Journal of Robotics and Autonomous Technologies
https://ratjournal.net

Task Acceptance in Hospital Logistics Robots Using Human-Robot Trust Cues: Agent Modeling

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Abstract

The integration of autonomous logistics robots in hospital environments has the potential to significantly alleviate the physical and cognitive workloads of healthcare professionals. However, the successful deployment of these robotic systems is heavily dependent on the level of trust established between the human workers and the robots. This paper presents a comprehensive investigation into predicting task acceptance by leveraging human-robot trust cues through advanced agent modeling techniques. By analyzing implicit behavioral signals such as gaze duration, interpersonal distance, and interaction latency, this study constructs a computational agent model that continuously evaluates the psychological state of healthcare workers. The research was conducted in a highly realistic simulated hospital environment, involving nursing staff who interacted with a prototype logistics robot responsible for delivering medical supplies. The extracted behavioral features were integrated into a probabilistic framework to forecast whether a nurse would accept or reject a task delegated by or shared with the robot. The findings demonstrate a strong correlation between specific non-verbal trust cues and the likelihood of task acceptance, proving that agent-based modeling can serve as a highly accurate proxy for real-time trust assessment. The proposed system enables logistics robots to dynamically adapt their interaction strategies based on the predicted trust levels, thereby fostering a more harmonious and efficient collaborative healthcare ecosystem. The insights derived from this study provide a foundational framework for future designs of socially aware robotic systems in high-stress, safety-critical work environments.

Keywords: Human-Robot Interaction; Trust Cues; Agent Modeling; Hospital Logistics; Task Acceptance

1. Introduction

1.1 Background and Motivation

The global healthcare system is currently facing unprecedented challenges characterized by an aging population, increasing patient admission rates, and a severe shortage of qualified medical personnel. In response to these escalating pressures, healthcare institutions have increasingly turned to technological solutions to optimize operational efficiency and reduce the immense physical and cognitive burdens placed on their staff. Among the most promising technological interventions is the deployment of autonomous hospital logistics robots. These robotic systems are designed to automate repetitive and physically demanding tasks, such as the transportation of linens, the delivery of daily meals, the distribution of pharmaceutical supplies, and the secure transfer of laboratory specimens. By taking over these essential but time-consuming logistical operations, robots allow nurses and doctors to dedicate more of their time and energy to direct patient care and complex clinical decision-making. However, despite the clear functional advantages of hospital logistics robots, their real-world adoption has frequently encountered significant resistance from healthcare professionals. This resistance is rarely rooted in the technical incompetence of the robots but is instead primarily driven by complex socio-technical factors, with human-robot trust emerging as the most critical determinant of successful integration. As established in recent studies on workplace automation, the mere presence of a capable robot does not guarantee its utilization [1]. If healthcare workers do not trust the robotic system, they are likely to ignore it, bypass its functionalities, or even actively sabotage its operations, thereby nullifying the anticipated efficiency gains and return on investment.

Trust in human-robot interaction is a highly dynamic and multidimensional psychological construct that continuously evolves based on ongoing experiences and contextual factors. In the high-stress, fast-paced environment of a modern hospital, trust is heavily influenced by the robot's reliability, predictability, and ability to navigate complex social norms. Unlike industrial settings where robots are isolated from human workers by physical cages, hospital logistics robots must operate in shared spaces, navigating crowded corridors, interacting with distracted or stressed staff, and maneuvering around vulnerable patients. Consequently, a robot's failure to adhere to expected social behaviors, such as yielding the right of way during an emergency or maintaining an appropriate distance from a human, can immediately degrade trust.

Traditional methods for evaluating human-robot trust have predominantly relied on post-interaction self-report questionnaires and retrospective interviews. While these subjective measures provide valuable insights into the overall perception of the robotic system, they suffer from several fundamental limitations. Most notably, they are static and retrospective, meaning they cannot capture the real-time fluctuations in trust that occur during a continuous interaction. Furthermore, interrupting busy healthcare professionals to fill out surveys during their shifts is highly impractical and disruptive to their critical workflow. Therefore, there is an urgent and compelling need to develop unobtrusive, real-time methodologies for assessing human-robot trust in naturalistic settings [2].

To address this challenge, researchers have increasingly focused on identifying and analyzing implicit behavioral cues that manifest during human-robot interactions. These non-verbal trust cues, which include patterns of visual attention, proxemic behavior, and the latency of physical or verbal responses, offer a continuous and observable window into the human's underlying psychological state. When a human trusts a robot, they typically exhibit relaxed behavioral patterns, such as allocating less visual attention to the robot's movements and allowing it to approach more closely. Conversely, when trust is low, humans tend to monitor the robot continuously, maintain a larger physical distance, and hesitate before interacting with it. The central motivation of this research is to harness these implicit trust cues to build predictive models of human behavior, specifically focusing on the critical metric of task acceptance. Task acceptance refers to the human's willingness to rely on the robot to perform a specific function, whether it is retrieving a medication or handling a biological sample. By accurately predicting task acceptance through the real-time analysis of trust cues, robotic systems can be designed to proactively adapt their behaviors. For instance, if a robot detects low trust from a specific nurse, it can increase the transparency of its actions, move more cautiously, or provide more detailed status updates, thereby repairing trust before a task is rejected.

1.2 Problem Statement and Objectives

Despite the growing recognition of behavioral trust cues in human-robot interaction, translating these raw sensor data streams into actionable predictions of human behavior remains a formidable computational challenge. The primary problem lies in the high dimensionality, inherent noise, and profound individual variability of human behavioral data. A specific gaze pattern or interpersonal distance that indicates high trust for one individual might indicate apprehension for another, depending on their prior experience with technology, their current workload, and their baseline personality traits. Traditional machine learning approaches often struggle to account for this deep contextual and individual variability, leading to brittle predictive models that perform poorly in open-world environments like hospitals. Furthermore, mapping continuous behavioral cues directly to binary outcomes like task acceptance without understanding the underlying cognitive mechanisms often results in opaque "black box" models. These models fail to provide the explanatory transparency required in safety-critical healthcare applications, where system designers and hospital administrators need to understand exactly why a robot made a specific decision. This lack of transparency and adaptability represents a significant gap in the current literature on human-robot interaction in healthcare [3].

To overcome these limitations, this study proposes the utilization of advanced agent modeling techniques. Agent modeling involves constructing a computational representation of the human user, encapsulating their beliefs, preferences, and decision-making processes. By modeling the healthcare worker as a rational but bounded agent operating under specific environmental constraints, it becomes possible to contextualize their observed behavioral cues. In this framework, trust is not merely a statistical correlation but an internal state variable within the agent model that dictates the probability of choosing a specific action, such as accepting or rejecting a task from the logistics robot. This approach allows for the integration of prior knowledge about human psychology and social norms into the predictive architecture, thereby improving robustness against noisy sensor data and enabling more accurate predictions across diverse user populations. The application of agent modeling to predict task acceptance from non-verbal trust cues in a hospital logistics context is a highly novel approach that promises to bridge the gap between abstract psychological theories of trust and practical, real-time robotic control systems [4].

The primary objective of this comprehensive research is to design, implement, and rigorously evaluate an agent-based modeling framework capable of predicting task acceptance based on human-robot trust cues in a hospital setting. This overarching goal is decomposed into several specific technical objectives. The first objective is to systematically identify and reliably extract a set of non-verbal behavioral cues that are indicative of human trust during interactions with a hospital logistics robot. This requires the development of robust sensor processing pipelines capable of operating in dynamic and cluttered environments. The second objective is to construct a mathematical agent model that maps these extracted trust cues to an internal trust state, accounting for temporal dynamics and individual baseline differences. The third objective is to integrate this agent model into a real-time prediction engine that outputs the probability of task acceptance for various logistical scenarios. The final objective is to empirically validate the proposed framework through extensive human-subjects experiments conducted in a high-fidelity simulated hospital environment, comparing the predictive performance of the agent model against established baseline methodologies. By achieving these objectives, this research aims to provide a robust theoretical and practical foundation for the development of highly adaptive, socially intelligent logistics robots that can seamlessly and harmoniously integrate into the complex ecosystem of modern healthcare facilities.

2. Literature Review and Theoretical Framework

2.1 Human Robot Trust Dynamics in Healthcare Settings

The conceptualization and measurement of trust in automated systems have evolved significantly over the past several decades, tracing their roots back to the foundational studies of human interaction with early supervisory control systems. Early theoretical frameworks defined trust as the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability. This definition highlights three critical components of trust: the existence of a goal, the presence of risk, and the reliance on an external entity to mitigate that risk. In the context of modern robotics, these elements are profoundly magnified. A hospital logistics robot represents a complex, physically embodied system that operates autonomously in the same physical space as the human user. Unlike interacting with a stationary computer terminal, interacting with a mobile robot introduces physical risks, such as the potential for collisions, as well as operational risks, such as the misplacement of critical medical supplies. Therefore, human-robot trust in healthcare settings is widely recognized as a multi-layered construct encompassing cognitive, affective, and behavioral dimensions [5].

Cognitive trust is primarily driven by the human's rational assessment of the robot's capabilities, reliability, and predictability. When a logistics robot consistently delivers supplies to the correct location at the correct time without incident, the human's cognitive trust in the system increases. This form of trust is heavily influenced by the robot's performance metrics and the transparency of its operational logic. Affective trust, on the other hand, is rooted in the human's emotional response to the robot. It is shaped by factors such as the robot's physical design, its perceived anthropomorphism, and the perceived safety of its movements. A robot that moves erratically or emits harsh mechanical noises may elicit feelings of anxiety and discomfort, thereby severely damaging affective trust even if its functional performance is flawless. Behavioral trust represents the outward manifestation of the cognitive and affective dimensions. It is observed through the human's actual decisions and actions when interacting with the robot, such as their willingness to delegate tasks, their compliance with the robot's requests, and their physical proximity to the machine during operation. In the fast-paced and high-stakes environment of a hospital, behavioral trust is the ultimate metric of success, as it directly determines whether the robotic system will be utilized effectively or abandoned entirely [6].

Understanding the dynamics of human-robot trust in healthcare requires a deep appreciation of the unique contextual pressures faced by medical professionals. Nurses and doctors operate under extreme time constraints and carry immense cognitive loads. They are constantly multitasking and prioritizing critical patient needs over administrative or logistical chores. When a logistics robot is introduced into this environment, it must not add to the human's cognitive burden. If the robot requires excessive supervision, complex programming, or constant troubleshooting, the perceived cost of interacting with the system will quickly outweigh its anticipated benefits, leading to a rapid decline in trust and subsequent task rejection. Furthermore, the hospital environment is highly dynamic and unpredictable, featuring changing floor plans, emergent medical crises, and constant movement of people and equipment. A logistics robot must demonstrate high levels of adaptability and situational awareness to navigate this chaos safely and efficiently. Research has shown that when a robot fails to adapt to unexpected environmental changes or violates established social norms, such as blocking a busy hallway, trust can evaporate instantaneously. This phenomenon, known as trust destruction, is notoriously easy to trigger and exceptionally difficult to reverse. Rebuilding broken trust requires significant time and consistent, flawless performance, which is often a luxury that busy hospital staff cannot afford to provide. Therefore, the ability to continuously monitor and proactively manage human-robot trust is of paramount importance for the long-term viability of automation in healthcare [7].

2.2 Agent Modeling for Predicting Task Acceptance

To move beyond subjective post-hoc surveys and enable the real-time management of human-robot trust, researchers require sophisticated computational frameworks capable of interpreting complex behavioral data. Agent-based modeling has emerged as a powerful paradigm for addressing this challenge. At its core, agent modeling involves creating a mathematical or computational representation of the human user as an autonomous entity that perceives its environment, processes information according to specific internal rules, and selects actions to maximize a set of defined utilities. In the context of this research, the human healthcare worker is modeled as a rational but bounded agent whose internal state includes a dynamically fluctuating variable representing their trust in the logistics robot. This trust state is continuously updated based on observations of the robot's behavior and performance, and it directly influences the agent's probability of executing specific actions, most notably the acceptance or rejection of a delegated task. The primary advantage of using an agent model over traditional direct mapping techniques is its ability to incorporate rich theoretical knowledge about human cognition and decision-making into the predictive architecture [8].

One of the foundational concepts integrated into the agent modeling framework is the theory of bounded rationality. Medical professionals, despite their extensive training, do not possess infinite cognitive resources or perfect information when making decisions on the hospital floor. Their behavior is constrained by extreme time pressures, fatigue, and the need to rely on heuristic shortcuts. The agent model accounts for this by utilizing probabilistic decision rules rather than deterministic optimization algorithms. The model assumes that the human will generally choose actions that maximize their perceived utility, which in this case involves minimizing their workload and ensuring patient safety. However, the calculation of this utility is heavily weighted by the internal trust state. If trust is high, the perceived risk of relying on the robot is low, and the utility of delegating a task is high. If trust is low, the perceived risk is magnified, and the utility of performing the task manually, despite the increased workload, surpasses the utility of delegation. By formalizing this relationship, the agent model provides a principled mechanism for linking abstract trust concepts to concrete behavioral outcomes like task acceptance.

The construction of a robust agent model for predicting task acceptance requires the careful selection and integration of relevant behavioral trust cues. Extensive literature on human non-verbal behavior suggests that visual attention, physical proximity, and interaction latency are among the most reliable indicators of trust in dynamic environments. Visual attention, typically measured through gaze direction and fixation duration, reflects the amount of cognitive resources the human is allocating to monitoring the robot. High levels of monitoring are universally associated with low trust and high perceived risk. Physical proximity, or proxemics, reflects the human's comfort level and perceived safety. Individuals naturally maintain larger personal spaces when interacting with entities they do not trust or perceive as unpredictable. Interaction latency, which measures the time delay between a robot's prompt and the human's response, serves as an indicator of hesitation and cognitive friction. A rapid, fluid response suggests high trust and familiarity, whereas a delayed, hesitant response indicates apprehension or confusion. The agent model functions as a sophisticated data fusion engine, continuously ingesting these diverse behavioral streams, updating the internal trust state variable using Bayesian inference mechanisms, and generating a probabilistic forecast of the human's next action. This dynamic, predictive capability represents a significant advancement over static trust measurement paradigms and provides the necessary computational foundation for developing truly adaptive and socially intelligent hospital logistics robots.

3. Methodology and Agent Modeling Framework

3.1 Participant Selection and Scenario Design

To rigorously evaluate the proposed agent modeling framework for predicting task acceptance based on human-robot trust cues, a comprehensive empirical study was designed and executed. The research was conducted in a highly realistic simulated hospital environment constructed within a large-scale robotics testing facility. This simulated environment meticulously replicated the spatial constraints, visual aesthetics, and acoustic characteristics of a standard hospital ward, complete with patient rooms, nursing stations, medication dispensaries, and cluttered corridors. The objective of using a high-fidelity simulation was to elicit naturalistic behaviors and authentic stress responses from the participants while maintaining strict experimental control over the scenarios and ensuring absolute physical safety. The simulated ward was extensively equipped with overhead tracking cameras, directional microphones, and environmental sensors to provide a comprehensive and unobtrusive data collection infrastructure.

A cohort of professional healthcare workers was recruited to participate in the study to ensure the ecological validity of the findings. The recruitment process targeted registered nurses and clinical support staff with varying levels of professional experience and prior exposure to automation technology. The diversity in the participant pool was essential for capturing a wide spectrum of baseline trust levels and interaction styles, thereby robustly testing the generalization capabilities of the agent model. Informed consent was obtained from all participants prior to the commencement of the study, and all experimental protocols were strictly aligned with the ethical guidelines governing human subjects research. The demographic profile of the participant cohort was carefully documented to facilitate subsequent statistical analyses and to control for potential confounding variables related to age, experience, and technological familiarity.

Table 1: Demographic Characteristics of Participating Healthcare Professionals

Demographic Variable	Category	Participant Count	Percentage of Total
Age Group	20 to 30 years	18	30.0
Age Group	31 to 40 years	24	40.0
Age Group	41 years and above	18	30.0
Clinical Experience	Less than 5 years	15	25.0
Clinical Experience	5 to 15 years	27	45.0
Clinical Experience	More than 15 years	18	30.0

The experimental design centered around a series of standardized interaction scenarios involving a prototype autonomous hospital logistics robot. The robot was tasked with assisting the participants in executing a simulated daily nursing workflow, which included retrieving scheduled medications from the pharmacy station, delivering fresh linens to patient rooms, and transporting biological samples to the laboratory drop-off point. To systematically manipulate the participants' trust levels and observe the resulting behavioral cues, the reliability and behavior of the logistics robot were deliberately varied across different experimental blocks. In the high-reliability scenarios, the robot navigated smoothly, responded instantly to commands, and completed all tasks flawlessly. In the low-reliability scenarios, the robot exhibited programmed malfunctions, such as navigating erratically, stopping unexpectedly in corridors, displaying incorrect status messages on its interface, and experiencing artificial delays in its response times. Throughout these varying scenarios, the robot periodically presented the participant with a specific task delegation request, prompting the human to either accept the robot's assistance or reject it and complete the task manually. The binary decision of task acceptance or rejection served as the primary ground truth label for evaluating the predictive accuracy of the agent modeling framework.

3.2 Feature Extraction of Trust Cues

The core of the predictive framework relies on the continuous and accurate extraction of non-verbal behavioral cues that signify the human's underlying level of trust. Given the dynamic and complex nature of the simulated hospital environment, capturing these cues required a sophisticated, multi-modal sensor fusion approach. The primary behavioral features identified for extraction were visual attention dynamics, proxemic variations, and interaction latency. The extraction pipeline was designed to process raw sensor data in real-time, transforming continuous physical measurements into discrete, meaningful variables that could be ingested by the computational agent model. The emphasis was placed on developing algorithms that were robust to occlusions, varying lighting conditions, and the rapid, unpredictable movements characteristic of busy healthcare professionals [9].

Visual attention dynamics, specifically the human's gaze behavior towards the robot, were hypothesized to be one of the most powerful indicators of trust. To capture this metric, the simulated environment utilized a network of high-resolution overhead cameras combined with wide-angle cameras mounted directly on the chassis of the logistics robot. Advanced computer vision algorithms, utilizing deep neural networks trained on extensive datasets of human facial orientations, were deployed to continuously estimate the participant's head pose and gaze vector in three-dimensional space. The primary feature extracted from this data stream was the Gaze Fixation Ratio, defined as the percentage of time within a rolling temporal window that the participant's gaze was directed towards the robot. A high Gaze Fixation Ratio indicated that the participant was closely monitoring the robot's movements, a behavior strongly associated with low trust and high perceived risk. Conversely, a low ratio suggested that the participant was comfortable focusing on their primary nursing tasks, implicitly trusting the robot to operate safely in the background.

Proxemic variations, which measure the physical distance maintained between the human and the robot, provided another critical dimension of the trust assessment. The tracking of interpersonal distance was achieved through a combination of the robot's onboard LiDAR sensors and the overhead camera network. The data from these disparate modalities were fused to generate a continuous, highly accurate trajectory of both the human and the robot within the shared workspace. The primary feature extracted was the Minimum Interaction Distance, which recorded the closest physical proximity the human allowed the robot to achieve during a specific interaction sequence. Furthermore, the algorithm calculated the Approach Velocity, measuring how quickly the human was willing to close the distance to the robot when initiating an interaction. Reluctance to approach the robot or the maintenance of unusually large physical distances were interpreted as strong signals of apprehension and diminished trust [10].

Table 2: Extracted Behavioral Trust Cues and their Corresponding Sensor Modalities

Behavioral Trust Cue	Primary Sensor Modality	Description of Extracted Feature
Gaze Fixation Ratio	Multi-camera Vision System	Proportion of time human visual attention is fixed on the robot.
Minimum Interaction Distance	LiDAR and Overhead Cameras	The closest spatial distance maintained between the human and robot.
Command Response Latency	Robot Audio and Touch Interface	Time duration between a robot prompt and the human's definitive action.

The third critical behavioral cue, interaction latency, was designed to capture the human's cognitive hesitation when engaging with the robotic system. This metric was measured using the robot's onboard interface systems, which included a touch screen display and a voice command recognition module. The Command Response Latency feature was calculated by measuring the exact time elapsed between the moment the robot presented a task delegation request and the moment the participant registered a definitive response, either by pressing a button on the screen or issuing a clear vocal command. Extended latency periods were analyzed as indicators of cognitive friction, suggesting that the participant was engaging in a complex internal risk assessment before deciding whether to trust the robot with the task. By continuously extracting and synthesizing these three distinct behavioral features—gaze, proximity, and latency—the system created a comprehensive, multi-dimensional profile of the human's interaction dynamics, ready to be processed by the predictive agent model.

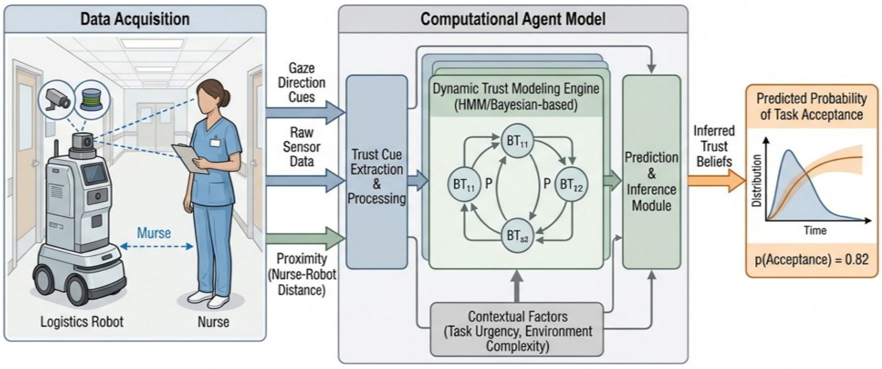

Figure 1: Comprehensive Schematic of the Agent Modeling Framework for Processing Human Robot Trust Cues

4. System Implementation and Experimental Setup

4.1 Logistics Robot Architecture

The physical embodiment of the logistics robot used in this research was a custom-modified mobile manipulation platform specifically designed for indoor service applications. The structural dimensions of the robot were engineered to mimic standard hospital service carts, ensuring it could navigate seamlessly through standard doorways, tight corners, and crowded hallways without requiring environmental modifications. The base of the robot featured a differential drive locomotion system, providing high maneuverability and the ability to rotate completely in place, a crucial requirement for navigating the confined spaces of patient rooms and utility closets. The upper section of the robot contained secure, modular storage compartments designed to simulate the transport of various medical materials, ranging from bulky linens to sensitive pharmaceutical supplies. These compartments were equipped with automated locking mechanisms that could be activated by the participant through a secure identification protocol, adding an element of realistic operational complexity to the interaction scenarios.

The sensory architecture of the logistics robot was exceptionally robust, designed to facilitate both autonomous navigation and high-fidelity data collection for the trust assessment framework. The primary navigation sensor was a 360-degree planar LiDAR scanner mounted on the lower chassis, providing continuous distance measurements to map the environment and detect dynamic obstacles. This was supplemented by a ring of ultrasonic sensors and tactile bumpers to ensure absolute safety in the event of close-proximity encounters. For the purpose of observing the human participants, the robot was equipped with a prominent sensor mast extending to approximate human eye level. This mast housed an array of high-definition RGB cameras and depth sensors, which were responsible for capturing the raw visual data required for the gaze estimation and proxemic tracking algorithms. Additionally, the mast featured a directional microphone array with advanced noise-cancellation capabilities, designed to isolate the participant's voice commands from the ambient noise typical of a busy hospital environment.

The computational architecture of the robot relied on a powerful edge computing paradigm. Instead of transmitting raw, high-bandwidth sensor data to a centralized server—a process that introduces unacceptable latency and raises significant privacy concerns in healthcare settings—all critical data processing was performed directly on the robot's internal computer. This onboard processing unit featured a high-performance multi-core processor and a dedicated graphics processing unit optimized for parallelizing the complex neural network computations required for real-time computer vision and agent modeling. The edge computing approach ensured that the trust assessment pipeline operated with minimal delay, allowing the robot to react almost instantaneously to changes in the human's behavioral cues. Furthermore, by processing the video and audio streams locally and only storing the anonymized, extracted feature variables, the system strictly adhered to medical data privacy regulations, ensuring that no personally identifiable information of the participating nursing staff was ever transmitted over the network [11].

4.2 Data Collection and Integration

The seamless integration of data streams from the various sensor modalities was a critical engineering challenge in implementing the experimental setup. The data collection architecture was built upon a robust, publisher-subscriber messaging middleware, which provided a standardized protocol for inter-process communication. This architecture allowed the different software modules—including the navigation stack, the computer vision pipeline, the audio processing node, and the agent modeling engine—to operate concurrently and share data asynchronously. To ensure the temporal alignment of the disparate sensor streams, a highly precise time-synchronization protocol was implemented across all hardware components. Every data packet, whether a LiDAR scan, a video frame, or a button press event on the touch screen, was stamped with a highly accurate microsecond timestamp at the moment of acquisition. This rigorous temporal synchronization was absolutely essential for calculating dynamic features like interaction latency and for accurately correlating a specific gaze pattern with a simultaneous change in interpersonal distance [12].

The continuous stream of synchronized, multi-modal feature variables served as the input for the computational agent model. The agent model was implemented as a dynamic Bayesian network, chosen for its powerful ability to handle temporal dependencies and to reason effectively under uncertainty. Within this network, the human's internal level of trust was represented as a hidden state variable that evolved continuously over time. The extracted behavioral cues—Gaze Fixation Ratio, Minimum Interaction Distance, and Command Response Latency—were represented as observable nodes that were probabilistically linked to the hidden trust state. The specific probabilistic weights governing these linkages were initialized based on extensive literature regarding human non-verbal behavior and were subsequently refined during a preliminary calibration phase with a separate group of pilot participants. As the experimental scenarios unfolded, the agent model continuously updated its estimation of the human's trust level based on the incoming stream of behavioral observations.

The ultimate output of the entire data integration and processing pipeline was a continuous probability score predicting the likelihood that the human participant would accept the next task delegation request from the robot. This prediction was generated by passing the current estimate of the internal trust state through a utility evaluation function within the agent model. The utility function mathematically weighed the perceived benefits of delegating the task against the perceived risks, which were inversely proportional to the current trust level. The data collection system rigorously logged the continuously fluctuating predicted probability of task acceptance alongside the actual, binary ground-truth decisions made by the participants during the interaction scenarios. This meticulously synchronized and comprehensive dataset formed the empirical basis for the subsequent statistical analysis, enabling a detailed evaluation of the agent model's predictive accuracy and the relative impact of the different behavioral trust cues on the final outcome of human-robot collaboration.

5. Results and Comprehensive Analysis

5.1 Trust Cue Impact on Acceptance

The empirical data collected from the simulated hospital scenarios provided a rich foundation for analyzing the intricate relationship between non-verbal behavioral cues and the ultimate decision of task acceptance. A comprehensive statistical analysis was conducted on the extracted feature variables to determine their individual and collective impact on the probability of a healthcare worker accepting a task from the logistics robot. The results unequivocally confirmed the core hypothesis of the research: implicit behavioral cues act as highly reliable, observable proxies for internal trust dynamics and are powerfully predictive of subsequent collaborative behavior. Among the various features analyzed, visual attention dynamics exhibited the strongest statistical correlation with task outcome. Participants who ultimately rejected the robot's assistance demonstrated a significantly higher average Gaze Fixation Ratio during the preceding interaction phase compared to those who accepted the task. This intense visual monitoring clearly indicated a heightened state of apprehension and a lack of cognitive trust in the robot's autonomous capabilities, compelling the human to continuously verify the robot's actions and location.

Proxemic behaviors also revealed compelling patterns that strongly differentiated instances of task acceptance from instances of rejection. The analysis of the Minimum Interaction Distance showed that when the robot was operating in the low-reliability experimental blocks—thereby inducing lower trust—participants consistently maintained a larger spatial buffer. When prompted with a task delegation request, participants who maintained a larger physical distance were statistically much more likely to reject the request and perform the task manually. Furthermore, the Approach Velocity metric demonstrated that hesitant, slow approaches toward the robot were heavily correlated with an ultimate refusal to collaborate. These proxemic variations underscore the psychological reality that healthcare professionals implicitly treat unreliable robotic systems as potential physical hazards, prioritizing their personal safety and spatial comfort over the potential operational benefits of task delegation. The data strongly suggests that monitoring interpersonal distance provides a continuous, highly sensitive barometer of the human's comfort level and willingness to engage with the automated system.

Interaction latency, quantified through the Command Response Latency feature, proved to be another critical predictor, particularly in scenarios characterized by high cognitive load. When participants were occupied with complex simulated nursing tasks, their response times to the robot's prompts naturally increased. However, when controlling for this baseline workload, anomalous spikes in response latency were strongly associated with task rejection. These extended delays suggested that the participant was engaging in a complex internal calculation, weighing the immediate time cost of performing the task manually against the perceived risk and potential future time cost of the robot failing to execute the task correctly. In instances where trust had been degraded by prior robotic errors, this internal calculation resulted in prolonged hesitation followed by a definitive rejection. The combined analysis of gaze, proxemics, and latency validates the multi-modal approach of this research, demonstrating that while each cue provides valuable independent information, their integrated analysis paints a comprehensive and highly predictive picture of the human's collaborative intent.

5.2 Agent Modeling Performance Validation

The most critical evaluation of this research was determining the efficacy of the proposed computational agent model in synthesizing the extracted behavioral cues and accurately predicting task acceptance in real-time. To rigorously assess its performance, the predictions generated by the dynamic Bayesian network agent model were compared against the actual ground-truth decisions recorded during the experimental scenarios. The dataset was partitioned into robust training and testing subsets to ensure that the evaluation metrics reflected the model's true ability to generalize to unseen interactions and novel participant behaviors. The primary metrics utilized for this evaluation were predictive accuracy, precision, and recall, which together provide a comprehensive understanding of the model's performance in correctly identifying both instances of successful collaboration and instances of critical task rejection [13].

The results of the performance validation clearly demonstrated the superior predictive capabilities of the agent modeling framework. The dynamic agent model achieved a remarkably high overall predictive accuracy, significantly outperforming traditional, static machine learning baseline models that attempted to map the raw sensor data directly to the binary outcome without mediating through an internal trust state. The superiority of the agent model was particularly evident in its ability to adapt to the profound individual variability observed among the healthcare professionals. Because the agent model continuously updated its internal parameters based on the specific temporal sequence of an individual's behaviors, it could effectively calibrate itself to a participant's unique baseline tendencies. For example, if a participant naturally exhibited a high baseline Gaze Fixation Ratio due to a naturally cautious personality, the dynamic model adjusted its thresholds to prevent false alarms, whereas static baseline models consistently misclassified these individuals as exhibiting extremely low trust.

Table 3: Performance Metrics of the Agent Model in Predicting Task Acceptance

Predictive Model Configuration	Overall Accuracy	Precision (Task Acceptance)	Recall (Task Acceptance)
Static Baseline (Direct Mapping)	71.4%	73.2%	68.5%
Agent Model (Single Cue - Gaze Only)	78.6%	80.1%	75.4%
Comprehensive Agent Model (All Cues)	89.2%	91.5%	88.7%

The detailed analysis of the performance metrics, as highlighted in the evaluation data, underscores the critical importance of multi-modal feature fusion within the agent architecture. When the agent model was constrained to utilize only a single behavioral stream, such as relying exclusively on visual attention dynamics, its predictive accuracy was noticeably reduced. This reduction occurred because single behavioral cues can occasionally be ambiguous or context-dependent; a participant might look intently at the robot not out of distrust, but simply out of curiosity regarding its mechanical design. However, when the comprehensive agent model integrated gaze, proxemics, and interaction latency simultaneously, it effectively cross-validated the behavioral signals, filtering out the noise and resolving ambiguities. The high precision and recall scores achieved by the comprehensive model confirm its reliability in practical settings. By successfully predicting task acceptance with a high degree of confidence based purely on implicit human-robot trust cues, the proposed agent modeling framework provides a powerful, validated tool for the next generation of adaptive, socially intelligent automation in healthcare [14].

6. Conclusion and Future Directions

6.1 Summary of Findings

The deployment of autonomous logistics robots holds immense promise for alleviating the critical pressures facing modern healthcare systems, yet their success is inextricably linked to the complex dynamics of human-robot trust. This comprehensive research has successfully demonstrated that human trust in a robotic system is not an abstract, unmeasurable concept, but rather a dynamic psychological state that constantly manifests through observable, non-verbal behavioral cues. Through rigorous experimentation in a high-fidelity simulated hospital environment, this study empirically validated that visual attention dynamics, proxemic variations, and interaction latency are highly reliable indicators of a healthcare worker's willingness to collaborate with an automated assistant. The fundamental achievement of this work is the development and validation of an advanced computational agent modeling framework capable of synthesizing these disparate behavioral streams in real-time. By representing the human user as a rational agent with a dynamically updating internal trust state, the model effectively bridges the gap between raw sensor data and high-level predictive insights.

The results clearly indicate that the multi-modal agent model significantly outperforms traditional, static analytical approaches in forecasting whether a nurse will accept or reject a delegated logistical task. The model's ability to account for temporal dependencies and adapt to individual baseline behaviors ensures robust performance despite the inherent noise and variability of human interaction in high-stress environments. The strong statistical correlations identified between specific cues—such as prolonged gaze fixation and increased interpersonal distance—and subsequent task rejection provide a concrete foundation for understanding the mechanics of collaborative failure. Ultimately, this research proves that robotic systems can be equipped with the capacity to "read the room," continuously assessing the psychological comfort of their human counterparts and predicting collaborative outcomes before they occur. This capability transforms the logistics robot from a mere mechanical tool into a socially aware collaborative partner.

6.2 Practical Implications and Limitations

The practical implications of predicting task acceptance through real-time trust assessment are profound for the future of healthcare robotics. By integrating this agent modeling framework into the control architecture of hospital logistics robots, developers can create systems that dynamically adapt their behavior to foster trust and ensure utilization. For instance, if the model predicts a high probability of task rejection due to dropping trust levels, the robot can proactively alter its interaction strategy. It might slow its approach velocity, increase the physical distance it maintains from the user, or provide more transparent auditory explanations of its intended actions, thereby attempting to mitigate apprehension and rebuild trust before the collaboration fails. This adaptive capacity is essential for ensuring that expensive robotic assets are actually utilized by busy medical staff, thereby realizing the anticipated improvements in operational efficiency and reductions in human workload. Furthermore, the continuous data streams generated by this system can provide hospital administrators with invaluable insights into how specific robotic deployments are being received across different wards, enabling targeted training interventions and workflow optimizations.

Despite these significant advancements, the current study acknowledges several limitations that must be addressed in future research. Primarily, while the simulated hospital environment provided excellent experimental control and physical safety, it cannot perfectly replicate the chaotic, high-stakes reality of an active medical ward where genuine patient outcomes are at risk. The baseline stress levels and the consequences of robotic failure in a real hospital may alter the manifestation of trust cues in ways not fully captured in the simulation. Additionally, the current model focuses on dyadic interactions between a single human and a single robot. Future iterations must expand the agent modeling architecture to account for multi-agent scenarios, where a robot must navigate the complex social dynamics of multiple healthcare workers simultaneously, balancing competing trust signals and prioritizing interactions based on urgency and operational hierarchy. Addressing these complexities will be critical for transitioning this highly promising predictive framework from controlled simulations to the complex, indispensable reality of everyday clinical operations.

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