

AI and Group Decision Making: An Information Processing Perspective

Thomas E. Gorman^{1,2} and Torsten Reimer³

¹Communication and Cognition Lab, Purdue University, USA

²College of Liberal Arts Research Academy

³Communication and Cognition Lab, Purdue University, USA

Author note

Thomas E. Gorman,  <https://orcid.org/0000-0001-5366-5442>

Torsten Reimer,  <https://orcid.org/0000-0002-7419-0076>

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Introduction

Artificial Intelligence (AI) is becoming a central component of group decision-making processes across a range of domains. From healthcare to finance, education to policymaking, AI systems are being integrated into group decision-making processes, offering new avenues for enhancing efficiency, accuracy, and innovation (BaniHani et al., 2024; Burton et al., 2024; Carter & Wynne, 2024). This growing collaboration between humans and AI brings forth both significant opportunities and pressing challenges. On one hand, AI systems offer the potential to enhance information processing efficiency, improve decision accuracy, and streamline communication within teams. On the other hand, the complexities inherent in human-AI interactions—such as issues of trust and over-reliance, susceptibility to cognitive biases, erosion of critical thinking skills, lack of transparency in AI algorithms, and ethical concerns regarding accountability and fairness.

The use of AI in group settings has evolved from basic decision-support tools to more sophisticated roles, such as collaborative partners capable of generating novel insights. Large language models (LLMs), for instance, can facilitate collective intelligence by synthesizing information, generating alternative solutions, and even mediating group discussions. However, the extent to which AI enhances group performance remains context-dependent. Recent meta-analyses reveal that human-AI collaboration can lead to either augmentation of individual performance or to performance decrements (Vaccaro et al., 2024), depending on the task and interaction design.

To navigate these complexities, this chapter adopts the information processing framework as a lens for examining AI-assisted group decision-making (Hinsz et al., 1997). This framework provides a structured method to analyze how AI systems interact with human cognitive processes at each stage of

decision-making. By dissecting the inputs (information acquisition and sharing), the processing mechanisms (interpretation and integration of information), and the outputs (decisions and actions), we can gain insights into the opportunities and challenges presented by AI integration.

Key questions we will seek to address within this framework::

- **Inputs:** How does AI influence the way groups search for, gather, and share information? For example, AI can augment information search through advanced data retrieval but may also introduce biases based on the algorithms' training data.
- **Processing:** In what ways do AI systems affect the interpretation and integration of information within the group? AI can facilitate complex data analysis but might obscure the reasoning process through opaque algorithms, impacting the group's shared understanding.
- **Outputs:** How do AI recommendations influence the group's final decisions and actions? The reliance on AI outputs raises questions about trust, accountability, and the potential diminishment of human agency.

By examining these questions through the lens of the information processing framework, we can better understand the complex interplay between humans and AI in group decision-making contexts and identify strategies for optimizing the benefits of AI-assisted collaboration while mitigating its risks.

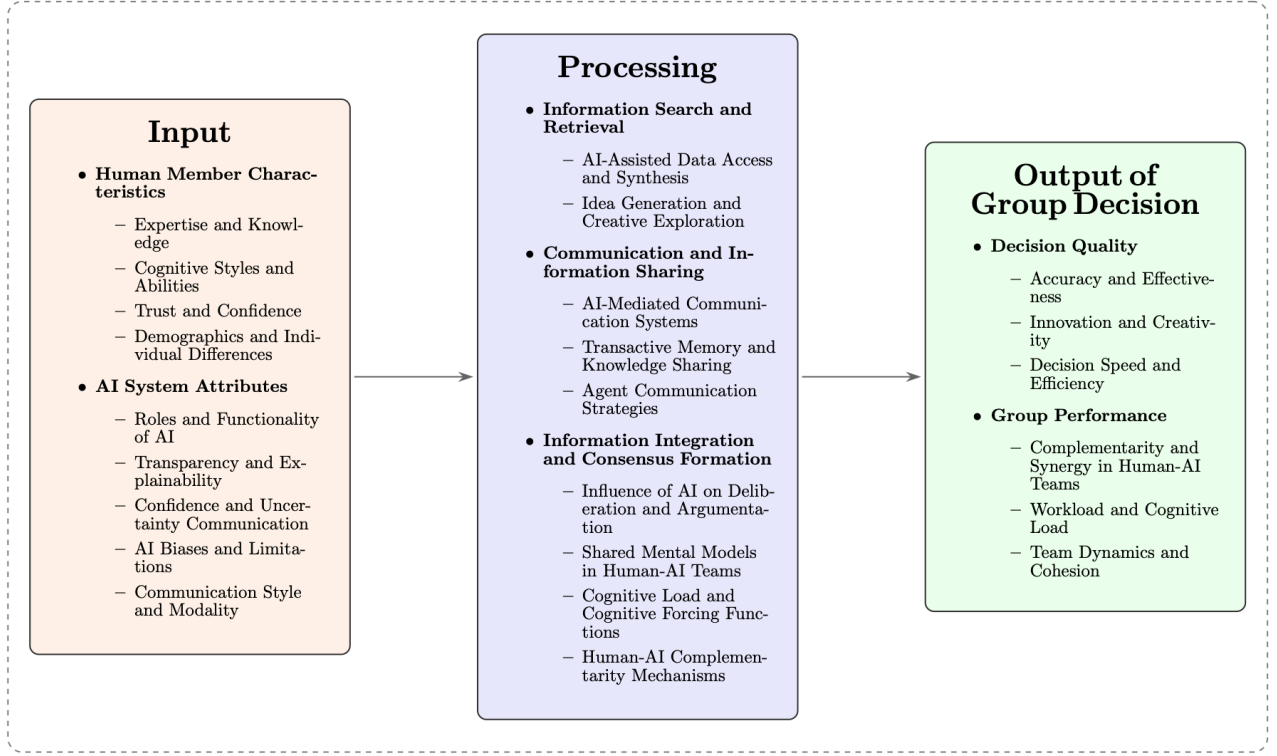


Figure 1: Framework

Inputs: Resources and Factors Shaping AI-Assisted Group Decision Making

The input stage is characterized by a multifaceted array of resources and factors, each contributing uniquely to the subsequent processing and ultimate decision outputs. These inputs can be broadly categorized into human member characteristics, AI system attributes, task and contextual factors, and initial trust, expertise assumptions, and biases, each playing a critical role in shaping the dynamics of human-AI collaboration.

Member Characteristics and Roles

Roles and Functionality of AI. The roles and functionality assigned to AI systems significantly impact group dynamics and decision-making processes (Bennett et al., 2023; Berretta et al., 2023; Carter & Wynne, 2024; Duan et al., 2025; Guo et al., 2024; Nomura et al., 2024). AI can act as an advisor, pro-

viding recommendations and insights; a peer collaborator, actively participating in discussions; a devil's advocate, challenging the group's assumptions; a mediator, facilitating consensus formation; or even a manager, coordinating tasks and assigning roles. The role of the AI will affect how humans interact with it and how much responsibility is assigned to the AI in the decision-making process.

For instance, an AI acting as an advisor might provide information and suggestions, which group members then evaluate and integrate into their decision-making process. In contrast, an AI acting as a peer collaborator might actively engage in discussions, contributing its own opinions and analyses. A devil's advocate AI could challenge the group's consensus, promoting critical evaluation and potentially reducing groupthink. A mediator AI might help to synthesize diverse perspectives and facilitate agreement, as demonstrated by the Habermas Machine (Tessler et al., 2024). The proactivity or reactivity of the AI also influences its role and impact (Diebel et al., 2025). A proactive AI might initiate suggestions or interventions, while a reactive AI would only respond to user prompts. Proactive AI can enhance efficiency but may also reduce user control and satisfaction, particularly if the AI's actions are perceived as intrusive or misaligned with user needs.

Deciding how best to assign team members to roles is crucial in group decision-making, particularly when learning who is best suited for what role within a team. Marjeh, Gokhale, et al. (2024) explore how humans allocate tasks within teams comprising both human and AI agents to maximize overall performance. The central theme of their research is understanding the mechanisms by which individuals discern and act upon their own strengths and those of their team members in a dynamic task allocation setting. In their experimental paradigm, participants had to repeatedly allocate three different types of tasks (visual, auditory, and lexical tasks) between themselves and two AI agents. Unbeknownst to participants, each AI agent was configured to have high competence (70% success rate) in one task type but low competence (15% success rate) in others.

Building upon this, McNeese et al. (2023) argue that human-autonomy teams (HATs) should be recognized as distinct from traditional human teams. They emphasize that HATs should not strive to replicate human-human team dynamics but instead should leverage the unique capabilities of AI agents. The authors propose several research trajectories to advance our understanding of HATs, including exploring diverse teaming models, redefining roles for AI teammates, expanding communication modalities, focusing on AI behavior design, developing specialized training, and emphasizing teamwork in AI design. These insights highlight the necessity of adjusting our approaches to team composition and role assignment when AI agents are involved, ensuring that both human and AI strengths are optimized in the decision-making process.

Recent advances in large language models have dramatically expanded the potential roles of AI in group decision-making, enabling AI agents to move beyond simple advisory functions to serve as mediators, devil's advocates, and active discussion participants. Chiang et al. (2024) investigated the potential of Large Language Models (LLMs) to act as devil's advocates in AI-assisted group decision-making - in the hopes of fostering more critical engagement with AI assistance. In their experimental task, participants were first individually trained on the relationship between defendant profiles and recidivism. For each defendant, participants were also shown the prediction of a recommendation AI model (RiskComp). Participants were then sorted into groups of three, where they reviewed and discussed novel defendant profiles, before making a group recidivism assessment. In the group stage, the recommendations from the RiskComp model were biased against a subset of the defendants (black defendants with low prior crime counts). Of interest was whether the inclusion of an LLM-based devil's advocate in the group discussions could help mitigate the bias introduced by the RiskComp AI model (note that the LLM devils advocate and RiskComp AI are separate AI models). The experimental manipulation consisted of four variants of an LLM-based devil's advocate using, varying both the target of objection (challenging either

RiskComp recommendations or majority group opinions) and the level of interactivity (static one-time comments versus dynamic engagement throughout the discussions). Their findings revealed that the dynamic devil's advocate led to higher decision accuracy and improved discernment of when to trust the RiskComp model's advice.

Human Member Characteristics. The composition of human teams, in terms of expertise, cognitive styles, and diversity, represents a foundational input layer. For instance, the expertise and knowledge that individual members bring to a team are crucial determinants of the quality of information available for processing (Aggarwal et al., 2023), influencing the depth and breadth of the group's understanding of the decision context. Furthermore, cognitive diversity, encompassing varied approaches to problem-solving and information processing, can enrich the group's cognitive resources, potentially enhancing its ability to tackle complex problems (Aggarwal et al., 2023). However, the benefits of diversity are not unqualified, as factors such as team longevity and task complexity can moderate the diversity-performance relationship (Wallrich et al., 2024). In addition to expertise and cognitive styles, the roles assigned to team members, particularly in hierarchical structures, shape how information is accessed, shared, and utilized within the group (Marjeh, Sucholutsky, et al., 2024; Narayanan et al., 2023). Moreover, demographic diversity, while having a statistically significant but practically small overall effect on team performance, can interact with contextual factors to influence group dynamics and outcomes (Wallrich et al., 2024). These varied human characteristics collectively form a crucial input layer, setting the stage for how groups interact with and leverage AI in decision-making processes.

Demographics and Individual Differences. Demographic factors such as age, gender, and education, as well as individual differences in personality traits, digital affinity, and cultural background, can moderate human-AI interaction (Diebel et al., 2025; Gerlich, 2025; Roesler et al., 2024). For instance, younger individuals or those with higher digital affinity may be more comfortable integrating AI into

their decision-making processes. Cultural background can also play a role, influencing attitudes towards authority, technology, and collaboration (Chugunova & Sele, 2022).

Task and Contextual Factors. The nature of the decision-making task itself and the broader context within which it is embedded form another essential layer of inputs. Task complexity, for instance, significantly influences the type of information processing required and the potential benefits of AI assistance (Eigner & Händler, 2024; Hamada et al., 2020). Complex tasks may necessitate more sophisticated AI support to manage information overload and enhance analytical capabilities. The decision environment, encompassing factors such as time pressure and risk levels, also shapes the input requirements and the dynamics of human-AI interaction (Zhang et al., 2023). For example, time pressure may alter reliance on AI assistance, as individuals adapt their decision-making strategies to balance speed and accuracy (Swaroop et al., 2024). Moreover, the specific decision-making setting, whether in healthcare, finance, or policy, introduces unique contextual factors that influence the relevance and effectiveness of AI inputs (Narayanan et al., 2023). These task and contextual factors, therefore, represent a critical input layer, moderating the interplay between human and AI contributions.

Initial Trust, Expertise Assumptions, and Biases

- Trust Baselines: Pre-existing attitudes toward AI, perceived reliability, anthropomorphism (Cui & Yasseri, 2024)
- Bias and Training Data: Potential for AI to introduce or amplify biases from training corpora (Bhatia, 2024; Cecil et al., 2024)

Information Search

The information search stage of decision-making, once reliant on human capacity to locate and synthesize data, has been transformed by the advent of artificial intelligence (AI), particularly Large Lan-

guage Models (LLMs). This section explores how AI reshapes information search, augmenting both data retrieval and synthesis, and fostering idea generation and creative discovery.

AI-Assisted Data Retrieval and Synthesis. LLMs significantly enhance the efficiency and comprehensiveness of information gathering, enabling access to a broader knowledge base and deeper insights (Bouschery et al., 2023). These models process vast datasets, identifying connections and patterns beyond human capacity. Furthermore, individual differences, such as computational thinking skills, influence how users interact with LLMs, with those possessing higher creativity and algorithmic thinking more effectively leveraging AI-generated content for deeper engagement within a specific information landscape (Flores et al., 2024). Programmers, for example, navigate between traditional web search and generative AI tools, strategically selecting between them based on factors like task familiarity and goal clarity, demonstrating the synergistic use of both resources (Yen et al., 2024). DiscipLink, for instance, uses LLMs to generate exploratory questions across disciplines, automatically expand queries with field-specific terminology, and extract themes from retrieved papers, effectively bridging knowledge gaps in interdisciplinary research (Zheng et al., 2024). Moreover, AI facilitates advanced techniques like retrieval-augmented generation (RAG), allowing LLMs to access and process real-time information, enhancing the accuracy and relevance of their output (Si et al., 2024; Wang et al., 2024). This capability empowers decision-makers with synthesized insights from diverse sources, crucial for informed choices across various fields, from scientific research to policy analysis (Burton et al., 2024).

LLM-based search tools offer natural language interfaces, streamlining complex queries and providing detailed responses, often leading to increased efficiency and user satisfaction (Spatharioti et al., 2023). However, this ease of use can also lead to overreliance on potentially inaccurate information and decreased critical evaluation, particularly when presented conversationally (Anderl et al., 2024). This can

contribute to confirmation bias and the formation of “generative echo chambers,” limiting exposure to diverse perspectives (Sharma et al., 2024). Furthermore, while LLMs can reduce cognitive load during information seeking, this may come at the cost of deeper learning and engagement with the material, leading to less sophisticated reasoning and argumentation (Stadler et al., 2024). Therefore, careful design and implementation are crucial to mitigate these risks and leverage the full potential of LLMs for enhanced information retrieval and synthesis.

Future Research Directions (Inputs)

Future research should address several gaps in our understanding of inputs in human-AI group decision-making.

1. **Interplay of Input Categories:** A more detailed exploration of the interplay between different input categories is warranted. This includes investigating how human characteristics interact with specific AI system attributes within varying contextual demands. For instance, how does the level of human expertise moderate the impact of AI transparency on trust and reliance? How do different communication modalities influence the integration of AI advice in groups with varying cognitive styles?
2. **Longitudinal Studies:** There is a need for longitudinal studies to investigate the long-term effects of input factors on the evolution of human-AI team dynamics and decision-making strategies over time. How do initial trust, expertise assumptions, and biases change with repeated interactions? How do groups adapt their communication patterns and shared mental models as they gain experience working with AI systems?
3. **Dynamic Role Adjustment:** Research should explore dynamic role adjustment in human-AI teams, where roles are not fixed but can change based on the task demands and the perfor-

mance of individual team members. This includes developing metrics to evaluate the effectiveness of AI-augmented team structures. Such metrics should go beyond traditional measures of team performance and consider factors like trust, communication quality, and the development of shared mental models.

Information Processing

The processing stage reveals the complex mechanisms through which humans and AI interact and transform information into collective decisions.

AI in Idea Generation and Creative Discovery. AI's role extends beyond data retrieval to fostering creative discovery. LLMs act as catalysts, offering alternative perspectives, challenging assumptions, and proposing unexpected connections (Bouschery et al., 2023). In structured tasks like semantic search, AI agents enhance group performance by selectively sharing information, amplifying collective intelligence (Ueshima & Takikawa, 2024). Studies comparing human and AI-generated ideas reveal a nuanced picture: while LLMs excel at generating ideas with higher average quality (e.g., purchase intent) and even surpassing human experts in novelty (Joosten et al., 2024; Meincke et al., 2024; Si et al., 2024), they may exhibit lower feasibility (Joosten et al., 2024) and reduced diversity (Meincke et al., 2024). This highlights the importance of strategic prompt engineering, as demonstrated by Boussioux et al. (2024), who found that human-guided prompts—specifically differentiated search (i.e., prompts designed to encourage diverse and varied responses) — enhanced the novelty of LLM-generated solutions while maintaining high value.

The type of AI interaction also significantly influences human creativity. Ashkinaze et al. (2024) found that exposure to AI-generated ideas increased the diversity of collective ideas without affecting individual creativity. In contrast, Kumar et al. (2024) observed that while providing direct answers had

minimal negative impact, exposure to LLM-generated strategies decreased both originality and creative flexibility in subsequent unassisted tasks.

Communication; information sharing

Transactive memory systems (TMS) represent a critical aspect of group cognition, referring to the shared understanding within a group regarding the distribution of knowledge and expertise among its members (Wegner, 1987; Yan et al., 2021). A well-functioning TMS enables team members not only to know who possesses specific knowledge but also to access and share this distributed expertise efficiently.

Bienefeld et al. (2023) conducted an observational study to examine the role of transactive memory systems and speaking-up behaviors in human-AI teams within an intensive care unit (ICU) setting. In this study, ICU physicians and nurses, divided into groups of four, who collaborated with an AI agent named “Autovent.” Autovent is an auto-adaptive ventilator system that autonomously manages patient ventilation by processing continuous, individualized data streams. Participants, all with a minimum of six months’ experience using Autovent, engaged in simulated clinical scenarios that required diagnosing and treating critically ill patients. Using behavioral coding of video recordings, the researchers analyzed how team members accessed information from both human teammates and the AI system, investigating how these human-human and human-ai interactions related to subsequent behaviors like hypothesis generation and speaking up with concerns. The researchers found that in higher-performing teams, accessing knowledge from the AI agent was positively correlated with developing new hypotheses and increased speaking-up behavior. Conversely, accessing information from human team members was negatively associated with these behaviors, regardless of team performance. These results suggest that AI systems may serve as unique knowledge repositories that help teams overcome some of the social barriers that typically inhibit information sharing and voice behaviors in purely human teams.

Bastola et al. (2024) further explored the potential of AI-mediated communication by examining how an LLM-based Smart Reply (LSR) system could impact collaborative performance in professional settings. They developed a system utilizing ChatGPT to generate context-aware, personalized responses during workplace interactions, aiming to reduce the cognitive effort required for message composition in multitasking scenarios. In their study, participants engaged in a cognitively demanding Dual N-back task while managing scheduling activities via Google Calendar and responding to simulated co-workers on Slack. The findings indicated that the use of the LSR system not only improved work performance—evidenced by higher accuracy in the N-back task—but also increased messaging efficiency and reduced cognitive load, as participants could more readily focus on primary tasks without the distraction of composing responses. However, it is important to note that participants expressed concerns about the appropriateness and accuracy of AI-generated messages, as well as issues related to trust and privacy. Thus, while AI-mediated communication tools like the LSR system may facilitate information sharing and alleviate cognitive demands in collaborative work, these benefits must be balanced against potential user experience challenges to fully realize their potential advantages.

- (Yang et al., 2024)
- (Ma et al., 2024)
- (Radivojevic et al., 2024)
- (Sidji et al., 2024)
- (Nishida et al., 2024)
- (Chuang et al., 2024)

- AI-Mediated Communication: Smart replies, devil’s advocacy, and AI as a discussion facilitator (Chiang et al., 2024; Duan et al., 2025)
- Transactive Memory and Shared Mental Models: How AI systems function as external knowledge repositories (Bienefeld et al., 2023; Narayanan & Feigh, 2024)
- chat-based collaboration (ChatCollab, Klieger et al., 2024)

Shared Mental Models

- (Collins et al., 2024)
- role of shared mental models in effective teamwork (N. J. McNeese et al., 2023; Narayanan & Feigh, 2024).
- challenge of developing shared mental models in human-AI teams due to the opacity of AI reasoning (Collins et al., 2024; S. Zhang et al., 2024).
- potential solutions, such as increasing AI transparency, providing explanations, or using interactive interfaces (Chiang et al., 2024; Klieger et al., 2024; Ma et al., 2024; Sidji et al., 2024).
- Role of training in developing effective mental models of AI and in calibrating trust (Kelly et al., 2023; Tejeda et al., 2022).

Future Directions: Research on how to measure and visualize shared mental models in human-AI teams, how to design AI systems that actively contribute to the development of shared understanding, how to adapt AI behavior based on the evolving mental models of human teammates.

Cognitive Load

AI assistance can influence the workload and cognitive load experienced by human team members (Bastola et al., 2024; Buçinca et al., 2021; Choi et al., 2024; Gerlich, 2025). While AI can reduce cognitive load by automating certain tasks and providing ready-made solutions (Hao et al., 2024), it can also increase cognitive load if the AI interface is poorly designed or if the AI’s reasoning is opaque (Buçinca et al., 2021; Westphal et al., 2023).

Buçinca et al. (2021) examined how interface design might influence cognitive engagement with AI recommendations through what they term “cognitive forcing functions.” Drawing on dual-process theory, they implemented three distinct interface interventions (e.g., requiring explicit requests for AI input, mandating initial independent decisions, introducing temporal delays) designed to disrupt automatic processing and promote more analytical engagement with AI suggestions. Their findings demonstrated that while these interventions successfully reduced overreliance on incorrect AI recommendations, they also increased perceived cognitive load and decreased user satisfaction. Of particular methodological interest was their systematic investigation of individual differences in cognitive motivation: participants with high Need for Cognition (NFC) showed substantially greater benefits from these interventions, suggesting that the effectiveness of such cognitive load manipulations may be moderated by individual differences in information processing preferences.

- Cognitive Load and Overreliance: Role of interface design in prompting deeper analytic thinking (Buçinca et al., 2021; Vodrahalli et al., 2022)
- Cognitive offloading effects (Stadler et al., 2024)

Consensus Formation

Tessler et al. (2024) investigated the potential of AI in facilitating consensus formation through their development of the “Habermas Machine” (HM), an LLM-based system fine-tuned to mediate human deliberation. The HM system receives input statements from individual participants, and attempts to generate consensus statements which will maximize group endorsement. The findings revealed that the AI-generated group statements were consistently preferred over comparison statements written by human mediators. Participants rated the AI-mediated statements higher in terms of informativeness, clarity, and lack of bias. This suggests that AI can effectively capture the collective sentiment of a group and articulate it in a way that resonates with its members. Notably, the researchers also verified that the HM system reliably incorporated minority opinions into the consensus statements, preventing dominance by majority perspectives. These results were replicated in a virtual citizens’ assembly with a demographically representative sample of the UK population. The AI-mediated process again resulted in high-quality group statements and facilitated consensus among participants on contentious issues.

Future Research Directions (Processing)

Future research should address several gaps in our understanding of cognitive processing in human-AI teams.

1. **Dynamic Interplay:** A deeper understanding of the dynamic interplay between different processing mechanisms is needed. This includes investigating how AI-mediated communication shapes shared mental models and how cognitive load influences information integration.
2. **Emotions and Social Factors:** The role of emotions and social factors in human-AI information processing should be explored. How do factors like trust, rapport, and social identity influence the way humans interact with and rely on AI teammates?

3. **Adaptive AI Systems:** More research is needed on how to design AI systems that can adapt to the cognitive styles and abilities of individual human team members. This includes developing personalized AI interfaces that provide tailored explanations, adjust the level of interactivity, and offer appropriate cognitive support.

Output

Decision Accuracy and Complementarity

The integration of AI into group decision-making holds significant promise for leveraging the complementary strengths of humans and machines. Rastogi et al. (2023) proposed a taxonomy to characterize differences in human and machine decision-making, providing a framework for understanding how to combine their unique capabilities optimally. This taxonomy highlights areas where AI can augment human decision processes, such as handling large data sets or identifying patterns beyond human perceptual abilities. Becker et al. (2022) demonstrated that AI-generated decision aids, when presented as interpretable procedural instructions, can significantly improve human decision-making by promoting more resource-rational strategies. In complex domains, Shin et al. (2023) showed that exposure to super-human AI, as in the game of Go, can enhance human decision-making by encouraging the exploration of novel strategies, thereby increasing overall performance and innovation. However, the effectiveness of human-AI collaboration depends on the dynamics of the interaction.

Recent research has revealed complex trade-offs in human-AI team performance that depend heavily on task structure and collaboration dynamics. Bennett et al. (2023) found that while both human-human and human-AI teams experienced performance costs relative to theoretical benchmarks, human-human teams showed particular advantages in collaborative versus competitive conditions—an effect that diminished when humans worked with AI partners. This aligns with findings from Liang et al. (2022)

showing that humans can learn to selectively rely on AI assistance based on task difficulty, but often require explicit feedback and training to optimize this collaboration. The reduced collaborative advantage in human-AI teams appears to stem from difficulties in developing shared mental models and coordinating actions effectively, suggesting that current AI systems may lack crucial capabilities for fluid team interaction.

- Performance Gains and Limits: Complementarity vs. overreliance (Liang et al., 2022)

Trust, Risk and Reliance

Trust in AI

Trust and confidence are crucial determinants of how individuals and groups interact with AI systems during decision-making processes. Research indicates that individuals' confidence levels significantly influence their propensity to seek and utilize AI-generated advice. Pescetelli & Yeung (2021) found that people are more likely to seek advice when their confidence in their own decisions is low; however, they often deviate from optimal Bayesian integration when incorporating this advice, sometimes relying on heuristic strategies instead. Carlebach & Yeung (2023) further demonstrated that the relationship between confidence and advice-seeking is context-dependent. When the reliability of an AI advisor is unknown, individuals may paradoxically seek advice even when they are confident, using their own confidence as a feedback mechanism to learn about the advisor's quality. Liang et al. (2022) explored how explicit performance comparisons between humans and AI affect reliance on decision aids, revealing that individuals adapt their use of AI recommendations based on task difficulty and perceived accuracy differences. Steyvers et al. (2024) demonstrated that humans tend to overestimate AI system accuracy when presented with default explanations, particularly when those explanations are lengthy. However, this miscalibration can be mitigated by explicitly communicating the AI's uncertainty levels.

In group settings, trust in AI systems significantly influences how teams interact and make decisions. Cui & Yasseri (2024) emphasize that trust between humans and AI is crucial for achieving collective intelligence in teams. They argue that factors such as the perceived competence, benevolence, and integrity of AI systems shape this trust, mirroring the dynamics of trust in human relationships. The level of anthropomorphism in AI agents can also affect trust; while human-like features may initially enhance trust, this effect can wane if the AI's performance does not meet team expectations. Zvelebilova et al. (2024) further demonstrate that even when teams do not fully trust an AI assistant or consider it a genuine team member, the AI can still significantly influence team discourse and collective attention. Their study found that teams adopted terminology introduced by the AI, indicating an automatic integration of AI input despite doubts about its reliability. This suggests that AI systems can impact group cognition and coordination regardless of explicit trust levels. These findings highlight the complexity of trust in AI within team environments, where both the design of AI agents and their subtle influences on team dynamics must be carefully managed to enhance collaborative outcomes.

- Contagion Effects of (Dis)Trust: Spread of distrust or overconfidence within human–AI teams (Duan et al., 2025)
- Uncalibrated vs. Well-Calibrated AI: Conditions under which uncalibrated AI might paradoxically enhance outcomes (Vodrahalli et al., 2022)

Utilization

Recent work by Buçinca et al. (2021) presents an innovative approach to addressing overreliance on AI systems through interface design rather than explanation quality. Their study evaluated three “cognitive forcing functions” - interface elements designed to disrupt quick, heuristic processing of AI recommendations. Although these interventions significantly reduced overreliance on incorrect AI recom-

mentations, an important trade-off emerged: interfaces that most effectively prevented overreliance were also rated as most complex and least preferred by users. Moreover, their analysis revealed potential equity concerns, as the interventions provided substantially greater benefits to individuals with high Need for Cognition. These findings suggest that while interface design can effectively modulate AI utilization patterns, careful consideration must be given to both user experience and potential intervention-generated inequalities.

Responsibility

- (Narayanan et al., 2023)

Recent work has begun examining how people attribute responsibility in human-AI collaborative contexts where control is shared and actions are interdependent (Tsirtsis et al., 2024). Their study employs a stylized semi-autonomous driving simulation where participants observe how a ‘human agent’ and an ‘AI agent’ collaborate to reach a destination within a time limit. In their setup, the human and AI agents shared control of a vehicle, with each agent having partial and differing knowledge of the environment (i.e., the AI knew about traffic conditions but not road closures, while humans knew about closures but not traffic). Participants observe illustrated simulations of a variety of commute scenarios, and then make judgements about how responsible each agent was for the commute outcome (reaching the destination on time, or not). The study reveals that participants’ responsibility judgments are influenced by factors such as the unexpectedness of an agent’s action, counterfactual simulations of alternative actions, and the actual contribution of each agent to the task outcome.

Risk

- (Bhatia, 2024)
- (Zhu et al., 2024)

Future Directions

- Opportunities for real-time AI moderation (Han et al., 2024)
- Evolving norms around AI accountability (Smith et al., 2025)
- potential negative impacts of AI on human skills, critical thinking, and agency (Gerlich, 2025; H. Kumar et al., 2024)
- Effects of AI on group extremity and the emergence of echo chambers or polarization phenomena (van Swol et al., 2023).
- privacy, accountability, and fairness in AI-assisted group decision making (Cui & Yasseri, 2024; Barredo Arrieta et al., 2020).

💡 Box 1: Glossary of Terms

Complementarity. In the context of human-AI teams, complementarity refers to the synergistic integration of human and artificial intelligence, leveraging the unique strengths of each to achieve performance outcomes that exceed those attainable by either humans or AI systems operating in isolation (Steyvers et al., 2022). Effective complementarity involves a balanced division of labor and mutual enhancement of capabilities.

Information Processing Framework. A theoretical framework in cognitive psychology that conceptualizes the human mind, and by extension, groups, as systems that acquire, process, store, retrieve, and transmit information, akin to computational systems (Hinsz et al., 1997). This framework provides a structured lens for analyzing decision-making as a sequence of stages, from inputs to outputs.

Large Language Model (LLM). A sophisticated type of artificial intelligence algorithm characterized by its use of deep learning techniques and training on massive datasets to enable the understanding, generation, and prediction of human language. LLMs, such as GPT-4, are foundational to many contemporary AI applications in decision support and communication.

Overreliance. A cognitive bias characterized by excessive trust in and dependence on AI recommendations, often leading to the uncritical acceptance of AI outputs, even when they are flawed or suboptimal. Overreliance can undermine human vigilance and critical evaluation in AI-assisted decision-making contexts.

Transactive Memory Systems (TMS). A system of distributed knowledge within a group, where members develop specialized knowledge and rely on each other for access to that knowledge.

References

- Aggarwal, I., Cuconato, G., Ateş, N. Y., & Meslec, N. (2023). Self-beliefs, Transactive Memory Systems, and Collective Identification in Teams: Articulating the Socio-Cognitive Underpinnings of COHUMAN. *Topics in Cognitive Science*, 1–31. <https://doi.org/10.1111/tops.12681>
- Anderl, C., Klein, S. H., Sarigül, B., Schneider, F. M., Han, J., Fiedler, P. L., & Utz, S. (2024). Conversational presentation mode increases credibility judgements during information search with ChatGPT. *Scientific Reports*, 14(1), 17127. <https://doi.org/10.1038/s41598-024-67829-6>
- Ashkinaze, J., Mendelsohn, J., Qiwei, L., Budak, C., & Gilbert, E. (2024). *How AI Ideas Affect the Creativity, Diversity, and Evolution of Human Ideas: Evidence From a Large, Dynamic Experiment* (arXiv:2401.13481). arXiv. <https://doi.org/10.48550/arXiv.2401.13481>
- BaniHani, I., Alawadi, S., & Elmrayyan, N. (2024). AI and the decision-making process: A literature review in healthcare, financial, and technology sectors. *Journal of Decision Systems*, 1–11. <https://doi.org/10.1080/12460125.2024.2349425>
- Bastola, A., Wang, H., Hembree, J., Yadav, P., Gong, Z., Dixon, E., Razi, A., & McNeese, N. (2024). *LLM-based Smart Reply (LSR): Enhancing Collaborative Performance with ChatGPT-mediated Smart Reply System* (arXiv:2306.11980). arXiv. <https://arxiv.org/abs/2306.11980>
- Becker, F., Skirzyński, J., van Opheusden, B., & Lieder, F. (2022). Boosting Human Decision-making with AI-Generated Decision Aids. *Computational Brain & Behavior*, 5(4), 467–490. <https://doi.org/10.1007/s42113-022-00149-y>
- Bennett, M. S., Hedley, L., Love, J., Houpt, J. W., Brown, S. D., & Eidels, A. (2023). Human Performance in Competitive and Collaborative Human–Machine Teams. *Topics in Cognitive Science*, 1–25. <https://doi.org/10.1111/tops.12683>

- Berretta, S., Tausch, A., Ontrup, G., Gilles, B., Peifer, C., & Kluge, A. (2023). Defining human-AI teaming the human-centered way: A scoping review and network analysis. *Frontiers in Artificial Intelligence*, 6. <https://doi.org/10.3389/frai.2023.1250725>
- Bhatia, S. (2024). Exploring variability in risk taking with large language models. *Journal of Experimental Psychology: General*, 153(7), 1838–1860. <https://doi.org/10.1037/xge0001607>
- Bienefeld, N., Kolbe, M., Camen, G., Huser, D., & Buehler, P. K. (2023). Human-AI teaming: Leveraging transactive memory and speaking up for enhanced team effectiveness. *Frontiers in Psychology*, 14. <https://doi.org/10.3389/fpsyg.2023.1208019>
- Bouschery, S. G., Blazevic, V., & Piller, F. T. (2023). Augmenting human innovation teams with artificial intelligence: Exploring transformer-based language models. *Journal of Product Innovation Management*, 40(2), 139–153. <https://doi.org/10.1111/jpim.12656>
- Boussiou, L., Lane, J. N., Zhang, M., Jacimovic, V., & Lakhani, K. R. (2024). The Crowdless Future? Generative AI and Creative Problem-Solving. *Organization Science*, 35(5), 1589–1607. <https://doi.org/10.1287/orsc.2023.18430>
- Buçinca, Z., Malaya, M. B., & Gajos, K. Z. (2021). To Trust or to Think: Cognitive Forcing Functions Can Reduce Overreliance on AI in AI-assisted Decision-making. *Proceedings of the ACM on Human-Computer Interaction*, 5(CSCW1), 1–21. <https://doi.org/10.1145/3449287>
- Burton, J. W., Lopez-Lopez, E., Hechtlinger, S., Rahwan, Z., Aeschbach, S., Bakker, M. A., Becker, J. A., Berditchevskaia, A., Berger, J., Brinkmann, L., Flek, L., Herzog, S. M., Huang, S., Kapoor, S., Narayanan, A., Nussberger, A.-M., Yasseri, T., Nickl, P., Almaatouq, A., ... Hertwig, R. (2024). How large language models can reshape collective intelligence. *Nature Human Behaviour*, 1–13. <https://doi.org/10.1038/s41562-024-01959-9>

- Carlebach, N., & Yeung, N. (2023). Flexible use of confidence to guide advice requests. *Cognition*, 230, 105264. <https://doi.org/10.1016/j.cognition.2022.105264>
- Carter, W., & Wynne, K. T. (2024). Integrating artificial intelligence into team decision-making: Toward a theory of AI–human team effectiveness. *European Management Review*. <https://doi.org/10.1111/emre.12685>
- Cecil, J., Lerner, E., Hudecek, M. F. C., Sauer, J., & Gaube, S. (2024). Explainability does not mitigate the negative impact of incorrect AI advice in a personnel selection task. *Scientific Reports*, 14(1), 9736. <https://doi.org/10.1038/s41598-024-60220-5>
- Chiang, C.-W., Lu, Z., Li, Z., & Yin, M. (2024). Enhancing AI-Assisted Group Decision Making through LLM-Powered Devil’s Advocate. *Proceedings of the 29th International Conference on Intelligent User Interfaces*, 103–119. <https://doi.org/10.1145/3640543.3645199>
- Choi, A. S., Akter, S. S., Singh, J. P., & Anastasopoulos, A. (2024). *The LLM Effect: Are Humans Truly Using LLMs, or Are They Being Influenced By Them Instead?* (arXiv:2410.04699). arXiv. <https://arxiv.org/abs/2410.04699>
- Chuang, Y.-S., Harlalka, N., Suresh, S., Goyal, A., Hawkins, R., Yang, S., Shah, D., Hu, J., & Rogers, T. T. (2024). *The Wisdom of Partisan Crowds: Comparing Collective Intelligence in Humans and LLM-based Agents*.
- Chugunova, M., & Sele, D. (2022). We and It: An interdisciplinary review of the experimental evidence on how humans interact with machines. *Journal of Behavioral and Experimental Economics*, 99, 101897. <https://doi.org/10.1016/j.socec.2022.101897>
- Collins, K. M., Sucholutsky, I., Bhatt, U., Chandra, K., Wong, L., Lee, M., Zhang, C. E., Zhi-Xuan, T., Ho, M., Mansinghka, V., Weller, A., Tenenbaum, J. B., & Griffiths, T. L. (2024). Building machines

- that learn and think with people. *Nature Human Behaviour*, 8(10), 1851–1863. <https://doi.org/10.1038/s41562-024-01991-9>
- Cui, H., & Yasseri, T. (2024). AI-enhanced collective intelligence. *Patterns*, 5(11), 101074. <https://doi.org/10.1016/j.patter.2024.101074>
- Diebel, C., Goutier, M., Adam, M., & Benlian, A. (2025). When AI-Based Agents Are Proactive: Implications for Competence and System Satisfaction in Human–AI Collaboration. *Business & Information Systems Engineering*, 1–20. <https://doi.org/10.1007/s12599-024-00918-y>
- Duan, W., Zhou, S., Scalia, M. J., Freeman, G., Gorman, J., Tolston, M., McNeese, N. J., & Funke, G. (2025). Understanding the processes of trust and distrust contagion in Human-AI Teams: A qualitative approach. *Computers in Human Behavior*, 108560. <https://doi.org/10.1016/j.chb.2025.108560>
- Eigner, E., & Händler, T. (2024). *Determinants of LLM-assisted Decision-Making* (arXiv:2402.17385). arXiv. <https://arxiv.org/abs/2402.17385>
- Flores, P., Rong, G., & Cowley, B. (2024). Information foraging in human-ChatGPT interactions: Factors of computational thinking dissociate exploration and exploitation. *Proceedings of the Annual Meeting of the Cognitive Science Society*, 46.
- Gerlich, M. (2025). AI Tools in Society: Impacts on Cognitive Offloading and the Future of Critical Thinking. *Societies*, 15(1), 6. <https://doi.org/10.3390/soc15010006>
- Guo, Z., Wu, Y., Hartline, J. D., & Hullman, J. (2024). A Decision Theoretic Framework for Measuring AI Reliance. *The 2024 ACM Conference on Fairness, Accountability, and Transparency*, 221–236. <https://doi.org/10.1145/3630106.3658901>

- Hamada, D., Nakayama, M., & Saiki, J. (2020). Wisdom of crowds and collective decision-making in a survival situation with complex information integration. *Cognitive Research: Principles and Implications*, 5(1), 48. <https://doi.org/10.1186/s41235-020-00248-z>
- Hinsz, V. B., Tindale, R. S., & Vollrath, D. A. (1997). The emerging conceptualization of groups as information processors. *Psychological Bulletin*, 121(1), 43–64. <https://doi.org/10.1037/0033-2909.121.1.43>
- Joosten, J., Bilgram, V., Hahn, A., & Totzek, D. (2024). Comparing the Ideation Quality of Humans With Generative Artificial Intelligence. *IEEE Engineering Management Review*, 52(2), 153–164. <https://doi.org/10.1109/EMR.2024.3353338>
- Kumar, H., Vincentius, J., Jordan, E., & Anderson, A. (2024). *Human Creativity in the Age of LLMs: Randomized Experiments on Divergent and Convergent Thinking* (arXiv:2410.03703). arXiv. <https://arxiv.org/abs/2410.03703>
- Liang, G., Sloane, J. F., Donkin, C., & Newell, B. R. (2022). Adapting to the algorithm: How accuracy comparisons promote the use of a decision aid. *Cognitive Research: Principles and Implications*, 7(1), 14. <https://doi.org/10.1186/s41235-022-00364-y>
- Ma, S., Chen, Q., Wang, X., Zheng, C., Peng, Z., Yin, M., & Ma, X. (2024). *Towards Human-AI Deliberation: Design and Evaluation of LLM-Empowered Deliberative AI for AI-Assisted Decision-Making* (arXiv:2403.16812). arXiv. <https://arxiv.org/abs/2403.16812>
- Marjeh, R., Gokhale, A., Bullo, F., & Griffiths, T. L. (2024). *Task Allocation in Teams as a Multi-Armed Bandit*.
- Marjeh, R., Sucholutsky, I., van Rijn, P., Jacoby, N., & Griffiths, T. L. (2024). Large language models predict human sensory judgments across six modalities. *Scientific Reports*, 14(1), 21445. <https://doi.org/10.1038/s41598-024-72071-1>

- McNeese, N. J., Flathmann, C., O'Neill, T. A., & Salas, E. (2023). Stepping out of the shadow of human-human teaming: Crafting a unique identity for human-autonomy teams. *Computers in Human Behavior*, 148, 107874. <https://doi.org/10.1016/j.chb.2023.107874>
- Meincke, L., Girotra, K., Nave, G., Terwiesch, C., & Ulrich, K. T. (2024). *Using Large Language Models for Idea Generation in Innovation*. <https://doi.org/10.2139/ssrn.4526071>
- Narayanan, S., Yu, G., Ho, C.-J., & Yin, M. (2023). How does Value Similarity affect Human Reliance in AI-Assisted Ethical Decision Making? *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society*, 49–57. <https://doi.org/10.1145/3600211.3604709>
- Nishida, Y., Shimojo, S., & Hayashi, Y. (2024). Conversational Agent Dynamics with Minority Opinion and Cognitive Conflict in Small-Group Decision-Making. *Japanese Psychological Research*. <https://doi.org/10.1111/jpr.12552>
- Nomura, M., Ito, T., & Ding, S. (2024). Towards Collaborative Brain-storming among Humans and AI Agents: An Implementation of the IBIS-based Brainstorming Support System with Multiple AI Agents. *Proceedings of the ACM Collective Intelligence Conference*, 1–9. <https://doi.org/10.1145/3643562.3672609>
- Pescetelli, N., & Yeung, N. (2021). The role of decision confidence in advice-taking and trust formation. *Journal of Experimental Psychology: General*, 150(3), 507–526. <https://doi.org/10.1037/xge0000960>
- Radivojevic, K., Clark, N., & Brenner, P. (2024). LLMs Among Us: Generative AI Participating in Digital Discourse. *Proceedings of the AAAI Symposium Series*, 3(1), 209–218. <https://doi.org/10.1609/aaais.v3i1.31202>
- Rastogi, C., Leqi, L., Holstein, K., & Heidari, H. (2023). A Taxonomy of Human and ML Strengths in Decision-Making to Investigate Human-ML Complementarity. *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, 11, 127–139. <https://doi.org/10.1609/hcomp.viii.27554>

- Roesler, E., Rieger, T., & Langer, M. (2024). Numeric vs. Verbal information: The influence of information quantifiability in Human-AI vs. Human-Human decision support. *Computers in Human Behavior: Artificial Humans*, 100116. <https://doi.org/10.1016/j.chbah.2024.100116>
- Sharma, N., Liao, Q. V., & Xiao, Z. (2024). Generative Echo Chamber? Effect of LLM-Powered Search Systems on Diverse Information Seeking. *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 1–17. <https://doi.org/10.1145/3613904.3642459>
- Shin, M., Kim, J., van Opheusden, B., & Griffiths, T. L. (2023). Superhuman artificial intelligence can improve human decision-making by increasing novelty. *Proceedings of the National Academy of Sciences*, 120(12), e2214840120. <https://doi.org/10.1073/pnas.2214840120>
- Si, C., Yang, D., & Hashimoto, T. (2024). *Can LLMs Generate Novel Research Ideas? A Large-Scale Human Study with 100+ NLP Researchers* (arXiv:2409.04109). arXiv. <https://doi.org/10.48550/arXiv.2409.04109>
- Sidji, M., Smith, W., & Rogerson, M. J. (2024). Human-AI Collaboration in Cooperative Games: A Study of Playing Codenames with an LLM Assistant. *Proc. ACM Hum.-Comput. Interact.*, 8(CHI PLAY), 316:1–316:25. <https://doi.org/10.1145/3677081>
- Spatharioti, S. E., Rothschild, D. M., Goldstein, D. G., & Hofman, J. M. (2023). *Comparing Traditional and LLM-based Search for Consumer Choice: A Randomized Experiment* (arXiv:2307.03744). arXiv. <https://doi.org/10.48550/arXiv.2307.03744>
- Stadler, M., Bannert, M., & Sailer, M. (2024). Cognitive ease at a cost: LLMs reduce mental effort but compromise depth in student scientific inquiry. *Computers in Human Behavior*, 160, 108386. <https://doi.org/10.1016/j.chb.2024.108386>

- Steyvers, M., Tejeda, H., Kumar, A., Belem, C., Karny, S., Hu, X., Mayer, L., & Smyth, P. (2024). *The Calibration Gap between Model and Human Confidence in Large Language Models* (arXiv:2401.13835). arXiv. <https://arxiv.org/abs/2401.13835>
- Swaroop, S., Buçinca, Z., Gajos, K. Z., & Doshi-Velez, F. (2024). Accuracy-Time Tradeoffs in AI-Assisted Decision Making under Time Pressure. *Proceedings of the 29th International Conference on Intelligent User Interfaces*, 138–154. <https://doi.org/10.1145/3640543.3645206>
- Tessler, M. H., Bakker, M. A., Jarrett, D., Sheahan, H., Chadwick, M. J., Koster, R., Evans, G., Campbell-Gillingham, L., Collins, T., Parkes, D. C., Botvinick, M., & Summerfield, C. (2024). AI can help humans find common ground in democratic deliberation. *Science*, 386(6719), eadq2852. <https://doi.org/10.1126/science.adq2852>
- Tsirtsis, S., Rodriguez, M. G., & Gerstenberg, T. (2024). *Towards a computational model of responsibility judgments in sequential human-AI collaboration*. <https://doi.org/10.31234/osf.io/m4yad>
- Ueshima, A., & Takikawa, H. (2024). Discovering Novel Social Preferences Using Simple Artificial Neural Networks. *Collabra: Psychology*, 10(1), 121234. <https://doi.org/10.1525/collabra.121234>
- Vaccaro, M., Almaatouq, A., & Malone, T. (2024). When combinations of humans and AI are useful: A systematic review and meta-analysis. *Nature Human Behaviour*, 1–11. <https://doi.org/10.1038/s41562-024-02024-1>
- Wallrich, L., Opara, V., Wesołowska, M., Barnoth, D., & Yousefi, S. (2024). The Relationship Between Team Diversity and Team Performance: Reconciling Promise and Reality Through a Comprehensive Meta-Analysis Registered Report. *Journal of Business and Psychology*, 39(6), 1303–1354. <https://doi.org/10.1007/s10869-024-09977-0>

- Wang, R., Zhou, X., Qiu, L., Chang, J. C., Bragg, J., & Zhang, A. X. (2024). *Social-RAG: Retrieving from Group Interactions to Socially Ground Proactive AI Generation to Group Preferences* (arXiv:2411.02353). arXiv. <https://doi.org/10.48550/arXiv.2411.02353>
- Wegner, D. M. (1987). Transactive Memory: A Contemporary Analysis of the Group Mind. In B. Mullen & G. R. Goethals (Eds.), *Theories of Group Behavior* (pp. 185–208). Springer. https://doi.org/10.1007/978-1-4612-4634-3_9
- Westphal, M., Vössing, M., Satzger, G., Yom-Tov, G. B., & Rafaeli, A. (2023). Decision control and explanations in human-AI collaboration: Improving user perceptions and compliance. *Computers in Human Behavior*, 144, 107714. <https://doi.org/10.1016/j.chb.2023.107714>
- Yan, B., Hollingshead, A. B., Alexander, K. S., Cruz, I., & Shaikh, S. J. (2021). Communication in Transactive Memory Systems: A Review and Multidimensional Network Perspective. *Small Group Research*, 52(1), 3–32. <https://doi.org/10.1177/1046496420967764>
- Yang, Z., Xu, X., Yao, B., Rogers, E., Zhang, S., Intille, S., Shara, N., Gao, G. G., & Wang, D. (2024). Talk2Care: An LLM-based Voice Assistant for Communication between Healthcare Providers and Older Adults. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 8(2), 1–35. <https://doi.org/10.1145/3659625>
- Yen, R., Sultanum, N., & Zhao, J. (2024). To Search or To Gen? Exploring the Synergy between Generative AI and Web Search in Programming. *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, 1–8. <https://doi.org/10.1145/3613905.3650867>
- Zhang, R., Duan, W., Flathmann, C., McNeese, N., Freeman, G., & Williams, A. (2023). Investigating AI Teammate Communication Strategies and Their Impact in Human-AI Teams for Effective Teamwork. *Proceedings of the ACM on Human-Computer Interaction*, 7(CSCW2), 1–31. <https://doi.org/10.1145/3610072>

- Zheng, C., Zhang, Y., Huang, Z., Shi, C., Xu, M., & Ma, X. (2024). DiscipLink: Unfolding Interdisciplinary Information Seeking Process via Human-AI Co-Exploration. *Proceedings of the 37th Annual ACM Symposium on User Interface Software and Technology*, 1–20. <https://doi.org/10.1145/3654777.3676366>
- Zhu, J.-Q., Yan, H., & Griffiths, T. L. (2024). *Language Models Trained to do Arithmetic Predict Human Risky and Intertemporal Choice* (arXiv:2405.19313). arXiv. <https://arxiv.org/abs/2405.19313>
- Zvelebilova, J., Savage, S., & Riedl, C. (2024). *Collective Attention in Human-AI Teams* (arXiv:2407.17489). arXiv. <https://doi.org/10.48550/arXiv.2407.17489>