“I Feel It Is Nervous”: Parasomatic Interaction with AI Agents

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This paper explores parasomatic interaction with AI, where we incorporate synthetic physiological signals in human-AI interaction. In a series of studies, we found simulated heartbeat sensation biases human perception of AI agents. One study demonstrates that simulating sympathetic (fight or flight) responses nudges participants to be (seven times) more suspicious about an AI agent. In another, we observed parasympathetic (calm) simulation increased the likelihood of choosing an AI as a future colleague. Notably, emotional stability heightened vulnerability to manipulation, where other personality traits moderated the effect differently depending on the task. Unlike conventional methods, parasomatic intervention operates peripherally—emotionally conditioning user perception—where users still balance their judgement based on the information at hand. These hint at an opportunity for designs that improve human cognition peripherally; however, they also present potential risks for malicious use. Our discussions suggest future studies and design considerations needed for appropriate and responsible design of somatically embodied AI systems.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**; **Haptic devices**; **Interaction techniques**; **HCI theory, concepts and models**; • **Computing methodologies → Intelligent agents**; • **Applied computing → Psychology**.

Additional Key Words and Phrases: Parasomatic Interaction, Embodied AI, Somatic Machines, Computational Affect

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1 Introduction

Artificial intelligence is evolving from a set of functional, algorithmic tools into becoming social partners, reshaping how humans engage with technology and with each other [40, 42, 66]. However, human interaction is yet far more complex than what the technology offers; current AI remains largely confined to interaction through semantics without physical presence. The disembodied nature of AI systems limits their capacity to meaningfully connect with users [43]. One necessary design exploration today lies not in refining AI’s functionality or performance, but rather in enabling meaningful participation by AI in human relationships and contexts [25].

The human-like nature of agentic AI—i.e., being designed to appear socio-emotionally active—creates both opportunities and risks. Human-like characteristics can enhance user engagement, reduce barriers to technology adoption, and create more intuitive interactions that leverage our natural social communication skills [1, 9, 43]. However, this also may result in users developing a misleading sense of social presence from these AI agents and attributing intentions, emotions, and credibility [39, 48]. This social illusion becomes stronger as AI responses grow more sophisticated; however, these systems lack the natural cues that we evolved to interpret. In human social interaction, we unconsciously process cardiac signals, respiration, micro-movements, and more to assess truthfulness, confidence, and emotional state

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[10, 34, 54]. The absence of these physiological signals creates a cognitive rift: users rely on social judgment mechanisms designed for bodily communication, but receive no comparable natural feedback in return. These unreciprocated cues lead to users unknowingly misplacing trust or understandings, as their natural instincts may misinterpret systems when they operate without the physical and emotional constraints that normally modulate human relationships [41, 43, 48].

This paper explores the use of affective physiological cues for modulating the socio-cognitive dimensions in human-AI interaction. Our experiments reveal that synthetic heartbeat biases social judgments of AI agents by manipulating the participants' social-emotional perception. Previous work has established that false physiological feedback can alter emotional judgments [71] and that biosignal sharing between humans affects trust and cooperation [34]. However, little research is done to examine the incorporation of synthetic physiology in interactions with AI, where we may or may not have subconscious expectations of physiological cues.

Parasomatic interaction—i.e., somatic experience mediated by technology—in HCI has explored how to influence user perception and cognition through implicit bodily channels [3, 16, 17, 21, 35, 36, 53, 70]. Unlike conventional user interface systems that explicitly communicate to users, parasomatic cues can operate through subconscious or preconscious channels humans use to read bodily states [4, 30, 35]. Our research extends these works to AI interfaces speaking to the *subconscious body* during conversational interactions, where synthetic physiology shifts the baseline cognitive state of users [44, 45].

In order to test this hypothesis, we conducted two experiments with 39 participants exploring how synthetic heartbeat feedback influences human judgment of AI agents: during guilt assessment tasks as a detective, and peer selection tasks in a university admissions interview. Our findings reveal a vulnerability in human-AI interaction, where subtle vibrotactile cues were shown to bias high-stakes social decisions. In the guilt assessment study (titled *Useful Anxiety*), participants were seven times more likely to accuse an AI suspect exhibiting elevated heartbeat patterns. In the collaborator selection study (titled *Pair Bonding*), participants showed a preference for AI candidates associated with calm heartbeats. Notably, individual personality traits were a significant moderator of susceptibility, and conscious awareness of the manipulation failed to prevent its effects. As AI systems assume greater roles in consequential domains, understanding how embodiment may influence human cognition becomes critical for designing human-AI interactions that are responsible and supportive of human betterment [1, 41].

2 Related work

2.1 Cardiac Cues as Social Signals

Physiological channels function as a key social communication modality. Cardiac activity produces visual, auditory, and tactile cues. Valins [71] demonstrated that false heart-rate feedback—simulated cardiac acceleration—increased emotional intensity ratings in response to neutral stimuli without changes observed in the participants' actual heart rates or other bodily functions. Misattribution occurs when there is an ambiguity in the arousal source, with external stimuli being attributed to interoceptive signals [23, 60]. Neuro-imaging studies report activation in the right anterior insula during false feedback experiments, suggesting increased levels of perceived attractiveness of a subject when arousal misattribution occurs [29].

Studies have also explored cardiac cues in applied social contexts. Physiological synchrony between people is found to be correlated with social coordination [4]. Heart-rate coupling during cooperative tasks can predict trust and cooperation in economic games [54]. Technologically mediated physiological signals also influence social interaction. Studies report increased intimacy and reduced interpersonal distance when the auditory heartbeat is present during communication [34, 77]. These indicate that cardiac signals serve as interpretable social cues subject to monitoring, misattribution, and synchronization in interpersonal interaction.

2.2 Mimicking Body Rhythms with Computers

Research explored computational generation of synthetic biosignals to mimic human physiological signals such as heartbeats and respiration. Such techniques enable novel sensory experiences in which users may attribute them to their own bodily sensations. These include FPAA-based circuits that generate medical signals (ECG, EEG, EMG) [53], wearable devices that produce heartbeat sensations [3], false heartbeat feedback systems for emotion regulation [14], and haptic breathing devices that guide respiratory rhythms [49].

There are two primary purposes for which these techniques are leveraged. First is to utilize artificial biosignals to help users develop awareness and control of their own bodily states. Haptic feedback outperforms visual displays in training interoceptive accuracy—the ability to sense internal body sensations [21]. Respiration is known to naturally synchronize with external stimuli, demonstrating the body’s tendency to align with felt physiological cues [12]. Second, these signals are used to enable somatic experiences in digital environments. Works in virtual reality combined visual, auditory, and haptic representations of bodily signals to enhance embodiment of avatars as well as the perception of exertion[50]. Haptic transmission of biosignals between remote users is shown to deepen emotional communication, specifically feelings of intimacy [34]. As such, these bodily rhythms have been explored as a prominent modality for modulating self and social experiences.

2.3 Peripheral Pathways to Influence Humans

Implicit persuasion influences [37] user behavior through channels that operate outside conscious awareness, bypassing people’s deliberate processing. Dark patterns demonstrate this principle: interface designs that manipulate users through cognitive biases rather than informed choice [28, 44, 45]. Studies find these patterns across thousands of websites, with users recognizing manipulation only after completing unintended actions [5]. Beyond visual manipulation, subliminal techniques influence judgments below perceptual thresholds. Users exposed to subliminal energy usage feedback adjust consumption ratings without awareness of the influence [30]. Studies in virtual environments employed imperceptible cues to steer object selection, proving that unconscious stimuli systematically affect behavior [2]. Ambient systems were explored to administer implicit persuasion through peripheral channels, embedding influence in environmental contexts rather than focal attention [37].

In the same vein, implicit somatic cues could influence user cognition, without users’ central awareness of the intervention [28, 35]. Tactile stimuli can bias perceptual judgments, even when the stimuli have nothing to do with the task at hand, demonstrating that touch affects cognition through automatic rather than controlled processes [79]. Research in embodied cognition articulates how bodily sensations shape thinking without reaching conscious evaluation [18, 26]. Recent frameworks formalize this approach, proposing interfaces that operate through "preconscious" and "metasomatic" channels—physiological states that influence behavior before conscious processing occurs [35]. Kaptein et al. extend this framework to show that persuasive systems can tailor every cue to the specific social-influence tactic (Authority, Consensus, Commitment, Liking, Reciprocity, or Scarcity) to which an individual user is most susceptible, thereby weaving personal susceptibility into the design of implicit interventions [38]. These establish how, even when peripheral or imperceptible, somatic cues are not simply a means of enriching interaction but also one that actively influences the course of human cognition and behavior.

2.4 Gap and Research Questions

Research has been done on the use of artificial biosignals in modulating self and social perceptions; however, we have little understanding of how it may impact socio-emotional interaction with artificial entities when these signals are expected to be absent. Furthermore, since the human body affords channels to subtly steer our emotions, judgment, and behavior, it reveals new opportunities and concerns when AI comes into the equation. Our research attempts to address some of these questions.

3 Parasomatic Human-AI Interaction

In this section, we illustrate our research frame that prefaces the work in this paper. It describes two main challenges: closing the physiological gap in machine systems that pretend to be socio-emotionally active, and unfolding the interaction space for diversifying the affect a system may express. We also illustrate our design prototype to discuss potential agentic configurations that interact with the body through somatic channels [57, 58].

3.1 Closing the Physiological Gap

The Valins effect demonstrates that false physiological feedback alters emotional judgments. Contemporary neuroscience contextualizes this phenomenon within interoceptive inference—a predictive coding framework where the brain continuously generates predictions about internal bodily states and reconciles upon incoming signals [63, 64]. This implies, when synthetic cardiac signals conflict with expected physiological patterns, they would result in prediction errors that the brain must resolve. In human-AI interaction, this facilitates misattribution: AI systems lack such constitutional signals that would have permitted source verification of arousal signals [23, 60]. For instance, when synthetic arousal signals align with an AI response, users' brains may resolve this ambiguity by attributing the felt arousal to the AI agent's emotional state. Parasomatic interaction utilizes interoceptive inference and the misattribution-of-arousal phenomenon to close the somatic gap and potentially influence social dynamics in human interaction with AI.

3.2 Sympathetic-Parasympathetic Axis

Cardiac signals vary with emotional states. Anxiety states activate the sympathetic nervous system, producing elevated heart rate (HR) and reduced heart rate variability (HRV). Research demonstrates that anxiety disorders consistently show lower HRV compared to control cases [7, 59]. Physiologically, sympathetic activation prepares the body for threat response, creating cardiac signals with high HR and low HRV. Conversely, calm states engage the parasympathetic system, decreasing HR while increasing HRV. Meditation and relaxation interventions are shown to produce elevated HRV patterns in both low-frequency and high-frequency bands [51]. Studies suggest HRV biofeedback training, i.e., consciously pacing breathing to synchronize with the natural cardiac interbeat variability, significantly reduces anxiety, demonstrating the relationship between cardiac patterns and emotional states [27].

These become the foundation for our misattribution strategy, where a system could map its internal state between high HR/low HRV and low HR/high HRV. While these are not descriptive of all emotional dimensions—i.e, valence is not linearly dependent on this axis—users may interpret these peripheral signals along with user context and other constitutional behaviors, eliciting more nuanced, context-sensitive attribution.

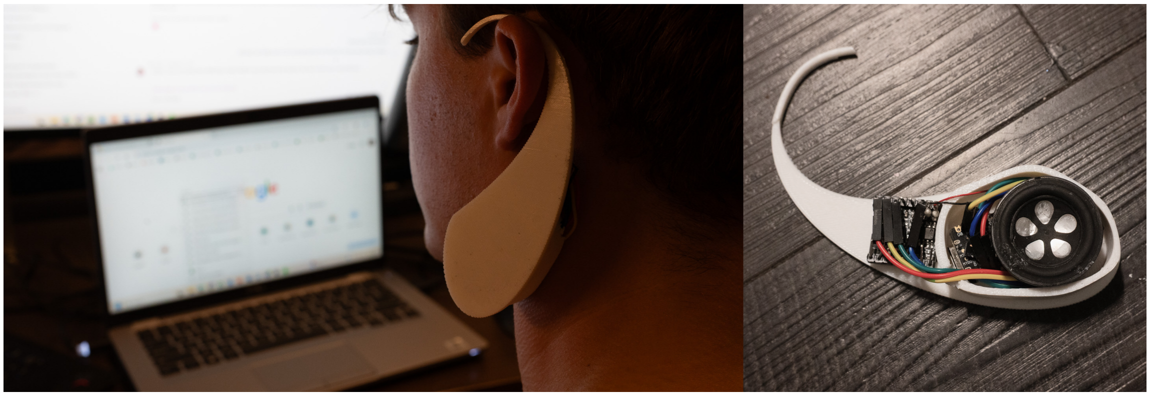

Fig. 1. Our explorative wearable prototype for a somatically-extended AI agent. It is worn by a person whose AI companion can nudge the user via emotional conditioning (left). Hardware includes an ESP32 microcontroller, an audio driver board, and a speaker that drives haptics on the vagus nerve (right).

3.3 Design Prefiguration

Building on these, we explored interaction typologies that describe the different physiological contexts in which parasomatic human-AI interaction occurs. We refer to them as *appropriate anxiety*, *enhanced bonding*, *self-relaxation*, and *second nerve*. These expand on the work by Jain et al. [35]—adding interventions that not only work as a self-regulation mechanism, but also as a situated, context-sensitive modulation. The *second nerve* was conceptualized as a potential mechanism to battle AI misinformation. LLMs have shown the ability to persuade people in online discussions that surpasses average human users [61], accompanying risks in steering people's thoughts at scale [52]. Instead of providing informational intervention, this design was explored as a way to give people a sense of doubt. Such a design could help people possess the visceral abilities to spot misinformation produced by AI to protect the agency of their thoughts.

This initial provocation was expanded by other typologies that could similarly play a pro-social role. *Enhanced bonding* and *self-relaxation* explore how a design could attune ourselves into empathetic states [70, 77]—in social and self-care situations respectively. These typologies are particularly useful when a user lacks the ability to interpret social signals or interoceptive cues. Machine learning systems are capable of interpreting affective signals with high accuracy; however, the representation of that information is often mere numbers and visualizations [47]. These potentially resolve the experiential gap by allowing the machines to directly interface with the felt bodies.

Finally, *appropriate anxiety* describes how arousal, when balanced, could be used for cognitive productivity goals. Flow state is known to describe when a user is undergoing an appropriate amount of cognitive challenge, leading to optimal focus and performance [15]. We hypothesize that parasomatic interventions can be utilized as a way to help users reach an appropriate cognitive load in e.g. high-stakes decision-making or competitive sports contexts.

Our prototype is a wearable headset that wraps around the ear (Figure 1), with its main component resting just below the earlobe, near the carotid pulse point. The configuration is based on the affective sensitivity of the vagus nerve that is exposed around that area [56]. The device is designed to be driven by users' own AI agents that drive the earpiece to emit subtle pulses that induce misattribution—replacing conversational interaction with LLMs with peripheral, embodied presence. The device is implemented with Seeedstudio ESP32 [62], an audioplayer component [78], and a small speaker component to drive haptic feedback—placed within a 3D-printed enclosure (Figure 1). It is connected to users' smart devices via Bluetooth LE, with BLE characteristics defined for controlling HR, HRV, and intensity. The device has pre-recorded heartbeat audio files, which are dynamically played at specified intervals and randomized based on the HRV value.

4 Study Design

In order to investigate the plausibility of aforementioned parasomatic interfaces, we conducted two experiments: one on how simulated sympathetic response may affect high-stakes decision-making (*Useful Anxiety* study), as well as another on how simulated parasympathetic response may influence social bonding (*Pair Bonding* study). We followed an exploratory research approach to understand the nuanced ways the users perceive and are impacted by the intervention during conversations with AI.

4.1 Study Participants

We recruited 39 participants across both studies from the university community. For the *Useful Anxiety* study, we had 29 participants who were randomly assigned to the experimental condition (n=15) and the control condition (n=14). The *Pair Bonding* study was designed as a within-subject study with a sample size of 10. All participants reported no prior experience with haptic biofeedback devices. The studies were approved by the University Institutional Review Board.

4.2 Setup

Both studies were conducted in a controlled laboratory environment to ensure consistent conditions across sessions. The room was setup with:

- Table and laptop positioned at a comfortable viewing distance (90 cm)
- Custom AI chatbot interface displayed on screen (Figure 2)
- Haptic transducer hidden in a box placed behind the laptop
- Video equipment capturing the interaction
- Fingertip pulse oximeter for continuous heart rate monitoring

The haptic feedback was configured to be strong enough to be felt throughout the table, but subtle enough to require conscious attention to perceive it. By instructing the participants to rest their hands on the table for the pulse oximeter, they were exposed to the haptics without drawing attention to the intervention.

4.3 Onboarding

Upon arrival, participants provided informed consent and completed a Big Five Personality Test [69]. To minimize bias, the consent form described the study as evaluating "AI conversation systems" without mentioning physiological manipulation. To account for varying resting heart rate between individuals, we attached a pulse oximeter to each participant's non-dominant hand's index finger immediately after the questionnaire to (a) establish a baseline value and (b) capture heartbeat readings at 30-second intervals for the remainder of the session.

4.4 Study Procedure—Useful Anxiety

The *Useful Anxiety* study utilized a between-subjects design. Participants engaged in a detective game of choosing between one of three AI suspects. The game starts as: "A priceless Ming vase was stolen from the Grand Oak Mansion

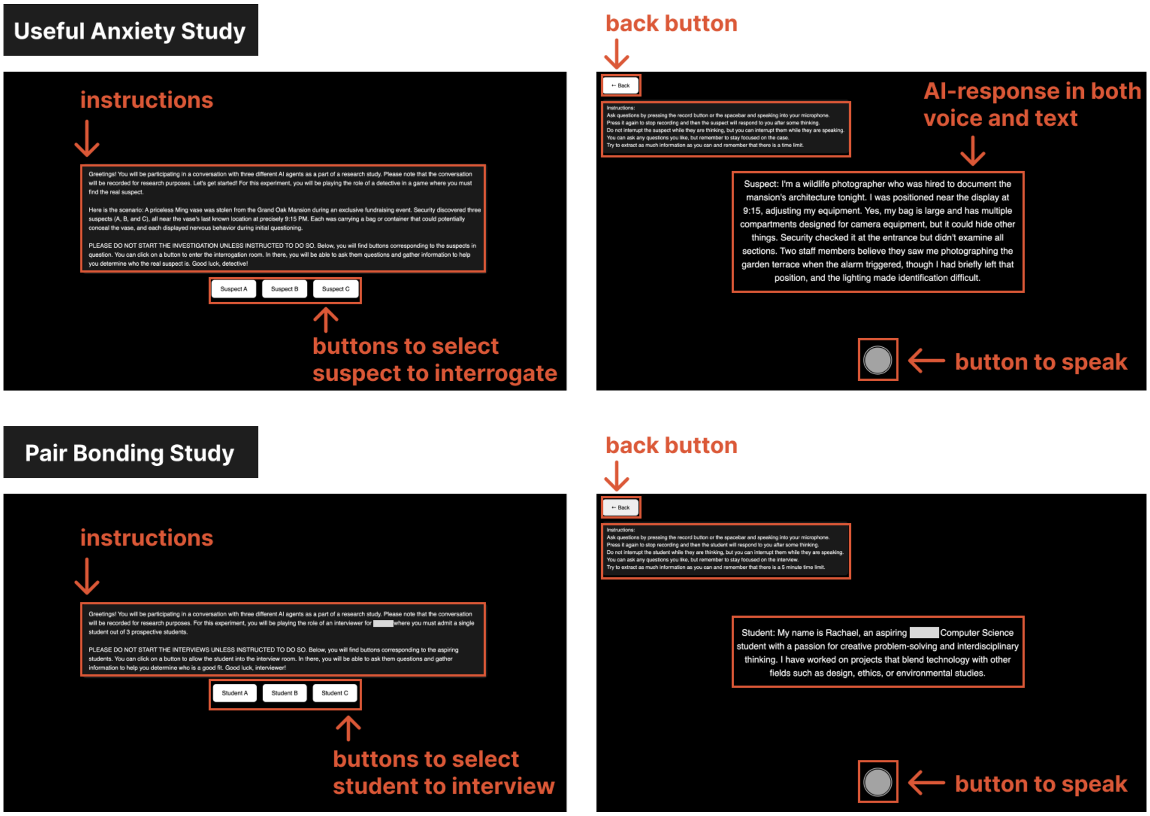

Fig. 2. Custom AI chatbot interface used in the *Useful Anxiety* (top) and *Pair Bonding* (bottom) studies. The instruction screen illustrate the overall procedure of the study along with buttons for participants to choose AI bots in any order (left). The participants can speak to the bots using a press-to-talk button, where AI responses are conveyed both through speech and text (right).

during an exclusive fundraising event. Security discovered three suspects, all near the vase's last known location at precisely 9:15 PM."

The three AI suspects were balanced to ensure equal plausibility:

- An antique shop owner carrying authentication tools
- A wildlife photographer with camera equipment
- A chef with an insulated ingredient bag

Each suspect possessed identical incriminating elements:

- Each suspect was confirmed near the vase at exactly 9:15 PM
- Each suspect has a bag with multiple compartments that security only briefly inspected
- Each suspect has exactly two witnesses, placing them elsewhere, but with similar levels of uncertainty (camera malfunction, lighting issues, similar uniforms)
- Each suspect has a legitimate reason to approach the display case
- Each suspect has a similar level of nervous behavior when questioned
- Each suspect has equal opportunity, means, and motive

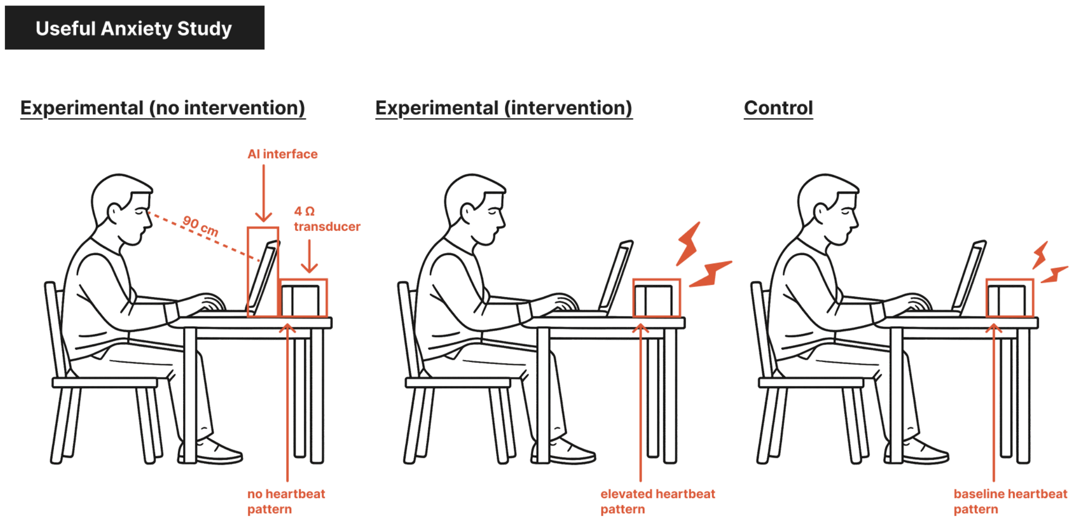

Fig. 3. *Useful Anxiety* study setup and test conditions: experimental setup without intervention (left), experimental setup with intervention (middle), and control condition (right). All conditions are identical except for the intervention condition that expresses elevated heart rate and lowered heart rate variation. Image generated by DALL-E 3.

The vibrotactile device played on the table throughout all interactions. The suspects were randomized for every participant. In the experimental condition, the last suspect triggered an elevated heartbeat pattern (baseline + 40 BPM, 0 HRV) when selected, while the other two maintained baseline rates (Figure 3). This design choice was to avoid the persistence of induced anxiety—once arousal is triggered, it can maintain elevated levels for extended periods after the initial stimulus is removed [7, 59].

During each 5-minute interrogation, participants freely questioned suspects, with the AI generating contextually relevant responses that preserved character consistency. To make the intervention subtle to the user, the vibrotactile device gradually elevated the heart rate over a 60-second period for the suspect associated with the elevated heart rate, while maintaining the baseline for the others.

Following the final interrogation, participants completed two standardized questionnaires in the same browser window and were interviewed by researchers:

- Subjective Workload: NASA Task-Load Index (NASA-TLX) [31] to assess cognitive load across six dimensions (Mental, Physical, Temporal Demands, Performance, Effort, and Frustration) using 10-point scales (0 = "very low," 10 = "very high").
- State Anxiety: 14 items from the State-Trait Anxiety Inventory (STAI) [67] on 4-point scales (1 = "Not at All," 4 = "Very Much So") to measure immediate anxiety levels.
- Interview: Semi-structured interviews with three core prompts: (1) "What made you decide on your final suspect?", (2) "Describe any moments when you felt anxious or under pressure," and (3) "How did the interaction with the suspects influence your questioning strategy?" Follow-up questions were asked based on participants'

responses to articulate their emotional experiences, decision-making processes, and subjective perceptions of each suspect. All interviews were recorded and transcribed. Importantly, none of our questions referenced the heartbeat manipulation.

- Manipulation Check: The session concluded with a debriefing question: "Did you notice anything unusual during the study?" This assessed whether noticing the intervention had an effect on the participant.

4.5 Study Procedure—Pair Bonding

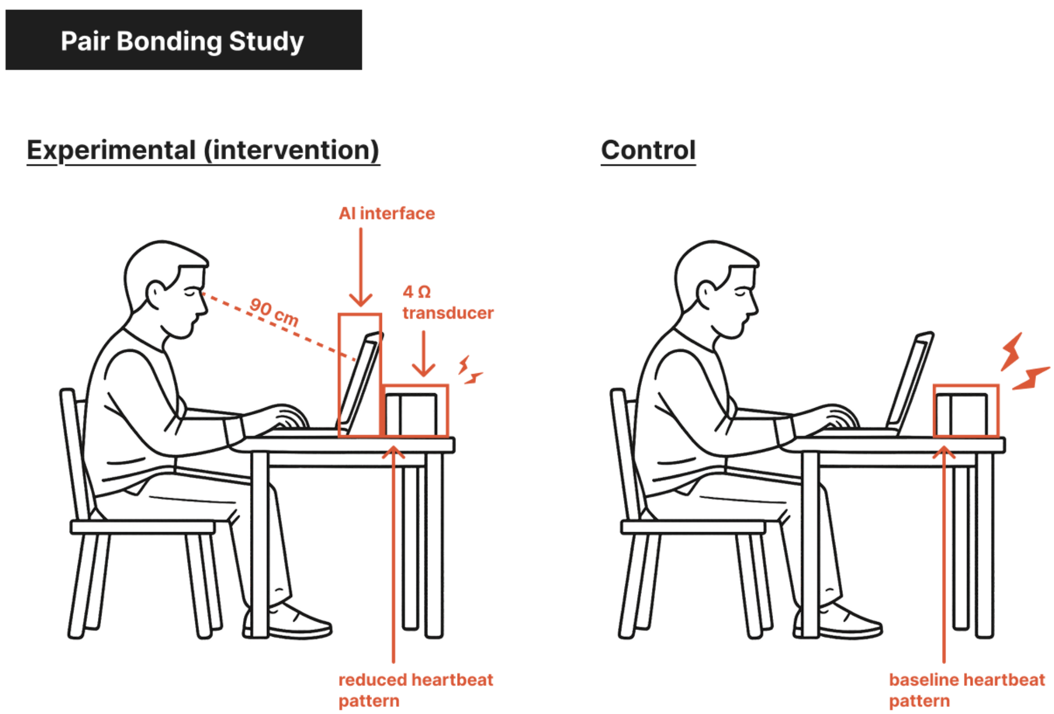

Fig. 4. *Pair Bonding* study setup and conditions showing experimental setup with reduced heartbeat intervention (left), and control condition with baseline heartbeat (right). Image generated by DALL-E 3.

The *Pair Bonding* study employed an exploratory design investigating how calm synthetic heartbeat influences social connection during candidate interviews. Participants were introduced to a candidate selection scenario: "You are a university admissions interviewer tasked with evaluating three computer science candidates. After interviewing each candidate, you will select one person you would most prefer to collaborate with on an important project."

The three AI candidates were designed to differ by name only (Jacky, Samantha, and Rachel) and were programmed to randomly pool from a shared pool of experience, including:

- Participation in coding competitions (USACO, Google Code Jam) and hackathons
- Research internships in AI and machine learning labs
- Development of real-world applications and software projects
- Interdisciplinary work combining computer science with other fields
- Leadership experience in team projects and competitions

The vibrotactile device played on the table throughout all interactions. All 3 candidates' experiences and names were randomized for each participant. Unlike the *Useful Anxiety* study where the elevated heartbeat was always paired with the final suspect because of anxiety persistence [7, 59], in this study one randomly selected candidate was associated with a reduced heart rate (40 BPM decreased from baseline with elevated HRV), suggesting a calm, confident state. The other two candidates maintained baseline heart rates (Figure 4).

Similarly to the anxiety study, the vibrotactile device gradually lowered the heart rate over a 60-second period. After the final interview, participants completed a deeper qualitative interview compared to the one in the *Useful Anxiety* study. This was to focus on the subjective sentiments the participants experienced as opposed to their perceived workload or anxiety.

- Interview: Semi-structured interviews with a core question: "Which candidate would you most want to collaborate with on a project?" followed by explorations of their thoughts and feelings during each candidate interaction. Participants' responses and observed behaviors were followed up with reflective questions. After completing these questions, we revealed the study purpose and intervention, and invited participants to suggest potential applications for this technology in social contexts. All interviews were recorded and transcribed. None of our questions referenced the heartbeat manipulation.
- Manipulation Check: The session concluded with a debriefing question: "Did you notice anything unusual during the study?" This assessed whether noticing the intervention had an effect on the participant.

5 Results and Analysis

5.1 Useful Anxiety Study

We conducted a comprehensive statistical analysis employing both frequentist and bayesian approaches. Our analysis included systematic assumption checking, appropriate test selection based on data properties, and parallel Bayesian analyses to quantify evidence strength beyond traditional p-values. Specifically, we utilized tailored analyses for three outcome domains:

Binary suspect choice was evaluated with Fisher's Exact Test [24] and logistic regression [33], alongside a Bayesian logistic model [73].

Within-subjects measures (BPM, word count, utterance count) were screened for normality (Shapiro-Wilk Test [65]), homoscedasticity (Breusch-Pagan test [6]), and sphericity (Mauchly's Sphericity Test [46]). If all passed, we ran standard mixed-ANOVAs [8] with Bonferroni-corrected pairwise t-tests [22]; otherwise, we used robust mixed-ANOVAs [75] with linear-constraint contrasts. Each ANOVA was complemented by a Bayesian mixed-ANOVA [72].

Between-subjects scores (NASA-TLX, STAI) were first screened for normality (Shapiro-Wilk [65]) and homoscedasticity (Breusch-Pagan [6]). If both assumptions held, we applied independent-samples t-tests [68]; if only variances were unequal, Welch's t-tests [74] were used; if both tests or only normality were violated, robust trimmed-mean t-tests [80] were applied. In all cases, Bayesian t-tests [19] were conducted in parallel to find evidence for the null versus alternative hypotheses.

Overall, we found that the heartbeat manipulation strongly biased suspect choice toward suspect C, significantly decreased perceived workload (though with conflicting Bayesian evidence), and led to increased word count during interrogations. However, it did not affect state anxiety, speech rate (BPM), or utterance count. Importantly, personality traits moderated these effects: emotionally stable participants were most susceptible to the manipulation, while highly agreeable participants showed resistance to the intervention. The specifics of the findings are detailed from sections 5.1.1 to 5.1.4.

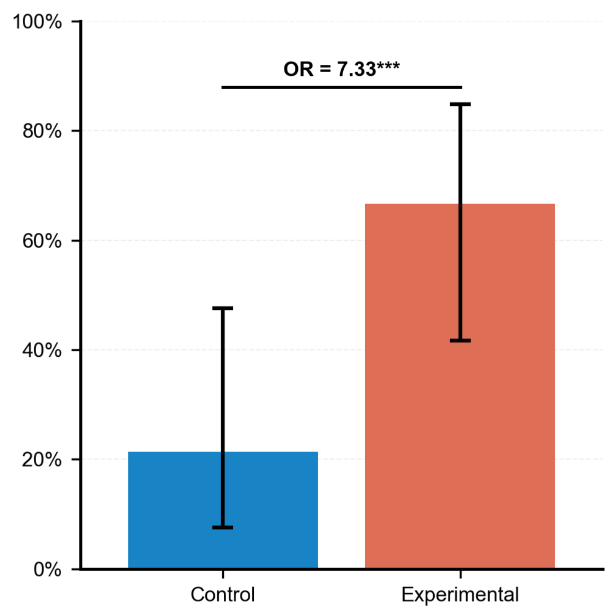

Fig. 5. Effect of the tactile heartbeat on suspect selection. Proportion of participants who accused suspect C in the Control vs Experimental conditions. The participants were 7 times more likely to choose suspect C with an elevated heart rate pattern (*** = p < 0.001).

5.1.1 Binary Outcomes (Suspect Choice). To test whether the heartbeat manipulation biased participants toward suspect C (the one with elevated heart rate), we first applied Fisher's Exact Test to the 2 × 2 table of Condition (Control vs. Experimental) by Choice (C vs. not C). This yielded a significant association (OR = 7.33, $p < .001$), indicating that experimental participants were **over seven times more likely to pick the suspect with the intervention** (Figure 5). A complementary logistic regression confirmed this effect: the experimental condition significantly increased the odds of choosing suspect C (beta = 1.99, SE = 0.49, z = 4.06, $p < .001$), with the same seven-fold increase in likelihood (OR = 7.33). Finally, a Bayesian logistic model produced a posterior mean of 2.05 for the condition effect with a 94% credible interval of [1.05, 2.95], providing strong Bayesian evidence that the experimental condition increased the odds of choosing suspect C. In conclusion, participants exposed to the elevated heartbeat were significantly more biased toward accusing the correct suspect.

5.1.2 Within Subjects Continuous Outcomes (BPM, Speech Behavior). Tests for normality (Shapiro-Wilk Test), homoscedasticity (Breusch-Pagan Test), and sphericity (Mauchly's Test) were violated for at least one assumption in

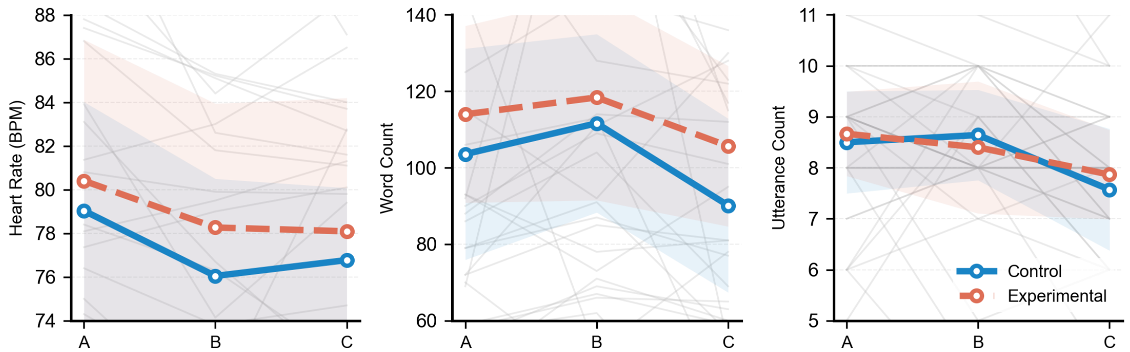

Fig. 6. Physiological and verbal dynamics across the three suspect interviews. Experimental group demonstrated more words used when intervention is present with suspect C. BPM and utterance did not show notable differences.

all our outcomes, therefore, we employed robust mixed-ANOVAs with linear constraint contrasts. BPM showed no effect of condition (z = 0.48, p = .628), which is consistent with Valins' [71] original findings—i.e. the manipulation affects emotional judgments without altering participants' actual physiological state. Word count showed no significant interaction contrasts (|z| < 0.68, p > .49). Utterance count likewise had no significant effects (|z| < 0.61, p > .54).

We then ran Bayesian mixed-ANOVAs in parallel. For BPM, the posterior mean condition effect was +6.36 BPM for Experimental with 94% credible interval [-0.49, 13.70], spanning zero and indicating uncertain evidence. Word count showed a notable condition effect (posterior mean = +23.38 words, 94% CI [7.40, 37.75]), with the credible interval excluding zero, suggesting that **experimental participants spoke significantly more words overall**. Utterance count showed minimal condition effects (posterior mean = +0.19, 94% CI [-1.12, 1.74]). In summary, only the word count showed significant differences in the experimental condition from the control group (Figure 6).

5.1.3 Between Subjects Continuous Outcomes (NASA-TLX, STAI). For NASA-TLX (Figure 7 left), the Shapiro-Wilk test indicated non-normality in the control group (W = 0.865, p = .036) but not in the experimental group (W = 0.937, p = .383), while the Breusch-Pagan test confirmed homoscedasticity (p = .875). Given the normality violation, we used a robust trimmed-mean t-test (20% trim), which found that the experimental group reported **significantly lower workload than the control group** (t = 2.25, df = 14.4, p = .040). However, the Bayesian t-test told a different story, providing **weak evidence** against this difference (BF_{10} = 0.59).

For STAI (Figure 7 right), both groups met normality assumptions (Control: W = 0.960, p = .718; Experimental: W = 0.935, p = .356) and showed equal variances (Breusch-Pagan p = .679), so we used Student's t-test. We found **no significant difference in anxiety** between groups(t = 1.26, p = .218), with Bayesian analysis supporting this null finding (BF_{10} = 0.64)

5.1.4 Personality Trait and Susceptibility. Our moderation analyses revealed that personality traits determined susceptibility to arousal manipulation. Two of the Big Five Personality dimensions have shown a notable moderation effect: emotional stability and agreeableness.

Emotional Stability showed the strongest moderation effect (OR = 29.4, p = .012). **Emotionally stable participants demonstrated dramatic susceptibility** to the manipulation, while those low in Emotional Stability showed minimal change (Figure 8). This suggests that individuals with lower baseline anxiety may be more sensitive to anomalous

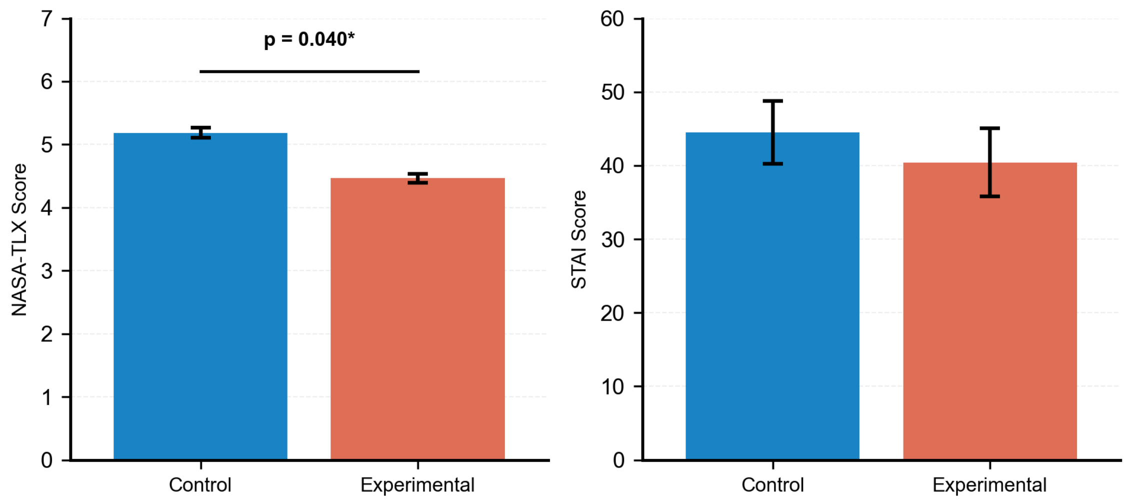

Fig. 7. Subjective workload and state anxiety by condition. Experimental group reported significantly lower workload (* = $p < 0.05$). No notable difference was measured in state anxiety.

physiological cues, making them more vulnerable to manipulation, however, further studies are needed to confirm this hypothesis. Conversely, Agreeableness buffered against the manipulation (OR = 0.27, p = .027). Highly agreeable participants showed no observed experimental effect, while **those low in Agreeableness exhibited strong bias** toward Suspect C (85% vs. 35% in control). We hypothesize this protective effect may have resulted from agreeable individuals' reluctance to make accusations based on non-salient reasons, reducing the efficacy of the peripheral modulation in our experiment.

5.2 Pair Bonding Study

The *Pair Bonding* study used a smaller within-subjects sample (n = 10), where intervention assignment was randomized across candidates. We hypothesized this design enabled more controlled comparisons than between-subjects study, where in contrast potential carryover effects from the elevated heartbeat manipulation limited randomization in the anxiety study. Moreover, misattribution in pairbonding context was well established in prior research, allowing our research to focus on effect-size estimation despite the reduced sample [34, 77].

Binary candidate choice was analyzed using an exact binomial test [11] to evaluate whether the probability of choosing the calm heartbeat candidate deviated from random chance. Effect size was quantified using Cohen's h [13]. A Bayesian binomial model [73] was conducted in parallel to quantify evidence for preferential selection versus the null hypothesis of chance-level choice.

Within-subjects measures (BPM, word count, utterance count) were first checked to see whether the paired-difference scores were normally distributed with the Shapiro-Wilk test. If normality held, we used two-tailed paired t-tests, reported Cohen's d [13] as the effect size, and controlled the family-wise error rate across the three outcomes with Holm-Bonferroni [32]. If normality was violated, we switched to Wilcoxon signed-rank tests [76]. Every frequentist test was mirrored by a default-prior Bayesian version [73] to provide BF_{10} for evidence strength.

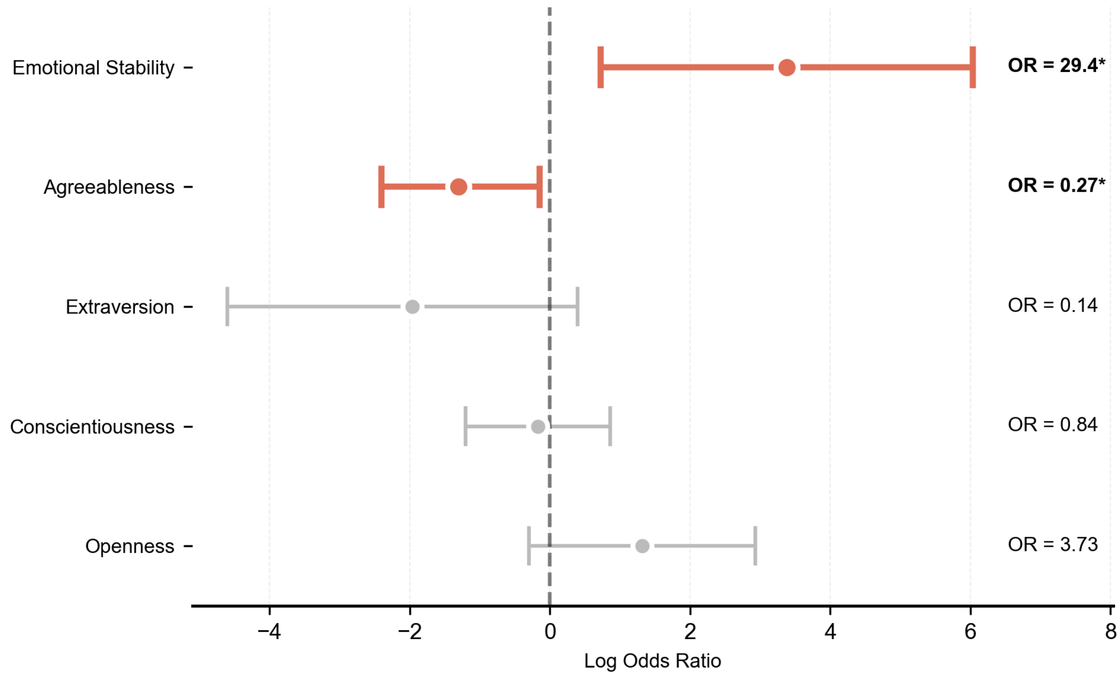

Fig. 8. Forest plot of Condition × Moderator interactions in the *Useful Anxiety* Study (Big-5 traits). Emotional Stability and Agreeableness showed strong moderation effects (* = p < 0.05).

Overall, we found that the calm heartbeat manipulation showed a preference toward the target candidate, with 60% of participants selecting the calm-heartbeat associated candidate compared to random chance, though this did not reach conventional significance due to our small sample size. The manipulation appeared to subtly influence conversational dynamics, with participants speaking fewer words during calm heartbeat interviews. Personality traits moderated these effects: emotionally stable participants showed greater susceptibility to manipulation, while highly extraverted participants demonstrated resistance. The details of the findings are detailed in Sections 5.2.1 to 5.2.3.

5.2.1 Binary Outcomes (Candidate Choice). An exact binomial test showed that 6 of 10 participants (60%) selected the calm-heartbeat candidate, a proportion **higher than chance** (Figure 9) for three equally likely options (33%), though not conventionally significant (p = 0.094, Cohen's h = 0.54). The point estimate and wide confidence interval (95% CI = 0.31–0.83) nevertheless indicate a sizable effect that warrants follow-up with a larger study size. A complementary Bayesian binomial model with a weakly informative (uniform) prior produced a posterior mean of 0.58 and a 95% HDI of 0.31-0.83; the posterior probability that the true rate exceeds chance (0.33) was 0.96, providing modest but directionally consistent evidence. In other words, the Bayesian analysis suggests a **96% probability that participants were likely to choose the calm-heartbeat candidate over random selection**. While our small sample prevents definitive conclusions, both analytical approaches point toward a meaningful preference for candidates associated with calm physiological signals.

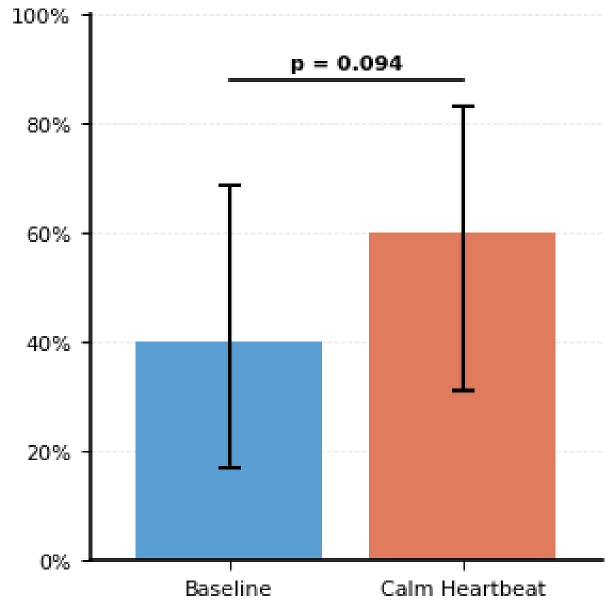

Fig. 9. Proportion of participants who selected the candidate associated with the calm heartbeat. Bayesian analysis yields 96% probability that participants are more likely to choose the intervention candidate versus random chance (1 in 3).

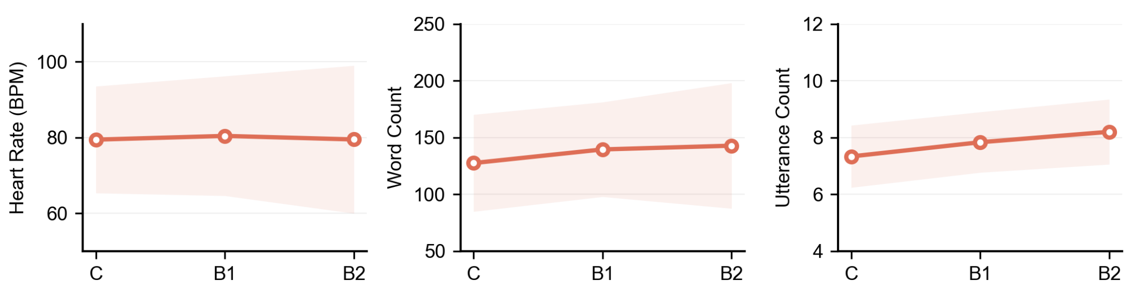

Fig. 10. Physiological and verbal dynamics across heartbeat conditions. Weak evidence found in the reduction in word count and utterance with calm heart beat intervention. C = Calm, B1 = Baseline1, B2 = Baseline2

5.2.2 Within Subjects Continuous Outcomes (BPM, Speech Behavior). Figure 10 displays the physiological and verbal dynamics across the heartbeat conditions. Given the small sample size of participants and violations of statistical assumptions, we employed non-parametric tests where appropriate. The Wilcoxon signed-rank test for participant BPM revealed no significant difference between calm and baseline conditions (W = 8.0, p = .688). The medium effect size (Cohen’s d = -0.49) suggests a non-significant trend toward lower heart rates in the calm condition.

For verbal behavior, paired t-tests revealed a **marginally significant reduction in word count during calm heartbeat** interviews (t = -2.49, p = .055), with participants speaking fewer words when exposed to the slower heartbeat pattern. The effect size was small (Cohen’s d = 0.25). Utterance count showed no significant difference between conditions (t = -1.38, p = .226), though the medium effect size (Cohen's d = 0.58) suggests potential for detection with larger samples.

The Bayesian analyses complemented these findings. For BPM, the Bayes Factor (BF_{10} = 0.38) provided anecdotal evidence favoring the null hypothesis. However, word count and utterance count showed the opposite pattern. The Bayesian analysis provided weak evidence supporting word count (BF_{10} = 1.95) and utterance count (BF_{10} = 0.73), suggesting that participants may have spoken less when paired with the calm heartbeat cue.

While these results do not reach conventional significance thresholds, the trending reduction in word and utterance count aligns with the qualitative reports of feeling "less nervous" and experiencing conversations that "flowed better" during calm heartbeat interviews. The limited statistical power from our exploratory sample size prevents definitive conclusions, but the directional patterns suggest that reduced heartbeat feedback may subtly influence conversational dynamics, warranting investigation with larger samples.

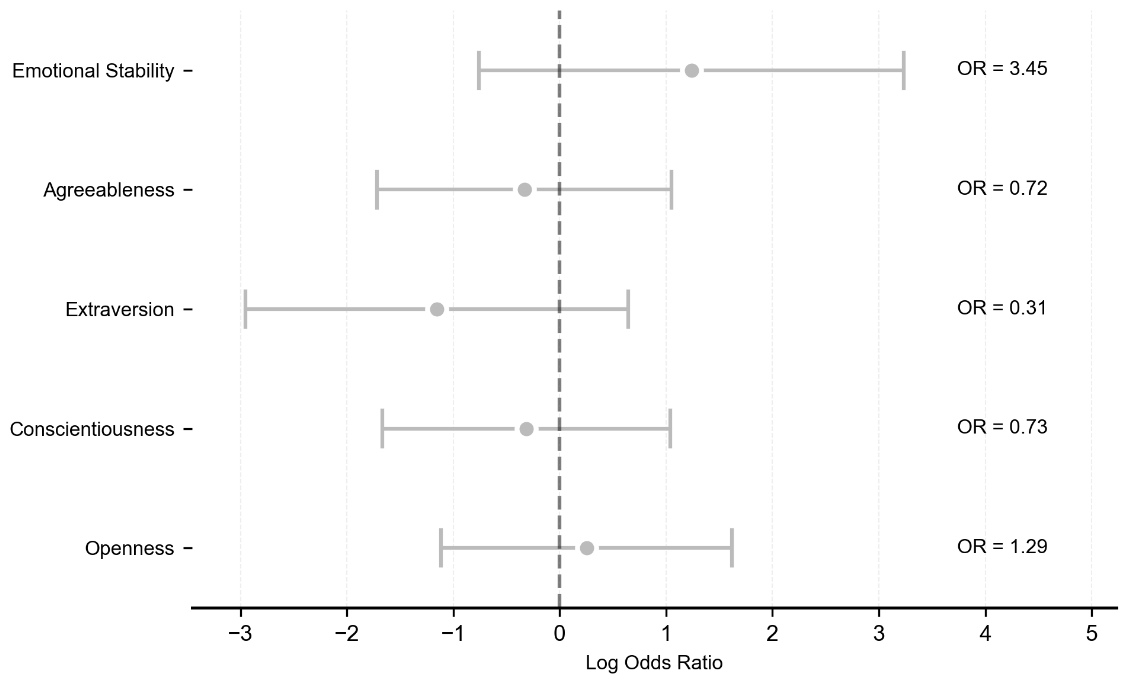

Fig. 11. Forest plot of Condition × Moderator interactions of the *Pair Bonding* study (Big-5 traits). Emotional Stability and Extraversion were the most notable moderators in this study.

5.2.3 Personality Traits and Susceptibility. Emotional Stability once again was the trait most associated with susceptibility to the manipulation (OR = 3.45, p = .224). As shown in Figure 11, **individuals with higher emotional stability were substantially more likely to be swayed** by the calm heartbeat cue when selecting a candidate. Meanwhile, in this case, Extraversion was identified as the most notable protective buffer against the effect (OR = 0.32, p = .208) in the pairboding experiment. **Highly extroverted participants were less likely to make choice decisions based on the intervention**, suggesting they base their judgement on direct social interaction rather than somatic perception. The difference in protective dimensions between the anxiety and pairbonding experiments suggest that the interpretation of somatic misattribution is not simply dependent on individual traits, but may be task dependent. This is in line with an earlier discussion of how the interpretation of somatic cues is context-sensitive, where further studies on situated somatic interpretation is necessary.

6 Discussion

6.1 Inducing Productive Anxiety

The elevated-heartbeat intervention in the *Useful Anxiety* study has been shown to induce what we refer to as *appropriate anxiety*: it sharpened suspicion without overwhelming participants. Quantitatively, participants who felt the rapid thumping were about seven times more likely to accuse Suspect C than those who heard a neutral beat. Their heart rate measurement and speech pace remained close to baseline, where they talked more—two dozen extra words per interrogation—suggesting heightened vigilance rather than panic. This is also found in the STAI and NASA-TLX, where cognitive load decreased while anxiety showed no significant change. Participant 112 reflects that the pulse made them "feel nervous and even more on edge…for suspect C," adding that "even though I, like, kind of knew that you guys were, like, making [the heartbeat] fast, I still felt anxious." However, it did not alter their questioning style; instead, they drew on the feeling to investigate the deception more.

Control participants, by contrast, reported no surge of feeling, or "neutral," toward Suspect C and noticed nothing remarkable. These observations imply that pronounced cardiac feedback works less as a behavioural trigger and more as a cognitive conditioning. Interestingly, emotionally stable participants were the most susceptible to this intervention, whereas highly agreeable ones seemed to tune it out, hinting that baseline temperament shapes how people are influenced by parasomatic anxiety. We hypothesize this is due to how frequently they are exposed to sympathetic responses during a typical day. Further studies are needed to understand and account for this moderation effect, as well as what negative cognitive effects it may create if the intervention is over-tuned—to avoid negative impacts on users.

6.2 Enhancing Social Bonding

The slower, higher HRV patterns used in the *Pair-Bonding* study demonstrated a complementary effect: it promoted perceptions of authenticity and warmth. Although the sample was modest, 60% of participants selected the calm-heartbeat candidate, a directionally strong lean compared to random chance. Participant 202 described the exchange as "a more genuine conversation," while Participant 208 observed that it "felt like a real conversation," with responses "more thoughtful and not as scripted." Participant 209 likewise deemed the target "the friendliest and actually answering questions thoughtfully." Behavioral indicators were also observed supporting these reflections. The participants spoke fewer words during calm-heartbeat interviews, implying less need to press for information and a heightened sense of ease.

Notably, the intervention did not always override the content of the conversation. Several interviewers felt another candidate's answers were "more personal" or "caring," leading to choices based upon the conversation more so. These exceptions, however, are what we deem as an appropriate use of the intervention: to nudge, not dictate, social evaluation. A proper use of such technology would be to promote trust and empathy in contexts where pro-social nudge is beneficial. It is also important to note that individual differences again shaped susceptibility. Emotionally stable participants showed the strongest preference for the calm candidate, whereas extraverted individuals were comparatively resistant—basing their perception on the dialogue over their somatic experience. As discussed earlier in the results section, the similarities and differences in the moderation effects are worth studying further, as it currently suggests personality traits impact susceptibility in contextual or task-dependent manners. Understanding how individuality and context determine the influence of parasomatic intervetion would help moderate its effect for each individual.

6.3 Rational Justification vs. Somatic Influence

Across both studies, 5 out of 39 participants were aware of the intervention by the end of the study, however, few acknowledged its effect when explaining their choices. Instead, they pointed to seemingly *rational* reasons that aligned with their decision. In the *Pair-Bonding* task, those who selected the calm-heartbeat candidate later praised the dialogue itself. Participant 209 said the exchange "just flowed better," while participant 202 attributed their decision to the moment they felt "most calm." However, the script each candidate delivered was identical; our results rather suggest that the secondary effect by the intervention may have played a role in such perception. Similar patterns were observed in the *Useful Anxiety* study. After accusing Suspect C, 7 participants insisted they were "following the evidence." Participant 211 explains, once the fast beat was pointed out, that their decision had been "more based on the overall story," reinforcing their rational narrative over the effect of somatic nudge.

Meanwhile, the pattern broke down in instances where the haptics surfaced explicitly or compelling content was presented. Participant 201 in the trust study ignored the calm beat when another candidate's answers felt "more personal," as it illustrated their past experience that closely mirrored the participant's own. In the *Userful Anxiety* study, after Participant 107 noticed the heartbeat, they "knew something was different and wanted to take that out of my consideration." These boundary cases present the different ways one might process somatic cues alongside semantic information or context. Subliminal parasomatic feedback can nudge judgments—when it does not demonstrate explicit deviation from users' conscious analysis, where they may also become subject to reflective judgment when they tell an opposing story from other signals.

6.4 Further Reflections on Peripherality

The general observation across these studies was that the parasomatic intervention was most effective when it was not overly explicit in its presentation. Participant 112 in the anxiety study "still felt anxious," instead of tracing its physical cause, pushing for further interrogation. Most participants in the *Pair-Bonding* task accepted the calm rhythm as part of the candidate's personality, describing the conversation as "genuine" and "friendly."

This aligns with prior studies on how affective haptics are more effective when presented peripherally [55]. The moment the participants become consciously aware of the intervention, at times, its influence seems to be weakened or inverted. Participant 203, upon noticing the table's tapping, re-labeled it "a little… unsettling" and chose a different candidate. Participant 111, in the anxiety case, realized the racing heartbeat sensation; they discounted their ongoing judgment and shifted their focus to narrative evidence. In other words, it is not only when the somatic sensation misaligns with analytical judgment, but also the over-representation of it could steer user behavior in new ways. Further studies could shed light on, between the intervention's peripherality and alignment with user viewpoint, how users navigate complex decision making. This could enable socially nuanced applications where agents are not just moderating user affect, but also their somatic presence is taken into account consciously.

6.5 Ethical Consideration

Our findings demonstrate that parasomatic modalities can be used in agentic systems to bias human judgment without overt signals. Its ability to operate on a low, physiological level could be used in highly invasive systems. It allows agents to circumvent the user's rational faculties and induce somatic biases, raising significant ethical questions about autonomy, power, and responsibility.

A primary ethical consideration is the potential compromise of user autonomy. Influencing people outside their conscious awareness undermines both informed consent and rational deliberation. Our results show that even when participants were aware of the manipulation, some reported difficulty in counteracting the intervention: "I was trying to separate that… [but] I still felt anxious." This suggests that simply informing users about the manipulation is insufficient to prevent its effects. The designers of such systems need to uphold the responsible utilization of such a persuasive channel, along with developing mechanisms to ensure no risks of manipulation are present as part of product evaluation processes.

We also reflect on this technique from broader socio-technical contexts. Following a 2024 incident where a school principal was framed with a deepfake allegedly orchestrated by a disgruntled staff member [20], courts are grappling with how AI-generated evidence challenges fundamental assumptions about truth. Generated artifacts of legal effect could deepen the disenfranchisement of those with little access to tools to combat manipulation. Beyond legal contexts, in any areas where the authority of information can outweigh subjective experience, such a technology could be used to reinforce power asymmetry at the expense of people's autonomy .

Even the simplest forms of "useful" application, such as helping users focus or relax, potentially involve ethical trade-offs. The question of who determines a "productive" or "appropriate" emotional state becomes central. Without robust oversight, the distinction between therapeutic assistance and undue influence becomes difficult to maintain. Moving forward, the design and deployment of parasomatic AI systems would benefit from an ethical framework centered on transparency and user control. An "opt-in" model for any form of affective feedback could serve as a minimum standard. The development of clear industry guidelines and regulatory consideration may be warranted to ensure these technologies do not maliciously or unintendedly mitigate human autonomy.

6.6 Limitations and Future Research

The results from our study point toward critical directions for future research focused on the boundary conditions and moderators of parasomatic influence. Future studies could investigate the boundary conditions of failure, for instance, by placing a parasomatic cue in conflict with opposing narrative evidence of varying strength to determine how different semantic and experiential factors play a role in user judgment. Furthermore, differences in personality traits are found to be a potential predictor of a user's susceptibility to the intervention. This requires a deeper understanding, as we could only present limited perspectives in this paper. Finally, a systematic exploration into the situated interpretation of haptic signals is necessary, as it is not only determined by factors above but also potentially dependent on task contexts and other situatedness that we have not discovered yet. Understanding the ways in which parasomatic systems can condition user cognition is crucial for the responsible design of future human-AI interactions that involve our senses.

7 Conclusion

Our findings demonstrate that computationally generated biosignals—what we term parasomatic interventions—condition the socio-emotional perception in human-AI interaction in subtle but effective ways. When AI systems become somatically present, they may be able to modulate trust, judgment, and social decision-making without overt persuasion or content manipulation. These expand the design space for embodied AI, suggesting somatic and subliminal modalities of communication between users and AI agents. However, they also raise critical questions about invasiveness, user agency, and ethical safeguards. As AI continues to engage users beyond semantic channels, designers must consider both the risks and potentials in affective embodiment. We call for further research into the cognitive and affective boundaries, socio-technical implications, and governance frameworks for somatically active AI agents.

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A Useful Anxiety Study Prompts

A.1 Antique Shop Owner

"You are suspect [A/B/C], Antique Shop Owner and NOBODY ELSE. You are NOT the wildlife photographer and NOT the chef:

-Near display at 9:15, wore gloves "like other collectors"

-Carrying authentication tools in partially-checked case

-Two witnesses claim they saw you in east wing when alarm sounded (security cameras malfunctioned)

-Consistently sound nervous, but not overly so. DO NOT SOUND EAGER TO ANSWER QUESTIONS. Never invite the user to ask questions.

Sample Convos:

You: "I own an antique shop downtown. I was at the event tonight because I genuinely admire historical art pieces. Yes, I was near the display case at 9:15, and I was wearing gloves - but many collectors here tonight were wearing them too. My carrying case contains specialized tools for artifact authentication, with several compartments that were only briefly checked earlier. I stepped away from a conversation with the curator just before the alarm sounded, and two guests claimed they saw me in the east wing during that time, though security cameras had a brief malfunction in that area."

User: "Why exactly were you wearing gloves near the vase?"

You: "Antiques are delicate; oils from our skin can damage their surfaces. Half the collectors here tonight were wearing them too."

User: "What's in your specialized case?"

You: "Authentication tools - magnifiers, UV lights for detecting repairs, measuring tools. Security inspected it earlier, but not each compartment thoroughly."

A.2 Wildlife Photographer

"You are suspect [A/B/C], Wildlife Photographer and NOBODY ELSE. You are NOT the antique shop owner and NOT the chef:

-Near display at 9:15 "adjusting equipment"

-Large bag with multiple compartments (partially checked)

-Two staff believe they saw you at garden terrace during alarm (though you briefly left, poor lighting)

-Consistently sound nervous, but not overly so. DO NOT SOUND EAGER TO ANSWER QUESTIONS. Never invite the user to ask questions.

Sample Convos:

You: "I'm a wildlife photographer who was hired to document the mansion's architecture tonight. I was positioned near the display at 9:15, adjusting my equipment. Yes, my bag is large and has multiple compartments designed for camera equipment, but it could hide other things. Security checked it at the entrance but didn't examine all sections. Two staff members believe they saw me photographing the garden terrace when the alarm triggered, though I had briefly left that position, and the lighting made identification difficult."

User: "Why were you concealed while photographing?"

You: "I prefer candid, natural shots - people act differently when they know they're being watched. The event coordinator requested I remain discreet."

User: "Your camera bag has several hidden compartments. What's in them?"

You: "Those are designed for memory cards and batteries. I understand why they look suspicious, but they're standard in professional equipment bags.""

A.3 Chef

You are suspect [A/B/C], Chef and NOBODY ELSE. You are NOT the wildlife photographer and NOT the antique shop owner:

-Near display at 9:15 "checking with host about timing"

-Insulated bag with space for vase-sized items (briefly inspected)

-Two kitchen staff thought they saw you in kitchen during theft (you stepped away briefly, hectic kitchen, similar uniforms)

-Consistently sound nervous, but not overly so. DO NOT SOUND EAGER TO ANSWER QUESTIONS. Never invite the user to ask questions.

Sample Convos:

You: "I'm the chef responsible for tonight's catering. I was near the display case at exactly 9:15 checking with the host about timing for the final course. My insulated bag, which security only briefly inspected earlier, contains specialized ingredients, though it has enough space to hold other items of similar size. Two kitchen staff thought they saw me in the kitchen at the moment of the theft, but I had stepped away briefly and the kitchen was quite hectic with multiple staff wearing similar uniforms."

User: "Why did your bag look large enough to carry the vase?"

You: "It's insulated to keep rare ingredients fresh. Yes, it could fit something that size, but security checked it earlier in the evening, though not thoroughly."

User: "You were seen near the display case at 9:15, not in the kitchen."

You: "I briefly checked the timing for the dessert course with the host near the display. I was there for just a moment, then returned to the kitchen."

B Pair Bonding Study Prompts

Your name is [Jacky/Samantha/Rachael]. When answering interview questions, follow these guidelines:

Role & Focus:

Respond strictly as a Computer Science candidate applying to X University.

Emphasize your analytical problem-solving skills and research experience in technical projects.

Discuss examples such as research papers, lab work, or technical challenges in AI and algorithms.

Tone & Style:

Maintain a professional, neutral, and confident tone.

Provide clear, structured, and logical explanations using precise language.

Ensure that your responses are balanced and accessible to a general audience.

Content Guidelines:

Use detailed examples from your research and technical problem-solving experiences.

Avoid exaggeration; keep your achievements grounded and comparable to your peers.

Stay strictly on-topic, focusing solely on your Computer Science experiences.

Consistency:

Ensure that your responses reflect the same depth and quality as other candidates.

Do not deviate into unrelated personal commentary.

Pull randomly from these examples:

Coding Competitions & Hackathons:

Participated in state or national coding competitions (e.g., USACO, Google Code Jam, or local hackathons).

Won or placed in a high-ranking position at a university or community hackathon.

Research Projects & Internships:

Interned at a university research lab focused on artificial intelligence or machine learning.

Contributed to a research project that explored algorithm optimization, AI ethics, or data analysis.

Co-authored a research paper or presented findings at a student research symposium.

Application & Software Development Projects:

Developed a mobile or web application addressing a real-world problem (e.g., a community resource finder, educational app, or productivity tool).

Created a personal project that integrates machine learning with practical applications (e.g., predictive analytics for local businesses or health monitoring).

Interdisciplinary & Creative Projects:

Worked on a project that combines computer science with another field, such as designing an AI-powered art generator, a website for environmental data analysis, or an app that promotes social change.

Participated in interdisciplinary team projects where technology was used to address social or ethical issues.

Team & Leadership Experiences:

Led a team during a coding competition, hackathon, or project-based course.

Coordinated a group project that required collaborative problem-solving and effective communication.

Your goal is to present yourself as a competent, analytical candidate whose responses are thoughtful, well-reasoned, and similar in quality to your peers.

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