Adaptive Biofeedback for Embodied Human-Robot Interaction: A Testbed

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Abstract—Human–robot teams (HRT) are integral to cognitively taxing tasks, where autonomous systems increasingly support individuals in complex, data-rich, and time-constrained environments. Much existing human–robot interaction (HRI) research relies primarily on behavioral outcomes or self-report measures, limiting insight into the objective physiological and neurocognitive mechanisms that shape performance in operational contexts. This proof-of-concept study integrates physiological sensing, neuroimaging, and embodied robotic interaction to provide an experimental testbed for adaptive feedback mechanisms in human–robot teaming. The system combines physiological indicators, like heart rate (HR) and heart rate variability (HRV), with functional near-infrared spectroscopy (fNIRS) to capture real-time indicators of attentional engagement and cognitive workload. In a within-subjects design, participants completed a sustained attention task while receiving adaptive feedback from an embodied humanoid robot and a conventional computer-mediated cues. This work establishes a multimodal testbed to study cognitive and behavioral dynamics in human–autonomy teams, informing the design of adaptive systems that leverage physiological and neural feedback to enhance performance.

Keywords— Human–Robot Teams, Human-Robot Interaction, Physiological Biofeedback, Cognitive Performance, Modeling and Simulation Testbeds

I. INTRODUCTION

Most research on human interaction with robotic agents relies on subjective self-report measures such as surveys and interviews, as well as observable behavioral performance metrics [1], [2], [3], [4], [5]. While these approaches provide valuable insight into users' perceptions and actions, they may fail to capture underlying physiological processes that shape cognition, affect, and decision-making during interaction. Physiological measures can therefore serve as a critical complement, offering objective markers of internal states that may not be accessible or expressed otherwise. Biofeedback—the real-time measurement and presentation of physiological signals for user awareness and self-regulation—has received limited attention in HRI contexts [6], [7]. In particular, few biofeedback-based testbeds integrate robotic agents with physiological sensing and noninvasive functional near-infrared spectroscopy (fNIRS). Existing fNIRS-based biofeedback studies have primarily relied on computer-mediated visual cues [8]; while foundational, these approaches leave more interactive feedback paradigms, such as closed-loop integration with brain-computer interfaces (BCIs) and embodied robotic agents, understudied (see [9] for a few exceptions).

This gap leaves questions surrounding the versatility of HRTs. This study develops a testbed capable of presenting physiological states to a participant from a humanoid agent during a cognitively demanding task in real-time. This testbed integrates systems that record physiological, neural, and behavioral data and relay these signals to a humanoid agent, enabling comprehensive, adaptive responses that support participant behavior modification. This approach allows participants to receive real-time information describing their underlying physical state from an embodied agent that would otherwise not be available.

II. BACKGROUND

A. *Human-Robot Interactions*

As autonomous systems become more advanced, the relationship between humans and technology is changing from simply using a tool to forming a partnership with the agent. This change underscores the need to tailor how these autonomous robotic systems are presented to humans to optimize performance. Human-robot-teaming (HRT), defined as interactions involving at least one autonomous agent and a human, is explored through self-report surveys and behavioral observations in the field [10], [11], [12], [13], [14], [15]. A key factor for successful HRT is the human's belief that the autonomous system is a true partner, also known as teammate-likeness, in which the system is perceived not merely as a tool but as a friendly, dependable, and communicative teammate. Prior literature suggests agents are helpful when participating in teamwork activities with coordination, task reallocation, and continuous interaction with humans and other autonomous robotic agents, but this depends on the teammate [16] and human-likeness within the HRT [2], [11].

Existing studies rarely integrate complex systems that utilize neural and physiological measurements, robotic/AI interactions, and cognitive tasks, leaving a gap in understanding how these elements function together. The Furhat social robot has emerged as a widely used platform for studying human-robot interactions [17], [18], [19], [20], [21], [22], [23]. Prior work suggests that responses to such agents are mixed, with Uncanny Valley effects reported in some cases and more positive responses observed in others (e.g., adolescents) [17], [19], [14]. Despite growing interest in platforms such as Furhat, little is known about how individuals respond to autonomous agents embedded in interactive biofeedback-loop systems or how embodiment influences HRT. The present study addresses these gaps by presenting a proof-of-concept testbed.

B. *Biofeedback using Heart Rate Variability*

Within the past twenty years, the use of Heart Rate Variability (HRV) as a method of biofeedback in clinical cases for body and brain dysfunction, as well as a performance-enhancing treatment [24], [25], [23], has grown. HRV reflects parasympathetic and sympathetic activity of the autonomic nervous system, capturing changes in heart rate in response to cognitive load, stress, and attentional demands [27], [28]. HRV can be quantified across multiple timescales, long-term HRV, short-term HRV, and ultra-short-term HRV. Prior work examining relationships between HRV and executive function or attention shows variability, with some studies linking higher HRV to improved executive function, while others report reductions in HRV under increased cognitive stress [27], [29]. Additional variability has been observed in women, with HRV modulated by hormonal fluctuations across the menstrual cycle [30]. Despite this complexity, short-term HRV reliably differentiates attentional control between rest and executive task conditions in real-time [23], supporting its use as an effective measure of cognitive state.

C. *Neurofeedback using Noninvasive Neuroimaging*

Functional Near-Infrared Spectroscopy (fNIRS) is a noninvasive neuroimaging method that measures changes in blood oxygen levels in the brain cortex [31]. fNIRS demonstrates sensitivity to changes in cognitive demand across both operational and controlled experimental settings [32]. Researchers monitoring the prefrontal cortex during cognitively demanding tasks have observed increased oxygenated hemoglobin and decreased deoxygenated hemoglobin, particularly in the right dorsolateral prefrontal cortex, as cognitive demand and stress increase [33]. These neural measures align with subjective workload and behavioral performance, supporting fNIRS as a reliable index of cognitive effort [32].

Neurofeedback has emerged as a promising approach in cognitively demanding tasks, with visual cue-based implementations demonstrating improvements in behavioral performance over time compared to no-feedback or sham conditions [8]. These findings are promising; however, the influence of autonomous agents on neurofeedback efficacy remains unclear, and metrics associated with attentional output require further quantification to enable more precise neurofeedback. To date, fNIRS studies of executive function, attention, and stress have rarely incorporated autonomous agents within neurofeedback paradigms. Integrating neural and physiological signals within embodied HRT interaction frameworks, therefore, represents a critical gap addressed in this work [9], [34], [35], [36].

III. CURRENT STUDY

This study develops a proof-of-concept testbed that integrates biofeedback into a HRT during a cognitive task. This approach is increasingly relevant as operational training environments incorporate humanoid agents and Artificial Intelligence (AI) that leverage behavioral, physiological (e.g., HRV), and neural data to enhance the prediction of human performance. Although recent research has started to explore these ideas in an operational context, few studies have integrated fNIRS and autonomous agents [37]. The purpose of this study is to explore the feasibility of this testbed.

Participants were cadets from the United States Air Force Academy (USAFA). Written informed consent was obtained, and the study was approved by the institutional review board. Behavioral, physiological, and fNIRS data were recorded during laboratory sessions. A within-subjects design was used, with participants completing the paradigm under two conditions: (A)

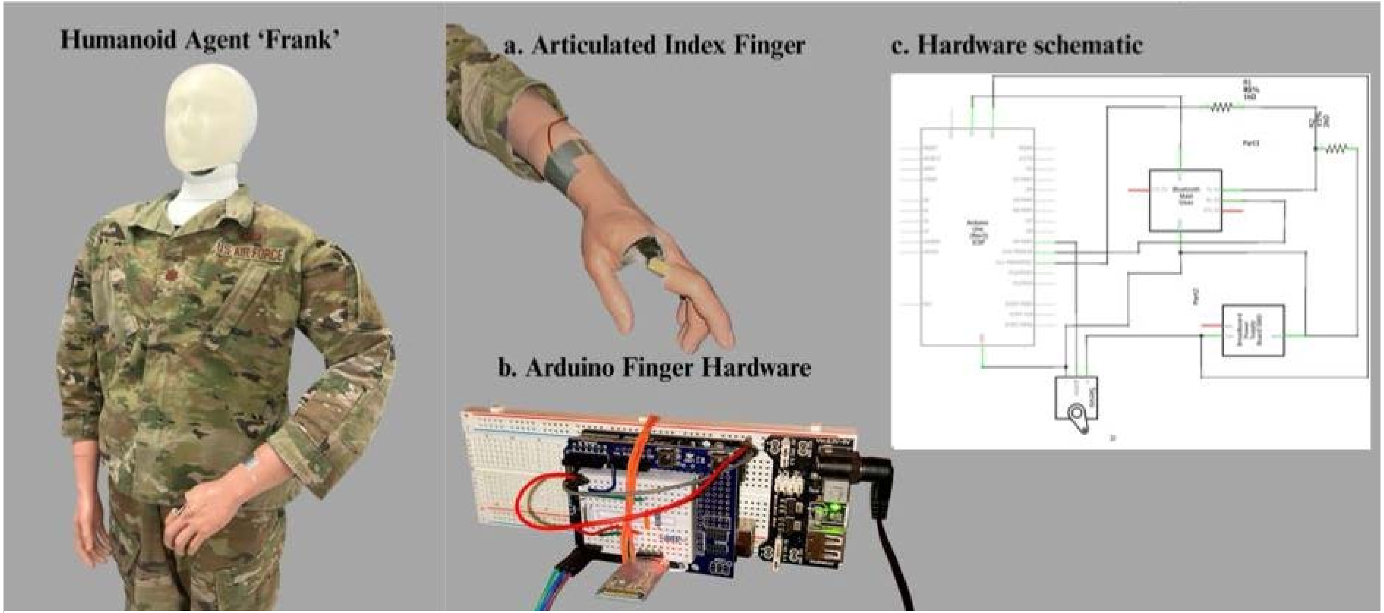

Fig. 1. The humanoid robot "Frank" comprised of a Furhat robot and a mannequin including an articulated index finger (a) enabled by Arduino hardware (b,c).

biofeedback delivered by the humanoid robot and (B) standard computer-based cues, with condition order counterbalanced. Participants received course credit. Preliminary data included male and female participants aged 18–24.

A. Testbed Development

1) Modification and Presentation of a Humanoid Robot

The presentation of a humanoid robot critically shapes perceived believability as a teammate in HRTs. Because prior work identifies limited human-likeness across variations in the projected facial presentations of Furhat [17], the present study embeds the robotic head within a physical body to enhance embodiment.

To transform the Furhat robot to a better representation of an embodied humanoid agent, we modified a stationary mannequin to accommodate the addition of a robotic head and an Arduino powered articulated index finger. The modification is shown in Fig. 1. The mannequin's head and neck were removed using a band saw, ensuring the shoulder profile remained intact for anatomical realism.

An internal shelf supported the Furhat head. the support platform was positioned approximately eight inches below the neck opening and constructed from a 2×4 wood beam within the hollow torso, secured beneath the arm regions with wood screws. The Furhat robot was mounted to this internal shelf, stabilized with adhesive duct tape, and connected to a 9V DC power supply.

For the mechanical hand modification, a band saw excised the left pointer finger, creating a 2-inch aperture. A Miuzei MG90S 9G micro-servo was embedded into this cavity, with the original pointer finger reattached to the servo horn, allowing an actuated 90-degree range of motion. System electronics, including an Arduino UNO R3 microcontroller powered by an Elego 5V breadboard power supply, were mounted to the lower posterior of the mannequin. The assembled humanoid robot was placed across a table from the participant, with its own computer in front of it. As the experiment is conducted, the robot turns its gaze to the computer and the finger moves periodically, giving the impression that the body is indeed part of the robot, and that the robot is actively doing something during the study. The finger movement was triggered by a Python program sending serial messages over Bluetooth either when the researcher clicked a button, or repeatedly at set intervals.

Due to the study population of cadets, appropriate clothing attire was meticulously chosen to mitigate visual abnormalities to the appearance of the humanoid robot. The completed assembly was outfitted in a U.S. Air Force Operational Camouflage Pattern uniform cadets consistent with cadet attire to enhance perceived teammate-likeness in HRT, with servo lead wires routed beneath the blouse for concealment and effective wire management. The agent was given a name, “Frank,” to reinforce teammate-likeness.

B. Procedure

Following informed consent, participants were fitted with two physiological measurement systems: a NIRSport2 continuous wave fNIRS device and a Polar H10 heart rate monitor. The fNIRS montage consisted of 16 sources and 16 detectors, with optodes positioned using caps standardized to the international 10–20 EEG coordinate system, targeting frontal and parietal regions associated with attention and cognitive load. For the humanoid condition, participants received a brief introduction to “Frank,” the autonomous agent, presented as a teammate. The experimental design is displayed in Fig. 2.

Demographic information was collected, and two scales were administered to assess initial opinions on autonomous agents: the general attitudes towards robots scale (GAToRs) and the adapted propensity to trust in technology scale [30], [31].

The Polar H10 sensor recorded resting and task-related heart rates (HRs), transmitting data via Bluetooth to an HP 17t-cn300 laptop. Using an in-house Python-based software (Polar2LSL), data from the Polar device were streamed to the Lab Streaming Layer (LSL). These physiological data were then routed to a custom Python program (“HRV-Stroop”), controlling the feedback from the humanoid robot. HR and HRV were computed in real time using a Python-based processing pipeline calibrated to individual baseline measures, after raw R-R interval data were collected from the Polar H10 monitor and converted into an HRV difference score used for audio biofeedback. This approach addresses inconsistencies in the literature regarding the effects of stress and cognitive load on HRV.

Prior to HRV calculation, RR intervals were screened using a two-stage outlier rejection procedure. First, a filter discarded intervals outside the range of 300–2000 ms; second, a moving Hampel identifier evaluated each beat within a sliding time window, flagging any interval that deviated from the local median by more than 3 × 1.4826 × MAD (median absolute deviation), where the 1.4826 scaling factor renders the MAD a consistent estimator of the standard deviation under a normal distribution. Remaining artifacts detected by a relative (>20%) or absolute (>200 ms) deviation from a 3-point local median were replaced via linear interpolation between neighboring valid intervals before RMSSD was computed. The difference score

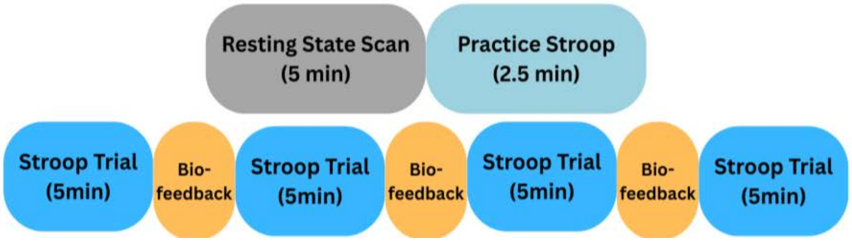

Fig. 2. Visual representation of experimental design and stimulus presentation to participant.

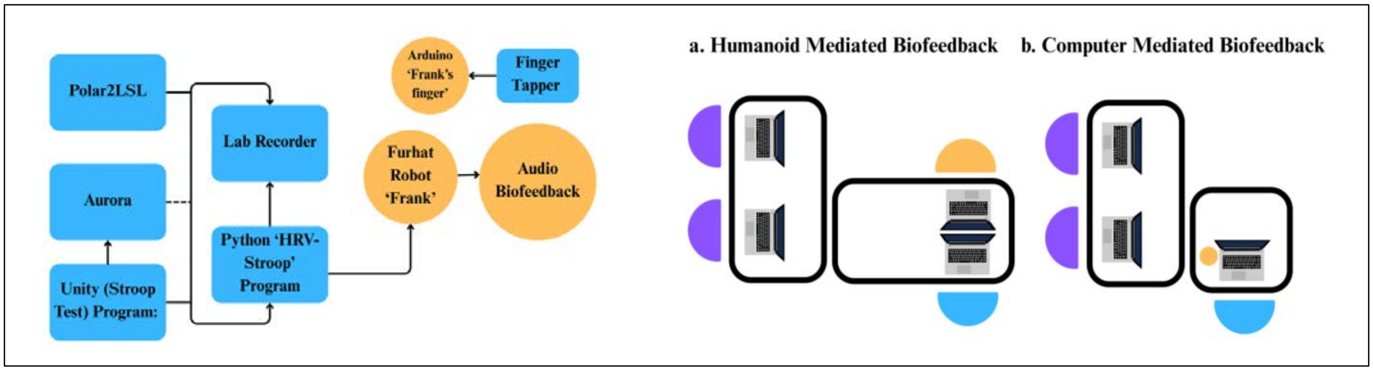

Fig. 3. (Left) Connection of all programs used in data collection. All programs are in blue boxes and have associated arrows that point to where the data is streaming to. Aurora has the ability to stream into this feedback loop, per the testbed design, but is not done so during this experiment. Orange circles represent parts of the robotic agent feedback performance. (Right) Condition-specific experimental setup. Both conditions take place seated and in the same room; a. Humanoid Mediated Biofeedback setup; purple half circle represent researchers, blue half circle represents the participant, and orange half circle represents the autonomous agent. b. Computer Mediated Biofeedback setup; instead of the autonomous agent, performance and biological feedback is presented through a disembodies voice from a speaker (orange circle) next to the computer the participant is completing the stroop task on.

was calculated as resting-state HRV (RSHRV) minus Stroop performance HRV (SPHRV) for each block:

|RSHRV-SPHRV|= reported HRV difference score.

Participants completed a 300 s resting-state scan to establish baseline HR and HRV, which were filtered as described above and used to generate feedback during the subsequent cognitive task. Next, participants completed the Stroop task, a widely utilized measure of cognitive control and attention control [38], [39], [40], [41]. The task consists of the presentation of visual cues of the words “Red”, “Blue”, “Yellow”, or “Green” in congruent or incongruent ink colors. Participants responded to the ink color in which the text appears rather than the color word by pressing the associated letter button on the keyboard.

When using fNIRS, the hemodynamic response must be considered when presenting stimuli. An event-related, jittered Stroop design was used to allow sufficient time to differentiate hemoglobin responses to task-related visual stimuli. This design, adapted from prior functional magnetic resonance imaging (fMRI) paradigms [42], began with a fixation cross presented for 1,000 ms, followed by a Stroop stimulus for 2,000 ms, during which participants responded as quickly as possible. The interstimulus interval was sampled from an exponential distribution ranging from 3 to 20 s (mean = 4 s; median = 3 s) to enable accurate deconvolution of the hemodynamic response.

Stroop trial types were pseudorandomized in an event-related fashion. A total of 192 test trials were presented to each participant (128 congruent, 64 incongruent), preceded by a practice block of 24 trials (16 congruent, 8 incongruent). A lower number of incongruent trials was used to reduce the expectancy of a stimulus conflict relative to the other conditions. The test trials were split into four approximately five-minute trial blocks. The primary behavioral variables of interest were response time, recorded as the time between cue onset and registered key press (in milliseconds) and response accuracy (as a percentage) on incongruent trials.

In both conditions, participants received feedback of trial accuracy, average response time, and HRV scores using the same phrasing. The only difference was the medium in which the feedback was delivered. The setup of the experiment is visualized in Fig. 3. After the fourth and final Stroop trial block, participants remove physiological sensors and then repeat the GAToRs and adapted propensity to trust in technology scale.

C. System Integration

To establish feasibility and promote reproducibility, this work documents the devices and software integration that enables the biofeedback loop and supports data extraction for analysis. The system integrates five individual programs for data collection: physiological and fNIRS acquisition software (Polar2LSL, NIRx Aurora), Stroop programmed in Unity, data synchronization software (LabRecorder), and a custom biofeedback Python script (“HRV-Stroop”).

The Unity program transmitted event triggers to a Python pipeline for HRV computation during resting and task conditions. Concurrently, synchronized triggers were sent to Aurora to support post hoc neuroimaging analysis, including markers for the onset and offset of resting-state scans, Stroop blocks, and individual stimulus presentations. Together, this system represents a proof-of-concept testbed integrating robotics, neuroimaging, physiological sensing, and cognitive task performance within a unified, closed-loop framework.

IV. DISCUSSION

This work presents a proof-of-concept human–robot teaming (HRT) biofeedback testbed that demonstrates the feasibility of integrating multiple data streams and interaction modalities within a single experimental platform. Specifically, the testbed combines physiological measures (HRV), neural measures, cognitive task performance, and embodied human–autonomy interaction in one cohesive system. This integration provides a foundation for studying HRT in controlled, repeatable contexts and enables more comprehensive characterization of user state by linking behavioral, physiological, and neural responses within the same interaction loop. The study also demonstrates the successful modification and deployment of the Furhat robotic agent within this framework.

The primary contribution of this work is methodological. Rather than testing a fully developed adaptive system, this study establishes that these components can be synchronized and deployed within a functioning experimental testbed. This framework enables future research to examine how biofeedback and neurofeedback—delivered through embodied agents—can shape user behavior, perception, and performance over time, offering a more integrated understanding of human–autonomy interaction than unimodal approaches.

Several limitations should be noted. First, although the testbed incorporates neural measurement, neural signals are not yet integrated into the real-time feedback loop. Future iterations could incorporate neural data directly into feedback delivery, enabling true neuroadaptive interaction. Second, the current implementation relies on scripted feedback delivered by either the robotic agent or a computer interface. While this controlled design is appropriate for a proof of concept, as it standardizes interaction and isolates system functionality, it does not capture the variability inherent in more dynamic, real-time autonomous systems.

Future work can build on this platform by expanding adaptive capabilities and examining how design choices influence user responses. For example, varying the framing of the agent's role (e.g., evaluator, assistant, peer) or enabling more interactive exchanges may reveal how embodiment and communication style shape trust, performance, and teammate-likeness. Additionally, integrating both biofeedback and neurofeedback within the same closed-loop system may allow for more precise and multidimensional modeling of user state, supporting more adaptive and effective human–autonomy teaming.

Overall, this study demonstrates the feasibility of a multimodal HRT biofeedback testbed and provides a methodological foundation for future experiments requiring synchronized physiological, neural, behavioral, and agent-based interaction data.This work presents a proof-of-concept HRT biofeedback-loop testbed that demonstrates the feasibility of integrating multiple streams of data and interaction within a single experimental platform. Specifically, the testbed combines physiological measures of HRV, neural measures, cognitive task performance data, and human–autonomy teaming in one cohesive system. This integration provides a foundation for studying HRT interactions in a controlled and repeatable manner. The study also demonstrates the successful modification and use of the Furhat robotic agent within this framework.

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