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► **To cite this version:**

Kimberly Meyer, Bernd-Friedrich Voigt. Process Wins and Losses in Dynamic Human-AI Interplay - A Socio-psychological Research Perspective on Collaborative Performance. 23th Working Conference on Virtual Enterprises (PRO-VE), Sep 2022, Lisbon, Portugal. pp.289-302, 10.1007/978-3-031-14844-6_23 . hal-04642039

HAL Id: hal-04642039

<https://inria.hal.science/hal-04642039v1>

Submitted on 9 Jul 2024

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Process Wins and Losses in Dynamic Human-AI Interplay - A Socio-Psychological Research Perspective on Collaborative Performance

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Abstract. We analyze socio-psychological process wins and losses in relation to Human-AI collaborative performance. The reported heterogeneous effects of the body of literature on group performance in relation to structural and processual determinants are briefly summarized. Based on this, two of the most relevant socio-psychological aspects of Human-AI collaborative performance are highlighted: Accuracy of the shared mental model and fulfillment of basic human needs. The paper concludes by proposing an empirical and experimental research program that addresses under-researched socio-psychological phenomena in Human-AI collaboration that can be held accountable for process wins and losses.

Keywords: Human-AI interaction, socio-psychology, collaborative performance

1 Introduction

While Industry 4.0 emphasized digitization and the associated transformation processes, the current swing toward Industry & Society 5.0 (re)focuses on the social dimension of a solution-oriented integration of humans and technology [1, 2]. At the same time, human-technology interaction further evolves as machines can be designed on anthropomorphic features and be perceived as having human-like attributes or even engaging in social behavior [3]. In practice, human employees are increasingly confronted with outsourcing their tasks to machines, receiving digital support for human weaknesses, and interacting with a team member that has perceived artificial intelligence (AI) instead of human intelligence [4, 5].

The relationship between people and machines is therefore changing. While the machine used to be a tool, AI-based technology is now capable of taking over human competencies such as pattern recognition, planning, and prediction [6]. Consequently, AI-powered applications can be called *intelligent agents*. Intelligent agents are defined as technology that can act and react proactively and autonomously so that interaction with other actors emerges [7].

A key change in human-machine interaction seems to lie in the pursuit of common goals: Humans do *not just use* the intelligent agent but *collaborate* with it in a dynamic interplay [8]. Humans need to coordinate with non-human team members, distribute autonomy and make decisions jointly. In this context, the actual technological capabilities of the intelligent agent play a subordinate role. Of primary importance appears to be the team's perception of the non-human team member as intelligent and social [9]. Thus, we argue that real collaboration between humans and intelligent agents is emerging and, that this collaboration is influenced by psychological and physiological human factors, technological requirements of AI, and socio-psychological processes that arise from the interactive nature of collaboration.

Empirical research examining the interplay between humans and intelligent agents has consistently identified socio-psychological processes between the two actors. For example, when interacting with an intelligent agent, people have been found to follow social norms such as politeness [9, 10], establish a trusting relationship [3, 11, 12], and perceive the agent based on the social cognitive dimensions of warmth and competence [13]. However, currently, the evidence gathered in this line of research seems to be heterogeneous and mostly neglects the socio-psychological processes at the group level. An exemption to this is the concept of autonomous agent teammate-likeness [14]. Autonomous agent teammate-likeness relates human attributes to those of the intelligent agent and characterizes the teammate-likeness based on the agentic ability, altruistic intent, task interdependence, task-independent relationship building, depth of communication, and synchronized mental models. Relevant determinants can therefore be captured to distinguish whether technology is an infrastructure element or a social actor. In addition, the concept defines moderators that determine the quality of collaboration (e.g., trust, attribution to failure, human knowledge, skills, and abilities) and its outcomes. Even social group phenomena are already addressed in the representations of these outcomes (e.g., group cohesion that describes the strength of the relationships that bind the members of a group [14]). What remains open is a deeper analysis of the underlying group processes. Which other socio-psychological processes can also be found and held accountable for collaborative performance in human-AI teams? And, by which conditioning factors are they triggered?

With respect to human-only teams, socio-psychological processes have been intensively researched. Various theoretical and methodological approaches have produced a heterogeneous body of knowledge regarding aspects such as (among others) group size and collaborative performance [15], relative richness and evenness of the team composition and the resulting of various outcomes [16], social identity, and the building of ingroups and outgroups [17], group heterogeneity and the building of faultlines in social conflict [18], social influence and the building of trust [19], functional diversity and the building of innovative capacity [20].

In summary team performance is a) strongly dependent on the task-related variety of characteristics and resources of team members [21] and b) on structural variables and team processes that support or hinder the utilization of the given resource base [22, 23]. Thus, the underlying body of psychological theories can be sorted into two clusters. Theories, that highlight the value in relative diversity can be attributed to a structural resource-oriented perspective [24]. Theories, that highlight processes wins and losses that effect collaborative performance can be attributed to a transaction-cost

perspective [25]. Even though the literature that relates to these theory families is extensive, it still provides a heterogeneous picture regarding performance outcomes [26].

For a structured exploration of these heterogeneous effects in human-AI teams, we relate to a well-established process-based framework of collaborative performance. From our point of view, Hackman and Morris' [27] framing model of group performance allows to interpret the diversity of findings on traditional human-to-human collaboration and to expand the scope of the model to the newer facets of human-AI-collaboration. The original model defines group performance as the possible performance being the sum of individual group members' potentials minus process losses plus process wins (see figure 1).

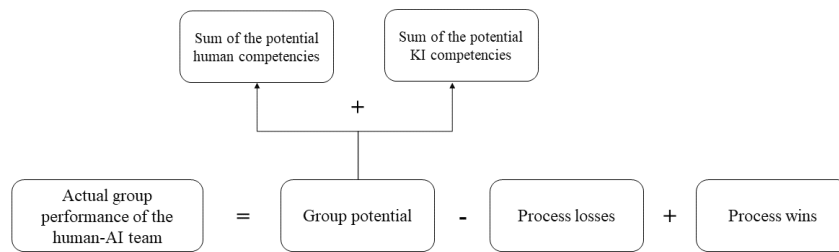


Fig. 1. The concept of group performance by Hackmann and Morris [27]

Process losses are influences that reduce the actual group potential (e.g., poor coordination, loss of motivation). Process wins would allow to harvest or even further increase the actual group potential (e.g., synergies between group members). In the case of human-AI teams, the group potential would be the sum of all the competencies – human as well as artificial competencies. Process losses would correspondingly be coordination or motivation losses triggered by the addition of the intelligent agent to the team. For example, coordination problems with the AI due to a lack of competence in handling or threats to the human identity would be conceivable. On the other hand, there would be process gains resulting from synergies between human and artificial intelligence (e.g., AI has greater memory capacity and quicker accessibility, whereas humans might easier find creative solutions beyond proven setups).

To illustrate this perspective, we introduce a demonstrative example: A team of psychologists has the task of putting together workgroups that have the highest possible fit. Competencies, personality variables, social behavior, likes, dislikes, and past work performances must be considered. The selected employees should fit as well as possible to their task and with the other team members. To solve this task, the team has an intelligent agent that receives information about the different variables and develops team-staffing suggestions. When these are being rejected, the psychologists must provide a rationale so that the intelligent agent can optimize its suggestions. Structural elements in this case would be all conditions that result from

the group coming together in this specific context. For example, these would be the skills of the psychologists, the data sources, the structure of the decision situation, the design of the AI, etc. Process elements would arise from the interaction taking place. This could be sympathy effects, the expansion of shared information when a proposal is rejected, or knowledge about the decision behavior of the AI. Whether the respective elements are process gains or losses will be determined during the literature work and further research.

The aim of this paper is to structure human-AI collaboration based on Hackman and Morris' process model of team performance [27] and thus to help categorize existing and future research insights on socio-psychological processes in human-AI interaction as process gains or losses. We considered the model's division into structural and process elements, too, so that a recourse to the underlying theory families of socio-psychology becomes transparent. Therefore, the results of this paper should be considered as initial conclusions on how collaboration in human-AI teams can be structured to be as productive as possible. Based on this, further research gaps could be identified and labelled more systematically across disciplines. This would again allow designing a consistent research program on collaborative performance in human-AI interplay to be pursued in subsequent research activities.

2. Identification of Relevant Research

To identify relevant research in human-AI interaction, we conducted a targeted search for research communities working on this topic. The following communities were identified: *ACM Transactions on Computer-Human Interaction* [4, 14], *Association for the Advancement of Artificial Intelligence* [9, 10] and *Advances in Information and Communication Technology* [28, 29]. In addition, papers regarding socio-psychological processes in human-AI teams have been published in various journals such as *Theoretical Issues in Ergonomics Science* [14], *Scientific Reports* [30], and *Journal of the Academy of Marketing Science* [3]. Within these communities and journals, we identified relevant contributions by theoretical reference to socio-psychological theories or models and then examined them in terms of processual wins and losses in human-AI teams.

2.2 Trust and Relatedness as Basis for Process Wins and Losses

Following the given research foci, a critical element in creating process wins in human-AI teams appears to be the matter of trust [3,11,12]. Jennings et al. [8] postulate trust as one of the most important processes in the collaboration between humans and AI. They assume that it is a necessary condition for functions such as coordination, decision-making, and flexible autonomy. Richards and Stedmon also support this assumption [31]. They define trust based on the human understanding of what the machine is currently doing and what it will do next. According to the authors, a shared mental model is created when this information is available. The concept of mental models is used in the understanding of Johnson-Laird [32]. He

describes a mental model as an internal representation of integrated information into an inner concept. Through these models, perceptual processes are navigated, new information is categorized, and conclusions are drawn. Takko et al. also describe in their study that shared mental models were able to increase team performance of human-AI teams [30]. Forming a shared mental model, therefore, seems to represent a process win for human-AI group performance. However, it is important to understand that this process win is initially rooted in a structural aspect of team composition because shared mental models are more likely to arise and sustain when team members are similar and form a homogenous group [33]. Paradoxically, shared mental models can also result in process losses. Once a shared mindset evolves, it is secured by a strong social ingroup effect, that tends to negate relevant external information or feedback [34].

We transfer the concept of shared mental models to the exemplary case of the team of psychologists in collaboration with an intelligent agent. The concept implies that a sufficient human-to-human as well as human-to-machine homogeneity is needed across all ties of the team network to enable the expected process wins. Not only need the human team members understand what the machine is currently doing and what it will do next, they also need to feel a shared identity with the AI. In addition to this, the Human-AI team needs to set up adequate measures to ensure that the shared mental model does not lead to the building of dysfunctional subgroups or hinder from seeing and interpreting contradicting external information objectively.

Some studies, which address the structural homogeneity aspect of how to describe the trust relationship in human-AI interaction, examine the influence of anthropomorphic traits. Anthropomorphic traits can be interpreted as a source of both, process losses and process wins. Yet, the effect of these characteristics is not clear. In the studies of Foehner and Germelmann [11] and Pitardi and Marriott [12], the humanization of AI had a positive impact on the trust relationship. However, Ferrari et al. [35] and Mende et al. [36], showed that anthropomorphic AI features posed a threat to human identity. Appel et al. [37] noted a sense of eeriness when service robots exhibited stronger humanization. Finally, Khadpe et al. [13] focused on the nature of humanized traits. To this end, they manipulated the representation of the metaphor through which the AI acted concerning the social-cognitive dimensions of warmth and competence. Individuals were found to have significantly more positive attitudes toward AI when its metaphor was high warmth and low competence.

2.3 Fulfillment of Basic Human Needs as Basis for Process Wins and Losses

According to Fiske et al. [38], the dimensions of warmth and competence are the foundation of social structures because they provide information about competition and status. Warmth is associated with friendly and approachable behavior, and it is considered an indicator, that the other person has good intentions. Competence, on the other hand, is an indicator of whether a person can conduct their good intentions and thus make the interaction successful. In human interactions, people who are rated high on one dimension and low on the other elicit ambivalent reactions. These are

expressed, for example, in mixed stereotypes. A common mixed stereotype toward the elderly might be that they are perceived as friendly and open (high warmth), but also as slow, needy, and incapable (low competence) [39].

This ambivalence was not detected in the interaction between humans and AI. On the contrary, if the AI metaphor was a teenager or toddler, the interaction with the AI was rated significantly better than if it was an executive or professor. One assumption could be that the perceived human competence poses a threat to human identity. As research by Mende et al. [36] shows, anthropomorphic characteristics of intelligent agents can cause humans to feel threatened and exhibit more behavior that serves as self-regulation (e.g., purchasing status goods, seeking social affiliation). This behavior ensures the need for competence in comparison to the AI. This would imply that humans compare themselves to AI in terms of competencies if this dimension is humanized. Humanization would therefore lead to a violation of the human need for competence. This again poses a problem because competence, along with social relatedness and autonomy, is considered one of the three basic human needs necessary to ensure elevated levels of performance and well-being. If these needs are not met, defensive needs develop that serve as substitutes but prevent actual need fulfillment [40]. Accordingly, the violation of the basic human need for competence represents a potential process loss not only at the level of competence, but also in terms of autonomy [4, 5].

Incorporating the research of Jiang et al. [4] and Wang et al. [5] into this discussion, one could argue that the participants' expressed desire for full agency may indicate a violation of the autonomy need. In each of these papers, participants were asked about their perceptions of semi-autonomous intelligent agents in their field of work (qualitative research and data science). In both cases, an ambivalent relationship became apparent. While participants assumed that the use increased efficiency, they expressed concerns [4] and a strong need for control, too [5]. Building on the concept of Jennings et al. [8], this desire represents a process loss because the flexible distribution of autonomy is a necessity in a human-AI team. However, the perspective on satisfying human needs in human-AI teams is not exclusively negative. Wynne and Lyons [14] argue that the need for relatedness can have a positive influence on the collaboration in human-AI teams. The intelligent agent is viewed as a social entity and can therefore provide a source of social connection so that the need for relatedness is satisfied. If human team members and non-human intelligent agents share an increased need for social relatedness, this characteristic can constitute a process win for the group's performance.

In addition to the strong need for social relatedness, there are other characteristics of team members that can be valued as process wins. Süße et al. [29] discuss nine human competencies that are beneficial when interacting with an AI. They distinguish between cognitive, emotional, and social competencies. The social competencies refer to communication with the AI. Communication should take place comprehensibly and constantly in the form of an ongoing dialogue. The emotional level also contains a communicative aspect, namely the negotiation of one's rest periods with the AI. The general perception of the AI as a virtual team member is also categorized under emotional competencies. Four competencies are grouped under cognitive competencies, which relate to understanding the AI (cues must be interpreted, abilities must be assessed, and ways of operating must be reflected upon) and dealing with

sensitive data. Frequent occurrence of these competencies among human team members thus represents a process gain within human-AI teams. However, it is still unclear, if and to what extent non-human team members are expected to have and show similar competencies through cognitive, social, or emotional team behaviors.

On an interactional level, so far, trust as a process win has been discussed primarily. However, other interaction effects that could represent process losses need also be considered. One of these effects, already well known from human-to-human socio-psychological research, could be the phenomenon of groupthink [41]. Groupthink describes a process that suppresses dissenting opinions for the sake of group harmony, leading to poor decision-making. A group's belief in invulnerability and superior group morality are typical groupthink indicators. Collaborative decisions are collectively justified, and individuals with dissenting opinions are stereotypically perceived. This creates a high pressure to conform, leading to self-censorship, information barriers, and an illusion of uniformity [41]. Groups with a high degree of cohesion or a directive leadership style are prone to this phenomenon.

Okamura and Yamada [42] investigated over-trusting in intelligent agents and discussed the resulting security risks. The authors propose so-called trust calibration cues to avoid over-trusting. The authors define over-trusting as the overestimation of the capabilities and reliability of intelligent agents. In their study, Okamura, and Yamada show that providing cues of over-trusting to team members significantly aligned trust and the actual capabilities of the AI [42]. Over-trust can be understood considering the groupthink phenomenon, especially when it occurs in human-AI teams. The overestimation of the AI's capabilities and thus of the overall group potential could lead to the invulnerability illusion described above and thus represent a process loss. In the light of this research focus we conclude that the role of intelligent agents as perceived social team members in preventing or upholding groupthink and subsequent performance issues still needs more attention in future research.

3 Preliminary Synthesis of the Underlying Body of Socio-Psychological Theorizing

How can socio-psychological process wins and process losses in human-AI teams be systemized for a better understanding of team collaborative performance? We approached this question by building on the concept of group performance by Hackman and Morris [27]. First, we argued, that intelligent agents can be seen and perceived as social actors on a team level. Next, we underlined that group performance consists of the potential performance of the individual human and non-human members minus the process losses plus the process wins. Finally, we identified socio-psychological perspectives in the existing body of human-AI literature and indicated, how they can be related to process wins and/or losses.

Our procedure showed that a socio-psychological perspective is well justified and applicable to research on human-AI collaborative performance. We also showed that the current discussion can be cataloged by two dominant perspectives, namely

correlates of shared mental models (e. g. groupthink effects) and effects of basic human needs (e. g. trust). For each of these approaches, we delivered unsolved questions for future research. We synthesized our transfer of socio-psychological approaches to an improved understanding of group performance in Human-AI collaboration as depicted in figure 2.

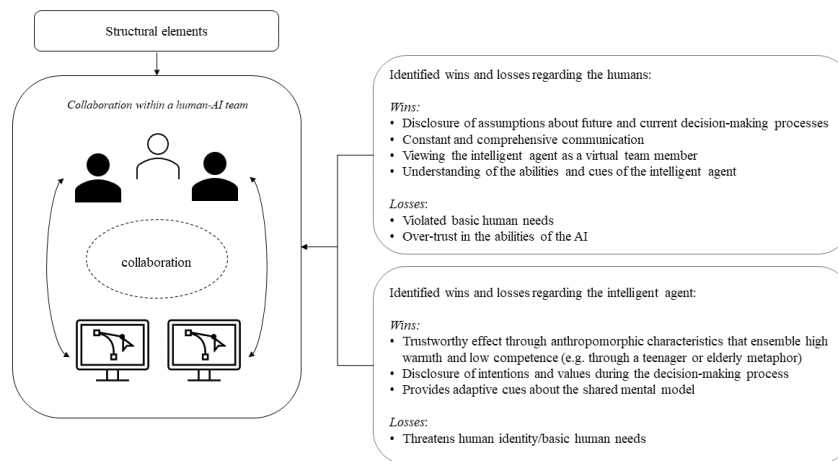


Fig. 2. Visualization of process wins and losses in human-AI teams

Process wins refer to the accuracy of the shared mental model and the associated explainability and predictability of the AI's actions. In addition, certain human characteristics of the AI (e.g., the perception of the AI as warm) promote trust and can promote the satisfaction of the human need for relatedness, especially when individuals exhibit a heightened need in this regard. On the human side, certain competencies are beneficial, which positively influence the communication process with AI. These relate to goal-oriented communication and the ability to understand and reflect on the mode of operation of the AI. Process losses also relate to the accuracy of the shared mental model and the possibility of satisfying basic human needs. Regarding the shared mental model, there is a risk of over-trusting the AI, which can lead to an illusion of infallibility and thus become a security risk. Furthermore, process losses can occur due to the violation of basic human needs, especially competence and autonomy.

What can be done to counteract these losses and promote benefits? To foster humans' trust in AI, enough information needs to be available so that they can create a mental model that provides reliable information about the current and future actions of AI. Especially the communication of intentions and values during the decision-making process seems to be of importance [14]. In addition, it might be possible to find ways to make the human mental model accessible to the AI and check it for inconsistencies. To ensure this insight, teams should implement structures that promote the sharing of the mental model. For example, after a decision by the AI,

team members could be asked for their assumptions about the decision-making process and their hypothesis about future decisions. The AI would integrate all the information into a connected model, thus making a phenomenon that is otherwise only mentally represented a subject of discussion. Inconsistencies, discrepancies, and misconceptions about the decision-making process could be revealed and corrected. This would increase the explainability and predictability of AI behavior, as the shared mental model is increasingly adapted to the actual decision-making process. Okamura and Yamada advocate a similar principle by with their trust calibration cues [42].

Following the work of Khadpe et al. [13], it is also recommended that AI be represented with a metaphor that involves a lot of warmth and little competence, such as children or the elderly. This is believed to spare the human's need for competence. It is also assumed that this will increase the fulfillment of social relatedness. The possible violation of the need for autonomy must also be considered. Team members need to feel that they can make decisions independently while allowing the AI to act (partially) autonomously as well. It is assumed that trust is a key mediator. The explainability and predictability of the AI create reliability, which may lead to overcoming an overbearing need for control and satisfying the actual need for autonomy.

4 Ideas for an Experimental Research Program on Socio-Psychological Aspects of Human-AI Collaborative Performance

The theoretical assumptions outlined above need further empirical evaluation in future research. Table 1 provides a list of variables to be tested. We differentiated by structural and process relevance and we referenced the research collected and presented in this paper. Even though closely related to the existing body of literature, the list does not claim to be exhaustive.

Tab. 1. Selected variables for further research on socio-psychological processes in human-AI teams

Variables	Refers to Structural or Process Elements	Is Already Studied by
Homogeneity	Structure element	to our knowledge not yet investigated
Diversity	Structure element	to our knowledge not yet investigated
Group Size	Structure element	to our knowledge not yet investigated
Task Requirements	Structure element	e.g., Takko et al. (2021)
Human Factors	Structure element	e.g., Süße et al. (2021)
Features of the Intelligent Agent	Structure element	e.g., Khadpe et al. (2020)
Trust	Process element	e.g., Okamura & Yamada (2020)
Building a Social identity	Process element	e.g., Mende et al. (2019)
Satisfaction of Basic Human Needs	Process element	e.g., Wynne & Lyons (2018)
Resources arising from Collaboration	Process element	e.g., Jennings et al. (2014)
Dysfunctional Group Processes arising from Collaboration	Process element	to our knowledge not yet investigated

4.1 Structural Elements to be Investigated in Human-AI Teams

Structural elements that should be investigated in human-AI teams with respect to their socio-psychological effects on collaboration are homogeneity, diversity, group size, task requirements, human factors, and features of the intelligent agent.

Some of these variables have already been studied by the authors presented here. For example, Takko et al. [30] show the positive influence of human control on collaboration in a human-AI team. Süße et al. [29] discuss the relevance of communication skills and understanding of the intelligent agent as relevant human factors, and Khadpe et al. [13] point out the relevance of the social-cognitive dimensions of warmth and competence in human-AI interaction.

Here, too, the research could be further intensified to establish a broad empirical basis. In addition, variables that have not been investigated so far (to our knowledge) should also be included in the research, as they prove to be relevant determinants for the functionality of collaboration in human-only teams. One of the determinants is homogeneity. Research in human-only teams shows that similarity in terms of personal variables (e.g., demographic characteristics) [43] is beneficial for effective collaboration. However, a diverse professional background may favor collaboration on tasks that require creativity [22]. Homogeneity is therefore closely linked to diversity and should be examined in dependence. Especially because these effects are dependent on the structure of the task. Adding this observation to human-AI teams it is required to ask the following questions: What similarities and differences do people perceive in human-AI teams? How can they be manipulated? And what group processes are triggered as a result?

Socio-psychology research shows that group size affects collaboration in social groups. These include effects such as the Ringelmann effect (performance decreases in large groups) [44], deindividuation (the person is so immersed in the social role that individual identity is barely perceived) [45], and the bystander effect (the likelihood of helping behavior decreases with group size) [46]. Studies should translate these processes to human-AI teams and answer the question: how would these processes manifest themselves in human-AI teams? A distinction should be made between the number of human team members and the number of artificial team members.

Team performance is highly dependent on task characteristics [47]. Therefore, it could be assumed that the effectiveness of human-AI collaboration varies depending on the task requirements. Here, it could be investigated which tasks can be processed in human-AI teams in a particularly goal-oriented manner and how these tasks are characterized.

4.2 Process Elements to be Investigated in Human-AI Teams

The following socio-psychological processes in human-AI teams should be studied in more detail: Trust, social identity, the satisfaction of basic human needs, resources from collaboration, and dysfunctional group processes from collaboration.

Trust, social identity, and resources generated by collaboration have already been studied [3,8,42]. Okamura and Yamada [42] investigated both over-trust and under-

trust and established both determinants and possibilities of adjusting the trust level. These findings could be applied to other populations and thus be deepened. Furthermore, processes of trust-building could be characterized in more detail. In this context, dysfunctional group processes, such as groupthink, could also be investigated. The over-trust described by the authors shows similarities with this classical socio-psychological phenomenon. The extent to which this also occurs in human-AI teams remains to be explored.

For functional group processes the work of Jennings et al. [8] may provide some indications. The authors establish a framework for human-AI teams with their HACs concept and define flexible autonomy as a resource in a HAC. Here, it could be investigated more deeply, what team members need to distribute autonomy flexibly and what influence this has on the basic human need for autonomy. According to Deci and Ryan [40], autonomy, competence, and relatedness are fundamental human needs necessary for optimal performance and well-being. The impact of relatedness on human-AI interaction is most notably discussed by Wynne and Lyons [14]. They assume that individuals can satisfy their need for relatedness in human-AI interaction. However, what impact this satisfaction and possible violation of needs may have remained open.

In addition to basic needs, human-AI interaction can also lead to the violation of human identity [36]. According to Tajfel and Turner [48], human identity has not only a personal aspect but also a social one. The latter is comprehensive and includes other group members. In human-AI teams, this would mean that the AI also becomes a part of the group identity. What influence this process has on the threat to human identity and whether this integration of a non-human identity is even possible needs to be investigated.

In addition to the structural and process elements presented here, other variables are conceivable. A standard classification of socio-psychological processes is e. g. social cognition processes, the construction of social identity, the influence of the social other on attitudes and attitude changes, and the accompanying social influence, group dynamics, and the resulting group performance. To profoundly characterize socio-psychological influencing factors in human-AI interaction, research in the relevant areas would be purposeful.

5 Conclusions

The considerations presented are founded conclusions. Although arguments were based on empirical studies, no empirical research was conducted. The structure of the report is based on the best of our knowledge but does not claim to be complete. Especially in interaction processes, additional processes wins and losses may have gone unnoticed. Decision-making processes in human-AI teams could be examined more closely in this context. The evaluation of AI regarding other relevant dimensions could also be of relevance. For example, the influence of perceived similarity between humans and the AI would be an interesting subject of investigation: Is the AI more trusted when perceived similarity increases? If so, which dimensions are decisive for

this? Also, the influence of processes between human actors in a human-AI team has been less considered in this paper. Here, the question could be asked: How does the mere presence of an AI influence interpersonal interaction? These questions remain unanswered and require further research. This paper aims to provide a socio-psychological perspective on group performance in human-AI teams that allows to integrate such open research questions more systematically in the future.

In summary, in human-AI teams, human factors, AI factors, and interaction factors simultaneously influence group performance. Group performance can be defined as the summed potential performance of all team members minus process losses plus process wins. Process wins and losses have been focused on in this paper as a group-level output of the dynamic interplay between human and human-like artificial agents. Building on the presented argumentation, the two most important factors seem to be the accuracy of the shared mental model and the possibility of fulfilling the basic psychological human needs. For the shared mental model to be as accurate as possible, communication processes should take place that increases the AI's explainability and predictability. This results in trust, which is considered a crucial process win. To ensure that the basic psychological needs of humans are not compromised, the competence dimension of social cognition should not be represented by humanized features of AI. However, humanizations of the AI that pay into the social cognition dimension of warmth promote the need for social relatedness and improve trust. The reasoning of this paper is conceptual and therefore limited. Moreover, it is a very specific socio-psychological perspective on group performance, which is presumably conditioned by diverse influencing factors. Possibilities for empirical testing of the postulated theoretical considerations are discussed.

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