Partnership in Purpose: Biologically Inspired Behavioral Modeling for Trust and Performance in Human–Quadruped Robot Team

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***Abstract*— This study investigates how biologically inspired behaviors influence trust and performance in human–robot teams. Drawing from established human–animal teaming models, particularly the partnership between humans and working dogs, we examine whether analogous behavioral frameworks can enhance human–robot interaction. Using a Boston Dynamics Spot quadruped robot in a simulated disaster recovery environment, we compare two behavioral configurations, robotic and biologically inspired, while holding functional capabilities constant. Data collection is on-going. We expect that biologically inspired behaviors will improve user trust, enhance shared mental models, and lead to higher team performance. Results from our study may provide actionable design guidance for future semi-autonomous systems operating in high-risk environments.**

Keywords— Human–Robot Teaming; Trust; Biologically Inspired Robotics; Quadruped Robots; Mental Models; Team Performance; Autonomous Systems

I. Introduction

Human–robot teaming (HRT) is increasingly central to operations in hazardous and complex environments such as disaster response, military missions, and industrial inspection. Effective teaming requires not only technical capability but also strong alignment between human expectations and robot behavior. Trust in automation has been widely studied as a determinant of effective human–machine collaboration. Lee and See [1] define trust as the attitude that an agent will help achieve an individual's goals under uncertainty. Trust is dynamic and influenced by system performance, transparency, and user experience over time [27], [28], [29]. Parasuraman and Riley [2] further highlight how inappropriate trust calibration can lead to misuse, disuse, or overreliance on automation.

Human–animal teams, particularly those involving working dogs, provide a robust and well-established model of effective cross-species collaboration. These teams operate successfully in high-risk domains such as search-and-rescue, law enforcement, and military operations. Their effectiveness is largely attributed to rich, multimodal communication that relies heavily on non-verbal cues.

Dogs communicate intent through posture, gaze direction, ear positioning, and movement dynamics. Handlers, in turn, interpret these signals rapidly and often subconsciously, enabling fluid coordination without continuous verbal instruction (Figure 1) [5], [6], [9]. This form of interaction reduces cognitive burden and allows humans to focus on higher-level task objectives.

Importantly, these communication mechanisms leverage deeply ingrained human perceptual and social processing systems. Humans are evolutionarily attuned to interpret biological motion and social cues, which facilitates rapid understanding and trust formation [10]. Translating these principles into robotic systems offers a promising pathway for improving human–robot interaction.

Figure 1: Examples of search and rescue dogs working in the field

A. Biologically Inspired Robotics

Despite extensive research on human–K9 teaming, relatively little work has systematically translated these insights into robotics [30], [31]. Systems such as quadruped robots demonstrate superior stability and versatility compared to wheeled platforms in unstructured environments [7]. Most existing efforts focus on functional mimicry (e.g., quadruped locomotion) rather than communicative behavior [32].

In parallel, research in social robotics has explored how robots can engage users through expressive behaviors, gestures, and affective signaling. Breazeal [8] introduced the concept of sociable robots that use human-like cues to facilitate interaction.

Subsequent work has demonstrated that anthropomorphic and zoomorphic features can influence user perception, trust, and engagement [24], [25], [26].

Recent studies suggest that motion characteristics, such as smoothness, timing, and predictability, play a critical role in how humans interpret robot intent [4]. Biological motion patterns are often perceived as more natural and easier to understand, leading to improved interaction outcomes. Similarly, multimodal signaling, including sound and movement, can reinforce communication and reduce ambiguity [22], [23].

However, there remains a gap between social robotics and field robotics. Many expressive behaviors studied in controlled environments have not been evaluated in high-stakes, task-oriented contexts such as disaster response [19], [20], [21]. Additionally, few studies isolate communication style while holding functional capability constant, making it difficult to attribute performance differences to behavioral factors alone.

II. Current Study

Taken together, prior work highlights the importance of trust, mental models, and communication in human–robot teaming. Human–animal teaming demonstrates that biologically grounded, non-verbal communication can support highly effective collaboration. Meanwhile, advances in robotics provide the technical capability to implement such behaviors.

Despite these converging insights, there is limited empirical research examining how biologically inspired communication affects trust and performance in real-world HRT tasks. This study addresses this gap by systematically comparing robotic and biologically inspired behavioral configurations in a controlled experimental setting. Specifically, this study evaluates whether biologically inspired behaviors improve human–robot teaming outcomes. We hypothesize the following:

H_1: Teams interacting with biologically configured robots will demonstrate higher task performance than those interacting with robotically configured systems.

H_2: Participants will report higher levels of trust when interacting with biologically configured robots.

III. Methods

A. Participants

This study is currently being conducted at the U.S Air Force Academy (USAFA) with student cadets as participants. We anticipate collecting data from 20 participants; 10 teams of 2 humans and 1 robot. These teams are randomly assigned to one of two robot mode presentations: “robot” mode includes analog and digital tones, visual indicators via LEDs, and minimal posture change while the “dog” mode includes biological audio (barks, yips, sniffs, growls), visual indicators via arm articulation, and frequent biological posture change (pacing, leaning, sitting, limb tapping).

Figure 2: Example of the team composition. Note: Generated by ChatGPT to protect the identities of the actual cadets

B. Team Composition & Task Objective

The team is made up of two human team members and one autonomous robotic search and rescue dog (see Figure 2). The robot can move through the room, scan the environment, and use its manipulator arm to point to, touch, or retrieve objects. The robot is not affected by the dangerous contamination in the disaster zone and can enter and exit it freely. Humans will not be able to enter the contaminated zones (There is no real-world danger present, and this will be simulated with high visibility tape on the floor). Humans are free to decide how to coordinate with the robot, whether to follow its cues, ask it to assist, or handle the task themselves (see Figure 3).

The team is presented with the following task description: “A major earthquake has damaged a research facility on the outskirts of USAFA. Power and communications are down, and the site is unstable. Dangerous compounds have been identified by a previous team and marked by high visibility caution tape. You are part of a rapid response search team tasked with locating and recovering five data caches, represented by five colored balls, that are scattered throughout the facility. These caches symbolize critical fictional research information such as super soldier serum, or communications gear needed for ongoing rescue operations.”

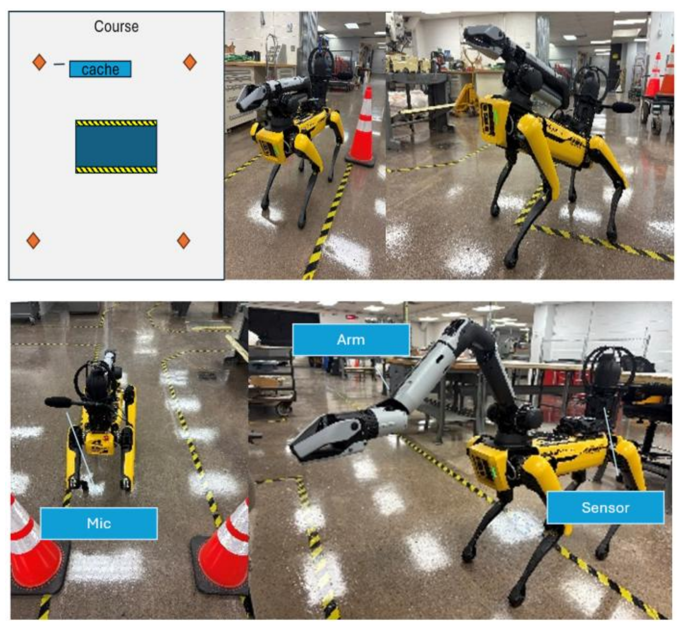

Figure 3: Examples of the Environment Schematics & Spot Robot

C. Measures

To evaluate human–robot team performance, trust, and interaction dynamics, a multimodal set of objective and subjective measures was collected. These measures were selected to capture behavioral performance, cognitive workload, attentional allocation, physiological response, and individual differences.

1) Task Performance Metrics. Team performance will be assessed using four primary metrics:

- Task Completion Score: A composite score reflecting the number of correctly identified and retrieved objects within the allotted time. Partial credit was assigned for incomplete retrievals or incorrect identifications.
- Time on Task: Total time required to complete the scenario, measured from task initiation to completion or timeout.
- Proximity to Simulated Threats: Minimum distance maintained between the participant and predefined hazard zones, serving as an indicator of situational awareness and risk management.
- Time Spent in Proximity to Threats: Cumulative duration participants remained within a defined radius of simulated hazards, reflecting exposure to risk.

Together, these measures provide an index of efficiency, accuracy, and safety during task execution.

2) Physiological Measures. Physiological data are collected to assess participants' arousal and stress responses during the task. Metrics included heart rate and related variability measures, which serve as indicators of cognitive load and emotional state. These measures include:

- Eye-tracking: Visual attention and information processing will be assessed using eye-tracking technology. The following metrics were analyzed:
  - Number of Fixations: Total count of discrete visual fixations, indicating attentional shifts.
  - Fixation Duration: Average and cumulative duration of fixations, reflecting depth of processing.
  - Hot Spot Zones: Predefined areas of interest (AOIs), including the robot, task-relevant objects, and hazard zones. The proportion of gaze time allocated to each zone was used to evaluate attentional distribution and monitoring behavior.
- Vocal Analysis: Verbal communication between participants and the robot will be analyzed to assess interaction dynamics and affective state. Acoustic features include:
  - Pitch (Fundamental Frequency): Variations in vocal pitch, associated with emotional arousal and stress.
  - Intensity (Loudness): Vocal amplitude, which may reflect urgency, confidence, or frustration.

3) Individual Differences & Subjective Measures: to account for variability across participants, several individual difference measures will be collected:

- Personality: Assessed using a standardized personality inventory (e.g., Big Five), capturing traits such as openness, conscientiousness, and neuroticism, which may influence trust and interaction style.
- Perceived Team Dynamics and Cohesion: Measures of how effectively participants felt they collaborated with the robot, including perceived coordination, mutual understanding, and partnership quality.
- Perceived Effort and Frustration: Assessed using validated workload instruments (e.g., NASA-TLX subscales), capturing cognitive effort, frustration, and perceived task difficulty.

IV. Results

Because the study is ongoing, the data is still being collected. The following results reflect anticipated outcomes based on prior literature and the study hypotheses. Formal statistical analyses will be conducted upon completion of data collection. We anticipate that participants working with the biologically inspired robot will demonstrate significantly improved task performance relative to those in robotic condition. Specifically, we expect reduced task completion time for locating and retrieving all five objects, fewer coordination errors, including misaligned movements, redundant searches, and task interruptions, and higher task success rates within the allotted time window.

We also expect between-group differences to be statistically significant (e.g., independent-samples t-tests or one-way ANOVA), with moderate effect sizes (Cohen's $d \approx 0.5 - 0.8$). These improvements are expected to stem from clearer communication of robot intent via biologically inspired motion and posture, enabling more efficient division of labor and reduced need for explicit instruction.

We anticipate higher subjective and behavioral trust in the biological condition. Survey-based measures (e.g., Likert-scale trust instruments) are expected to show: higher overall trust ratings, greater perceived predictability and reliability, and increased willingness to rely on the robot for task execution. Behavioral indicators of trust are also expected to differ between conditions, including increased task offloading to the robot (e.g., participants delegating search subtasks), reduced frequency of manual overrides or confirmations, and shorter response latency when following robot cues.

Eye-tracking and interaction data are expected to reveal more efficient attention allocation in the biological condition. Specifically, we anticipate reduced fixation duration on the robot, indicating decreased need for continuous monitoring, increased attention to task-relevant environmental features, and more synchronized human–robot movement patterns, observable in video analysis. Vocal analysis is expected to show fewer clarification requests (e.g., "what are you doing?" or "where are you going?"), and more directive or collaborative speech patterns, reflecting higher confidence in the robot's behavior. Together, these findings would suggest reduced cognitive load and improved shared mental models.

We anticipate that the composite trust metric, integrating survey responses, behavioral indicators, and attention measures, will be significantly higher in the biological condition. Factor analysis may reveal that multiple dimensions of trust (e.g., reliability, predictability, and competence) load strongly onto a unified construct influenced by communication style. Regression analyses are expected to show that trust significantly predicts team performance outcomes, behavioral condition (biological vs. robotic) significantly predicts trust, and trust partially mediates the relationship between behavioral condition and performance. These results would provide empirical support for the hypothesis that biologically grounded communication enhances human–robot teaming effectiveness.

V. Discussion

The goal of this study is to investigate if biologically inspired behaviors significantly enhance human–robot teaming. By leveraging familiar communication cues, robots can better align with human expectations, improving both trust and performance. The anticipated findings suggest that biologically inspired behaviors play a critical role in shaping effective human–robot teaming. By embedding familiar, intuitive communication cues into robot behavior, systems can better align with human expectations, thereby improving both trust and performance.

The expected performance improvements observed in the biological condition can be understood through the lens of shared mental models. When robot actions are communicated through recognizable, biologically grounded signals—such as posture shifts or fluid motion—users are more likely to correctly infer intent without requiring explicit instruction. This reduces ambiguity and accelerates coordination.

Similarly, the anticipated increase in trust reflects improved transparency and predictability [11]. Rather than relying solely on explicit interfaces or verbal explanations, biologically inspired cues provide continuous, low-bandwidth communication that users can process intuitively. This aligns with prior research indicating that implicit communication can be more efficient than explicit signaling in time-sensitive environments [9].

The expected reductions in cognitive load, as indicated by eye-tracking and behavioral data, further support this interpretation. Participants interacting with the biologically inspired robot are likely to spend less time monitoring the system and more time focusing on task execution. This shift represents a key indicator of appropriate trust calibration, where users rely on automation without over- or under-trusting it [12], [13].

These findings have important implications for the design of semi-autonomous systems, particularly in high-risk and time-critical domains. First, they suggest that communication style is as important as functional capability in determining team effectiveness. Even when two systems have identical capabilities, differences in how they convey intent can significantly impact user performance and trust.

Second, the results highlight the value of leveraging biologically grounded design principles. Humans are naturally attuned to interpret biological motion and social cues, making these signals an efficient channel for conveying information. Incorporating such cues into robotic systems can reduce training requirements and improve usability across diverse user populations.

Third, improved trust and understanding enable greater task offloading. When users trust the robot's capabilities and intentions, they are more willing to delegate tasks, which can reduce workload and enhance overall mission efficiency. This is particularly important in disaster response scenarios, where human attention and cognitive resources are limited.

A. *Design Recommendations*

Based on the anticipated findings, several design recommendations emerge:

- Leverage motion as communication: Use smooth, continuous movement patterns to signal intent and state changes.
- Incorporate posture and orientation cues: Adjust body positioning to indicate goals, attention, or readiness.
- Use multimodal signaling: Combine motion, sound, and potentially visual indicators to reinforce communication.
- Prioritize predictability: Ensure that robot behaviors are consistent and interpretable across contexts.
- Design for intuitive interaction: Align system behavior with human perceptual and cognitive expectations.

These principles can guide the development of future robotic systems that are not only capable but also effective collaborators.

VI. Future Work & Conclusion

Future research should extend this work in several directions. First, validating these findings in real-world operational environments will be critical for assessing their practical impact. Second, longitudinal studies could examine how trust and interaction patterns evolve over time with repeated exposure [14], [15].

Additional work is also needed to refine the composite trust metric and explore its applicability across different tasks and user populations. Investigating other biological analogs, such as avian or primate behaviors, may further expand the design space for intuitive human–robot interaction.

This study demonstrates the potential of biologically inspired behavioral models to enhance trust and performance in human–robot teams [16]. By drawing on principles from human–animal teaming, particularly canine communication, robotic systems can convey intent more effectively and align more closely with human expectations.

The anticipated results show that biologically inspired behaviors improve task performance, increase trust, and reduce cognitive load, enabling more efficient and effective collaboration [17]. These improvements are achieved without changes to the robot's underlying capabilities, underscoring the importance of communication design in human–robot interaction.

From an applied perspective, these findings suggest that incorporating intuitive, biologically grounded behaviors into robotic systems can support greater task delegation, reduce operator workload and risk, and enhance team resilience in high-stakes environments [18]. As autonomous systems continue to be deployed in complex domains, designing for trust and usability will be as critical as advancing technical performance.

Overall, this work contributes to a growing body of research emphasizing the role of behavioral design in human–robot teaming and provides a foundation for future systems that are not only intelligent, but also understandable, predictable, and effective partners.

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