Birds of a Different Feather Flock Together: Exploring Opportunities and Challenges in Animal-Human-Machine Teaming

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Abstract

Animal-Human-Machine (AHM) teams are a type of hybrid intelligence system wherein interactions between a human, AI-enabled machine, and animal members can result in unique capabilities greater than the sum of their parts. This paper calls for a systematic approach to studying the design of AHM team structures to optimize performance and overcome limitations in various applied settings. We consider the challenges and opportunities in investigating the synergistic potential of AHM team members by introducing a set of dimensions of AHM team functioning to effectively utilize each member's strengths while compensating for individual weaknesses. Using three representative examples of such teams—security screening, search-and-rescue, and guide dogs—the paper illustrates how AHM teams can tackle complex tasks. We conclude with open research directions that this multidimensional approach presents for studying hybrid human-AI systems beyond AHM teams.

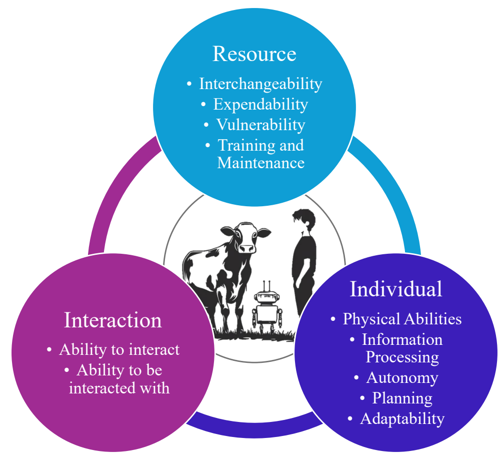

Figure 1: The properties of Animal-Human-Machine team.

Introduction

Animals, machines, and humans each possess unique capabilities that, when combined meaningfully, can result in systems that enable new feats. For example, technology augmentations are already prevalent in human-animal systems: automated feeders, tracking devices, and monitoring systems (Staszesky, Craig, and Befus 2005; Sparrow and Howard 2021). Machine potentials have also been augmented by animals, such as in the detection of underwater mines using dolphins (Moore 1997).

Consider a Blind or Visually Impaired (BVI) person training to be assisted by a guide dog. When the pair reaches an obstacle along their path, they can aim to employ a learned protocol: the dog stops, then the BVI person investigates the cause for the stop, be it a wall, a stair, etc. With modern vision technologies, the pair could be equipped with a designated camera and a vision algorithm that automatically identifies the reason for the dog's stop (Ichikawa, Zhang, and Lim 2022), reducing the need for the BVI person to investigate manually. Given modern smartphone technologies, such a system might even be augmented in the person's phone (Taylor et al. 2012). These systems can be considered as an animal-human-machine (AHM) team that functions as a synergistic unit tackling complex tasks. Conversely, the absence of any of the members makes AHM teams less capable: without a vision system, a BVI person must exert inefficient and potentially risky efforts to interpret why their guide dog pair made a stop; even the most cutting-edge robots cannot fully replace a guide dog (Morris et al. 2003; Sakhardande, Pattanayak, and Bhowmick 2012; Mirsky and Stone 2021; Hwang et al. 2024); and obviously, the team's goal ceases to exist without the BVI person.

In the ideal scenario, each member of an AHM team is given a role that maximizes their respective strengths and compensates for individual weaknesses to optimize the team's functionality. However, in high-stakes, rapidly changing scenarios, individual workloads are often exceeded, whether through anticipated or unanticipated circumstances. In those situations, flexible reallocation is needed to redistribute responsibilities across other team members (Bye, Hollnagel, and Brendeford 1999). This paper investigates AHM teams as a type of a multiagent system (MAS) and discusses the unique research challenges and opportunities in this setup. We define an AHM team as follows:

Definition 1 *An Animal-Human-Machine team is a multiagent system with three or more members: at least one is an animal, one is a human, and one is a machine. Each member* *has agency grounded in unique sensing, decision-making, and acting capabilities.*

Previous work has also highlighted some conceptual similarities between domestic animals and machines (Darling 2021). When robots are made of organic matter (Blackiston et al. 2023) and animals are incorporated into machines (Sanchez et al. 2015), we might reach a point where the distinction between the different agents is blurred (Mazis 2008). At this time, however, we assume that the boundaries between them are clear. We note that this paper focuses on the technological aspects of AHM rather than its legal or ethical implications, which are not negligible. Interested researchers can refer to (Mazis 2008; Schaerer, Kelley, and Nicolescu 2009; Hou, Cheon, and Jung 2024).

We move on to discuss AHM from the lens of related work, including team functional allocation from industrial/organizational psychology and computational work linking human-animal and human-agent interaction paradigms. We conclude with three use cases that highlight the utility of this framework for advancing the conversation on AHM team design considerations.

Related Works

In organizational psychology, teams are often defined as groups of people with a shared sense of identity who collaborate with distinct roles for a limited time to achieve a common goal (Salas et al. 1992). By this definition, AHM teams seem paradoxical due to having non-human members. But treating components like sense of identity or role distinction as variable elements of teaming (i.e., "teamness"; (Cooke et al. 2024)) can aid in understanding a broad range of collaborations. Consider ad-hoc teamwork, where amorphous team compositions may result in a lack of clear shared identities among collaborators (Stone et al. 2010). Treating shared identity as a variable has borne algorithmic solutions that aid teammates in establishing common ground, inferring each other's capabilities, and interpreting other *agents*' underlying cooperative intents (Grosz and Kraus 1999; Mirsky et al. 2022). Similarly, considering "humanness" as a spectrum rather than a requirement of teaming has benefited the recent surge in research and development of human-machine systems wherein people and machines collectively achieve feats they could not apart (O'Neill et al. 2022; Cooke et al. 2024). The same logic has long been used to describe human-animal systems (Haraway 2003).

Human-animal teams are increasingly used as a metaphor for human-machine teams. Both are interactive systems that achieve joint outcomes despite having different cognitive processes between animal, human, and machine members (Lum and Phillips 2023; Coeckelbergh 2011; Krueger et al. 2021; Billings et al. 2012). Human-animal teams and human-machine teams also share intractable physical and cognitive asymmetries between each member type, limiting the tasks they can perform and their understanding of the team's overarching goals (Phillips et al. 2016). These asymmetries are amplified in AHM teams due to the concurrent presence of at least two types of non-human teammates (Gerencsér 2016), defining a complex range of research paradigms and application domains. For example, how to support the development of shared mental models between human and machine teammates (Baker, Saxe, and Tenenbaum 2011; Fiore et al. 2023; Schelble et al. 2022; Andrews et al. 2023; Narayanan and Feigh 2024); however, the impacts of these efforts will likely be limited in full AHMs due to animal cognitive limitations. Conversely, the evolutionary origin of human-animal relationships results in interaction dynamics that are more social and emotional than human-robot ones (Coeckelbergh 2011).

Another related research area that has been investigating collaboration between agents with varying capabilities and objectives is **Ad-Hoc Teamwork** (AHT): the task of collaborating with previously unmet agents (Stone et al. 2010; Mirsky et al. 2022). In AHT, one agent needs to learn how to collaborate with other agents on-the-fly, without the ability to directly control them, in a collaborative setup. One such example task is a drop-in soccer game where other players on the team might be attack- or defense-oriented, but this preference will only be revealed through playing together (Barrett and Stone 2015). One notable example of AHT inspired by machines and animal teaming investigated how to influence a flock of European starlings (Genter 2017).

One quality that AHM teams ostensibly share is role heterogeneity, i.e., each member is assigned a unique set of tasks to fulfill a role within a team (Belbin 1993). Role heterogeneity often results from delegating tasks to individuals based on their abilities. In all-human teams like surgical teams, task assignment decisions are based on limited pools of team members who can fulfill roles like surgeon, anesthesiologist, or nurse at a given time (Carayon et al. 2006; Gorman et al. 2020). However, further training can enable today's nurse to be assigned the role of surgeon in the future. In contrast, such decisions in AHM teams are limited by ethical, legal, and technological concerns that come with assigning non-human members to potentially consequential tasks (Bonfanti 2014; Coman and Aha 2018; Parasuraman and Wickens 2008).

In human-machine systems, Fitts' list (Fitts 1951; De Winter and Dodou 2014) is an influential framework that operates on the principle of non-overlapping task allocations based on the relative strengths and weaknesses of people and machines (often called "HABA-MABA", short for "humans-are-better-at/machines-are-better-at"). Current functional allocation paradigms in human teams and human-machine teams are still predominantly based on individual members' capabilities (Howard et al. 2023; Caldwell, Nyre-Yu, and Hill 2019; Lai et al. 2021; Crawford and LePine 2013). This premise remains true amid calls for more nuanced consideration of interactions between complex human and machine teammates rather than individual capabilities alone (Caldwell, Nyre-Yu, and Hill 2019; Johnson et al. 2011; Feigh and Pritchett 2014; Metcalfe et al. 2021).

To illustrate, in an AHM security screening setting, trained sniffing dogs are fairly reliable in detecting scent markers of various illicit items (Jezierski et al. 2014; Myers 1992); "sniffing" capabilities for machines have been developed and deployed as machine teammates or alternatives to dogs, and can be more or less effective depending on the target items (Furton and Winialski 2022); last, and the least useful candidate for the scent detection task, is the human. However, for other tasks like physical inspection of suspicious items, people may be better than machines, who in turn are likely better than dogs. The original Fitts' list does not account for the strengths and weaknesses of animals; nonetheless, its strengths-and-weaknesses framework correctly predicts current AHM security screening configurations (Furton and Winialski 2022). Other AHM teaming contexts, like field search-and-rescue, have less structured team goals and tasks. Thus, additional factors are needed to inform functional allocation decisions.

Functional Allocation Dimensions

We propose a set of functional allocation considerations for Animal-Human-Machine (AHM) teams, divided into three categories: (1) the *Individual* roles and functions each agent must fulfill to meet shared goals; (2) the *Interaction* capabilities required for effective team operation; and (3) the *Resource* constraints or costs associated with deploying AHM teams versus traditional ones.

Individual Dimensions

Physical Requirements. Many functional allocation decisions in AHM teams stem from physical capability tradeoffs. Tasks requiring high exertion but low precision, like plowing, can be assigned to animals or simple machines. Conversely, tasks requiring fine motor skills or delicate handling may be better suited to humans or machines designed for precision. The nature of the task and the endurance, control, or dexterity required will guide allocation.

Information Processing Requirements. Differences in sensory and cognitive capabilities shape which agents are best suited for processing specific types of information. Animals can often be trained to detect evolutionary-relevant cues, such as scents or sounds. Machines can handle data streams and processing loads beyond human or animal capabilities, while humans remain key for interpreting complex, ambiguous, or sociocultural information.

Level of Autonomy. The extent to which agents can act independently influences how functions are distributed. AI agents, for example, may enhance team performance if given enough agency to initiate or interrupt actions, especially in dynamic settings. However, the team must balance autonomy with predictability and oversight, especially where high-stakes tasks are involved.

Planning Capabilities. Each agent must have sufficient understanding of tasks and procedures to contribute meaningfully. While humans typically manage overall planning, non-human agents must comprehend and follow task sequences. Mutual understanding of one's own tasks and teammates' intentions supports shared planning and effective delegation. Emerging research in AI and animal cognition highlights promising pathways for extending such capabilities beyond humans.

Adaptability. In unpredictable, high-risk domains the ability of agents to adjust in real time is vital. Adaptability refers not to the external cost of preparing agents, but to their internal capacity for re-planning and behavioral flexibility. This includes learning from new situations and modifying actions based on changing goals or environments.

Interaction Dimensions

Ability to Interact. Effective AHM teaming requires agents to both communicate and coordinate. Communication may be asymmetric and constrained, for example, when humans issue commands to animals or operate drones, but can also involve bidirectional signaling. Coordination hinges on timing, information flow, and shared goals, made more complex by differing communication channels. Skills like social intelligence (understanding others' states and intentions), co-learning (adapting together), and trust (expecting cooperation under uncertainty) are central to robust interaction.

Ability to Be Interacted With. Beyond initiating interactions, agents must also support being coordinated with. Traits such as trustworthiness and reliability help teammates anticipate behavior. These may manifest differently—for example, machine reliability involves system stability, while animal reliability depends on behavioral consistency and training. Transparency and scrutability further enhance interaction by making agents' intentions and limitations easier to understand. Predictability, knowing how a teammate will respond in context, is essential to synchronizing actions across the team.

Resource Dimensions

Interchangeability. Swapping team members without loss of functionality is more complex in AHM teams due to variability in physical capabilities, task-specific training, and operational constraints. While interchangeability is common in traditional teams, it requires more planning in heterogeneous systems where roles are tightly coupled to agent abilities.

Expendability. In high-risk scenarios, such as military or disaster relief operations, teams must consider what is at stake when agents are lost. The distinct cognitive, emotional, and physical profiles of humans, animals, and machines affect how expendability is assessed. Cost–benefit analyses become essential to determine the acceptability of loss for different agent types.

Vulnerability. Vulnerability refers to how easily each team member can be harmed or disabled. Each agent's susceptibility must be accounted for when assigning tasks, especially those involving physical risk or harsh conditions. Protecting more vulnerable agents or choosing more resilient ones can significantly affect team performance and sustainability.

Training & Maintenance. Training and maintaining team members requires significant investment. Humans and animals may take months or years to prepare, with ongoing costs in education, care, or compensation. Machines often demand expensive sensors, specialized hardware, or large training datasets. Even when tasks are technically learnable by AI, data and computation costs may render them impractical in the short term.

Use-Cases

We consider some real-life examples of AHM teaming in light of the dimensions of our proposed functional allocation framework, namely security screening, search and rescue, and machine-enhanced guide dog setups.

Security Screening

In security screening systems, the goal is to detect and address the presence of potentially dangerous items. These often involve two screening steps, i.e., preliminary screenings and manual inspections. *Information processing capabilities* plays a crucial role: Sniffing dogs can only serve as preliminary screening agents for detecting suspicious odors. Machines also perform only preliminary screening tasks with specialized sensors like metal detectors and X-ray scanners. Interaction considerations help explain the presence of several human roles in AHM security screening teams, which can be differentiated depending on which non-human agents they interact with: (1) dog handlers, who respond to sniffing dog reactions to screened items and manage sniffing dogs (Myers 1992); (2) x-ray operators, who interact with x-ray screening machines, manipulating and interpreting images to flag suspicious items or persons for further inspection (Hättenschwiler, Mendes, and Schwaninger 2019); and (3) manual inspectors, who manually inspect flagged items. *Training and maintenance costs* are intertwined with limited role interchangeabilities. For example, dog handlers often only handle specific sniffing dogs to accommodate *reliability* and *trust* considerations. In contrast, x-ray operators typically rotate between machines they are trained to operate, having general performance expectations from the technology in general. Sniffing dogs themselves must be extensively trained, with a cost compounded by the need to train them with dog handlers as a human-animal dyad. Because security screening tasks normally occur in places like airports where there is a high volume of screening tasks in a fast-paced environment, managing dog exhaustion is also a concern. However, although "sniffing machines" may be an alternative, the deployment and maintenance costs of these nascent technologies remain an obstacle today.

Search and Rescue

In search and rescue missions, the synergy between animals and humans is crucial for maximizing success in life-threatening situations. The attributes that define this relationship, such as *adaptability*, *communication*, and *planning*, play a vital role in team performance. For instance, the ability of both animals and humans to quickly *process* and *adapt* to changing environments is essential when navigating hazardous disaster areas, as previously seen in the aftermath of Hurricane Katrina. Effective *communication* and mutual *trust* between animal and human team members form the backbone of successful operations. Clear, consistent signals and commands enable seamless coordination, while trust allows team members to rely on each other's unique capabilities. This is particularly important when leveraging complementary skills, such as a rescue dog's superior sense of smell combined with a human handler's problem-solving abilities, to locate victims in complex rubble structures.

The shared capacity for information processing among animals and humans is a critical factor in search and rescue effectiveness. Both must process the environment and develop accurate spatial representations to navigate treacherous areas efficiently. This cognitive skill, coupled with stress resilience and interspecies empathy, allows teams to maintain high performance under extreme pressure. By focusing on these attributes in training and team composition, search and rescue organizations can significantly enhance their ability to locate and save victims in disaster scenarios, addressing the fundamental question of how individual spatial cognition contributes to overall team performance in applied settings.

Guide Dogs

Consider the use-case presented at the beginning of the paper of a guide dog setup extended with AI capabilities: Modern vision systems can identify these different scenarios and alert the person regarding the reason for stopping using voice. This example highlights each individual's unique contribution to this team: the person provides high cognitive ability and decision-making; the dog provides sensing and physical responsiveness; the vision systems provide enhanced sensing and inference capabilities. *Interchangeability* in this scenario is uniquely low, as the person cannot replace the role of the dog, the dog cannot speak in detail about why it stopped, and the vision system cannot physically lead a person. *Expendability* is high because dog training is expensive and cannot be easily replaced. The *ability to communicate* and *be communicated with* are also especially important in this context, as each member's actions are highly coupled with the other teammates' actions.

Conclusion

This paper outlines the dimensions of Animal-Human-Machine (AHM) teaming, planning, and execution in relation to current HRI research. It also presents three compelling use cases that underscore the distinct advantages of AHM teams.

As with any complex system, it is important to assess when such intricacy is truly necessary. AHM teaming is needed when the complexity, risk, or multidimensional nature of a task surpasses the capabilities of any two-agent combination. In search-and-rescue missions, for instance, the sensory acuity of animals, the cognitive oversight of humans, and the data-processing and mapping abilities of machines form a triad that outperforms any duo. These teams excel in tasks requiring real-time, cross-modal coordination that no pair can fully achieve.

Our goal is to empirically examine the functional roles of each agent across diverse operational contexts to inform reliable simulations for future function allocation. This requires controlled studies that measure interactions under constraints like time pressure, environmental hazards, and communication limits. Such investigations will help clarify when adding a third agent is redundant or promotes synergy.

We invite researchers to consider how their work might contribute to AHM teams—enhancing team performance while generating novel insights. For example, a machine's alarm may alert a human but disturb an animal; studying such trade-offs can refine communication strategies and reveal new dynamics in real-world settings.

References

Andrews, R. W.; Lilly, J. M.; Srivastava, D.; and Feigh, K. M. 2023. The Role of Shared Mental Models in Human-AI Teams: A Theoretical Review. *Theoretical Issues in Ergonomics Science*, 24(2): 129–175.

Baker, C.; Saxe, R.; and Tenenbaum, J. 2011. Bayesian theory of mind: Modeling joint belief-desire attribution. In *Proceedings of the annual meeting of the cognitive science society*, volume 33.

Barrett, S.; and Stone, P. 2015. Cooperating with unknown teammates in complex domains: A robot soccer case study of ad hoc teamwork. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 29.

Belbin, R. M. 1993. *Team Roles at Work*. Oxford: Butterworth-Heinemann, 1st edition. ISBN 978-0-7506-0925-8.

Billings, D. R.; Schaefer, K. E.; Chen, J. Y.; Kocsis, V.; Barrera, M.; Cook, J.; Ferrer, M.; and Hancock, P. A. 2012. Human-Animal Trust as an Analog for Human-Robot Trust: A Review of Current Evidence. *Army Research Laboratory*, 1–28.

Blackiston, D.; Kriegman, S.; Bongard, J.; and Levin, M. 2023. Biological robots: Perspectives on an emerging interdisciplinary field. *Soft robotics*, 10(4): 674–686.

Bonfanti, M. E. 2014. From Sniffer Dogs to Emerging Sniffer Devices for Airport Security: An Opportunity to Rethink Privacy Implications? *Science and Engineering Ethics*, 20(3): 791–807.

Bye, A.; Hollnagel, E.; and Brendeford, T. S. 1999. Human–machine function allocation: a functional modelling approach. *Reliability Engineering & System Safety*, 64(2): 291–300.

Caldwell, B. S.; Nyre-Yu, M.; and Hill, J. R. 2019. Advances in Human-Automation Collaboration, Coordination and Dynamic Function Allocation. In Hiekata, K.; Moser, B. R.; Inoue, M.; Stjepandić, J.; and Wognum, N., eds., *Advances in Transdisciplinary Engineering*. IOS Press. ISBN 978-1-64368-020-0 978-1-64368-021-7.

Carayon, P.; Schoofs Hundt, A.; Karsh, B.-T.; Gurses, A. P.; Alvarado, C. J.; Smith, M.; and Flatley Brennan, P. 2006. Work System Design for Patient Safety: The SEIPS Model. *Quality in Health Care*, 15(suppl 1): i50–i58.

Coeckelbergh, M. 2011. Humans, Animals, and Robots: A Phenomenological Approach to Human-Robot Relations. *International Journal of Social Robotics*, 3(2): 197–204.

Coman, A.; and Aha, D. W. 2018. AI rebel agents. *AI magazine*, 39(3): 16–26.

Cooke, N. J.; Cohen, M. C.; Fazio, W. C.; Inderberg, L. H.; Johnson, C. J.; Lematta, G. J.; Peel, M.; and Teo, A. 2024. From Teams to Teamness: Future Directions in the Science of Team Cognition. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 66(6): 1669–1680.

Crawford, E. R.; and LePine, J. A. 2013. A Configural Theory of Team Processes: Accounting for the Structure of Taskwork and Teamwork. *Academy of Management Review*, 38(1): 32–48.

Darling, K. 2021. *The new breed: what our history with animals reveals about our future with robots*. Henry Holt and Company.

De Winter, J. C.; and Dodou, D. 2014. Why the Fitts list has persisted throughout the history of function allocation. *Cognition, Technology & Work*, 16: 1–11.

Feigh, K. M.; and Pritchett, A. R. 2014. Requirements for Effective Function Allocation: A Critical Review. *Journal of Cognitive Engineering and Decision Making*, 8(1): 23–32.

Fiore, S. M.; Johnson, M.; Robertson, P.; Diego-Rosell, P.; and Fouse, A. 2023. Transdisciplinary Team Science: Transcending Disciplines to Understand Artificial Social Intelligence in Human-Agent Teaming. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 67(1): 419–424.

Fitts, P. M. 1951. *Human Engineering for an Effective Air-Navigation and Traffic-Control System*. Human Engineering for an Effective Air-Navigation and Traffic-Control System. Washington, D.C.: National Research Council.

Furton, K. G.; and Winialski, D. 2022. Comparing the Olfactory Capabilities of Dogs with Machines Designed to Detect Odors. In *Canines*. Jenny Stanford Publishing. ISBN 978-1-00-326113-1.

Genter, K. L. 2017. *Fly with me: algorithms and methods for influencing a flock*. Ph.D. thesis.

Gerencsér, L. 2016. *The Integration of Dogs into Collaborative Human-Robot Teams - An Applied Ethological Approach*. Ph.D. thesis, Eötvös Loránd Tudományegyetem.

Gorman, J. C.; Grimm, D. A.; Stevens, R. H.; Galloway, T.; Willemsen-Dunlap, A. M.; and Halpin, D. J. 2020. Measuring real-time team cognition during team training. *Human factors*, 62(5): 825–860.

Grosz, B. J.; and Kraus, S. 1999. The evolution of SharedPlans. In *Foundations of rational agency*, 227–262. Springer.

Haraway, D. 2003. *The Companion Species Manifesto: Dogs, People, and Significant Otherness*. Chicago: Prickly Paradigm Press. ISBN 978-0-9717575-8-5.

Hättenschwiler, N.; Mendes, M.; and Schwaninger, A. 2019. Detecting Bombs in X-Ray Images of Hold Baggage: 2D Versus 3D Imaging. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 61(2): 305–321.

Hou, Y. T.-Y.; Cheon, E.; and Jung, M. F. 2024. Power in Human-Robot Interaction. In *Proceedings of the 2024 ACM/IEEE International Conference on Human-Robot Interaction*, 269–282.

Howard, J. J.; Rabbitt, L. R.; Shuggi, I. M.; and Sirotin, Y. B. 2023. A Framework for Human-Algorithm Teaming in Biometric Identity Workflows. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 67(1): 523–528.

Hwang, H.; Jung, H.-T.; Giudice, N. A.; Biswas, J.; Lee, S. I.; and Kim, D. 2024. Towards Robotic Companions: Understanding Handler-Guide Dog Interactions for Informed Guide Dog Robot Design. In *Proceedings of the CHI Conference on Human Factors in Computing Systems*, 1–20.

Ichikawa, R.; Zhang, B.; and Lim, H.-o. 2022. Voice expression system of visual environment for a guide dog robot. In *2022 8th International Symposium on System Security, Safety, and Reliability (ISSSR)*, 191–192. IEEE.

Jezierski, T.; Adamkiewicz, E.; Walczak, M.; Sobczyńska, M.; Górecka-Bruzda, A.; Ensminger, J.; and Papet, E. 2014. Efficacy of Drug Detection by Fully-Trained Police Dogs Varies by Breed, Training Level, Type of Drug and Search Environment. *Forensic Science International*, 237: 112–118.

Johnson, M.; Bradshaw, J. M.; Feltovich, P. J.; Hoffman, R. R.; Jonker, C.; van Riemsdijk, B.; and Sierhuis, M. 2011. Beyond Cooperative Robotics: The Central Role of Interdependence in Coactive Design. *IEEE Intelligent Systems*, 26(3): 81–88.

Krueger, F.; Mitchell, K. C.; Deshpande, G.; and Katz, J. S. 2021. Human–Dog Relationships as a Working Framework for Exploring Human–Robot Attachment: A Multidisciplinary Review. *Animal Cognition*, 24(2): 371–385.

Lai, V.; Chen, C.; Liao, Q. V.; Smith-Renner, A.; and Tan, C. 2021. Towards a Science of Human-AI Decision Making: A Survey of Empirical Studies. arXiv:2112.11471.

Lum, H. C.; and Phillips, E. K. 2023. Understanding Human-Autonomy Teams Through a Human-Animal Teaming Model. *Topics in Cognitive Science*, tops.12713.

Mazis, G. A. 2008. *Humans, animals, machines: Blurring boundaries*. State University of New York Press.

Metcalfe, J. S.; Perelman, B. S.; Boothe, D. L.; and Mcdowell, K. 2021. Systemic Oversimplification Limits the Potential for Human-AI Partnership. *IEEE Access*, 9: 70242–70260.

Mirsky, R.; Carlucho, I.; Rahman, A.; Fosong, E.; Macke, W.; Sridharan, M.; Stone, P.; and Albrecht, S. V. 2022. A survey of ad hoc teamwork research. In *European conference on multi-agent systems*, 275–293. Springer.

Mirsky, R.; and Stone, P. 2021. The seeing-eye robot grand challenge: rethinking automated care. In *Proceedings of the 20th International Conference on Autonomous Agents and Multiagent Systems (AAMAS 2021)*.

Moore, P. W. 1997. Mine-hunting dolphins of the Navy. In *Detection and Remediation Technologies for Mines and Minelike Targets II*, volume 3079, 2–6. SPIE.

Morris, A.; Donamukkala, R.; Kapuria, A.; Steinfeld, A.; Matthews, J. T.; Dunbar-Jacob, J.; and Thrun, S. 2003. A robotic walker that provides guidance. In *2003 IEEE International Conference on Robotics and Automation (Cat. No. 03CH37422)*, volume 1, 25–30. IEEE.

Myers, L. J. 1992. Dog-Handler Team as a Detection System for Explosives: A Tail to Be Told. In *The Aviation Security Problem and Related Technologies: A Critical Review*, volume 10264, 172–182. SPIE.

Narayanan, R.; and Feigh, K. 2024. Influence of Human-AI Team Structuring on Shared Mental Models for Collaborative Decision Making. In *Proceedings of Workshop on Theory of Mind in Human-AI Interaction at CHI 2024 (ToMinHAI at CHI 2024)*.

O'Neill, T.; McNeese, N.; Barron, A.; and Schelble, B. 2022. Human–Autonomy Teaming: A Review and Analysis of the Empirical Literature. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 64(5): 904–938.

Parasuraman, R.; and Wickens, C. D. 2008. Humans: Still Vital After All These Years of Automation. *Human Factors*, 50(3): 511–520.

Phillips, E.; Schaefer, K. E.; Billings, D. R.; Jentsch, F.; and Hancock, P. A. 2016. Human-Animal Teams as an Analog for Future Human-Robot Teams: Influencing Design and Fostering Trust. *Journal of Human-Robot Interaction*, 5(1): 100–125.

Sakhardande, J.; Pattanayak, P.; and Bhowmick, M. 2012. Smart cane assisted mobility for the visually impaired. *International Journal of Electrical and Computer Engineering*, 6(10): 1262–1265.

Salas, E.; Dickinson, T. L.; Converse, S. A.; and Tannenbaum, S. I. 1992. Toward an Understanding of Team Performance and Training. In Swezey, R. W.; and Salas, E., eds., *Teams: Their Training and Performance*, 3–29. Westport, CT, US: Ablex Publishing. ISBN 978-0-89391-852-1 978-0-89391-942-9.

Sanchez, C. J.; Chiu, C.-W.; Zhou, Y.; González, J. M.; Vinson, S. B.; and Liang, H. 2015. Locomotion control of hybrid cockroach robots. *Journal of The Royal Society Interface*, 12(105): 20141363.

Schaerer, E.; Kelley, R.; and Nicolescu, M. 2009. Robots as animals: A framework for liability and responsibility in human-robot interactions. In *RO-MAN 2009-The 18th IEEE International Symposium on Robot and Human Interactive Communication*, 72–77. IEEE.

Schelble, B. G.; Flathmann, C.; McNeese, N. J.; Freeman, G.; and Mallick, R. 2022. Let's Think Together! Assessing Shared Mental Models, Performance, and Trust in Human-Agent Teams. *Proc. ACM Hum.-Comput. Interact.*, 6(GROUP): 13:1–13:29.

Sparrow, R.; and Howard, M. 2021. Robots in agriculture: prospects, impacts, ethics, and policy. *precision agriculture*, 22: 818–833.

Staszesky, D. M.; Craig, D.; and Befus, C. 2005. Advanced feeder automation is here. *IEEE Power and Energy Magazine*, 3(5): 56–63.

Stone, P.; Kaminka, G.; Kraus, S.; and Rosenschein, J. 2010. Ad hoc autonomous agent teams: Collaboration without precoordination. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 24, 1504–1509.

Taylor, B.; Lee, D.-J.; Zhang, D.; and Xiong, G. 2012. Smart phone-based Indoor guidance system for the visually impaired. In *2012 12th International Conference on Control Automation Robotics & Vision (ICARCV)*, 871–876. IEEE.