Real-Time Trust Measurement in Human-Robot Interaction: Insights from Physiological Behaviours

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Abstract

Existing work has shown that physiological behaviours (PBs) can effectively measure trust. However, there is a limited exploration of using multiple PBs concurrently to calibrate human trust in robots during real-time HRI. Additionally, most datasets are based on one-off interactions or a single context. This project addresses this gap by examining differences in PBs between trust and distrust states and investigating how these PBs change over repeated interactions in different contexts. We conducted two experiments to collect data on electrodermal activity (EDA), blood volume pulse (BVP), heart rate (HR), skin temperature (SKT), blinking rate (BR), and blinking duration (BD) from participants across multiple HRI sessions. The results showed significant differences in HR and SKT between trust and distrust states in Study 1, and significant differences in HR in Study 2. Furthermore, the Decision Tree classifier achieved the highest accuracy of 79% in classifying trust when using the incremental transfer learning algorithm for collective datasets. These results highlight the potential of using PBs for real-time trust measurement in HRI and suggest further exploration of incremental transfer learning methods to enhance trust prediction across different interaction contexts.

CCS Concepts

• **Human-centered computing → Human computer interaction (HCI)**; User studies; • **Computer systems organization →** Robotics.

Keywords

Trust, Measurement, Physiological Behaviour, Repeated Interactions, Human-Robot Interaction

ACM Reference Format:
Abdullah Alzahrani and Muneeb Imtiaz Ahmad. 2024. Real-Time Trust Measurement in Human-Robot Interaction: Insights from Physiological Behaviours. In *INTERNATIONAL CONFERENCE ON MULTIMODAL INTERACTION (ICMI '24), November 04–08, 2024, San Jose, Costa Rica.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3678957.3688620

ICMI '24, November 04–08, 2024, San Jose, Costa Rica

ACM ISBN 979-8-4007-0462-8/24/11
https://doi.org/10.1145/3678957.3688620

1 Introduction

Robot deployment is being implemented across various sectors, such as healthcare, manufacturing, and public services [9]. This has led to a growing need to understand human trust in these robotics agents [16]. Trust is crucial to ensure that people can trust them appropriately, neither over-trusting nor under-trusting them [22]. A key aspect of this trust calibration is the ability to accurately measure and model human trust in robots. Trust is a multifaceted concept influenced by various factors, such as the robot's performance, reliability, and failure rate [3]. Traditionally, researchers have measured trust using subjective methods, like questionnaires and surveys, and objective methods, such as performance metrics and behavioural analysis [17]. However, these methods frequently fail to fully capture the real-time and dynamic nature of trust, which may vary based on ongoing interactions and situational context [16].

To address these limitations, there has been a growing interest in using physiological metrics as indicators of trust during HRI [6]. Physiological responses, such as heart rate, skin conductance, and eye blinking, provide continuous and real-time data reflecting the user's emotional and cognitive states [7]. Monitoring these physiological responses can offer valuable insights into the underlying trust dynamics that are not easily captured through self-reported measures or observable behaviours alone [8]. For instance, changes in heart rate and skin conductance can indicate levels of stress or relaxation, which correlate with trust and distrust states [18]

In this work, we aim to investigate the following research questions:

- RQ1 How do human physiological behaviours (PBs) differ between trusting and distrusting states during repeated HRIs across different contexts?
- RQ2 Can human physiological behaviours be used to predict trust in robots during repeated HRIs across different contexts using machine learning algorithms?
- RQ3: How does the interaction context (competitive and collaborative) affect PBs during trust and distrust states?
- RQ4 How does the use of incremental transfer learning algorithm with multiple datasets impact the accuracy of trust prediction models?

To address these RQs, we conducted a multi-stage methodology. Stage 1 assessed human trust in robots during competitive interactions. Stage 2 measured human trust in robots in a repeated collaborative context. Stage 3 compared the datasets from both studies to enhance classification accuracy and improve trust prediction models using incremental transfer learning techniques.

2 Background & Related Work

2.1 Conceptualisation and Measurement of Trust

Trust is a complex and multifaceted concept that varies significantly across different disciplines and contexts. Despite extensive research efforts, a universally accepted definition remains a challenge [13]. Abbass et al. [1] describe trust as a psychological construct comprising beliefs and expectations about an individual's trustworthiness, shaped by experiences and interactions in uncertain and risky situations. Meanwhile, Ajenaghughrure et al. [6] characterize trust as a complex cognitive process that operates at a subconscious level, involving mental deliberation, reasoning, and the processing of memory, learning, and accumulated knowledge. These definitions highlight the dynamic and evolving nature of trust and the relationship between trust and human PBs, indicating that using PBs can be beneficial in assessing human trust in robots.

Trust in HRI can be measured using subjective, objective, and physiological methods. subjective methods involve self-report questionnaires that measure an individual's perceived trust in robots [23]. Although easy to use, these methods often fail to capture the complex real-time nature of trust during interactions. Objective methods analyse observable behaviours and performance metrics during interactions with robots [19]. These include decision-making patterns and task performance, which provide indirect measures of trust. However, they may not fully capture the emotional and cognitive states underlying trust. Physiological methods offer real-time insights into an individual's trust levels through PBs such as electrodermal activity (EDA), blood volume pulse (BVP), heart rate (HR), skin temperature (SKT), blinking rate (BR), and blinking duration (BD) [4]. These physiological responses provide continuous data that reflect emotional arousal and cognitive effort during interactions with robots. For instance, increased heart rate and skin conductance can indicate stress and distrust [12].

Several studies have explored the use of PBs in trust measurement. Khawaji et al. [18] investigated the use of galvanic skin response (GSR) to measure trust and cognitive load in a text-based chat environment, finding that GSR signals were significantly affected by trust conditions. Lu and Sarter [21] examined eye movements as a measure of trust in automation, suggesting that eye tracking can be a valuable tool for trust calibration. Gupta et al. [12] assessed trust in a virtual assistant using HRV, skin conductance, and facial electromyography, finding HRV to be a reliable indicator of trust levels.

Machine learning to estimate trust has shown promise in predicting trust levels based on physiological signals. Ajenaghughrure et al. [5] developed a model using heart rate variability and skin conductance to assess trust in a conversational interface, achieving high accuracy. Similarly, Khalid et al. [15] used a neuro-fuzzy neural network to estimate trust levels in human-robot-human interactions with significant accuracy. Other studies, such as Hu et al. [14] and Lochner et al. [20], have employed machine learning techniques to map PBs to trust levels, demonstrating the effectiveness of these methods in real-time trust assessment.

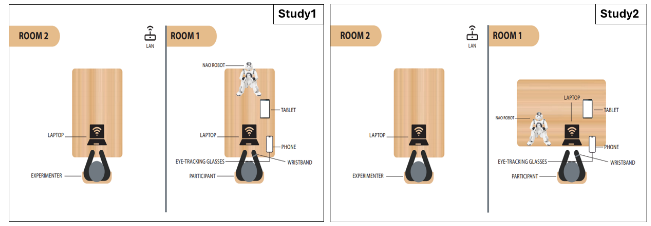

Figure 1: Experimental setup of study 1 and study 2: The experimenter remotely controls the robot from one room (left) while the participant plays the game with the robot in a separate room (right).

In summary, while empirical studies have employed various PBs to assess trust and have shown promising results, they have notable limitations. These studies did not integrate PBs from different sources, were conducted in one-off interactions, and often utilised simulated environments. Additionally, they typically involved a small number of participants. This project aims to bridge these gaps by analysing multiple PBs during repeated interactions across various contexts of actual HRI. We will also collect data from a larger pool of participants and explore incremental transfer learning to increase accuracy.

3 Methodology and Approach

We addressed the RQs through a multi-stage methodology as follows:

3.1 Stage 1: Study 1

Stage 1 investigates the use of physiological behaviours (PBs) to sense human trust in robots during repeated competitive interactions. Participants engaged in four game sessions with a Nao robot, playing an interactive card game designed to elicit trust and distrust. This study was approved by the university's ethics committee [160322/5031]. Participants played a card game, the *Bluff Game*, as used by Ahmad et al. [2], against the Nao robot. The game involved craeting trust and distrust situations. Trust the case when a participant accepts the robot's claim, and distrust the case when a participant rejects the robot's claim. PBs recorded using the Empatica E4 wristband and Pupil Invisible Eye Tracking Glasses. A total of 43 participants (16 females, 26 males, 1 undisclosed; M = 29.53 years, SD = 6.71) were recruited, with varying levels of prior experience with robots.

Participants played the game in four sessions, each lasting a few minutes. During the game, the Nao robot interacted verbally, and PBs were recorded during decision periods. We collected PBs, including electrodermal activity (EDA), blood volume pulse (BVP), heart rate (HR), skin temperature (SKT), breathing rate (BR), and blink duration (BD), during these decision periods. Data were preprocessed to remove noise and artifacts, segmented by decision period, and averaged for analysis. The dataset was created by averaging PBs for trust and distrust decisions across all sessions, resulting in a comprehensive dataset for classification.

3.1.1 Results & Discussion. To address RQ1, we conducted a repeated-measures ANOVA on PBs (EDA, BVP, HR, SKT, BR, and BD). Significant effects of decision (trust vs. distrust) were found for HR ($F(1, 84) = 11.652$, $p < .001$, $\eta_p^2 = .122$) and SKT ($F(1, 84) = 13.473$, $p < .001$, $\eta_p^2 = .138$) consistent with prior research identifying these as key indicators of trust in HRI [6, 15]. However, other PBs (EDA, BVP, BR, and BD) did not show significant differences, potentially due to the relaxed nature of the task and the lack of pressure elements, which may have resulted in lower arousal levels. Also, there were no significant interaction effects of session and decision on any PBs. The consistent behaviour of the game across sessions likely contributed to this outcome, and future research should explore the impact of individual experiences with the robot on PBs during repeated HRI.

We conducted a post-hoc Bonferroni test to compare HR, SKT, and other measures between trust and distrust groups in sessions (1, 2, 3, and 4). HR significantly differed between trust and distrust states in session 1 ($p < .030$), session 3 ($p < .010$), and session 4 ($p = .010$). SKT also significantly differed between trust and distrust decisions in session 1 ($p < .030$), session 3 ($p < .010$), and session 4 ($p < .010$).

To address RQ2, we implemented five classifiers (SVM, RF, LR, DT, AB) to classify trust levels using 5-fold cross-validation. The Random Forest (RF) achieved the highest accuracy (68.6%), followed by Decision Tree (62.2%). The remaining classifiers performed above chance level (see Table 1). This supports the notion that using multiple PBs can improve trust prediction accuracy, particularly in real-time scenarios [6].

We analysed the dataset to identify which features predicted trust or distrust. The RF classifier displayed superior performance. The features important for trust and distrust in this classifier are EDA (0.56, 0.49), BVP (0.58, 0.56), HR (0.66, 0.64), SKT (0.61, 0.35), BR (0.66, 0.69), and BD (0.70, 0.67). HR, BR, BD, and SKT were the best-performing features, with significant mean differences observed between trust and distrust behaviours.

Classifier	Accuracy (%)					F1-scores	
	Session 1	Session 2	Session 3	Session 4	All Sessions	Trust	Distrust
SVM	58.9	53.8	55.5	50.5	**53.5**	0.644	0.304
RF	68.2	46.8	69.1	60.2	**68.6**	0.708	0.658
LR	55.5	49.4	49.9	46.4	**50.5**	0.572	0.402
DT	63.4	64.2	64.9	59.3	**62.2**	0.692	0.492
AB	63.4	57.8	67.6	54.0	**53.6**	0.534	0.536

Table 1: Classifier Accuracies and F1-scores for Physiological Behaviors in Trust Classification (Study1).

Overall, the analysis shows that HR and SKT are significant indicators of trust, and using machine learning classifiers, particularly RF, can effectively predict trust levels in HRI.

3.2 Stage 2

Stage 2 aimed to measure human trust in robots through the same PBs used in Stage 1 in a collaborative human-robot interaction (HRI) context. Participants interacted with the NAO robot in four sessions, each lasting 7.45 minutes with 5-minute breaks. We modified the Bluff Game, a game used by Alzahrani and Ahmad [8], to be played collaboratively, with participants and the NAO robot playing against an adversary agent. The NAO robot provided pre-scripted advice during the game before participants decided to accept or reject the opponent's claim. Accepting the robot's advice is considered trust, while ignoring the advice is distrust. PBs were recorded using the Empatica E4 wristband and Pupil Invisible Eye Tracking Glasses. We recruited 42 participants (20 females, 20 males, 2 undisclosed; M = 30.45, SD = 4.14) categorized by their experience with robots. The study was approved by the university ethics board (reference number 2202370516013). Participants played four sessions with the robot, and physiological data and decisions were recorded. Real-time PBs (EDA, BVP, HR, SKT, BR, BD) were collected during decision periods. Data were preprocessed (noise removal, segmentation, feature extraction) and logged as binary trust/distrust decisions. The dataset was generated by averaging PB values for each session and merging them to be ready for classification.

3.2.1 Results & Discussion. To address RQ1, a repeated-measures ANOVA revealed a significant effect of the decision on HR ($F(1, 71) = 15.346$, $p < .001$, $\eta_p^2 = .178$) consistent with prior research identifying HR as a key indicator of trust in HRI [6]. However, we did not find significant effects for EDA, BVP, SKT, BR, and BD. The absence of significant differences in other PBs suggests these may be less sensitive to trust variations in this specific context or require stronger stimuli to show changes. This highlights the complexity of using physiological data to assess trust, underscoring the importance of context and individual variability.

We also found no significant interaction effects of session and decision on these PBs. SKT showed significant session effects ($F(3, 69) = 22.599$, $p < .001$, $\eta^2 = .496$), with Session 1 differing significantly from Sessions 2, 3, and 4. This could contribute to context-specific factors and individual variability when interpreting physiological data in HRI.

We used a post-hoc Bonferroni test to compare SKT values between sessions 1, 2, 3, and 4. The results showed significant differences between Session 1 and Sessions 2, 3, and 4 ($p < .001$). Session 1 had higher mean values than the other sessions, indicating session-specific effects on SKT measurements.

To address RQ2, we applied the (SVM, RF, LR, DT, AB, NN, NB) classifiers. Random Forest (RF) and Logistic Regression (LR) achieved the highest accuracies at 69% and 65%, respectively. RF displayed superior performance in predicting trust and distrust, with trust correctly predicted at 66% and distrust at 69% (see Table 2). This suggests that utilizing multiple PBs can enhance trust prediction accuracy, especially in real-time [8].

We analysed the dataset to identify which features predicted trust or distrust. The RF classifier displayed superior performance. The features important for trust and distrust in this classifier are EDA (0.44, 0.45), BVP (0.59, 0.6), HR (0.62, 0.51), SKT (0.48, 0.52), BR (0.61, 0.57), and BD (0.56, 0.6).

3.3 Stage 3

The objective of this stage is to conduct a comparative analysis of the two studies and utilise their datasets to enhance classification accuracy and improve predictive performance.

Classifier	Accuracy (%)					F1-scores	
	Session 1	Session 2	Session 3	Session 4	All Sessions	Trust	Distrust
RF	67%	60%	59%	50%	**69%**	**0.66**	**0.69**
LR	54%	63%	50%	66%	**65%**	0.62	0.66
SVM	55%	68%	47%	68%	**64%**	0.63	0.60
DT	64%	51%	54%	43%	**64%**	0.61	0.64
AB	62%	53%	56%	46%	**65%**	0.61	0.62
NN	55%	62%	55%	51%	**63%**	0.58	0.60
NB	42%	60%	60%	62%	**62%**	0.62	0.61

Table 2: Classifier Accuracy's for Physiological Behaviours in Trust Classification (Study2).

To address **RQ3**, which aimed to investigate potential differences in PBs between the competitive and collaborative settings, we conducted a repeated-measures ANOVA. The results showed significant effects of Setting on EDA ($F(1, 155) = 5.071$, $p = .026$, $\eta^2 = 0.032$), BVP ($F(1, 155) = 6.282$, $p = .013$, $\eta^2 = 0.039$), HR ($F(1, 155) = 13.249$, $p < .001$, $\eta^2 = 0.079$), BR ($F(1, 155) = 192.188$, $p < .001$, $\eta^2 = 0.554$) and BD ($F(1, 155) = 205.616$, $p < .001$, $\eta^2 = 0.570$). This demonstrates that the context of interaction plays a crucial role in the factors that influence trust, as represented by PBs [9]. In competitive settings, the desire to outperform the robot leads to increased physiological arousal, indicated by higher EDA, BVP, HR, BR, and BD [11]. In contrast, in collaborative settings, a more cooperative and relaxed atmosphere can reduce stress and anxiety, leading to lower physiological arousal. However, we did not observe a significant effect of the setting on SKT [11].

To address **RQ4**, we combined datasets from different contexts (Stages 1 and 2) using an incremental transfer learning approach by Chui et al. [10]. Dataset 1 (Stage 1) was the source, and Dataset 2 (Stage 2) was the target. Each dataset was divided into equal subsets. We trained an initial model on the first subset of Dataset 1 and transferred its knowledge to Dataset 2, continuing with subsequent subsets. Classifiers demonstrated high accuracy: RF achieved 70% (source), 53% (target); LR 59%, 66%; SVM 73%, 70%; DT 72%, 79%; AB 64%, 53%; NN 76%, 78%; NB 57%, 63%. This method improved classification performance by effectively integrating data from different contexts. (see 2. This improvement compared with dummy classification is because this algorithm can transfer relevant information without incorporating irrelevant or conflicting data, which can lead to negative outcomes [10]. Combining datasets from collaborative and competitive contexts resulted in a diverse and extensive dataset, leading to enhanced classifier performance. These findings highlight the potential of incremental transfer learning to improve real-time trust assessment in human-robot interaction (HRI), supporting the development of more adaptive robotic systems.

4 Contribution

The contributions of this study are novel and valuable for future research in the field and are as follows:

• We present an analysis of the relationship between human PBs and trust levels during repeated HRIs across different contexts, providing insights into how trust and distrust states manifest in physiological responses.
• We investigate the use of human PBs to predict trust in robots using machine learning algorithms, demonstrating the potential of these physiological metrics for real-time trust measurement and prediction.

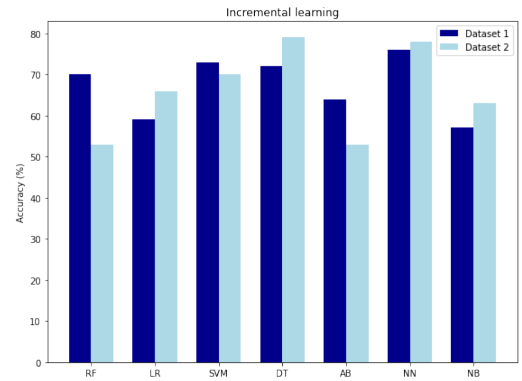

Figure 2: Classification Accuracies Using Incremental Transfer Learning

• We investigate the effect of interaction context (competitive and collaborative) on PBs during trust and distrust states.
• We demonstrate the application of incremental transfer learning techniques to improve the predictive accuracy of trust models by utilizing data from both competitive and collaborative contexts.
• To further support and enable ongoing research in this field, we provide access to the study materials and the evolving dataset. These resources are made available to the academic community and can be accessed here.

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5 Conclusion

The use of multiple physiological behaviours from different contexts has shown significant potential in assessing and predicting human trust in robots during HRI. This study analysed the differences in physiological behaviours between trust and distrust states in different contexts of repeated HRI and explored the potential of combining data from different settings to enhance trust prediction accuracy using incremental transfer learning techniques. The findings confirmed that physiological measures such as HR and SKT are significant indicators of trust, and the use of multiple physiological behaviours collectively can enable real-time sensing of human trust in robots. This project has potential, but it comes with limitations. The findings are specific to game-based robot interactions and may not apply to other contexts or human interactions. Future research will involve testing in various environments and exploring additional physiological features from multiple relevant body organs, along with facial emotion and voice features, to develop adaptive robotic systems based on real-time trust measurements, ultimately leading to more effective HRI.

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