021a), and shared mental models of human-AI teams (Schelble et al., 2022). However, due to the complexity involved in human-AI collaborations in sociotechnical environments, a common understanding of how to design the interaction is still missing (Vössing et al., 2022; Maedche et al., 2019).

Against this background, a holistic understanding of the emerging mechanisms that influence and shape the interaction between humans and AI is needed to improve human-AI collaboration and tailor the interaction to organizational contexts. We address this need through the theoretical lens of human teamwork which has thoroughly studied concepts that are currently investigated in human-AI collaboration (e.g., shared mental models and task delegation - Rousseau et al. 2006; Schelble et al. 2022). Moreover, human teamwork also explains how the concepts are dependent on each other and how they contribute toward team maintenance (i.e., the functioning of a team) and team performance (the efficiency and effectiveness of a team) (Marks et al., 2001; Rousseau et al., 2006). Taken together, existing knowledge about human teamwork can support human-AI collaboration research in understanding how to design it in organizational contexts. Drawing on these considerations, we address the following research question:

> **RQ:** How can we synthesize the emerging stream of research about human-AI collaboration using the theoretical lens of human teamwork?

To answer this research question, we conducted an organizing review following Leidner (2018) and Webster and Watson (2002). We used the model of human teamwork phases (Marks et al., 2001; Rousseau et al., 2006) as an overarching lens for this review. Based on this foundation, our literature review synthesizes existing research, shows how current topics of human-AI collaboration are connected, and answers recent calls for the utilization of the broad knowledge of human teamwork (Grote & Ulfert Eindhoven, 2023) to better understand human-AI collaboration from an organizational perspective (Vössing et al., 2022). In total, we analyzed 41 human-AI collaboration studies through the lens of human teamwork. The resulting framework of temporal phases in human-AI collaboration advances our understanding of how human-AI collaboration needs to be designed depending on the organizational context. Moreover, utilizing the new framework, we shed light on avenues of future research.

Conceptual Background

In the following section, we introduce the conceptual background and relevant concepts used to analyze the literature. First, we explain the core concepts of current human-AI collaboration and its interaction forms. We then shortly outline how tasks of human-AI collaboration can be analyzed regarding their complexity using concepts found in the IS literature. Finally, we give an overview of teamwork activities that originate from human teamwork research.

Human-AI Collaboration Research in Organizational Contexts

With the introduction of AI, a new "frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems" (Berente et al. 2021, p. 1435) has been created. While AI-based systems are also employed in similar contexts as 'traditional' systems (i.e., systems that rely on pre-defined rules (Seeber, Bittner, et al., 2020)), they differ strongly in their inner working and are usually not as comprehensible for humans as traditional systems (Vössing et al., 2022).

Moreover, human-AI collaboration goes one step further and does not consider AI-based systems as tools that humans use but as partners with whom humans can collaborate (Grønsund & Aanestad, 2020).

This changing notion from human-computer-interaction (HCI) to human-AI collaboration is addressed by Vössing et al. (2022). The authors utilize the definition of Terveen (1995) and define human-AI collaboration as "two or more agents [that] work together to achieve shared goals [...] involving at least one human and at least one computational agent" (p. 67). Drawing on the seminal HCI framework by Zhang et al. (2002), and the extended human-AI interaction framework by Rzepka and Berger (2018), we know that the influencing factors of this collaboration are the human, the AI, and the task and context which influence the collaboration that creates an outcome. According to Rai et al. (2019), this collaboration can be designed in different: AI can substitute a human during a task (*task substitution*) (e.g., service encounters), AI or the human can augment one another to conduct a task (*task augmentation*), or AI and humans can complement each other to work on a task together (*task assemblage*) (Rai et al., 2019). This review focuses on task augmentation and assemblage because they involve collaboration between humans and AI. Current research on collaborative dynamics has focused on task delegation (Cvetkovic & Bittner, 2022; Lubars & Tan, 2019), the provision of information to explain the AI's decisions during teamwork (V. Lai & Tan, 2019), and the impact of group size on team performance (Fügener et al., 2021a) to achieve these collaboration modes.

Moreover, human-AI collaboration research is currently scattered among a wide range of domains (e.g., IS—Fügener et al., 2021b, psychology – Yin et al., 2019, and business-related domains such as finance (Basu et al., 2019), personnel administration (H. Liu et al., 2021), healthcare (Y. Lai et al., 2021), and logistics (Loske & Klumpp, 2021). The topics investigated are all closely linked to the overarching research stream of human-AI collaboration; however, they investigate the phenomena in different organizational contexts (i.e., they employ various tasks with different characteristics and domains). Hence, several authors have called for more transparency regarding the organizational context of human-AI collaboration because it is an essential part of the IS discourse (Bansal et al., 2021; Buçinca et al., 2020). To systematize the findings of the empirical studies involved in these organizational contexts, we need to find ways to generalize and compare findings. However, to the best of our knowledge, there is no agreed-upon classification of tasks based on their characteristics in human-AI collaboration research.

Therefore, we propose to assess the team task complexity of human-AI collaboration research. We argue that team task complexity is, on the one hand, the only characteristic of organizational contexts that can be assessed regardless of the involved domain; and, on the other hand, has a high impact on the needed human-AI collaboration (Fügener et al., 2021a). Campbell (1988) structured tasks according to complexity by identifying the number of outcomes, solution paths, interdependencies, and uncertainty. This resulted in 16 tasks, which the author aggregated into five task types. These task types have different requirements for IS and their designs (Zigurs et al., 1999). *Simple tasks* have one outcome and one solution path (e.g., filling out a form). *Problem tasks* have one outcome but can be solved in several ways (e.g., route planning or personnel scheduling). In contrast, decision *tasks* have multiple outcomes but are narrowed in their solution path (e.g., selecting a supplier). For *judgment tasks*, the number of outcomes and solution paths is irrelevant; instead, these tasks involve assessing multiple sources of information and predicting an outcome or the judgment of an object (e.g., a market analysis). Lastly, *fuzzy tasks* have the highest degree of complexity, involve multiple outcomes and solution paths, and usually include interdependencies of several decisions (e.g., creating a business plan) (Campbell, 1988).

Teamwork Activities

Teams are essential units for creating an organization's structure through the assignment of tasks and the definition of responsibilities and consist of at least two individuals (Rousseau et al., 2006). In this context, teamwork can be defined as teams "working together to achieve a common goal" (Rousseau et al. 2006, p. 550). Marks et al. (2001) elaborate further on this term and specify that teamwork concentrates on how the interaction between individuals is designed. Research on human teamwork identifies several activities teams undertake to successfully conduct a task (Marks et al., 2001; Rousseau et al., 2006). These activities are usually performed sequentially and aim at either conducting the taskwork as a team (i.e., all activities that need to be conducted to work in a team successfully) or at team maintenance (i.e., "holding team members together"; Rousseau et al., 2006, p. 548). Moreover, research on teamwork emphasizes the importance of so-called regulation phases, performed alongside the actual taskwork, which can highly impact team performance. Following Rousseau et al. (2006), these phases include preparation, execution, evaluation, and adjustment (see Figure 1). While there are other classifications of these phases (e.g., Marks et al. 2001), the activities remain mostly the same. In the preparation phase, teams plan how to conduct a specific task, including analyzing the mission, and specifying the goal. The mission analysis supports members in understanding the capabilities and competencies of other team members and determining who can conduct which activity to reach the team's goal. Based on the goal specification, the team can plan how they want to achieve it. The planning activity also defines how the team wants to reach the team's goal and who will execute which task (Rousseau et al., 2006).

After completing the preparational activities in the first phase and the creation of a common understanding of the task, the team transitions to the execution phase, conducting the planned activities. Throughout this stage, the team engages in what Rousseau et al. (2006) describe as "task-oriented collaborative actions" (p. 551), encompassing coordination, cooperation, and the exchange of information. To achieve their goal in time, the team must coordinate the activities and ensure that every member contributes to the goal according to the plan. Cooperation refers to the activity of two or more team members conducting a (sub) task together and is important to create synergies between team members to collaborate on tasks that cannot be completed alone (Yeatts & Hyten, 1998). Information exchange describes the process of sharing information with other team members about the task, which is beneficial for task accomplishment (Pearce & Ravlin, 1987; Rousseau et al., 2006).

In the evaluation phase, the team assesses its work by monitoring its performance and systems. Performance monitoring involves tracking the team member's task progress and ensuring error-free task execution. In contrast, system monitoring involves observing the environment, such as the team's material and personnel resources. System monitoring is important for reacting to dynamically changing environments and adapting accordingly (Marks et al., 2001; Marks & Panzer, 2004). The adaptation process may encompass redefining the team's objective (teamwork behavior) or increasing team efforts to accomplish the goal (non-teamwork behavior). Adjustment of behavior involves team members assisting each other in completing individual activities in cases of failure. Moreover, the team has the opportunity to provide feedback to enhance a team member's performance if failures or misbehavior are identified (Rousseau et al., 2006). Feedback can be provided through advice, suggestions, and additional guidance throughout and after the task execution phase (Rasker et al., 2000).

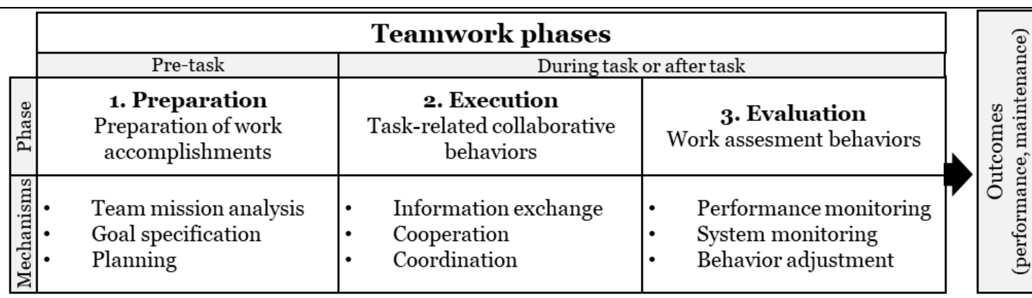

Figure 1. Phases of Human Teamwork (based on Rousseau et al., 2006)

In summary, human teamwork is designed as a process with multiple, interdependent phases that split activities into cohesive groups of activities. This process-based view on collaboration is currently missing in human-AI collaboration research. As Vössing et al. (2022) pointed out, we currently lack a common understanding of how to design human-AI collaboration in organizational contexts. Against this backdrop, adopting the lens of teamwork phases has several benefits. First, it allows us to map past studies and investigate phenomena in the teamwork process and thereby structure them. Second, we can identify potential gaps for future research by analyzing current topics of human-AI collaboration and potential activities that have not yet been investigated within this emerging stream of IS research.

Method

To synthesize current research on human-AI collaboration in organizational contexts, we follow the proposed method of Leidner (2018) and conduct an organizing review. An organizing review is particularly suited because it allows us "to extract insights and uncover assumptions that might otherwise be undetectable" (p. 556). Thereby it contributes toward understanding human-AI collaboration and how it needs to be designed with respect to the organizational context. An organizing review aims to synthesize an emerging broad research stream (human-AI collaboration), often by using theories and frameworks from other domains. For this review, we draw on the well-established teamwork phases synthesized by Rousseau et al., (2006) along with key teamwork concepts (see Table 1). To identify and analyze the literature, we followed the method of Webster and Watson (2002). The literature search and screening process was conducted between August 2022 and January 2023. In the following, we describe our stepwise methodological approach.

Concepts	Description
Teamwork phases [Preparation, Execution, Evaluation]	Temporal phases organize teamwork activities and are important for complex interactions (Marks et al., 2001).
Teamwork role [Augmentation, Assemblage]	Humans and AI employ different collaboration modes depending on the task and outcome (Rai et al., 2019).
Teamwork tasks [Decision Task, Problem Task, Judgment Task, Fuzzy Task]	Teamwork task complexity is independent of its domain (Campbell, 1988) and allows a comparison of different research streams. Research indicates that task complexity is crucial for the resulting human-AI collaboration (Zanatto et al., 2019).
Teamwork outcomes [Team Performance, Team Maintenance]	Teamwork activities contribute directly to performance outcomes and better team functioning (Rousseau et al., 2006).

Table 1. Teamwork Concepts used in this Literature Review

Search strategy: We conducted a keyword search in IS journals (incl. Senior Scholars' List of Premier Journals) and adjacent research streams that also investigate human-AI collaboration (e.g., computer science, management, and psychology). Since the research field of human-AI collaboration is still being established, we also included major IS conferences (e.g., International Conference on Information Systems and European Conference on Information Systems). To fully grasp all relevant studies, we added the meta-database Web of Science because it allowed us to search in many databases and find potentially missed studies.

Search string: As the thematic interest in human-AI collaboration is multidisciplinary, the wording varies widely (e.g., augmentation, interaction, teamwork). Thus, the search term consisted of three parts: (1) 'artificial intelligence/AI*/intelligent/smart,' (2) interaction/ augmentation/collaboration' and (3) 'user/human' This search generated 1,684 search results, which were then screened.

First screening: We first defined the inclusion and exclusion criteria to identify relevant literature. First, only peer-reviewed studies were considered suitable. Second, we limited our search to the past ten years (2013-2023) due to the rapid advancements of AI and, thus, human-AI collaboration. We included studies if they involved some form of human-AI collaboration in an organizational context. We excluded studies that solely investigated the performance of an AI algorithm because these are not of interest to human-AI collaboration. Literature reviews and editorials were also excluded during the screening process. Finally, we screened the abstracts of the articles and filtered the articles based on these inclusion and exclusion criteria.

Second screening including forward and backward search: In the second screening iteration, we thoroughly reviewed the full text of each paper and again excluded papers that lacked any form of human-AI collaboration in an organizational context. Next, we performed a forward and backward search, resulting in the final number of 41 studies included in this literature review.

Analysis and synthetization of results: We analyzed the studies based on the presented main phases of teamwork. We tested our proposed coding scheme (see Table 1 for the main constructs) on a random subsample of 20% of the papers. The two authors then compared their results to identify coding differences; however, there were no significant differences. Hence, we proceeded to code the complete literature sample based on the approach of Wolfswinkel (2013). We read each paper and coded them to a specific phase if they addressed and investigated an element of this phase. For example, studies that investigated human feedback mechanisms were assigned to the evaluation phase. Studies that dealt with multiple topics were assigned multiple teamwork phases. After we assigned studies to a teamwork phase, the study was coded in accordance with the remaining concepts (e.g., if the study investigated the impact of feedback mechanisms on human trust the study was assigned the label of team maintenance). We then applied a concept matrix to the resulting literature (Webster & Watson, 2002), utilizing the lens of teamwork. The process was conducted iteratively and concepts were adapted if needed (Saldanna, 2022). Finally, we embedded the results of our literature review in the HCI framework of Zhang and Li (2004) similar to the approach by Rzepka and Berger (2018) and Seiffer et al., (2021). This enabled us to synthesize our results in a framework of temporal phases in human-AI collaboration.

Results

Sample Description

The final sample consists of 41 studies (see Table 2). Eight studies investigated the preparation phase, whereas 33 studies investigated the execution phase (task conduction). Five studies explored the assessment and adaptation of teamwork while tasks were being conducted or after completion. Some studies investigated multiple phases. The interaction type of human-AI collaboration was determined as task augmentation (33). In contrast, eight studies investigated the interaction type of task assemblage. Studies in these categories included tasks with higher complexity, requiring humans and AI to collaborate more closely. The task complexity analysis reveals interesting insights into the current focus of human-AI collaboration. We observe a clear focus on decision tasks (24), i.e., tasks that involve multiple outcomes but only one solution path. The decision tasks usually involved some type of predictive component, where the AI recommended a decision, and the human had to decide whether to accept the recommendation or not. This focus can be explained by the simplicity of decision tasks that are easily implementable for AI. In contrast, problem tasks (5) are more complex if AI solves them because they usually require the AI to make multiple decisions to reach the desired goal (e.g., logistics planning - Loske and Klumpp, 2021). In addition to this, we found studies that also investigated fuzzy tasks (6) (e.g., Schoonderwoerd et al., 2022) and judgment tasks (6) (e.g., Park et al., 2019).

Studies	Teamwork phases			Teamwork role		Teamwork tasks				Teamwork outcomes	
	Preparation	Execution	Evaluation	Augmentation	Assemblage	Decision Task	Problem Task	Judgment Task	Fuzzy Task	Team Performance	Team Maintenance
Aslan et al., 2022		x		x		x					x
Bansal et al., 2021		x	x	x		x				x	
Basu et al., 2019	x			x		x				x	
Braun et al., 2022		x		x		x				x	
Bucinca et al., 2021		x	x	x		x				x	
Chong et al., 2022		x		x			x			x	
Chu et al., 2020		x		x		x				x	
Costello et al., 2019		x		x				x		x	
Fügener et al., 2021a			x	x		x				x	
Fügener et al., 2021b		x		x		x				x	
Gajos and Mamykina, 2022		x		x		x				x	x
Gonzalez et al., 2022		x		x		x				x	
Green and Chen, 2019		x		x				x		x	
Kim et al., 2023		x		x				x			x
Haesevoets et al., 2021	x				x			x		x	
Lai and Tan, 2019		x	x	x		x				x	
Lai et al., 2020	x			x		x				x	
Lebovitz et al., 2021		x		x		x				x	x
Lebovitz et al., 2022		x		x		x				x	
Liu et al., 2021	x			x		x				x	x
Liu and Du, 2022		x		x					x	x	
Lou and Wu, 2021		x	x	x					x	x	

Loske and Klumpp, 2021		x		x			x			x	
McNeese and Cooke, 2021		x			x		x			x	
Mirbabaie et al., 2021		x			x	x					x
Mozannar et al., 2021	x			x		x				x	
Musick et al., 2021		x			x				x	x	x
Park et al., 2019		x		x		x				x	
Riefle et al., 2022		x		x				x			x
Schelble et al., 2022	x	x			x				x	x	
Schoonderwoerd et al., 2022		x			x		x			x	x
Shin et al., 2021		x		x		x				x	
Song et al., 2022		x		x					x		
Strich et al., 2021		x		x				x			x
Taudien et al., 2022		x		x		x				x	
Ulfert et al., 2022	x	x			x		x			x	x
Vassilakopoulou et al., 2023		x		x					x	x	
Wang et al., 2019		x		x		x				x	x
Wang et al., 2022		x		x		x				x	
Weiler et al., 2021	x				x	x				x	x
Yin et al., 2019			x	x		x				x	
Sum* *Concepts are non-exclusive	**8**	**33**	**6**	**33**	**8**	**24**	**5**	**6**	**6**	**35**	**13**

Table 2. Concept Matrix of Reviewed Literature

Finally, we examined whether the primary outcome variables in the studies were instrumental (team performance, also including variables such as task delegation) or humanistic (team maintenance) (Sarker et al., 2019). Most studies investigated performance-related outcomes (35). Moreover, we identified the studies where team maintenance activities are examined with constructs such as trust and team cognition (13) when interacting with AI. Here, we observe that with more complex tasks, team maintenance (i.e., activities that directly impact the relationship between humans and AI and indirectly impact team performance) becomes more essential for human-AI collaboration.

To structure the results of our review, we use the teamwork phases as an overarching lens. These phases are integral to teamwork and allow the logical clustering of the other concepts and mechanisms identified. In the following, we will analyze the literature with the concepts of the provided matrix.

Preparation

During the preparation phase, the team creates a common understanding of the task and its respective goal, leading to the formulation of a strategy that the team executes to reach the set objectives. Extensive research in the field of teamwork emphasizes the crucial role of the preparation phase and its impact on team performance during the execution phase (Marks & Panzer, 2004; Rousseau et al., 2006). The identified mechanisms focus on team maintenance (improving a team's functioning) and information exchange between humans and AI. First, we identify studies that focused on the information provided to the user about AI (*team capability*). Second, some studies investigated how users can be introduced to collaboration with AI team members (*team cognition*). Third, we identify studies that investigated how humans delegate tasks to AI (*task delegation*). In the following, we describe and interpret these mechanisms.

The concept of team capability pertains to individual team members sharing information about their skills and weaknesses before engaging in teamwork (Rousseau et al., 2006). In general, we identify several methods used in human-AI collaboration to inform the human about an AI-based system's capability. Lai et al. (2020) investigated how these different forms (i.e., guidelines, random classified examples, and machine-selected examples) can help to improve human performance. Their results indicate that all forms of information exchange before the tasks improve human accuracy. However, guidelines and random examples seemed to improve the team's performance the most. Liu et al. (2021) conducted another study investigating the difference in how 'out-of-distribution' and selected examples before a task impact human performance. Their results emphasize the importance of providing real, out-of-distribution examples, especially for more complex tasks (H. Liu et al., 2021). These results align with another work, finding that real examples are most beneficial for human performance (Mozannar et al., 2021). The studies demonstrate the importance of transparency of the AI to the human, i.e., being able to interpret the outputs of the AI, know the error boundaries of the AI, and, ultimately, judge the correctness of the output generated (Lai et al., 2020). From the lens of teamwork, this emphasizes the need for a human to understand the strengths and weaknesses of AI. Notably, this topic is currently researched unidirectional (information provision from or about the AI to the human). But with the growing capability of AI-based language models such as ChatGPT, bidirectional information provision becomes possible, i.e., the AI can also learn about the human's strengths and weaknesses and adapt its behavior accordingly. However, no study addressed this topic during the preparation phase.

Team cognition is connected to team capability, i.e., preparing humans to collaborate with AI. Team cognition differs from team capability since it does not focus on the AI but on the task and future collaboration. By creating a shared mental model of the team's goal, Schelble et al. (2022) find that a shared understanding of the goal is much more important for human-AI teams than for human teams. Weiler et al. (2021) utilized so-called 'inoculation messages' to desensitize the human during service failure. The primary concept behind inoculation messages is to present information in a specific pattern to provoke counterarguing, a cognitive process that safeguards individuals from persuasion. They find that these inoculation messages boost the resistance of humans against failures of the AI team member (Weiler et al., 2021). This finding is underlined by other studies that indicate the importance of direct communication between human-AI teams (Schoonderwoerd et al., 2022).

Finally, we identify the research topic of task delegation in the preparation phase, which is a typical human teamwork activity. Task delegation is strongly connected to the first two topics; by understanding the strengths, weaknesses, and overarching goal of the task at hand, teams can better allocate their resources to upcoming activities and tasks (Marks et al., 2001; Marks & Panzer, 2004). The analyzed studies demonstrate the strong similarities between human-human and human-AI collaboration. Fügener et al. (2021a) examined how humans and AI delegate decisions to each other and found that team performance metrics declined when a human delegated the tasks instead of the AI. Interestingly, if AI oversaw delegating tasks, the overall team performance increased. Moreover, the authors emphasize the importance of metaknowledge during task delegation, i.e., knowing the complementary skills of oneself and team members to judge who can perform which tasks best (Fügener et al., 2021b). Haesevoets et al. (2021) investigated how managers delegate managerial decisions to AI and found that humans want to have control over machines but are willing to let AI influence the decision by up to 30%.

In total, we synthesize three major mechanisms within this phase that contribute toward team maintenance. Moreover, we find that this increased team maintenance in turn influences team performance. Despite this, team performance is the main outcome measure (8). Nevertheless, team maintenance constructs such as team cognition (e.g., Schelble et al., 2022) are also measured. The studies vary strongly in both task complexity and teamwork roles.

Execution

The execution phase includes all activities that involve the actual taskwork (Rousseau et al., 2006). Our analysis reveals the mechanism of collaboration adaptation, which is strongly connected to the organizational context, and explainability, which in turn is dependent on the collaboration mode between humans and AI. In the following, we elaborate on the two main mechanisms of this phase.

The first identified mechanism, collaboration adaptation, describes the collaboration mode switch from augmentation to assemblage triggered by increased task complexity. We find a two-sided effect of task complexity on human-AI collaboration. The synthesized literature reveals that with increasing (task) complexity, human-AI collaboration moves from traditional human-computer interaction (e.g., Zhang et al., 2002) to more sophisticated interaction patterns. The task complexity increases solution paths and interdependencies of sub-tasks; hence, the role of the AI becomes more autonomous. This leads to the second effect. With an autonomous role, an information asymmetry is created — the human is not able to observe or even comprehend every processing step of the AI. Human teamwork literature emphasizes the importance of utilizing the preparation and evaluation phases to understand the task and the team member and learn and adapt from past teamwork (Marks et al., 2001; Marks & Panzer, 2004). Especially, knowing the team member's weaknesses in advance and learning from past mistakes is an essential part of teamwork. Studies in human-AI collaboration have also indicated that this information asymmetry can be reduced by additional communication between humans and AI (team maintenance) (McNeese et al., 2018; Schelble et al., 2022). Team maintenance in turn is strongly dependent on the preparation and evaluation phase (Paris et al., 2000; Rousseau et al., 2006).

Our literature analysis provided further insights into the impact of task complexity on the two collaboration modes. On the one hand, we identify tasks of lower complexity (mostly decision tasks where the team needs to decide between two or more alternatives) which are researched the most (e.g., Costello et al., 2020; Shin et al., 2021; Green and Chen, 2019; Chu et al., 2020). In these tasks, the AI acts as an augmentation and recommends the decision that can be either accepted or rejected by the human. Thereby, the collaboration is generally limited to this decision-making context, and there is no further communication between humans and AI. On the other hand, we find that in more complex tasks, as teamwork activities increase, the collaboration mode switches from augmentation to assemblage. This is supported by Vassilakopoulou et al. (2023), who suggest that in complex tasks, augmentation and assemblage activities between humans and AI are more fluid and not strictly divisible. In these complex tasks, studies investigate how humans and AI collaborate when they have a common goal but distinct tasks and responsibilities. The studies' scenarios are often conducted in a game-like context involving different roles of humans and AI (e.g., Musick et al., 2021; Schelble et al., 2022; Schoonderwoerd et al., 2022). In contrast to low-complexity tasks, humans do not have control over the whole situation; on the contrary, they depend on their AI team member's outcomes. This is emphasized because all studies involving task assemblage also include explicit communication mechanisms with the human team member (e.g., Schelble et al. 2022). Schelble et al. (2022) emphasize the importance of team composition and show that explicit goal definitions are more important for human-AI teams than human teams, underlining the necessity to utilize the preparation phase, especially for the more complex human-AI interaction form of task assemblage. Other studies within this phase back this finding. McNeese and Cooke (2018) underline this finding by showing that human-AI teams behave differently than human teams due to the lack of social components of the AI. Musick et al. (2021) report that human players did not cooperate with their team members if they thought it was an AI instead of another human but instead focused on their objectives. Interestingly, in their study, all team members were humans that performed the same steps; thus, it was solely the perception of the team member that influenced their activities. Similarly, Schoonderwoerd et al. (2022) find that a common understanding of the team needs to be present to promote team functioning. In this context, the human teamwork concept of social loafing was investigated by Mirbabaie et al. (2021), who find that humans might reduce their cognitive effort when collaborating with an AI in order to save capacity (i.e., the authors coined this behavior as 'smart loafing').

The second mechanism, explainability, enables humans to comprehend the actions of the AI. Across both collaboration modes, the explainability of AI decisions was a crucial topic; however, the mechanism was designed differently depending on the mode. During the process of augmentation, humans tend to rely on the recommendations made by AI, which can sometimes result in a decrease in the overall performance of the human-AI team. This happens because humans are unable to identify AI-produced errors. As a result, the team may perform worse than the AI working alone. A common approach for the process of augmentation is the provision of explanations for AI decisions (Bansal et al., 2021; Chu et al., 2020; Gajos & Mamykina, 2022). The form of explanation provided is strongly dependent on the type of information that the user needs to process (e.g., textual or visual information). For example, Bansal et al. (2021) used colored highlights to inform the user about critical textual passages that determined AI decisions. However, their study also indicates that explanations can convince users of wrong AI recommendations. Moreover, there are other attempts to promote the cognitive engagement of the user to reduce accepting incorrect AI decisions. Bucinca et al. (2021) demonstrated how cognitive forcing functions (e.g., showing the AI recommendation delayed or after the user made his initial decision) could help reduce the negative effect of incorrect recommendations. The importance of cognitive engagement of the human before being supported by AI has also been acknowledged by other authors that conducted similar studies (Bansal et al., 2021; Green & Chen, 2019; Park et al., 2019).

In contrast, explainability mechanisms are designed differently in scenarios of assemblage mode. Studies in this context do not explain the AI's actions locally, such as in augmentation, but rather implement information exchange before the task. Emphasis is put on humans understanding the AI's behavior, strengths, and weaknesses (Song et al., 2022) and not on the explanation of single decisions. A possible explanation for this changing behavior is the increasing number of actions of the AI in assemblage contexts and the increased coordinative efforts of the team. Here, explaining the overall behavior pattern of the AI might be more helpful in comprehending the actions than explaining the actions individually.

In conclusion, most studies investigated the execution phase (33). Like the preparation phase, most studies use low complexity (decision tasks) (17) and team performance as the main measures (26). Eleven studies investigate team maintenance. With increasing task complexity (collaboration adaption), human-AI collaboration switches from augmentation to assemblage, leading to a more autonomous role of the AI and an adapted human behavior. Connected to this, we find that humans adapt their communication style when they are aware of interacting with an AI and tend to value task-related information more. Second, we identify that the mechanism of explainability should be designed differently depending on the mode of collaboration. The analysis of task complexity in the context of human-AI collaboration reveals its integral role in the design of the interaction.

Evaluation

The evaluation phase is used to adapt teamwork to changing conditions and to further improve it (Rousseau et al., 2006). Through our analysis, we find studies that utilize performance monitoring as a mechanism to inform the human about areas of improvement (system feedback). Moreover, we identify studies that integrate human experts to optimize their AI-based partners (expert feedback).

The first monitoring mechanism, system feedback, describes the information provision of the human-AI team performance to the user. We find that system feedback is mostly provided during iterative tasks that involve multiple similar decision contexts in order to enable user learning from past mistakes (e.g., Bansal et al., 2021). Another study provided feedback to participants of an experiment after the completion of the first half (twenty decision tasks). The feedback provided to participants encompassed their own performance, the AI's performance, and the degree of alignment between the two. Moreover, the studies conducted by Yin et al. (2019) revealed that feedback on the performance of the AI has a significant impact on human trust in the AI and is also influenced by the human's perception of the AI's performance. Additionally, one work investigated how behavior adjustment can be conducted in human-AI teams. Schoonderwoerd et al. (2022) investigate how human feedback can be incorporated into an AI team member by utilizing a rule-based approach, promoting co-learning, and increasing team performance. While the feedback approach increased the human's understanding of the AI's actions, it did not increase team performance.

The second identified monitoring mechanism, expert feedback, focuses on human input to improve the AI's collaborative behavior. Lou and Wou (2021) emphasize the importance of this mechanism in complex tasks such as drug development. Humans are needed to first detect and then refine the working of the AI. Therefore, the human team members need an understanding of the inner working of the AI (Lou & Wu, 2021), which indicates that this mechanism connects the evaluation to the preparation phase. Similarly, Lebovitz et al. (2021) find in their qualitative study that evaluation from human experts is needed to incorporate AI into daily work, especially in knowledge-heavy, complex work, where a high degree of uncertainty is present (e.g., diagnostic decisions). Similar to the preparation phase, mechanisms in the evaluation phase are currently designed unidirectionally in human-AI collaboration. Moreover, current studies demonstrate that evaluation mechanisms only partly contribute to higher team performance directly but are needed to foster team maintenance.

Furthermore, six studies exploring the process of performance evaluation and adjustment in human-AI collaboration were identified. We observe that with increasing task complexity and increasing autonomy of the AI, teamwork evaluation becomes more important for human-AI teams. All six studies explored the evaluation phase in the context of augmentation combined with a decision task. The evaluation phase solely focused on increasing team performance (all studies investigated team performance as the main outcome) as it is strongly connected to the execution phase.

Discussion

This literature review takes an initial step in organizing current research on human-AI collaboration. Drawing on established concepts of human teamwork, we reviewed and analyzed 41 studies. We identified temporal phases and mechanisms of human-AI collaboration that become more important with the increasing complexity of organizational contexts. The key findings of our work can be synthesized in a framework that splits human-AI collaboration into three phases: preparation, execution, and evaluation.

These phases incorporate different design mechanisms in the context of human-AI collaboration (see Figure 2).

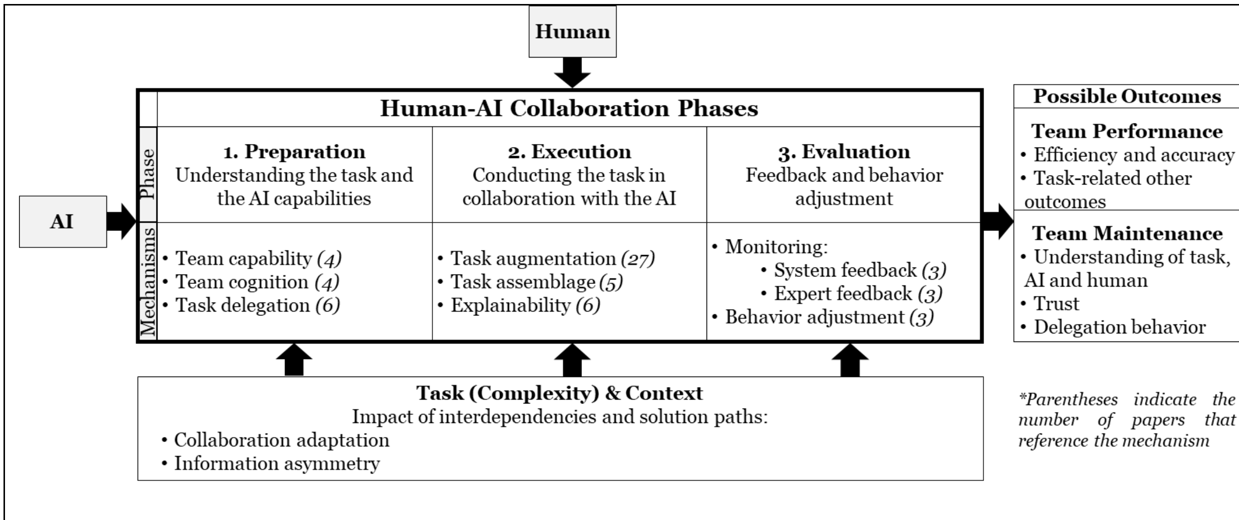

Figure 2. Framework of Temporal Phases in Human-AI Collaboration

We incorporate these phases into the HCI framework (Zhang & Li, 2004) as it allows us to embed the findings of our work into the existing research stream. We do not further analyze the characteristics of humans and AI, as they have been investigated previously within the human-AI interaction framework of Rzepka and Berger (2018). Our framework sheds light on three temporal phases of human-AI collaboration and clusters current research among them. These phases are distinct and provide different functionalities for human-AI team functioning. The preparation phase contributes mainly toward team maintenance by creating a shared understanding of the task, the AI's capabilities, and the activities of the collaboration at hand. During the execution phase, the actual taskwork and related activities, such as coordinating subtasks to AI, are conducted. The evaluation phase is used to feedback information about the team's performance to the humans or to collect experts' feedback and adapt behavior based on this information and proceed with the task execution. The outcomes of human-AI collaboration can differ. While team performance is an essential part of the outcome, our results suggest that with increasing task complexity, team maintenance becomes more important for successful collaboration.

Theoretical Contributions and Practical Implications

This paper makes three theoretical contributions. First, it contributes to the broad, multidisciplinary stream of research on human-AI collaboration by analyzing the current literature through the lens of human teamwork. While there are numerous empirical studies on specific aspects of human-AI collaboration, our work extends this research stream by providing an overarching conceptual framework of temporal human-AI collaboration phases that sheds light on the mechanisms and complex interaction patterns of such collaborations. By applying concepts and principles from human teamwork, we identify eight key mechanisms that contribute to effective collaboration and performance in human-AI collaboration. Overall, the framework provides a first step toward a holistic understanding of human-AI collaboration, which can inform the design and implementation of AI systems in organizational contexts. Second, we reveal differences between human-human teamwork and human-AI collaboration. For example, while human-human teamwork research emphasizes the importance of team maintenance for successful teamwork independent of task complexity, we observe that current human-AI collaboration research pays more attention to team performance aspects. Moreover, our results indicate that humans tend to have different information requirements and also behave differently when interacting with AI team members compared to human team members (Musick et al., 2021), which points to a different level of information asymmetry when collaborating with AI. Third, based on our framework, we derive avenues for future research on human-AI collaboration, which can guide researchers to topics that are currently underresearched.

For practitioners, our work highlights the challenges that organizations face when implementing AI-based systems to work alongside humans and proposes several strategies to address these challenges. First, unlike human-human teams, organizations must intentionally structure the collaboration between human-AI teams to ensure effective teamwork (e.g., defining relevant task-related information that the AI needs to exchange with the human). Moreover, our work emphasizes the importance of team maintenance activities for human-AI teams to increase the team's performance and beat the solo performance of AI, especially in more complex tasks. By utilizing the preparation phase, such as providing guidelines and examples before the task, studies indicate that human-AI team performance could be increased significantly (V. Lai et al., 2020; Schelble et al., 2022). Software developers can leverage this insight to create preparation phases that introduce users to the interaction with the individual AI (e.g., through custom tutorials). When organizations introduce AI-based systems, they can acquire real-world examples of AI-generated errors using real AI decisions and provide training to employees for effective human-AI collaboration. Furthermore, our discoveries suggest that alternative approaches, like postponing AI recommendations, can positively impact team performance, depending on the respective task type. (e.g., Park et al., 2019).

Future Agenda of Human-AI Collaboration Research

We summarize the most promising future research avenues and the rationales of human teamwork in Table 3. In the preparation phase, we identify the major topic of preparational information provision to the user. Current literature suggests that onboarding a user and preparing them for human-AI collaboration by providing information about the inner workings of the AI (i.e., transparency) can positively impact team performance by decreasing information asymmetry (Holzinger et al., 2017; Vössing et al., 2022). In our review, most studies focused on low-complexity decision tasks; hence, it remains unclear how information asymmetry can be reduced for high-complexity tasks, especially when these involve the collaboration mode of assemblage. Moreover, tasks are not standardized (e.g., text vs. image-based) (Bansal et al., 2021; Fügener et al., 2021a), making the generalizability of findings very limited as of now. A current approach to human-AI collaboration is to provide explicit explanations to the human to enable the augmentation of results. However, we are starting to see the limitations of such explanations, as humans tend to accept these explanations and not scrutinize them. Hence, innovative ways are needed to encourage human-AI teams to carefully reflect on the results provided by the AI. Drawing on human teamwork, we identify constructs such as shared mental models as effective tools to do this. However, we only found one work that explicitly created such an understanding and proved it had a beneficial impact on team performance (Schelble et al., 2022). Finally, there might be contexts where (partial) delegation by AI can be useful (Haesevoets et al., 2021) due to its unique strengths.

Our results suggest that the execution phase is the most researched domain of human-AI collaboration. Nevertheless, we identify several research directions for this phase. We observe a clear dependency between the task's complexity and the type of human-AI collaboration. Studies utilize various strategies to communicate recommendations of the AI to the human, for example, by providing explanations on the (un)certainty of the AI to support the human in detecting AI-produced errors. These studies yield contradictory results (e.g., Park et al., 2019; Bansal et al., 2021; Fügener et al., 2021b; Braun et al., 2022) and point toward the ambiguity of information provided concerning an AI system's recommendation. Future research is needed on how explanations must be designed to make the human question the recommendation instead of simply accepting them. In this context, the question arises of how the preparation phase and the evaluation phase can be utilized to complement recommendations by reducing information asymmetry. Gajos and Mamykina (2022) use contrasting explanations (compare two decisions and argue why decision A was chosen compared to decision B) from human interactions and provide promising results. Due to the diverse configurations of human-AI collaboration, future research could test the effect of such a dual explanation scheme on other tasks.

Overall, little human-AI collaboration research has investigated the evaluation phase. We attribute this to the growing complexity of such a study because it needs several phases where the user either receives feedback or provides feedback to the AI. As of now, user feedback based on the measured team performance seems to have no direct positive impact on teamwork, despite knowing that in human teamwork, feedback fulfills an important function and has a strong influence on performance (e.g., Rousseau et al., 2006; Saedon et al., 2012). Future work should investigate means for providing meaningful feedback to humans.

Phases	Current state of research	Rationale from human teamwork	Possible research questions
Preparation	• The preparation phase is important for complex human-AI collaboration because it can help to reduce information asymmetries between humans and AI. • Humans need to understand their AI Team member's error boundaries and inner workings to detect errors and enhance their decision-making abilities during task delegation. • Research indicates that explicitly communicated information about the upcoming teamwork is more important if a team member is an AI.	• Team members need a clear understanding of the team's roles, competencies, and weaknesses to distribute tasks and set goals accordingly as well as reduce information asymmetries (Paris et al., 2000; Rousseau et al., 2006). • Human teamwork emphasizes the benefit of team performance as well as coordinating activities such as task delegation (Paris et al., 2000).	• How should AI capability be communicated to humans to reduce information asymmetry? • How can the preparation phase be leveraged to overcome the phenomenon of humans accepting AI's advice instead of questioning it during the execution phase? • In which contexts is delegation conducted by AI useful?
Execution	• The type of interaction between humans and AI changes depending on the task's complexity. With high task complexity, the information asymmetry between humans and AI is increased. • To overcome information asymmetry and enable effective collaboration, information exchange (e.g., explanations) is needed. However, explanations are not suited for every type of task.	• Human teamwork suggests that higher task complexity requires higher coordination efforts. • Moreover, task complexity makes teams prone to coordination errors (e.g., generating high time pressure on the team (Xiao et al., 1996)). • Information exchange during task execution helps team members to align their understanding of the task. Moreover, it supports them in detecting progress deficiencies (Rousseau et al., 2006).	• How do the collaboration modes of augmentation and assemblage change the requirements to explain AI behavior? • Which task characteristics are (or are not) suited for which collaboration mode? • How can information asymmetries between human and AI in during task execution be addressed?
Evaluation	• Team performance is measured and communicated to the human during teamwork. • Findings indicate that feedback only rarely improves the human-AI team's performance. • Feedback is mainly communicated from the system to the human. First works emphasized the importance of expert feedback for the system.	• Performance monitoring enables team members to track their progress as well as the progress of others and to intervene if necessary. • Feedback is an essential tool of human teamwork and helps to reach the team's goal (Rousseau et al., 2006).	• How can AI adapt to human feedback and vice versa? • What information do humans need as feedback to reduce information asymmetries and to adjust their behavior during human-AI collaboration? • How does task complexity impact the effectiveness of integrating evaluation phases?

Table 3. Future Research Agenda for Human-AI Collaboration

Concluding Remarks

Our study is not free of limitations. As empirical studies on human-AI collaboration are scattered across many domains and uses different terminology, we cannot rule out the possibility of missing relevant studies. Moreover, we focused on a specific set of concepts in order to investigate the temporal phases of human-AI teamwork in more depth. While these concepts were carefully selected to grasp the individual notion of human-AI collaboration there might be other teamwork frameworks and human-AI collaboration concepts that could have been utilized to analyze the existing literature. In addition, AI systems may have distinct capabilities that are not covered by human teamwork literature. It is also important to note that dimensions that are condensed in our framework potentially have more facets than depicted by our work. For example, we did not delve into further analysis of regulatory or ethical constraints that impact AI, which could be relevant for real-world implementations of human-AI work processes.

In the present work, we frame human-AI collaboration using the perspective of human teamwork. In doing so, we organize actively researched topics within this domain in a sequential order, thereby paving the way for new research avenues. The derived future research agenda considers possible topics of interest and connects them with rationales of human teamwork. Hence, we hope to enrich current perspectives on human-AI collaboration through the proposed temporal components.

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