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Rewarding Trust: How Reward Power Shapes Security Robot Acceptance

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Abstract

As security robots take on more societal roles, public resistance can hinder their effectiveness. This study examines how a security robot's ability to offer rewards ("reward power") affects public acceptance and trust, which is vital for integrating robots into communities. Using a between-subjects experiment with 106 participants, we tested the impact of high versus low reward power through online video interactions. The results showed that reward power significantly increased robot acceptance by fostering trust during initial interactions. This research contributes to the field of human-security-robot interaction by highlighting the importance of reward power in building trust and acceptance. These findings provide design guidelines for improving public trust and acceptance, essential for successful real-world deployments of security robots.

Keywords

security robots, social power, reward, trust, acceptance, human-robot interaction

Introduction

The increasing deployment of security robots has underscored the critical need for public acceptance (Marcu et al., 2023). Security robots are designed to deter unwanted activities through their presence, surveillance, and ability to alert authorities about unauthorized individuals or actions (Ye & Robert, 2024). However, their effectiveness is often compromised by public resistance and skepticism (Marcu et al., 2023). The success of security robots in fulfilling their roles largely depends on their acceptance and the trust they engender among the populations they are meant to protect (Lyons et al., 2021). Consequently, promoting public acceptance has become essential for effectively integrating and operating security robots in community settings.

Recent human-robot interaction (HRI) research has increasingly focused on the role of reward power as a key factor influencing people's responses to robots (Hashemian et al., 2019, 2020; Saunderson & Nejat, 2021). Defined as the ability to control and distribute rewards, reward power has complex, context-dependent effects (French & Raven, 1959; Stojkovic et al., 2003). While it can encourage compliance, it can also lead to negative outcomes such as learned helplessness and resistance if perceived as illegitimate (Tosi et al., 1994). As security robots become more prevalent and gain the power to perform various tasks, examining how their use of reward power affects their acceptance in daily operations is essential. Should they incorporate reward power in their deployment strategies? Could reward power enhance public acceptance and trust?

This study employed a between-subjects design with 106 participants, each viewing online videos of security robots interacting with the public under high vs. low reward power conditions. Findings indicated that reward power significantly increased the acceptance of security robots by fostering trust. This study makes key contributions. First, it underscores the significant role of robot reward power in shaping trust and acceptance. Second, the findings reveal the interplay between reward power, trust, and acceptance, demonstrating that reward power promotes acceptance through its influence on trust. Finally, the results offer design guidelines to enhance public trust and acceptance of security robots.

Related Work

Reward power, one of the five fundamental social power bases identified by French and Raven, is widely studied in human social interactions (French & Raven, 1959). As a fundamental concept in social science, it is pervasive in social relationships and influences daily interactions. This paper focused on reward power for several reasons. First, reward power is among the most important power sources

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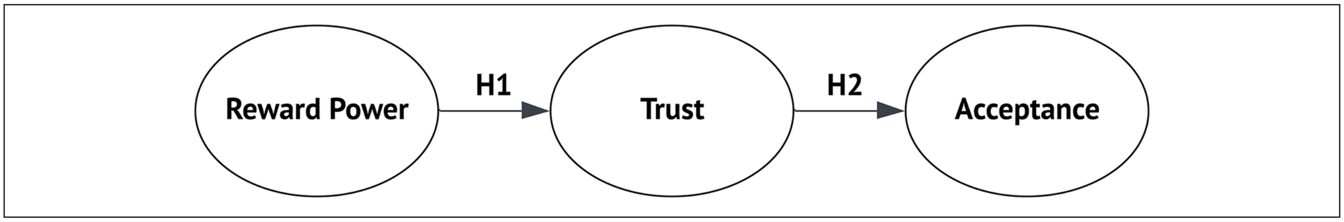

Figure 1. Research hypotheses.

(French & Raven, 1959; Stojkovic et al., 2003). Second, reward power has been shown to impact human behavior and compliance in various contexts. Third, reward is likely particularly relevant to a security context (Tyler, 2003; Tyler et al., 2013). Security agents are often designed with the capability to provide or withhold rewards (e.g., access, privileges, resources) as part of their security and enforcement roles. Understanding how this power dynamic affects public perceptions is crucial.

Research shows reward power has complex and multifaceted effects on relationship dynamics (Rotter, 1964). While rewards often increase compliance, their impact depends on the situation and individuals involved (Rotter, 1964; Stojkovic et al., 2003). In human interactions, reward power is more effective when perceived as legitimate, leading to the justification of behavior. However, illegitimate use can lead to negative outcomes like learned helplessness or resistance (Rotter, 1964; Tosi et al., 1994).

Recent HRI research has explored the role of reward power in persuasion. Hashemian et al. (2019) found that using joke-telling rewards could enhance its persuasiveness. However, their subsequent studies revealed that while reward power increased the number of people persuaded, no significant differences in perceived persuasiveness emerged between power levels (Hashemian et al., 2020). Further research indicated that higher rewards did not necessarily enhance persuasion over repeated interactions (Hashemian et al., 2021). Saunderson and Nejat (2021) found that robots using monetary rewards were more persuasive than those employing punishments. While these findings suggest that robot power can be effective, the specific dynamics and mechanisms involved require further investigation.

Robot acceptance and trust are key metrics for evaluating human-robot relationships, particularly for security robots (Ye & Robert, 2024). Acceptance reflects a person's willingness to use a robot (Davis, 1989), while trust is the willingness to be vulnerable to the robot's actions (Mayer et al., 1995). Factors like robot gender, autonomy, weapon lethality, and reliability influence acceptance and trust (Bliss et al., 2019; Gallimore et al., 2019; Lyons et al., 2021; Ye et al., 2024). However, the effect of a robot's reward power remains unexplored. Understanding how reward power impacts trust and acceptance is crucial for enhancing the design and deployment of security robots, given the importance of robot power in human-robot interaction.

Hypotheses

Two main research hypotheses are proposed to examine the relationship between reward power, trust, and acceptance. This relationship is illustrated in Figure 1.

First, we hypothesize that reward power will positively increase trust in security robots (*H1*). Since security robots are designed to maintain public safety, their use of reward power is likely to be perceived as legitimate. This perceived legitimacy may lead individuals to rationalize the robot's requests, increasing their willingness to be vulnerable to and dependent on the robot—a key component of trust (Mayer et al., 1995).

This hypothesized relationship assumes that the public generally perceives the security robot's use of reward power as legitimate, given its safety-maintaining function. This proposition extends theories of power dynamics and trust formation (Cartwright & Zander, 1960; Tosi et al., 1994) to the novel context of human-robot interactions in security settings. By examining this relationship, we can better understand how reward power influences trust in security robots, potentially informing future design and deployment strategies.

Second, we hypothesize that trust in security robots is positively related to their acceptance (*H2*). Research has shown that trust fosters positive attitudes toward robots, leading individuals to simplify potential risk (Gaudiello et al., 2016; Ghazizadeh et al., 2012). These positive attitudes, in turn, strengthen the intention to use and accept the technology.

Method

A one-factor (reward power: low or high) between-subjects online experiment was conducted. Participants were randomly assigned to one of two conditions. During the procedure, they watched a short video depicting interactions between a security robot and a human interactor, followed by questionnaires about the robot. The study received exempt approval from the Institutional Review Board (IRB). The videos and questionnaires utilized were all provided: https://anonymous.4open.science/r/HFESvideo-0BFC/.

Participants

This study recruited 106 participants from CloudResearch's Connect platform (Hartman et al., 2023). Participants

Figure 2. Security robot in the experimental video.

completed an online questionnaire (average time: 12 min) and received $4 (USD) as compensation. The inclusion criteria required participants to be at least 18 years old, fluent in English, and residing in the United States. Eight participants were excluded from the final analysis for failing the attention check questions, resulting in 98 valid participants (37 male; mean age = 37.4 years, standard deviation [SD] = 10.88 years; minimum age = 19 years, maximum age = 76 years). The sample was diverse in region (14.3% Midwest, 22.5% Northeast, 40.8% South, 22.4% West) and ethnicity (10.2% Asian, 14.3% Black/African American, 1.0% Hispanic/Latin American, 72.4% White, 2% Other, including Multiracial and Peruvian European).

An a priori power analysis (G*Power 3.1) indicated a required sample size of 89 participants to detect a medium effect ($f^2 = 0.15$) with $\alpha = .05$ and .95 statistical power, accounting for one grouping variable and three covariates.

Task and Procedure

Participants completed a three-part study. First, they provided consent and answered pre-questionnaires. Next, they watched one of two versions of a 2-minute video (see Figure 2) featuring the Knightscope K5 security robot. The videos showed a security robot interacting with a visitor at a building entrance. The dialogue was the same in both versions, except the "high reward" video included two extra lines where the robot offered a free meal ticket and a parking voucher.

In contrast, no such rewards were provided in the low-reward condition video. Participants were exposed to one of these two videos. After the video, participants completed questionnaires about the robot they had just seen. Participants could quit the study at any time.

Measures

Manipulation Check Measures. Participants' perceived reward power was measured to assess whether the study's manipulation of reward power was effective. A three-item, 7-point scale questionnaire adapted from Ferdik and Smith (2016) and Stichman (2003) was used.

Control Variables. Gender, age, and expectations of security robots were recorded as control variables. Expectations of security robots were measured using a three-item, 7-point scale adapted from Zhang et al. (2022).

Dependent Variables. Trust was assessed with a three-item, 7-point Likert scale adapted from Robert et al. (2009), and acceptance with a four-item, 7-point questionnaire adapted from Ye et al. (2024).

Results

In this section, we present the results of our study. The analysis was conducted using R. *All key assumptions—homogeneity of variance, normality, parallel slopes, and*

Table 1. Correlation Matrix.

Variable	Mean	*SD*	Reliability	1	2	3	4	5	6
1. Reward	0.52	0.50	NA	(NA)					
2. Gender	0.38	0.49	NA	−0.05	(NA)				
3. Age	37.38	10.88	NA	0.00	−0.12	(NA)			
4. Expectations	3.99	1.42	0.84	−0.05	0.10	−0.04	(0.78)		
5. Trust	3.82	1.72	0.91	0.17	−0.11	−0.13	0.64**	(0.77)	
6. Acceptance	4.29	1.64	0.89	0.14	−0.01	−0.05	0.58**	0.76**	(0.81)

Note. 1. Values on the diagonals within the parentheses represent the square root of the average variance extracted (AVE). 2. "Gender" was coded binary (1 = male, 0 = female). "Reward" was coded binary (0 = low, 1 = high). 3. $N = 98$. 4. Significance of correlations: $^{*}p < .05$. $^{**}p < .01$

multicollinearity—were tested and met. Below, we present the model outputs, including linear coefficients (β), standard errors (*SE*), and significance levels (*p*-values).

Manipulation Check

To ensure the effectiveness of the reward power manipulation, an ANOVA was conducted, confirming a significant difference in perceived reward power between the high ($M = 5.73$, $SD = 0.87$) and low ($M = 3.42$, $SD = 1.56$) reward power conditions ($F = 83.68$, $p < .001$, $\eta_p^2 = 0.466$).

Measurement Validity and Reliability

We conducted a factor analysis to assess structural validity. All items loaded at 0.7 or above on their corresponding constructs, except the second item from the acceptance questionnaire, which was removed due to low loading. To evaluate discriminant and convergent validity, we assessed the square roots of the Average Variance Extracted (AVE) for expectations (0.61), trust (0.60), and acceptance (0.65); all exceeded the 0.5 threshold recommended by the Fornell–Larcker criterion (Fornell & Larcker, 1981), indicating good convergent validity. Correlations among the variables (see Table 1) were lower than the square roots of their respective AVE values, supporting discriminant validity. Internal composite reliability (ICR) values for expectations (0.79), trust (0.77), and acceptance (0.81) all surpassed the 0.70 benchmark, indicating good internal consistency. Cronbach's alpha values also exceeded .7 benchmark (Carmines, 1979), confirming high reliability: expectations ($\alpha = .84$), trust ($\alpha = .91$), and acceptance ($\alpha = .89$).

Hypothesis Testing

H1 posited that reward power would increase trust in security robots. A multiple linear regression model (ANCOVA) was conducted to test the effect of reward power on trust, adjusting for the covariates gender, age, and expectations. Results showed that reward power significantly positively impacted trust ($\beta = 0.70$, $SE = 0.26$, $p = .009$); therefore, *H1* was supported.

H2 suggested that trust in security robots would increase acceptance of security robots. Another multiple linear regression model was conducted to test the effects of reward power and trust on acceptance, controlling for gender, age, and expectations. The results showed that trust positively and significantly influenced acceptance ($\beta = 0.62$, $SE = 0.09$, $p < .001$), while the effect of reward power on acceptance was non-significant ($\beta = 0.09$, $SE = 0.22$, $p = .679$). A *Sobel test* was conducted to explore the mediating role of trust further. The Sobel test indicated that the mediation effect of trust was significant (test statistic = 2.52, $p = .012$), suggesting that reward power indirectly influences acceptance through its impact on trust. *H2* was supported.

Discussion

This study examined how reward power affects trust and acceptance of security robots. Findings indicate that higher reward power significantly boosts trust in these robots, enhancing their acceptance. Trust served as a crucial mediator, linking reward power to acceptance. Below, we discuss the implications of these findings, the study's limitations, and potential avenues for future research.

This research offers several implications. First, our findings contribute to the literature on robot power. Previous HRI studies have primarily focused on the efficacy of robot power in eliciting human compliance (Cormier et al., 2013; Hashemian et al., 2019, 2020, 2021), with little attention paid to the mechanisms underlying acceptance. Yet, the influence of reward power is complex, as it may lead to behavioral conformity without necessarily achieving internalized acceptance (Warren, 1968). Understanding how reward affects perceptual acceptance of robots is therefore crucial.

Second, these findings also align with power theories from human-human interactions, where legitimate reward power yields positive effects (Tosi et al., 1994), suggesting that power theories applicable to human interactions may also be relevant to HRI context. Additionally, this finding confirms our underlying assumption that people generally perceive the use of reward power by security robots as legitimate. Future research should consider the importance of power legitimacy in examining robot power, especially in the security context, as legitimacy has been shown to affect other power bases, such as coercive power (Cartwright & Zander, 1960).

Third, the study contributes to the literature on security robot acceptance. Unlike prior literature (Lyons et al., 2021; Ye & Robert, 2024), which primarily considers trust as a dependent variable, we examined the mediating effect of trust on the relationship between robot-related factors and security robot acceptance. Our results demonstrate the antecedent role of trust, showing that the higher individuals' trust in security robots, the more likely they are to accept them. They also highlight the significant role of trust as a bridge that conveys the influence of robot factors on security robot acceptance. This also aligns with the Automation Acceptance Model (Ghazizadeh et al., 2012). Future research should consider the potential mediating role of trust and investigate why trust matters and how it functions in this context.

Finally, this study's findings offer practical implications for designing and deploying security robots in real-world settings. The positive impact of reward power suggests that integrating reward-based interaction mechanisms into security robots could enhance public trust and increase acceptance. However, further research is needed to determine the optimal types, scope, and amount of rewards (Hashemian et al., 2019) and examine how reward effectiveness varies across different interaction partners. By addressing these questions, researchers and designers can develop nuanced and effective reward strategies for security robots, potentially leading to higher public acceptance and more successful integration into community settings.

Limitations and Future Research

This study has limitations. First, the online experiment used videos to simulate human-robot interactions, which may lack the realism of direct interaction. Participants observed the robot giving rewards to another person, which, while validated as an effective method (Esterwood et al., 2025), might not elicit the same emotional responses as a real-world encounter. Future research should explore these effects in lab settings with direct human-robot interaction.

Second, the study only examined short-term effects during initial encounters with the robot offering incentives to first-time visitors. It's unclear how these effects would change with repeated interactions or if the reward strategy would remain effective for regular users. We also don't know how second-hand accounts of the robot's rewards might influence perceptions. Importantly, reward systems can create expectations that, if unfulfilled, could decrease trust or lead to negative outcomes (Diekmann et al., 1997; Greenberg, 1978; Tosi et al., 1994). Future research should investigate the long-term sustainability of reward effects and the potential consequences of stopping the reward program.

Third, the sample was limited to participants from the United States, potentially restricting the generalizability of the findings. Public perceptions of security robots, attitudes toward the authority they represent, and views on monetary rewards may vary across cultures (Long et al., 2017; Tang, 2016). Future research could explore cultural factors to assess how these power dynamics vary in broader populations.

Conclusion

Understanding the acceptance of security robots is crucial as they increasingly become part of human society. In this study, we conducted a between-subjects experiment to test the impact of robot reward power on people's trust and acceptance. The results, based on a U.S. sample and simulated interactions, showed that reward power significantly enhances trust in security robots during initial interactions, promoting acceptance of security robots. Further research is needed to assess the long-term effects and sustainability of such strategies, as well as their broader implications.

Declaration of Conflicting Interests

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