Security Robot Power and Acceptance: Exploring French and Raven's Five Forms of Power

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***Abstract*—The increasing deployment of robots in authority roles, such as security, necessitates understanding public acceptance of robot-exercised power. This study investigated the relationship between perceived power bases (expert, legitimate, referent, reward, coercive) and public acceptance of security robots. One hundred participants viewed videos depicting robot-citizen interactions. Results revealed positive correlations between perceived expert and legitimate power and acceptance and a negative correlation between perceived coercive power and acceptance; reward power showed no significant relationship. These findings contribute to the human-robot interaction (HRI) literature by demonstrating the influence of perceived power on public acceptance and offering design guidelines for enhancing the acceptance of security robots by emphasizing expertise and legitimate authority while minimizing coercive tactics.**

***Index Terms*—Social Power, Robot, Security, Acceptance**

I. Introduction

The growing use of security robots in real-world settings highlights the importance of public acceptance [1], [2]. Security robots are defined as any robot used to deter unwanted activities through their presence, surveillance, and ability to alert authorities about unauthorized individuals or actions [3]. Recent studies in human-robot interaction (HRI) emphasize the need to explore how power dynamics affect robot acceptance [4], [5]. Social power, defined as the ability to influence others, can have context-dependent effects on human perceptions of robots [6]–[8]. While power may encourage compliance, forms such as reward power can lead to negative outcomes, including learned helplessness and resistance, if viewed as illegitimate [9]. Understanding these dynamics is crucial as security robots become more prevalent and employ various forms of power in their operations. This raises questions about whether increasing power in deployment strategies could improve public acceptance.

To explore these issues, this study conducted an exploratory study aimed at understanding people's perceptions of power in security robots and their relationship with acceptance. A hundred participants viewed two video clips of security robots in real-world scenarios—one showcasing positive interactions and the other negative. Perceptions of five power types and acceptance were measured. Results indicated that perceptions of expert and legitimate power positively correlated with acceptance, while coercive power negatively related to acceptance. Reward power, however, was not related to acceptance.

This study contributes several key insights to the literature on human-security-robot interaction. First, it reveals the distinct relationships between the bases of power that the public views robots as using and their acceptance toward the robots. Second, the study bridges theories of human-human power to HRI, suggesting the importance of considering the legitimacy of power use. Finally, the findings provide design guidelines for improving public acceptance of security robots.

II. Related Work

A. *Power and influence*

Power is a fundamental concept in social science, influencing social relationships and daily interactions [10]. This paper adopts the definition of power as the capacity to influence others [11], based on French and Raven's influential model, which identifies five bases of power: reward, coercive, referent, legitimate, and expert power [12].

Reward power involves controlling rewards, coercive power involves administering punishments, referent power is based on admiration and identification, legitimate power derives from perceived authority, and expert power stems from specialized knowledge. Researchers have explored power in fields such as psychology [10], [13], sociology [14]–[16], and organizational behavior [17]–[19], examining its effects on relationships [20], [21], and organizational dynamics [22], [23].

Power dynamics can have both positive and negative effects. Expert, referent, and legitimate power generally lead to positive outcomes like satisfaction, while reward and coercive power have more complex effects [24], [25]. These effects depend on situational and individual factors [26], [27]. Tosi et al. [9] proposed that legitimate, referent and expert power foster acceptance of goals, encouraging rationalized behavior. However, reward and coercive power only achieve similar acceptance when recipients perceive their use as legitimate. If perceived as illegitimate, they can lead to negative outcomes like resistance [9], [16], [28]. For example, Warren [16] found that principals using expert, legitimate, and referent power encouraged internalized norm acceptance, whereas reward and coercive power only pushed for behavioral conformity.

Studies on power structures in various settings show diverse applications. Julian [29] observed that voluntary hospitals prefer legitimate power, while veterans' hospitals often use coercive power. In prisons, inmates perceive legitimate and

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referent power as most prevalent among officers [30]. Teachers who use expert, referent, and legitimate power are favored by students [31]. Power bases vary across relationships and organizations, serving distinct primary goals.

B. Power in Human-Robot Interaction

Power is gaining attention in HRI research. Few studies have focused on robots' social power. Ju [4] highlighted concerns about power dynamics in HRI, noting sensitivity similar to human interactions. Hou et al. [5] suggested using Fiske and Berdahl's power model [10] and French and Raven's power bases [12] to explore these dynamics within HRI.

Existing literature on robot power focuses primarily on the efficacy of robot power in eliciting human compliance behaviors, such as how persuasive and influential a robot can be. Hashemian et al. [6], [7], [32]–[34] examined robots' social power through French and Raven's power structure [12], finding that power enhances robot persuasiveness but without significant differences among the power bases. In 2019, [33] focused on reward and expert power, showing that robots using these powers are perceived as more persuasive, with introverts favoring expert power and extroverts preferring reward power. Their 2020 studies [6], [34] investigated reward and coercive power, finding similar levels of persuasiveness and perceptions regardless of power level. The 2021 study [7] revealed that increased rewards did not necessarily enhance persuasion and that the effects of social power remained consistent over time.

Other studies also examined robot power, finding it makes robots more influential and able to gain compliance. Hou and Jung [35] found powered robots (legitimate and reward power) were more influential than those without, though perceptions of intelligence, warmth, and discomfort were unaffected. Karli et al. [36] found supervisor robots were seen as more trustworthy and gained compliance, even with errors.

HRI studies on authority, a concept related to legitimate power [37], have found more varied effects. Young et al. [38]–[40] found robots elicit less obedience than humans, though many participants still complied with robot requests. Sembroski et al. [41] revealed participants followed robot instructions when aligned with their in-group and when the human experimenter's authority was low. Saunderson and Nejat [8] found peer-role robots were more persuasive than authoritative ones, with rewards outperforming punishments.

Despite the importance of power in HRI, there needs to be more understanding of how different power bases affect human-robot interactions, not only in terms of efficacy in compliance but also in fostering internalized acceptance. Moreover, most research centers on experimenter-subordinate dynamics, leaving gaps in applying power to real-world settings like security robots. Expanding research in these areas could enhance our understanding of power in practical robot applications.

C. Security Robot Acceptance

Robot acceptance is a critical metric for evaluating human-robot relationships, especially in the context of security robots [2], [42]–[47]. Acceptance refers to individuals' intention or willingness to use a robot [48]. This measure is particularly important for security robots, which must exert power and significantly affect public safety [1], [49]. Understanding acceptance can guide optimal power strategies and system improvements, promoting the effective deployment of security robots in society.

Research has identified factors influencing acceptance in security robots, such as robot gender, anthropomorphism, and autonomy [2], [42]–[44], [46]. Studies indicate that male-gendered robots garner higher acceptance than female-gendered ones [50], [51], while more significant anthropomorphism also boosts acceptance [46]. Besides, increased autonomy in low-risk tasks reduces acceptance [2].

Despite the growing focus on security robot acceptance, the role of power remains underexplored. Investigating how social power shapes acceptance in security robots is vital for enhancing their design and deployment. This paper aims to fill this gap by exploring the relationships between social power perceptions and acceptance.

III. HYPOTHESES

First, existing literature on human power has consistently shown that expert, referent, and legitimate power positively correlate with outcomes like satisfaction and performance. These power types facilitate the acceptance of goals and help individuals rationalize their behaviors. A similar trend is evident in robot power research, where robots with higher expert power are perceived as more persuasive and competent [33]. Additionally, supervisory robots that perform trust repair are seen as more trustworthy than subordinate robots [36]. Therefore, this study hypothesizes that perceptions of legitimate, referent, and expert power in security robots will positively relate to acceptance.

Second, reward and coercive po1wer typically exhibit complex and paradoxical effects on relationship dynamics [9]. While these powers can promote behavioral conformity as individuals seek to align with group expectations [26], [52], their effects largely depend on perceived legitimacy. Reward and coercive power can lead to rationalized behavior when viewed as legitimate. Conversely, if perceived as illegitimate, they may result in negative outcomes, such as resistance and disengagement [9]. This study assumes that security robots' role in public safety inherently signals legitimate power use, leading the public to generally perceive their use of power as legitimate. Therefore, this study hypothesized:

H1: Perceived legitimate power (a), perceived referent power (b), perceived expert power (c), perceived reward power (d), and perceived coercive power (e) in security robots are positively related to robot acceptance.

IV. METHOD

A correlational study was conducted to test the hypotheses in Fig. 1. Participants were randomly assigned to view one of two positive and negative interaction videos of real-world human-security robot interactions and then completed questionnaires. This approach was designed to ensure that

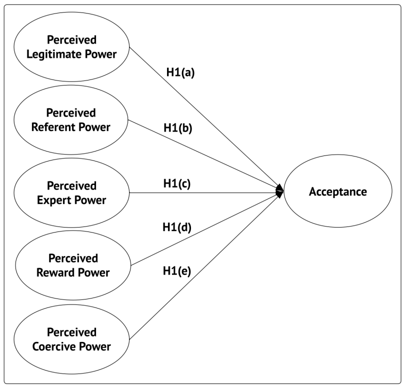

Fig. 1. Research Model

Fig. 2. Screenshots of Videos

participants could perceive different power types, as certain power types usually rely on positive or negative interpersonal interactions [53]. All videos and questionnaires used are available at https://github.com/XinYe-Eva/HRI25LBR. The study received exempt approval from the University of Michigan Institutional Review Board (IRB).

A. Participants

One hundred participants were recruited from the CloudResearch platform [54] to complete an online questionnaire (6–12 minutes), receiving $3 as compensation. Inclusion criteria included being at least 18 years old, fluent in English, and based in the U.S. After excluding three participants who failed attention checks, 97 participants were included in the analysis (49 male, 45 female, 2 transgender males, 1 nonbinary). The average age was 37.1 years (SD = 11.53). The sample was diverse in region (16.5% Midwest, 27.8% Northeast, 36.1% South, 19.6% West) and ethnicity (5.2% Asian, 18.6% Black, 4.1% Hispanic, 68.0% White, 4.1% multiracial).

B. Task and Procedure

The study had three main parts. First, participants completed a pre-questionnaire to gather demographic information. Next, they watched two short clips of a security robot interacting with a human in a real-life setting: one showed a positive interaction where the human complied with the robot's instructions and followed security protocols, and the other depicted a negative interaction where the human violated a rule and the robot took action (Fig. 2 shows example screenshots). The sequence of positive and negative interaction videos was balanced between participants. Video lengths ranged from 15 to 60 seconds. Participants completed a questionnaire about the robot after watching each video clip.

C. Measures

Perceived power and acceptance were measured. A fifteen-item, 7-point scale was used, adapted from [30], [55], [56], to measure perceptions of expert, legitimate, referent, reward, and coercive power. Each power is measured using three corresponding items. Acceptance was measured with a 4-item, 7-point scale from [2]. Participants' perceptions of the interactions in the videos were also measured to ensure they perceived one positive and one negative interaction, using an 8-item, 7-point scale adapted from [57].

V. Results

The analysis was conducted using R. Multiple linear regression was performed in the main analysis, with the model tested for key assumptions like linearity, residual independence, and normality. No issues with multicollinearity were detected, as confirmed by the variance inflation factor (VIF). No outliers were detected. However, the equal variance assumption was violated. Therefore, robust standard errors were applied to correct the standard errors. The model outputs are presented below, including the linear coefficients (β), standard errors (SE), and significance levels (p-values) for each predictor.

A. Manipulation Check

To verify participants' perceptions of the interactions in the positive and negative interaction videos, a one-way ANOVA was conducted to test the effect of interaction type (positive vs. negative) on participants' interaction perceptions. The results revealed a significant difference based on interaction type ($F(1, 192) = 61.0$, $p < 0.001$, $\eta^2_{\text{p}} = 0.241$) between the positive and negative interaction videos. Participants perceived the interaction in the positive interaction video as more positive ($M = 4.6$, $SD = 1.2$) and the interaction in the negative interaction video as more negative ($M = 3.1$, $SD = 1.4$).

B. Measurement Validity and Reliability

Reliability was assessed using Cronbach's alpha, with all measures exceeding the recommended threshold of 0.7 [58], indicating high reliability: perceived reward power(α = 0.94), perceived expert power(α = 0.95), perceived referent power(α = 0.91), perceived legitimate power(α = 0.89), perceived coercive power(α = 0.88), and acceptance (α = 0.94). Factor analysis showed all items loaded above 0.7 on their constructs, except perceived referent power, which indicated low structural reliability. Two low-loading items—one from perceived reward power and one from perceived legitimate power—were removed. AVE values confirmed good convergent validity for perceived reward power, perceived expert power, perceived coercive power, and acceptance, but perceived legitimate power (0.47) was slightly below the threshold of 0.5 [59], while perceived referent power (0.25) showed poor validity. Discriminant validity was assessed by calculating correlations among the variables and comparing them with the square roots of their individual AVE values. Most constructs demonstrated strong discriminant validity, except for perceived legitimate power, which was slightly low, and perceived referent power, which was extremely low. Internal Composite Reliability (ICR) showed good consistency for most constructs (ICR $>$ 0.7), except perceived referent power (0.50). In summary, perceived reward power, perceived expert power, perceived coercive power, and acceptance showed strong validity, while perceived legitimate power were slightly weaker. Perceived referent power was excluded due to very low validity.

C. Hypothesis Testing

A multiple linear regression model was conducted to examine the relationships between perceptions of power and acceptance. The results revealed that perceived expert power ($\beta = 0.42$, $SE = 0.08$, $p < 0.001$) and perceived legitimate power ($\beta = 0.37$, $SE = 0.07$, $p < 0.001$) were significantly positively associated with acceptance. In contrast, perceived coercive power demonstrated a significant negative association with acceptance ($\beta = -0.14$, $SE = 0.06$, $p = 0.03$). However, perceived reward power did not show a significant relationship with acceptance ($\beta = 0.12$, $SE = 0.07$, $p = 0.10$). Therefore, hypothesis 1 (a) (c) was supported.

TABLE I
HYPOTHESIS TESTING RESULTS

Hypothesis	Result
H1a) Perceived **legitimate** power is positively related to security robot acceptance.	Supported
H1b) Perceived **referent** power is positively related to security robot acceptance.	Not Supported
H1c) Perceived **expert** power is positively related to security robot acceptance.	Supported
H1d) Perceived **reward** power is positively related to security robot acceptance.	Not Supported
H1e) Perceived **coercive** power is positively related to security robot acceptance.	Not Supported

VI. Discussion

This study examined the relationships between perceived power and acceptance in security robots. Findings show that higher perceived expert and legitimate power are associated with greater acceptance, while perceived coercive power is linked to lower acceptance. Interestingly, perceived reward power was the only type not significantly related to acceptance.

This research offers several contributions. First, the findings contribute to the literature on robot power. Previous HRI studies have largely focused on the efficacy of robot power in eliciting human compliance behavior [6], [32], [38], with little attention paid to the mechanisms underlying acceptance. Yet, power can lead to behavioral conformity without achieving internalized acceptance [16], making it crucial to understand how robot power shapes perceptual acceptance. The results established key relationships between robot power perceptions and acceptance, providing exploratory evidence and guidance for future investigations into robot power. Notably, the findings on reward power suggest a mechanism that warrants further study. It's potential that reward power does not directly influence acceptance but may mediate its influence by other key mediators such as trust. Future research could build on this work by employing causal designs to examine the effects of power on acceptance, further validating the identified power relationships and deepening understanding of robot power.

Second, the findings of this study align with human-human power theories, where legitimate and expert power yield positive relationships [9], [24], [25], suggesting the applicability of power theories to the HRI context. The negative relationships between perceived coercive power and acceptance offer an intriguing perspective on public perceptions of power legitimacy. Coercive power's negative impact indicates its use by security robots may be viewed as illegitimate. This perception could be influenced by the deployment context, as the study's videos depicted private security robots operating in settings such as parking lots. In contrast, the use of coercive power by public law enforcement security robots may be perceived as more justified. Future research could explore whether perceptions of legitimacy differ between private and public security robots and how these differences influence acceptance.

Finally, this study offers practical implications for designing security robots. The results found that the coercive power displayed by security robots may play a negative role in public acceptance. However, coercive power could be a critical power for security robots in future deployment. Deterrence-based power such as punishment has long been one of the most effective tools in U.S. law enforcement for maintaining public safety and addressing threats [60]–[62]. Further research is needed to not only verify the influence of coercive power on public acceptance but also to explore the types of coercive power that the public can find acceptable in security robots.

This study also raises ethical questions about allowing security robots to exercise power, as the findings highlight potential harm associated with certain power types. Ethical considerations surrounding the use of power must be thoroughly evaluated and scrutinized before further deployment. For instance, is it appropriate to grant security robots specific powers, and how can safeguards be established to prevent potential harm? Developing ethical and safeguarding frameworks [63] to guide the design and responsible deployment of such power-based robotic systems is critically needed.

VII. Conclusions

Understanding the acceptance of security robots is critical as they increasingly integrate into human society. This exploratory study examined the relationship between the bases of power people perceive security robots using and their acceptance. The findings advance the understanding of the social power of security robots and offer practical implications for designing future robots to achieve greater public acceptance.

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