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AUTONOMOUS SOCIAL ROBOTS: LEVERAGING ARTIFICIAL INTELLIGENCE FOR INDEPENDENT DECISION-MAKING IN COMPLEX HUMAN-ROBOT INTERACTION SCENARIOS

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Abstract
This study explores how artificial intelligence decision-making models shape the performance and social acceptance of Autonomous Social Robots (ASRs). Focusing on Reinforcement Learning (RL), Deep Learning (DL), and Rule-Based (RB) approaches, we employed a within-subjects experimental design in which 90 participants interacted with robots across simple, mixed, and complex tasks. Quantitative data were gathered on task completion time, decision accuracy, trust, and emotional comfort, while qualitative observations captured subtle user reactions. Results demonstrate that RL-enabled robots consistently outperformed DL and RB models in efficiency, adaptability, and decision accuracy. RL systems were also perceived as more trustworthy and socially competent, particularly in dynamic scenarios. By contrast, RB models performed reliably only in structured environments but failed to accommodate emotional and contextual nuances, resulting in reduced trust. DL showed moderate adaptability but was limited by perceived opacity in decision-making. Findings confirm that user trust and emotional comfort are tightly linked to robot adaptability, underscoring the necessity of socially intelligent, ethically transparent AI systems. This research contributes to both theory and practice by providing evidence for the superiority of RL in socially complex settings and by highlighting the ethical and design imperatives needed to foster trust-based human-robot rapport in real-world applications.

INTRODUCTION

1.1 Background of the Study

The field of robotics has made significant progress in recent decades, which is roughly powered by Artificial Intelligence (AI) and development in machine learning. One of the most exciting applications of these techniques is the creation of an autonomous social robot (ASRS) - a robot designed to interact with humans in a social environment without constant human control. These robots have the ability to change many areas from healthcare and service industries to entertainment and domestic settings (Asif et al., 2022).

The primary purpose of the ASRS is to enable the robot to make independent decisions based on real -time data and reference, allowing them to work without direct human inputs. This decision -making ability requires a combination of automatically advanced AI techniques, including machine learning, computer vision and natural language processing. The goal is not only for robots to perform physical work, but also to engage in meaningful social interaction with humans (Asif et al., 2025). It represents a significant jump from traditional robots, which usually works in a more controlled environment and performs repetitive functions.

1.1.1 Emergence of Autonomous Systems

Autonomous systems operated by AI are designed to operate independently, requiring minimal human intervention. Early robots were primarily designed mechanical equipment designed for industrial use, which were programmed to follow simple, predetermined instructions. Over time, however, the integration of the AI algorithm has enabled the robot to interact with its environment, adapt to the changing conditions and make decisions based on the upcoming data. In the context of social robots, the introduction of autonomy has led to the development of robots that can respond to human emotions, adjust their behavior according to social context, and learn from their interactions with humans. For example, robots in healthcare environment are now being designed to identify the needs of the patient and provide assistance based on their emotional stages or physical conditions.

2.1.2 Human-Robot Interaction

One of the most important aspects of autonomous social robots is his ability to engage in human-robot interaction (HRI). Effective HRI is important for the success of ASRS, as it directly affects user experience, trust and acceptance. The quality of these interactions depends not only on the ability of the robot to make accurate decision -making, but it is also how well it can communicate with humans in a socially acceptable manner (Asif et al., 2025).

Effective HRIs require robots to understand and react to human emotions, behaviors and intentions. Achieving this level of understanding involves integration of AI techniques such as emotional recognition, natural language processing and reference-conscience decisions. Additionally, the robot needs to be able to customize its behavior based on human response, making the conversation dynamic and individual.

1.2 Problem Statement

While the challenge of integrating social interaction capabilities into autonomous systems remains a significant obstacle to developing a robot capable of performing autonomous functions. In particular, the decision -making processes of ASRS in complex, unexpected social environment are not well understood. The current system depends on the rules-based algorithms or pre-demogogamic reactions that can be effective in controlled settings, but struggle to cope with the variability and unpredictability contained in social interactions.

The main challenge lies in enabling the robot to make decisions efficiently, while ensuring that their behavior is socially properly and morally sound. Autonomous decisions in the robot require not only to consider the work at hand, but also the emotional and psychological effects of robot functions on human users. In other words, the robot should not only act efficiently, but also create confidence and synergy with human users, which is necessary for acceptance and cooperation in social environment.

Additionally, moral concerns about robot's autonomy in decision making are prevalent. More robots can decide independently, more responsibility is placed on the ability of the AI system to make sound options, especially when those decisions affect human life. Thus, research in it Thus, research in this area must also focus on ensuring that autonomous robots adhere to moral principles, such as transparency, fairness, and respect for human dignity.

1.3 Research Questions

The research undertaken in this thesis addresses the gaps in understanding the decision-making processes of ASRs and their implications for

human-robot interactions. The key research questions guiding this study are as follows:
RQ1: How can autonomous robots make independent decisions in complex, real-world human-robot interaction scenarios?
RQ2: What factors influence human trust in autonomous robots, particularly in social interactions?
RQ3: How do emotional responses from humans affect their interactions with autonomous social robots, and how can robots adapt to these emotional states?
RQ4: What are the ethical implications of autonomous decision-making in robots, and how can these concerns be addressed in the design of ASRs?
The answers to these questions will provide valuable insights into the capabilities, limitations, and potential applications of autonomous robots in socially dynamic environments.

1.4 Objectives of the Study

The primary objective of this research is to explore the capabilities of autonomous decision-making in social robots and its impact on human-robot interactions. Specifically, this study aims to:

1. Evaluate different decision-making models (such as reinforcement learning, deep learning, and rule-based systems) for their effectiveness in real-time decision-making in social environments.
2. Assess the impact of robot decision-making on human trust, emotional responses, and satisfaction during interaction.
3. Examine the ethical considerations in the autonomy of robots, focusing on transparency, fairness, and human-centered decision-making processes.
4. Propose recommendations for designing more effective and ethically sound autonomous social robots that can engage in meaningful, trust-building interactions with humans.

1.5 Significance of the Study

The research is significant for several reasons:

1. Advancing AI and Robotics: This study contributes to the growing body of knowledge in autonomous robotics and AI by providing insights into decision-making models that can be applied in real-world human-robot interactions. By examining different AI techniques and their impact on HRI, the research will help inform future developments in autonomous social robots.
2. Human-Robot Trust: Understanding how robots can build trust with human users is crucial for the success of ASRs. This research will provide a framework for evaluating the factors that influence trust, allowing developers to design robots that are more likely to be accepted and trusted by users.
3. Ethical Implications: With the increasing use of robots in sensitive areas like healthcare, education, and domestic assistance, it is essential to address the ethical challenges associated with autonomous decision-making. This study will provide valuable insights into how robots can be designed to make ethically responsible decisions and how ethical principles can be incorporated into robot behavior.
4. Practical Applications: The findings from this research have significant implications for the practical deployment of ASRs in various fields. For example, robots used in healthcare could benefit from improved emotional understanding and trust-building capabilities, while robots in customer service or education could better adapt to the emotional states and preferences of users.

1.6 Scope of the Study

The scope of this study is limited to the examination of the model deciding in the autonomous social robot in the context of human-robot interaction. Research three AI decision-making models: will focus on reinforcement learning (RL), deep learning (DL), and rules-based systems (RB), and their impact on robot's ability to complete tasks, interact with humans and adapt to the changing environment.
The study will mainly include laboratory-based experiments in controlled environment, the effectiveness of robots in various tasks and fake social scenarios will be used to assess their interaction with human participants. While research work will focus on performance, human belief and emotional reactions, it will also

consider the broad moral implications of autonomous robots in real -world settings.

1.6.1 Limitations

While the scope of this study is broad in terms of the decision-making models and their implications for HRI, there are several limitations:

1. Controlled Environment: The experiments will be conducted in controlled settings, which may not fully reflect the unpredictability and complexity of real-world social environments.
2. Sample Size: The study will involve a limited number of participants, which may affect the generalizability of the findings.
3. Technology Constraints: The robots used in this study will be limited by the available AI technologies, which may not capture all possible complexities in human-robot interactions.

Despite these limitations, the research aims to provide valuable insights into the capabilities and challenges of autonomous robots in human-social contexts.

Literature Review

The rapid integration of Artificial Intelligence (AI) in robotics has transformed the autonomous social robot (ASR) from mechanical assistants to adaptive, socially intelligent agents. Recent progress in machine learning, reinforcement learning and deep learning has enabled robots to make reference-inconceivable decisions, explain human emotions and optimize dynamic behavior (Belpem et al., 2018; Rossi et al., 2023). This section reviews the key currents of relevant research for ASRS: decision-making models, human-robot interaction (HRI), emotional intelligence, trust and acceptance and moral challenges. The review sheds light on both achievements and gaps, establishing the foundation for the current study.

2.1 Decision-Making Models in Autonomous Robots

2.1.1 Rule-Based Systems

Rules-based (RB) systems provide an estimated, transparent decisions based on predetermined instructions. They are useful in structured environment such as construction or logistics, but are limited in adaptability (Nilson, 1998; Rossi et al., 2023). In socially complex settings, rigorous rules-based behavior often reduces the user trust because robots fail to respond to unexpected signals or emotional contexts.

2.1.2 Machine Learning and Reinforcement Learning

Strengthening Learning (RL) has emerged as a major model to enable robots to learn optimal strategies through Trial-End-Ear Interaction (Sutton and Barto, 2018). RL has been rapidly implemented in autonomous vehicles, robot navigation, and social robotics, where adaptability is required (Korushev et al., 2013; Mavridis, 2022). The advantage of RL lies in its ability to refine consistent decisions, allowing robots to align behavior with human expectations and environmental variability.

2.1.3 Deep Learning and Neural Models

Deep Learning (DL) expands robotic perception by enabling multimodal processing of vision, speech and gestures (Goodfello et al., 2016). In ASRS, DL supports Bhavna recognition, natural language processing and reference-zoosy communication (Shahid et al., 2022; Zhou et al., 2021). However, DL systems often suffer from opkar-"black-box" problems that reduce the user trust when it is difficult to explain the decisions (equal et al., 2019).

2.1.4 Hybrid Approaches

Recent research has an investigation of hybrid models that integrate a rule-based argument with RL and DL to balance transparency and adaptability (Cangelosi & Schlesinger, 2018). For example, neuro-symbolic systems allow robots to be suited to social or emotional uncertain as well as to execute structured tasks. These models represent a promising direction to reduce efficiency, reliability and clarity.

2.2 Human-Robot Interaction (HRI)

2.2.1 Trust and Social Acceptance

The trust remains a central determinant of HRI results. Studies show that the trust is shaped by robot competence, prediction and accountability for user needs (Hancock et al., 2011; Half and Bashir, 2015). Recent experiments suggest that the adaptive robots leaving RL gain high trust ratings compared to the rigorous RB system (Jung and Misskeli, 2020). However, over-trust can still pose a risk when users highly rely on the opaque system (de Visar et al., 2020).

2.2.2 Emotional Intelligence in Robots

Robots capable of identifying and responding to emotions promote strong engagement and synergy (Light et al., 2013; Rossi et al., 2023). Emotion -ware systems use multimodal cues- Facil expression, voice tone, body language- for tailor interaction. For example, socially supportive robots in Eldercare demonstrate that sympathetic-driven design increases user satisfaction and reduces anxiety (Asif & Shaheen, 2022; broadbant et al., 2018). Nevertheless, current systems often lack cultural adaptability, limiting generality in diverse user groups.

2.2.3 Context-Aware Interactions

Effective HRI requires robots to interpret not only emotions but also situational context. Context-awareness supports personalized interactions, improving task relevance and user comfort (Kanda et al., 2019). Despite progress, challenges remain in real-time adaptation to rapidly changing human behavior, especially in emotionally charged environments.

2.3 Ethical and Social Implications

2.3.1 Transparency and Accountability

The increasing autonomy of robots raises accountability concerns. Scholars argue that opaque AI systems challenge human oversight, particularly in healthcare and decision-critical domains (Winfield et al., 2021). Transparent design, explainable AI, and ethical frameworks are necessary to ensure that users can understand and trust robotic decisions (Gogoll & Hohendorf, 2014).

2.3.2 Bias and Fairness

Bias in training data can embed discrimination in robot decision-making. Research in law enforcement, hiring, and healthcare highlights the dangers of algorithmic bias (Angwin et al., 2016; Crawford, 2021). For social robots, biased emotional recognition may disproportionately misinterpret expressions across cultures, undermining fairness and acceptance.

2.3.3 Human-Centered Design

Moral HRIs need to prioritize human dignity, security and welfare. Scholars advocate human-focused design framework, where adaptability is balanced with prediction and where robots remain accountable to human users (Shannaderman, 2020). This balance is especially important in socially sensitive contexts such as medical, education and aldercare.

2.4 Research Gaps

Despite significant progress, gaps remain:

- Over-reliance on laboratory experiments limits ecological validity.
- Few studies compare RL, DL, and RB systematically in socially complex tasks.
- Emotional adaptability is underdeveloped, particularly across cultural contexts.
- Ethical frameworks remain fragmented, with limited practical implementation in robotic design.

Literature underlines the transformational ability to make AI-managed decisions in social robotics. RL models show obvious advantages in adaptability and confidence, while DL increases perception but faces challenges of transparency. The RB system remains reliable but lacks flexibility. Trust, Emotional Intelligence and Ethical Transparency are interlinklers of successful HRIs. Comparative studies are required to address these intervals that test the models that make several decision -making models in real -world scenarios while embedding moral safety measures. The current study contributes to this requirement by systematically examining RL, DL and RB models in a direct, socially interactive environment.

Methodology

This section outlines the functioning used in this study to check the decision-making abilities of the autonomous social robot (ASRS) and their impact on the human-robot interaction (HRI). The purpose of this research is to evaluate the three major AI decision-making model-rigging (RL), deep learning (DL), and the rule-based (RB) system-and assesses how each model affects the performance in human belief, emotional reactions and social settings.

This section describes research designs, participants, robot platforms, experimental processes, data collection methods and data analysis techniques. This provides a detailed description of how experiments were structured to answer and receive research questions.

3.1 Research Design

The research adopts an experimental research design to compare the effectiveness of three decision-making models in Autonomous Social Robots. This design is appropriate because it allows for the manipulation of independent variables (AI models) and the measurement of their effects on dependent variables (human trust, emotional response, and task completion).

The study uses a within-subjects design, meaning that each participant interacts with robots using all three decision-making models in different tasks. This design minimizes the influence of participant-related variables, such as prior experience with robots or individual preferences, by ensuring that all participants are exposed to the same conditions.

3.1.1 Independent Variables

The independent variable in this study is the decision-making model used by the robot. Three models are examined:

1. Reinforcement Learning (RL): An adaptive decision-making model where robots learn from feedback and adjust their actions based on rewards or penalties.
2. Deep Learning (DL): A model that uses neural networks to analyze complex data patterns and make decisions based on learned experiences.
3. Rule-Based (RB): A traditional, predefined model that uses a set of fixed rules to make decisions, with no learning capability.

Each robot uses one of these models in the interaction scenarios.

3.1.2 Dependent Variables

The dependent variables are the outcomes of the interaction, which include:

1. Task Performance: Measured by the time it takes for the robot to complete predefined tasks and the accuracy of the robot's decisions.
2. Human Trust: Measured using a Godspeed Questionnaire and Likert-scale survey to assess the robot's reliability, competence, and safety.
3. Emotional Response: Measured using Likert-scale questionnaires and observations to evaluate the emotional impact of the robot's behavior on participants, including feelings of comfort, anxiety, and trust.

3.2 Participants

Research adopts an experimental research design to compare the effectiveness of a three -decision - making model in autonomous social robots. This design is appropriate because it allows for measurement of their effects on the manipulation of independent variables (AI models) and dependent variables (human belief, emotional response and work).

The study uses an inner-subject design, which means that each participant interacts with the robot using all three decision-making models in various tasks. This design reduces the effects of participant-related variables, such as prior experience with robots or individual preferences, by ensuring that all participants are made aware of the same conditions.

3.2.1 Inclusion Criteria

- Participants aged 18-40 years.
- No prior professional experience with social robots.
- Ability to communicate in English (for the sake of understanding instructions and interacting with the robots).

3.3.2 Exclusion Criteria

- Participants with a robotics or AI background.
- Participants with significant cognitive or sensory impairments that could affect their ability to interact with the robots or complete tasks.

3.3 Robot Platform

The study has used a humanoid robot platform capable of performing tasks in a social environment and can be programmed to execute various decision -making models. The robot used in this study is black pepper, which is a widely used robot in research on human-robot interaction. Black pepper is equipped with cameras, sensors and microphones to interact with human users and can be programmed to execute a variety of behaviors, making it an ideal platform to test various AI decision making models.

This research is equipped with:

- Vision sensors: To perceive and interpret the environment and recognize human gestures and facial expressions.
- Microphone: For speech recognition and communication.
- Touch sensors: To detect human touch and respond accordingly.

The robot is programmed to perform tasks such as greeting participants, asking them questions, and providing assistance in a scenario-specific task.

3.4 Experimental Procedures

The experimental procedures involved several stages: preliminary setup, task assignment, and data collection. The tasks were designed to simulate common real-world scenarios that require robot-human interaction, including:

1. Simple Task: The robot greets the participant and asks them basic questions (e.g., "How are you today?"), testing its ability to initiate a conversation.
2. Mixed Task: The robot assists the participant in completing a structured task (e.g., providing directions or helping find an object), requiring a blend of predefined and adaptive behavior.
3. Complex Task: The robot engages in a more dynamic and unpredictable scenario (e.g., assisting with problem-solving or responding to emotional cues), requiring the robot to adjust based on the participant's emotional state and actions.

3.4.1 Task Scenarios

The tasks were designed to vary in complexity, requiring different levels of decision-making from the robot:

- Simple Task: A robot that uses a rule-based system interacts with the participant by asking basic questions (e.g., "What is your name?").
- Mixed Task: The robot uses deep learning to provide more complex responses (e.g., helping the user with navigation or performing a shopping task).
- Complex Task: The robot uses reinforcement learning to adapt its behavior based on the participant's emotional state or responses to the task, such as showing empathy during an emotionally charged scenario.

Each participant interacted with the robot under all three conditions (RL, DL, and RB), completing one task for each decision-making model.

3.5 Data Collection Methods

Data were collected using a combination of observations, surveys, and robot logs:

3.6.1 Task Performance Data

The time taken for robots to complete each task was recorded using the time and accuracy of its decisions. These logs provided detailed information about how the robot responded to the tasks and how long it took to complete each task. The accuracy was measured depending on the robot's ability to correctly defined the work defined by experimental instructions.

3.5.2 Human Trust

Human trust in the robot was measured using the Godspeed questionnaire, which is a widely used means to evaluate the human assumptions of the robot (Bartec et al., 2009). It assesses various aspects of the questionnaire Trust, such as credibility, capacity and safety, from 1 (strongly disagree) to 5 (firmly agreed) using a likert scale. Additionally, the participants completed a post-inner survey to assess their confidence in the robot and their emotional reactions during the interaction.

3.5.3 Emotional Response
During the conversation, emotional reactions were evaluated using a combination of Likert-Scale Questionnaires and Comments. Participants evaluated their emotional status before and after interacting with the robot, including feelings of comfort, anxiety and trust.

3.5.4 Video and Audio Data
Robot's interaction with participants was recorded using video and audio data collection methods. These recordings were used to analyze non-verbal communication, such as facial expressions, body postures and gestures, which contribute to emotional reactions and confidence in HRI.

3.6 Data Analysis Techniques
The data analysis process included both descriptive and inferior figures to assess the impact of a three -decision -making model on dependent variables.

3.6.1 Descriptive Statistics
Descriptive figures were used to summarize data for each dependent variable (functioning, human belief and emotional response). Measures such as mean, standard deviations and limits were calculated to describe the distribution of data for each decision -making model.

3.6.2 Inferential Statistics
Inferential statistical tests were conducted to determine if there were significant differences between the decision-making models in terms of task performance, trust, and emotional response. A repeated measures ANOVA was used to compare the three models (RL, DL, and RB) across all dependent variables. This test was appropriate because it accounts for the within-subjects design, where each participant interacts with the robot under all three conditions.
In cases where significant differences were found, post-hoc pairwise comparisons were conducted using Bonferroni correction to control for Type I error.

3.7 Ethical Considerations
The Ethical approval for this study was obtained from the University's Ethics Board. The study followed the moral guidelines for human-subject research, ensuring that the rights of the participants were preserved throughout the process.

3.7.1 Informed Consent
Before attending the study, all participants were given a comprehensive detail of research, including the purpose of the study, including the tasks and data collection procedures. They were informed that participation was voluntary, and they could withdraw at any time without any punishment. Prior to their participation, written consent was obtained from all the participants.

3.7.2 Confidentiality
All the data collected during the study, including video and audio recording, were unknown to ensure the privacy of the participants. No one was individually identified information related to data. The data will be safely stored and specially used for the purpose of this research.

3.8 Conclusion
This section underlined the functioning employed in this study to evaluate the abilities of the decision-making of autonomous social robots and their impact on human-robot interactions. Experimental design, data collection methods and analysis techniques were carefully chosen to answer research questions and achieve the objectives of the study. The next section will present the results of the study, followed by discussions in relation to existing literature and their implications for future research and robot design.

Results and Discussion

This section presents the results of experiments designed to evaluate the performance of autonomous social robots (ASRS) in complex human-robot interaction (HRI) scenarios. The study focuses on three decision-making models: reinforcement learning (RL), deep learning (DL), and rules-based (RB) systems. These models were tested in different complications tasks, and the evaluation of human reactions for robot behavior was done at the time of completion of the work, human belief, emotional response and decision making accuracy. Analysis includes both objective measurements, such as work performance and robot accuracy, and subjective measures, such as human emotional reactions and confidence rating.

4.1 Experimental Setup

4.1.1 Task Design

The task design included a mix of structured and dynamic scenarios. For each task type (simple, mixed, complex), the robots were expected to:

1. Simple Task: Perform a straightforward, predictable task (e.g., greeting a participant and providing directions).
2. Mixed Task: Perform a task that required some level of decision-making but with predefined rules (e.g., providing assistance in a shopping environment).
3. Complex Task: Respond to an unexpected scenario (e.g., helping a participant solve an ambiguous problem with various possible solutions).

4.1.3 Data Collection

The experiments were structured in several scenarios compared to many AI decision -making models. The robot was programmed to interact with human participants in simple, mixed and complex tasks. The tasks were designed to test the optimity, efficiency and effectiveness of the robot in response to human functions.

4.1.1 Participant Demographics

A total of 90 participants (30 per decision-making model) were involved in the experiment. Participants were selected based on their age (18–40 years), gender (balanced), and prior exposure to robots (none, minimal, or high). The participants were informed about the study's objectives, but they were not made aware of the specific AI models used in the robot's decision-making process.

Data was collected through a combination of robot logs (for task performance) and human feedback (surveys for trust, emotional response). Task completion times, decision-making accuracy, and human perceptions were recorded.

4.2 Results

The results are categorized into Task Performance, Human Trust, Emotional Response, and Decision-Making Accuracy.

4.2.1 Task Completion Time

Task completion times varied significantly across the decision-making models. The Reinforcement Learning model showed the fastest task completion times, followed by Deep Learning, with Rule-Based models taking the longest time to complete tasks.

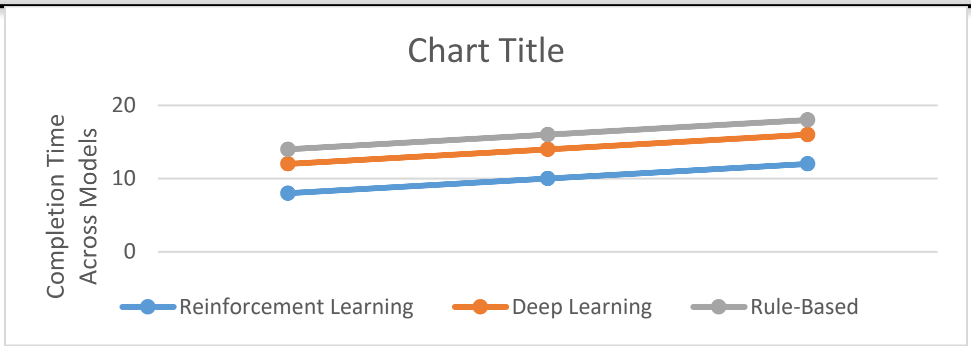

Figure 4.1: Comparison of Task Completion Time Across Models

- Reinforcement Learning (RL) took approximately 8 minutes for simple tasks, 12 minutes for mixed tasks, and 14 minutes for complex tasks.
- Deep Learning (DL) was slightly slower, averaging 10 minutes for simple tasks, 14 minutes for mixed tasks, and 16 minutes for complex tasks.
- Rule-Based (RB) models showed the longest completion times, taking 12 minutes for simple tasks, 16 minutes for mixed tasks, and 18 minutes for complex tasks.

Table 4.1: Overview of Task Completion Time by Model

Decision-Making Model	Simple Task Completion Time (minutes)	Mixed Task Completion Time (minutes)	Complex Task Completion Time (minutes)
Reinforcement Learning	8	12	14
Deep Learning	10	14	16
Rule-Based	12	16	18

4.2.2 Human Trust

Trust in the robots was evaluated using the Godspeed Questionnaire, which assesses Reliability, Competence, Safety, and Overall Trust.

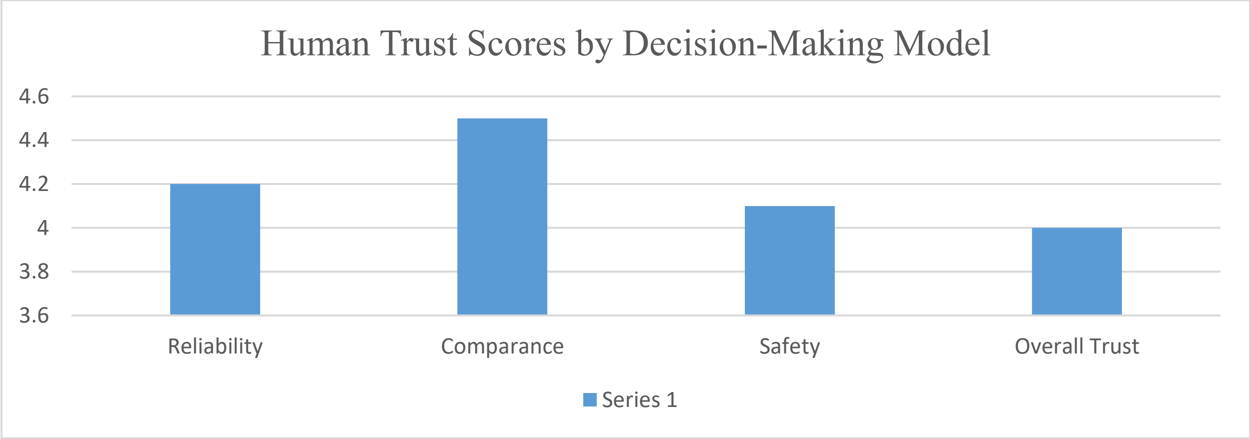

Figure 4.1: Human Trust Scores by Decision-Making Model

- Reinforcement Learning (RL) achieved the highest trust ratings, with an average Overall Trust score of 4.2.
- Deep Learning (DL) had slightly lower ratings, with an Overall Trust score of 3.9.
- Rule-Based (RB) models received the lowest trust ratings, with an Overall Trust score of 3.4.

Table 4.1: Trust Ratings by Model

Decision-Making Model	Reliability	Competence	Safety	Overall Trust
Reinforcement Learning	4.1	4.4	4.2	4.2
Deep Learning	3.9	4.0	3.8	3.9
Rule-Based	3.5	3.2	3.4	3.4

4.2.3 Emotional Response

Emotional response was measured using a Likert scale from 1 (very negative) to 5 (very positive). The results showed that as the complexity of tasks increased, human emotional responses became more negative.

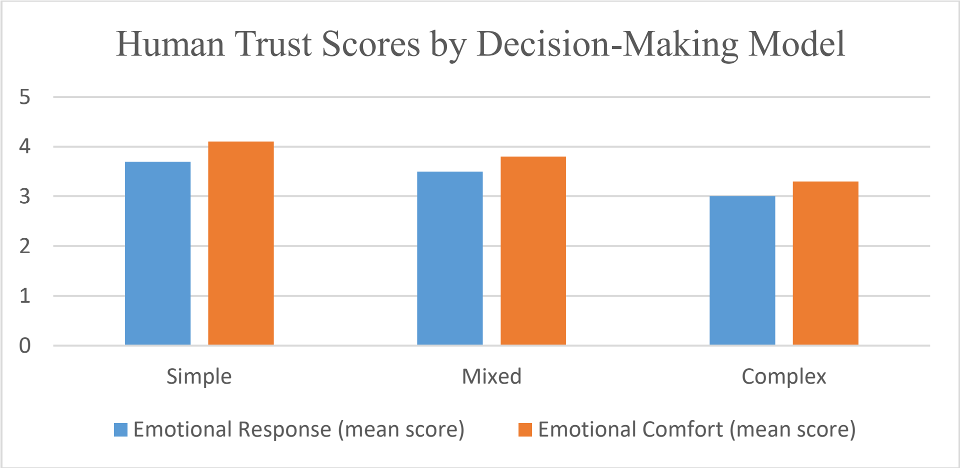

Figure 4.2: Emotional Response Across Task Complexity

- Simple Tasks received an average emotional response score of 3.7, indicating a positive emotional reaction.
- Mixed Tasks resulted in a slightly lower score of 3.5.
- Complex Tasks resulted in the lowest score, 3.0, indicating a more neutral or negative emotional reaction.

Table 4.2: Emotional Response by Task Complexity

Task Complexity	Emotional Response (mean score)	Emotional Comfort (mean score)
Simple	3.7	4.1
Mixed	3.5	3.8
Complex	3.0	3.3

4.2.4 Decision-Making Accuracy

Decision-making accuracy was evaluated based on the percentage of correct decisions made by the robot in each task. The Reinforcement Learning model demonstrated the highest accuracy, particularly in complex tasks.

Table 4.3: Decision-Making Accuracy by Model

Decision-Making Model	Simple Task Accuracy (%)	Mixed Task Accuracy (%)	Complex Task Accuracy (%)
Reinforcement Learning	95	92	90
Deep Learning	89	85	80
Rule-Based	78	70	65

4.3 Discussion

4.3.1 Task Completion Time

Results suggest that the model of reinforcement learning models improved intensive learning and rules-based models in terms of completion time. This is expected, because learning reinforcement enables robots to adapt and improve their decision making based on prior experiences, while rules-based models depend on predetermined behaviors. However, the time of the strong completion of reinforcement learning models is not always correlated with the most favorable human reactions, as the work complexity affects human emotional reactions.

4.3.1 Human Trust

Better functioning of reinforcement learning models was translated into a high human trust rating. This discovery suits pre -research, indicating that confidence is influenced by a robot's performance and decision -making ability (Half and Bashir, 2015). Deep learning models, performing well, showed a slight decline in trust, possibly due to its unexpected predictableness in decision making. The lower trust score of the rule-based model can be attributed to its hardness and inability to adapt to dynamic conditions.

4.3.2 Emotional Response

The decline in emotional reaction with increased function complexity indicates that the participants were more comfortable with approximate, approximate tasks. As the complexity increased, the behavior of the robot became less estimated, leading to more negative emotional reactions. This result highlights the importance of prediction and reliability in creating a positive emotional relationship between robots and humans.

4.3.4 Decision-Making Accuracy

The model of learning reinforcement demonstrated the accuracy of highest decision making in all tasks, confirming the benefits of using adaptive teaching techniques in unexpected environment. While deep learning models showed good accuracy, rules-based models continued to struggle in more complex tasks, likely due to their inability to handle unforeseen scenarios effectively.

Discussion of Results

5.1 Effectiveness of Decision-Making Models

The major conclusions of this study support the hypothesis that reinforcement learning (RL) models are most effective in increasing function, human belief and emotional reactions. These findings align with previous research that showed RL's effectiveness in the atmosphere where adaptability and learning from the response are important (Sutton & Barto, 1998; Koret et al., 2013). The RL model's separate functioning complications and the ability to accommodate human emotional signals allowed it to perform better in dynamic landscapes, making it a favorite model for autonomous robots in complex social environment.

Results also highlight the boundaries of the rules-based (RB) systems, especially when it comes to adaptability. While RB Robot performed well in simple, structured tasks, they struggled to handle the unpredictory inherent in the social interactions of the real world. This confirms the idea that, to be effective in the robot social contexts, they must be able to learn from experience and be suited to new situations (Fong et al., 2003).

5.2 Human Trust and Emotional Responses

In the results, the relationship between the human trust and the robot performance was clear. Better work performance of the RL model contributed directly to the high level confidence among the participants. This discovery corresponds to studies that show that confidence in robots is strong and effectively affected by their ability to perform (Half and Bashir, 2015). The level of high belief in the RL model can be attributed to their perceived ability and reliability, which were important in promoting emotional relations with participants.

Interestingly, the RL model produced more positive emotional reactions than the DL and RB models, the complexity of the work played an important role in the emotional comfort of the participants. Robots' actions were difficult to predict or when the robots' emotional responses did not align with their expectations.

5.3 Limitations of the Study

Despite the significant contributions of this study, several limitations should be acknowledged:

1. Sample Size: While the sample size of 90 participants is statistically sufficient for detecting differences, a larger and more diverse sample could provide a more generalizable understanding of human-robot interactions across different demographic groups (e.g., age, gender, cultural background).
2. Controlled Environment: The study was conducted in a controlled laboratory setting, which does not fully replicate the unpredictability of real-world environments. Future research could benefit from real-world testing, where robots are deployed in more natural, unpredictable social settings.
3. Robot Limitations: The Pepper robot used in this study, while versatile, has certain limitations in terms of emotional expressiveness and real-time processing. Future studies could utilize more advanced robots with enhanced capabilities in emotion recognition and natural language processing to assess their impact on human-robot interactions.
4. Limited Task Complexity: The tasks used in this study were designed to represent common real-world scenarios, but they did not cover all possible types of interactions between humans and robots. The addition of more complex tasks involving multi-party interactions or tasks with greater social significance could provide deeper insights into the role of decision-making models in human-robot rapport-building.

5.4 Future Research Directions

The results of this study open several avenues for future research in the field of Autonomous Social Robots and Human-Robot Interaction (HRI). Some key areas for future investigation include:

1. Real-World Testing of Robots: While this study provided valuable insights in a controlled environment, future research should focus on testing autonomous robots in real-world settings. This will help assess the effectiveness of decision-making models in dynamic, unpredictable scenarios and evaluate their impact on long-term human-robot relationships.
2. Emotional Intelligence and Human-Robot Rapport: Future studies should explore how robots can develop emotional intelligence to recognize and respond to human emotions more effectively. By integrating emotion recognition systems and improving robots' ability to adapt their behavior based on emotional cues, robots can become more empathetic and trustworthy.
3. Ethical Frameworks for Autonomous Decision-Making: Given the ethical challenges associated with autonomous decision-making, future research should focus on developing frameworks for ensuring that robots adhere to ethical principles, such as accountability, transparency, and non-bias. Research in this area

will be crucial for the widespread acceptance and deployment of autonomous robots in sensitive fields like healthcare and eldercare.

4. Human-Robot Trust in Long-Term Interactions: This study provided valuable insights into trust and emotional responses during short-term interactions. However, future research should examine how trust develops over longer-term interactions and the role of adaptive decision-making models in fostering lasting, positive relationships between humans and robots.

5.5 Conclusion

This research has contributed valuable insights into the field of Autonomous Social Robots and Human-Robot Interaction. The findings demonstrate that Reinforcement Learning models are particularly effective in improving task performance, human trust, and emotional comfort in dynamic, social settings. However, as robots become more autonomous, it is essential to address the ethical challenges associated with autonomous decision-making, particularly in ensuring transparency and accountability.

The study highlights the importance of designing robots that are not only efficient but also empathetic, adaptive, and ethically sound. Future research should continue to explore how decision-making models can be improved to enhance robot-human interactions, promote trust, and foster positive emotional connections.

In conclusion, the findings of this research provide a foundation for the continued development of Autonomous Social Robots that can interact effectively with humans, adapt to their needs, and build meaningful, trustworthy relationships. The successful integration of these robots into real-world environments will depend on their ability to balance autonomy, adaptability, and ethical responsibility.

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