“Sweet Spot” in Human-Machine Teamwork

ANONYMOUS AUTHOR(S)

No Institute Given

Abstract. Moon Base is humanity’s first lunar outpost, enabling advances in science and technology while providing insights into future human spaceflight missions to Mars and beyond. At Moon Base, humans will work with multiple entities, including robots and Artificial Intelligence (AI) to accomplish mission goals. To better maximize benefits from such non-human entities, improving Human-Machine teaming is essential. However, studies have shown that Human-AI teams are prone to underperform when compared to human alone or AI alone, and this tendency holds across various types of tasks undertaken by the teams. This result underscores the complex nature of Human-AI teaming. This paper addresses the underperformance of Human-Machine teams by first summarizing key analytical lenses for characterizing different types of Human-Machine teams: interdependence and input compositionality. Then, we present an experiment using a simulated Urban Search and Rescue (USAR) mission, where human and machine work together to search and locate disaster victims. Preliminary results imply that how often humans utilize a type of machine-issued information that is optional for task completion, but potentially improves task efficiency (i.e., opportunistic interdependence) is indicative of higher-performance teams and could serve as a useful metric for analyzing Human-Machine teamwork. Dissecting opportunistic interdependence and its relationship to team performance can inform the design and timing of effective notifications issued by machines. We believe that observing patterns of Human-Machine teams and identifying a “sweet spot” is promising to advance Human-Machine teamwork research, and we propose future work avenues in this paper.

Keywords: Human-Machine Teamwork · Opportunistic Interdependence · Human Spaceflight.

1 Introduction

During the Ignition event on March 26, 2026, NASA announced a plan to build Moon Base, humanity’s first lunar outpost in the lunar South Pole region, which is expected to serve as a crucial stepping-stone towards future human spaceflight missions to Mars and beyond[1]. The Moon Base will be built in a phased, iterative manner throughout a series of crewed and uncrewed missions. In Phase 1, robotic missions will be conducted focusing on testing new technologies and exploring

[1] https://www.nasa.gov/moonbase (accessed on 7/17/2026)

the lunar environment. Phase 2 will then assemble semi-permanent infrastructure and initiate early habitation and logistics operations. Phase 3 establishes a sustained human presence on the Moon through routine crew rotations and continuous surface operations.

Across all the phases, multiple surface assets will work together to accomplish a wide range of tasks such as scientific exploration and infrastructure establishment in preparation for crew arrival. It is imperative that they collaborate and coordinate well with each other to complete the tasks safely, effectively, and efficiently. In crewed missions, astronauts are expected to work together with non-human entities (e.g., robots); human-robot teaming is considered a key aspect to ensure safe, effective, and efficient operations as identified in Moon to Mars Architecture Definition Document| Revision C[2].

Additionally, because of the recent remarkable advances in Artificial Intelligence (AI) technologies as seen in Large Language Models (LLMs) [1, 28], crew will increasingly interact with AI-powered systems that support a variety of activities, making Human-AI teaming another critical facet of future human spaceflight missions. These increasingly capable AI agents have been playing an important role in space missions [19]. The goal of integrating such sophisticated AI agents into human workflow is to augment human capabilities rather than to replace human roles [38]. How to achieve human capability argumentation by understanding how humans and AI agents can work together as a team has been a central question for researchers [3, 24, 10, 29, 7, 41, 31].

However, contrary to this research trend, Vaccaro et al. [42] found that Human-AI systems, on average, exhibit significantly worse performance than either the best of humans or AI alone. They also found that such degraded performance in Human-AI collaboration is more pronounced in joint decision-making tasks as compared to generative creation tasks (e.g., producing artistic images). Their findings highlight not only the difficulty in achieving Human-AI teaming, but the importance of considering the nature of the tasks performed when integrating AI-powered systems into human workflows.

Recognizing this difficulty, this paper presents key considerations for Human-Machine [3] teamwork, including interdependence and input compositionality, which can be used to analyze different types of tasks and team structures. After addressing the two lenses, we provide some potential examples of team structures in the context of human spaceflight missions. We then present an experiment using a simulated Urban Search and Rescue (USAR) mission with the aim of investigating patterns of effective Human-AI teams. From this experiment, we provide insights into Human-Machine teamwork evaluation and enhancement and then

[2] https://www.nasa.gov/wp-content/uploads/2025/12/add-revision-c-20251211.pdf?emrc=02371b (accessed on 7/17/2026)

[3] In this paper, we use the term machine to encompass robots, AI, and other non-human entities with a certain degree of agency that are capable of sensing their environment, collecting information, communicating with people, taking actions, learning, and evolving [11].

offer future work avenues for better studying and amplifying Human-Machine teamwork.

2 Interdependence in Human-Machine Teams

Researchers have identified, and generally agree upon, several key characteristics of teams, including having multiple members with roles, goals, and interdependence [25, 16, 27, 37, 15, 22]. Within a team, there are two types of activities, described in the next section, that team members engage in when they work together: taskwork and teamwork [14, 34].

2.1 Taskwork and Teamwork

Taskwork is a goal-oriented, task-related action that may be performed by individual team members, which does not necessarily require interdependent interactions between team members [36, 30]. Figure 1a is a task structure diagram that illustrates how an action is executed by individuals [30] and shows an association with the OODA loop [4]. Pre-conditions are states of the world that must be true for the action to be executed whereas post-conditions are the resulting state of the world after the action is taken [33, 41, 30]. Figure 1b represents different states of the task structure based on whether pre- and post-conditions are true; if they are true, a triangle turns green; otherwise, a triangle is depicted with a dashed-line.

In contrast to taskwork, teamwork involves interdependent relationships and focuses on how team members manage interdependent interactions to facilitate individuals engaged in taskwork [22, 30]. Interdependence is a critical aspect in teamwork, and researchers have examined different types of interdependence [39, 40, 26, 23, 12, 41, 30]. For instance, Johnson et al. [23] introduced *required* and *opportunistic* interdependence.

Required Interdependence Required interdependence occurs in situations where one team member must complete their task for others to initiate their own tasks [23]. Therefore, one entity’s post-condition must be satisfied for another’s pre-condition to be true. Required interdependence stems from multiple factors such as team members’ unique roles and/or environmental constraints. Consider a situation where two robots work together on a box delivery task in a warehouse. Each robot, however, has its own unique role; one is a color-sensing robot that is responsible for identifying a color of a box, but cannot deliver the box to a drop-off area. The other robot is a box delivery robot that cannot distinguish colors of boxes, but once the color-sensing robot identifies the color, the delivery robot picks up and carries the box to the drop-off area.

Opportunistic Interdependence Opportunistic interdependence is optional and occurs in situations where one team member assists a second team member in accomplishing the second team member's goal. Opportunistic interdependence is never strictly required, but if it is used, the efficiency of goal attainment for the team may be increased [23]. Consider a situation where two entities work on the warehouse box delivery task without required interdependence. There are Rooms A and B, and one entity knows no boxes are in Room A, but the other entity has decided to visit Room A and is moving towards it. In this situation, the first entity may exploit opportunistic interdependence by letting the other know about the state of Room A (e.g., no more boxes in Room A). For this message to be issued, the first entity has to observe the state of the world (i.e., boxes, the other's behavior), predict what will happen (i.e., the other will visit Room A), and offer a directional guidance (i.e., encourage the other to visit Room B). This message helps the receiver narrow down the search area and makes it easier to satisfy its pre-condition (i.e., no need to visit Room A to check if the pre-condition for the box delivery task exists), leading to a more efficient goal attainment [41].

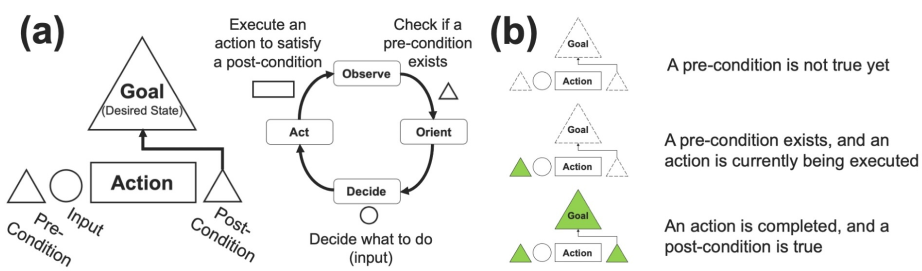

Fig. 1. (a) Task Structure Diagram with OODA Loop and (b) Different Task States (adapted from [30])

2.2 Input Compositionality in Human-Machine Teams

Humans can work with machines in various team structures. Momose [30] introduced input compositionality as a lens to examine team structure and discussed two types of Human-Machine teams.

Compositional Control Teams In a compositional control team, each team member makes an independent decision on the action (e.g., "turn left" or "turn right") or magnitude of the action to take (e.g., "turn left 10 degrees") and these decisions are combined to result in a single action taken [32, 30]. The input to the team's action is determined by the simultaneous composition of inputs from all team members via a composition function (Figure 2a). The definition of the composition function is not prescribed and can be any combination of team inputs, with common functions being averaging or weighted averaging. Momose [30] also introduced two types of compositional control teams. *Continuous* compositional control teams blend inputs on a regular periodic or continuous basis. In such teams, members may intentionally or unintentionally provide no decision for the action or action magnitude. An example of this is human-AI collaborative driving via a servo-level shared control scheme, where no move of the steering wheel is interpreted as the decision to continue straight e.g., [43]. In contrast, *discrete* compositional control teams blend their inputs on a demand basis; human-AI collaborative decision-making work is an example, where team members can discuss and negotiate considering individual inputs to produce a single team input (e.g., [3, 2]).

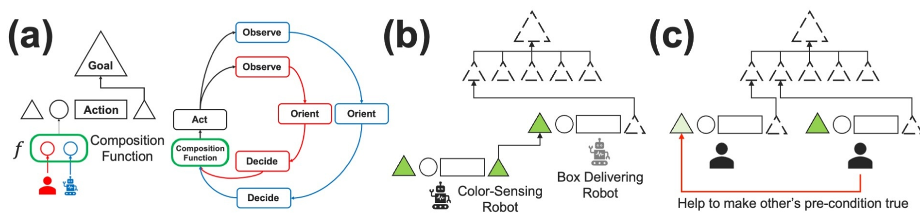

Fig. 2. (a) Comp Team, (b) Non-Comp Team (Required), (c) Non-Comp (Opportunistic) (adapted from [30])

Non-Compositional Control Teams Team members in a non-compositional control team work independently by making decisions and taking actions on their own [30, 32]. Examples in real-world settings include a package delivery service with multiple drones and USAR with multiple human and robot entities. Figures 2b and c show non-compositional task structure diagrams of the provided examples of required and opportunistic interdependence, respectively.

A key distinction between compositional and non-compositional control teams is where increases in performance come from. In compositional teams, performance increases by improving the quality of decisions through the combination or deliberation of decisions from multiple points of view. In non-compositional teams, the performance is increased through the parallelization of tasks made possible by the addition of new team members.

2.3 Examples of Team Structures in Human Spaceflight Missions

With the two analytical lenses in mind, Table 1 shows some examples of potential tasks in the context of human spaceflight missions.

Rover collaborative driving While we acknowledge that some design changes on Lunar Terrain Vehicle (LTV) and/or pressurized rovers need to be made,

Table 1. Potential Team Structured in Human Spaceflight Missions

Example	Compositionality	Required	Opportunistic
Rover collaborative driving	C-Comp	No	Convey uncertainty
Collaborative-decision making	D-Comp	No	Share information
Lunar surface reconnaissance	Non-Comp	No	Share progress
Sample collection EVA	Non-Comp	Yes	Provide information

C-Comp: Continuous Compositional; D-Comp: Discrete Compositional.

collaborative autonomous driving is one of the opportunities to employ the continuous compositional control team structure. Such collaborative driving can be achieved via the Horse-Mode (H-Mode) control [18, 17, 20], where a human driver lets an autonomous driving agent know intended driving direction, and when any deviations are observed, the human driver can easily take over. In collaborative driving, the autonomous driving agent can convey its uncertainty (confidence) level about the current driving situation as opportunistic interdependence, allowing the human driver to better gain situational awareness and participate in collaborative driving in a more effective, timely manner.

Collaborative decision-making Assume astronauts determine an excursion route for an upcoming Extravehicular Activity (EVA), which is an example of a discrete compositional control team. An autonomous agent provides a recommended route, and the astronauts also developed their own candidate routes. Then, they determine one single team final route by selecting one of the proposed routes or composing elements from the proposed routes to create a new one. During this input composition process, the autonomous agent could be designed to communicate the factors it prioritized (e.g., time, efficiency, safety, coverage of scientifically valuable locations). This additional shared information is not necessary, but could help humans explore alternatives that they had not considered initially, potentially resulting in a better final route.

Lunar surface reconnaissance Assume a scenario in which a single Lunar Terrain Vehicle (LTV) performs a lunar surface reconnaissance task to collect data for geological mapping. This task requires X hours to complete with one LTV. However, when a second LTV is added, the task can be completed in X/2 hours, highlighting a key advantage of non-compositional control teams (i.e., adding team members can improve task efficiency). In this reconnaissance scenario, opportunistic interdependence may involve each LTV communicating the areas it has already explored so that the others can avoid redundant coverage and complete the task more effectively.

Sample collection EVA Assume a scenario where two astronauts conduct a sample collection EVA with the assistance of an autonomous robot. The robot's primary role is to follow the astronauts and transport sample extraction equipment, but it cannot independently collect geological samples. Therefore, the astronauts depend on the robot to provide the necessary equipment for sample extraction, introducing required interdependence. While the astronauts search the lunar surface to identify scientifically valuable sampling locations, the equipment-carrying robot may detect a location of interest. By communicating this information to the astronauts, the robot makes the pre-condition for their sample extraction task true and enables them to proceed directly to sample extraction. The robot's shared information is opportunistic interdependence; it is not strictly required but can improve task efficiency by reducing the time needed to locate sampling locations.

With performance increases originating from key differences in team structure, we expect to see significant differences in the patterns of decisions made between high- and low-performing teams. The next section describes a preliminary experiment designed to highlight those differences.

3 Patterns of Effective Human-Machine Teams

3.1 Simulated USAR Mission Experiment

Human-Computer Interaction (HCI) researchers have attempted to apply knowledge and findings from the literature concerning human teams to teams with mixed humans and synthetic agents (e.g., [9, 8, 31]). Our theoretical framework is based on a social physics study by Pentland [35], showing that productive human teams exhibit consistent interaction patterns and maintain a balance between how individuals contribute to the team (energy) and how they communicate with each other (engagement). More specifically, the study suggested a “sweet spot” where both energy and engagement are well-balanced, leading to higher efficiency, while the imbalance in either direction reduces overall performance. We believe that Human-Machine teams also exhibit patterns of interactions and a “sweet spot”, resulting in higher team performance.

In an attempt to gain insights into patterns of interactions in Human-Machine teams, we conducted a preliminary experiment[4] using a simulated USAR mission built with CARLA [13]; a USAR scenario was selected since it has served as a testbed for human-machine teaming studies [8, 21]. In the simulated USAR mission, one human entity and three robots with autonomous driving capability are working together in both compositional and non-compositional control structures. The goal of the simulated USAR mission is to explore an urban city (Figure 3a) with a set of obstacles (debris) and to locate and save as many survivors as possible within a fixed time limit. The human and the three robots share compositional functions for robot maneuvering (i.e., continuous compositional control). However, the three robots are also capable of exploring (i.e., deciding where to go) and rescuing survivors independently (i.e., non-compositional control). Therefore, even without human participation, the simulated USAR mission

[4] The experiment protocol was reviewed and approved (IRB Number: XXXXXX)

could eventually be accomplished by the three robots, although this approach could be inefficient. The human operator is allowed to actively participate in one of the three robots' compositional control at any time by regulating the composition ratio (e.g., weighted average the steering inputs from the human and the robot) to assist in maneuvering their vehicles. Figure 3b shows one of the User Interface (UI) designs used in the preliminary experiment, where the composition ratio was displayed via sliders below the camera view. Figure 4a shows a task structure diagram of the simulated USAR mission.

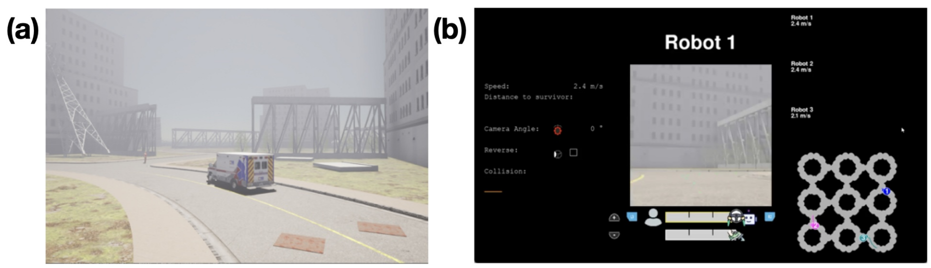

Fig. 3. (a) USAR map in CARLA; three ambulance vehicles acted as the robots. (b) UI design showing selected robot's camera view, city map, and other control related information.

In the simulated USAR mission, while the robots are designed to drive on roads by following waypoints on paved roads, the human can drive more flexibly and maneuver the vehicle without waypoints on grass fields and/or sidewalks, which can significantly shorten routes to survivors or to exploring new areas. Also, each robot announces "I found a survivor" when they detected a survivor within its search area. This notification feature is intended to create an opportunistic interdependence situation; the human operator may choose to utilize the opportunity to engage in the compositional control of the robot and possibly reduce the time to recover the survivor, but is not required to do so.

In the preliminary experiment, we evaluated four UI designs as the independent variable. The dependent variable was USAR performance measured by number of saved survivors and explored areas. We also recorded the number of opportunistic interdependence instances initiated by the robots. A total of 40 participants aged between 18 and 37 years old (M = 22.0, SD= 5.17) performed the simulated USAR mission. Each participant completed four missions, each lasting five minutes.

3.2 Notable Findings from Preliminary Experiment

In the preliminary experiment, we did not find a significant difference in USAR performance between the UI designs. Therefore, we performed exploratory data analysis, and this paper focuses on two key findings. The first key finding is

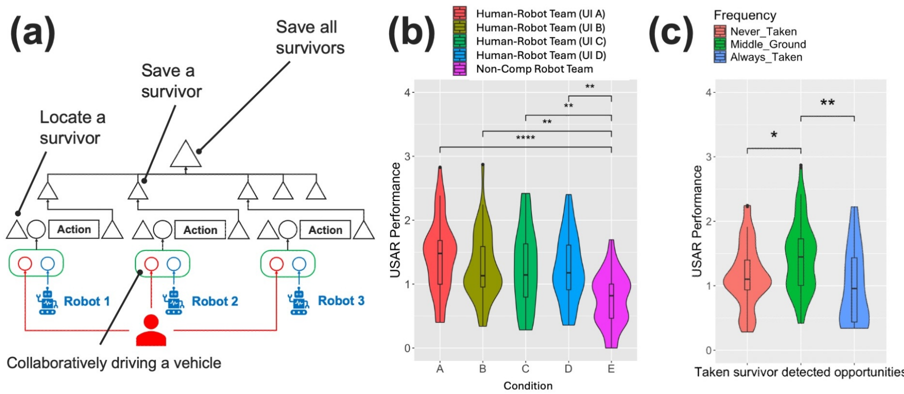

Fig. 4. (a) Task Structure Diagrams in the Simulated USAR Mission, (b) Comparisons of USAR performance between the four experiment conditions (A-D) and the purely non-compositional control team performance (E), and (c) Ratio of Realized Opportunistic Interdependence vs. USAR Performance: (* $p < 0.05$, ** $p < 0.01$, **** $p < 0.0001$)

that Human-Robot teams outperformed teams with only the three robots working independently regardless of UI conditions (Figure 4b). Given the finding by Vaccaro et al. [42], this observation is promising because human involvement via compositional control did not worsen the USAR performance achieved by the purely non-compositional control collaboration teams, but improved the performance level. We believe that extending non-compositional control systems with compositional control is a useful, effective approach to enhancing team performance.

The second key finding is the implication of a "sweet spot" in the response to the opportunistic interdependence opportunity. We divided all study participants into three groups based on a ratio of all opportunistic interdependence notifications issued to the number of opportunistic interdependencies realized (i.e., after receiving an opportunistic interdependence notification, the human chose to participate in compositional control involving the corresponding robot). Figure 4c suggests a parabolic relationship between team performance and the utilization of opportunistic interdependence and a "sweet spot" in the middle ground yielding the highest performance, whereas performance decreases at both extremes. While it is intuitive that utilizing no opportunities led to lower performance, we also observed a situation where the team encountered opportunities and excessively realized them, but still exhibited low performance. This could indicate that the team is experiencing information overload [41], or that the receiver could benefit from considering these opportunities more carefully. In such cases, we should aim to nudge the human operator to make a more informed decision on whether they should take it, or continue on their current tasks. Alternatively, the senders could limit or prioritize the amount of opportunistic interdependence information to avoid overloading and distracting the teammates (receivers).

4 Future Work

4.1 Ratio of Realized Opportunistic Interdependence

We presented some examples of potential tasks that multiple entities work together in different team structures in Subsection 2.3. Future work should first develop and analyze more realistic scenarios and then identify where opportunistic interdependence could be realized in interactions between team members. Approaches to identifying interdependence include drawing a task structure diagram, populating an interdependence analysis table [23], and/or utilizing Planning Domain Description Language (PDDL) with an intetrdependence point extraction capability [41]. As the preliminary experiment indicated, analyzing the ratio of opportunistic interdependence taken by humans to all those issued may help practitioners identify patterns and distinguish high- and low-performing teams. With the ratio of realized opportunistic interdependence, we could investigate what kinds of notifications/announcements could better nudge humans to seize opportunities to improve team performance and how to provide such notifications/announcements in an effective, timely manner.

4.2 Composition Function in Human-AI Collaborative Decision-Making

Trust and reliance studies show that encouraging critical reasoning by human operators significantly reduces overreliance and groupthink e.g., cognitive forcing functions [6]. We believe that this can also encourage engagement and skill growth while working with AI systems. For example, in a decision-making task setting (i.e., discrete compositional control team), Buçinca et al. [5] investigated the effect of contrastive explanations that clarify the difference between AI's decision and a predicted human response and found contrastive explanations significantly improve humans' independent decision-making skills without sacrificing decision accuracy compared to a control explanation design that simply justifies the AI's choice. Thus, future work could further explore the effects of a composition function — how to compose inputs from human and AI — on task performance (accuracy) and human skill development, where we could also observe patterns of effective Human-AI teams.

4.3 Transitions of Team Structures

We also propose focusing on transitions of team structures over the course of Human-Machine collaborative work to investigate patterns of effective Human-Machine teams. For instance, a Human-Machine team initially works in a parallel, non-compositional control manner without required interdependence. However, at some point, the team may decide that each member should work on a different task, introducing required interdependence. In this case, the team purposefully works with the "required" interdependence, and it may increase task efficiency. Depending on the context, the team may tailor their team structure and effective Human-Machine teams might exhibit patterns of transitions of team structures corresponding to their workflow, allowing us to identify a "sweet spot" and investigate how to facilitate such timely, effective transitions.

5 Conclusion

In human spaceflight missions, humans will increasingly work with advanced, sophisticated machines with AI-powered systems. Studies have suggested that Human-AI teams tend to underperform than human alone or AI alone [42]. In this paper, we discussed two lenses that can be used to analyze team structures: interdependence and input compositionality. Then, we presented a key insight from the preliminary experiment using the simulated USAR mission, indicating that the ratio of realized opportunistic interdependence is a useful Human-Machine teamwork metric. Lastly, we proposed several future work avenues to better study and improve Human-Machine teamwork, which could be applicable to different team structures. We believe that investigating patterns of effective Human-AI teams is a promising approach to improving team performance, and the proposed future work could help us identify a "sweet spot" in Human-Machine teamwork.

References

1. Adiwardana, D., Luong, M., So, D.R., Hall, J., Fiedel, N., Thoppilan, R., Yang, Z., Kulshreshtha, A., Nemade, G., Lu, Y., Le, Q.V.: Towards a human-like open-domain chatbot. CoRR **abs/2001.09977** (2020), https://arxiv.org/abs/2001.09977
2. Bansal, G., Nushi, B., Kamar, E., Lasecki, W.S., Weld, D.S., Horvitz, E.: Beyond accuracy: The role of mental models in human-ai team performance. Proceedings of the AAAI Conference on Human Computation and Crowdsourcing **7**(1), 2–11 (Oct 2019). https://doi.org/10.1609/hcomp.v7i1.5285, https://ojs.aaai.org/index.php/HCOMP/article/view/5285
3. Bansal, G., Wu, T., Zhou, J., Fok, R., Nushi, B., Kamar, E., Ribeiro, M.T., Weld, D.: Does the whole exceed its parts? the effect of ai explanations on complementary team performance. In: Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems. pp. 1–16 (2021)
4. Boyd, J.R.: The essence of winning and losing. Unpublished lecture notes **12**(23), 123–125 (1996)
5. Buçinca, Z., Swaroop, S., Paluch, A.E., Doshi-Velez, F., Gajos, K.Z.: Contrastive explanations that anticipate human misconceptions can improve human decision-making skills. In: Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems. CHI '25, Association for Computing Machinery, New York, NY, USA (2025). https://doi.org/10.1145/3706598.3713229, https://doi.org/10.1145/3706598.3713229
6. Buçinca, Z., Malaya, M.B., Gajos, K.Z.: 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 (2021)

7. Capel, T., Brereton, M.: What is human-centered about human-centered ai? a map of the research landscape. In: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems. pp. 1–23 (2023)
8. Chiou, E.K., Demir, M., Buchanan, V., Corral, C.C., Endsley, M.R., Lematta, G.J., Cooke, N.J., McNeese, N.J.: Towards human–robot teaming: Tradeoffs of explanation-based communication strategies in a virtual search and rescue task. International Journal of Social Robotics pp. 1–20 (2021)
9. Chiou, E.K., Lee, J.D., Su, T.: Negotiated and reciprocal exchange structures in human-agent cooperation. Computers in Human Behavior **90**, 288–297 (2019)
10. Cila, N.: Designing human-agent collaborations: Commitment, responsiveness, and support. In: Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems. CHI '22, Association for Computing Machinery, New York, NY, USA (2022). https://doi.org/10.1145/3491102.3517500, https://doi.org/10.1145/3491102.3517500
11. Cila, N., Smit, I., Giaccardi, E., Kröse, B.: Products as agents: Metaphors for designing the products of the iot age. In: Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems. pp. 448–459 (2017)
12. Courtright, S.H., Thurgood, G.R., Stewart, G.L., Pierotti, A.J.: Structural interdependence in teams: An integrative framework and meta-analysis. Journal of Applied Psychology **100**(6), 1825 (2015)
13. Dosovitskiy, A., Ros, G., Codevilla, F., Lopez, A., Koltun, V.: CARLA: An open urban driving simulator. In: Proceedings of the 1st Annual Conference on Robot Learning. pp. 1–16 (2017)
14. Endsley, M.R.: Supporting human-ai teams: Transparency, explainability, and situation awareness. Computers in Human Behavior **140**, 107574 (2023)
15. Endsley, M.R., Bolté, B., Jones, D.G.: Designing for situation awareness: An approach to user-centered design. CRC press (2003)
16. Ferran-Urdaneta, C.: Teams or communities? organizational structures for knowledge management. In: Proceedings of the 1999 ACM SIGCPR conference on computer Personnel Research. pp. 128–134 (1999)
17. Flemisch, F., Kelsch, J., Löper, C., Schieben, A., Schindler, J., Heesen, M.: Cooperative control and active interfaces for vehicle assistance and automation. In: FISITA World automotive Congress (2008), f2008-02-045
18. Flemisch, F.O., Adams, C.A., Conway, S.R., Goodrich, K.H., Palmer, M.T., Schutte, P.C.: The h-metaphor as a guideline for vehicle automation and interaction. Tech. Rep. NASA/TM—2003-212672, NASA, Langley Research Center, Hampton VA 23681-2199, USA (2003)
19. Frank, J.D.: Artificial intelligence: Powering human exploration of the moon and mars. In: ASCEND 2020. American Institute of Aeronautics and Astronautics, Reston, Virginia (Nov 2020)
20. Goodrich, K., Williams, R., Schutte, P.: Piloted evaluation of the h-mode, a variable autonomy control system, in motion-based simulation. In: AIAA Atmospheric Flight Mechanics Conference and Exhibit. p. 6554. American Institute of Aeronautics and Astronautics (2008). https://doi.org/10.2514/6.2008-6554, https://doi.org/10.2514/6.2008-6554
21. Humann, J., Pollard, K.A.: Human factors in the scalability of multi-robot operation: A review and simulation. In: 2019 IEEE International Conference on Systems, Man and Cybernetics (SMC). pp. 700–707 (2019). https://doi.org/10.1109/SMC.2019.8913876
22. Johnson, M., Bradshaw, J.M.: How interdependence explains the world of teamwork. In: Engineering Artificially Intelligent Systems, pp. 122–146. Springer (2021)

23. Johnson, M., Bradshaw, J.M., Feltovich, P.J., Jonker, C.M., Van Riemsdijk, M.B., Sierhuis, M.: Coactive design: Designing support for interdependence in joint activity. Journal of Human-Robot Interaction **3**(1), 43–69 (2014)
24. Johnson, M., Vera, A.: No ai is an island: the case for teaming intelligence. AI magazine **40**(1), 16–28 (2019)
25. Katzenbach, J.R., Smith, D.K.: The wisdom of teams: Creating the high-performance organization. Harvard Business Review Press (2015)
26. Kiggundu, M.N.: Task interdependence and the theory of job design. Academy of management Review **6**(3), 499–508 (1981)
27. Larson, C., Larson, C.E., LaFasto, F.M.: Teamwork: What must go right/what can go wrong, vol. 10. Sage (1989)
28. Liu, A., Feng, B., Xue, B., Wang, B., Wu, B., Lu, C., Zhao, C., Deng, C., Zhang, C., Ruan, C., et al.: Deepseek-v3 technical report (2025), https://arxiv.org/abs/2412.19437
29. McNeese, N.J., Demir, M., Cooke, N.J., Myers, C.: Teaming with a synthetic teammate: Insights into human-autonomy teaming. Human Factors **60**(2), 262–273 (2018). https://doi.org/10.1177/0018720817743223, https://doi.org/10.1177/0018720817743223, pMID: 29185818
30. Momose, K.: Patterns of Interactions in Human-Machine Teams. Ph.D. thesis, Florida Institute of Technology (2024), https://repository.fit.edu/etd/1505
31. Momose, K., Mehta, R., Moukpe, J., Weekes, T.R., Eskridge, T.C.: Human-ai teamwork interface design using patterns of interactions. International Journal of Human–Computer Interaction **0**(0), 1–24 (2024). https://doi.org/10.1080/10447318.2024.2389350, https://doi.org/10.1080/10447318.2024.2389350
32. Momose, K., Weekes, T.R., Eskridge, T.C., Kidwell, D.: Trust and reliance in compositional control teams. In: Workshop on Trust and Reliance in AI-Assisted Tasks (TRAIT) at CHI 2023. pp. 1–11. Association for Computing Machinery, New York, NY, USA (2023)
33. Nisbett, R.E.: Rules for Reasoning. Lawrence Erlbaum Associates, Philadelphia, PA, USA (Jan 1993), https://www.amazon.com/Rules-Reasoning-Richard-Nisbett/dp/0805812571
34. Nissen, H.A., Evald, M.R., Clarke, A.H.: Knowledge sharing in heterogeneous teams through collaboration and cooperation: Exemplified through public–private-innovation partnerships. Industrial Marketing Management **43**(3), 473–482 (2014)
35. Pentland, A.S.: The new science of building great teams (2012), https://hbr.org/2012/04/the-new-science-of-building-great-teams-2, harvard Business Review, https://hbr.org/2012/04/the-new-science-of-building-great-teams-2 [Accessed 14. Aug. 2024]
36. Salas, E., Cooke, N.J., Rosen, M.A.: On teams, teamwork, and team performance: Discoveries and developments. Human factors **50**(3), 540–547 (2008)
37. Salas, E., Dickinson, T.L., Converse, S.A., Tannenbaum, S.I.: Toward an understanding of team performance and training. In: Swezey, R.W., Salas, E. (eds.) Teams: Their training and performance., pp. 3–29. Ablex Publishing, Westport, CT, US (1992)
38. Shneiderman, B.: Human-centered artificial intelligence: Reliable, safe & trustworthy. International Journal of Human–Computer Interaction **36**(6), 495–504 (2020)
39. Thompson, J.D.: Organizations in action: Social science bases of administrative theory. New York, McGraw-Hill (1967)
40. Thompson, J.D.: Technology, polity, and societal development. Administrative Science Quarterly pp. 6–21 (1974)

41. Tummala, V.: Advancing Human-Agent Teamwork. Ph.D. thesis, Florida Institute of Technology (2022)
42. Vaccaro, M., Almaatouq, A., Malone, T.: When combinations of humans and AI are useful: A systematic review and meta-analysis. Nat. Hum. Behav. **8**(12), 2293–2303 (Dec 2024)
43. Wang, W., Na, X., Cao, D., Gong, J., Xi, J., Xing, Y., Wang, F.Y.: Decision-making in driver-automation shared control: A review and perspectives. IEEE/CAA Journal of Automatica Sinica **7**(5), 1289–1307 (2020)