Generalization of social rejection in social networks

by

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Table of Contents

List of Tables

List of Figures

Abstract

Social rejection is prevalent in human society and consequential to health. Although past research has extensively examined the antecedents and consequences of rejection between a source and target of rejection, social rejection often takes place in social networks involving more than two people. In the current research, we test the hypothesis that people *generalize* rejection in social networks. That is, after rejection, people not only avoid interacting with the rejector but also avoid their friends. We tested this hypothesis by manipulating participants' rejection and acceptance experiences as they interact with members of an artificial social network. In Study 1, we showed that generalization happens. Following rejection and acceptance, people avoided novel targets close to the rejector while approaching those close to the accepter in the friendship network. In Study 2, we disentangled the generalization effects of rejection and acceptance and showed that each happens independently. In Study 3, we further investigated mechanisms underlying the generalization of rejection and found that it depends on the type of network ties. Together, our studies provide novel evidence of how social learning guides people's response to rejection in social networks.

Keywords: Social Rejection, Learning, Social Network

Introduction

Humans are social animals and have a basic need for stable relationships with others (Baumeister and Leary, 2005). However, this need is not always fulfilled as people experience social rejection[1] on a regular basis (Williams, 2007; Wesselmann et al., 2016). In the short term, social rejection leads to "hurt feelings" that are analogous to physical pain (Eisenberger et al., 2003; MacDonald and Leary, 2005), while in the long term it predicts mortality and susceptibility to various diseases (Eisenberger 2013, Snyder-Mackler et al., 2020). Past work on social rejection focuses on how people behave towards the rejector or unrelated others. When people are rejected, they tend to avoid the rejector and seek connections with novel interaction partners (Maner et al., 2007; Smart Richman and Leary, 2009). However, in real-life, social rejection often happens in broader social networks, where the source and target of rejection and the available interaction partners are bound by network ties. For example, when rejection takes place in a workplace, the source and target of rejection likely belong to the same colleague network. As a result, rejection should not only affect one's attitude towards the rejector, but also other members of the rejector's social network. In this paper, we examine the possibility that rejection can be generalized across social network ties. That is, following rejection, people should not only tend to avoid the rejector, but also those that are closely connected with the rejector in the social network.

Response to rejection in social contexts and the limitations of past research

[1] In our research, we follow Smart Richman and Leary (2009) to define social rejection as the threat to one's "goal of being valued and accepted by other people", and distinguish it from *ostracism*, which means "being ignored by an individual or group." (Wesselmann et al., 2016)

People tend to respond to social rejection in one of three ways. According to the "reconnection hypothesis", social rejection activates affiliative motivations and leads people to seek alternative social connections (Maner et al., 2007). As such, people who are rejected, while disliking the rejector, may nevertheless become more socially active *in general*. Consistent with this idea, people compensate for rejection by attempting to strengthen their social connections, for instance, by contributing more to subsequent group-based tasks (Williams and Sommer, 1997; Sleebos et al., 2006).

However, people may also respond to rejection in two other ways, depending on how they *appraise* the situation (Smart Richman and Leary, 2009; Kawamoto et al., 2015). When people perceive the rejection to be unfair, they tend to react antisocially by directly confronting the rejector. In contrast, when rejection compromises people's relational values, that is, when people believe that others do not value having relationships with them, people tend to withdrawal from social interactions, instead of seeking to reconnect. Likewise, rejection leads to avoidant behaviors among people who are highly fearful of negative evaluation (Maner et al., 2007).

In this work, we examine a novel factor that influences people's response to rejection. We propose that whether people approach or withdraw from social interaction following rejection depends on the relationship between their alternative potential interaction partners and the original rejector in the social network. People tend to avoid interacting with targets who are closer to the rejector in the network while approaching targets who are farther away.

This question remains largely untouched in the social rejection literature because most past work treats the source and target of rejection as isolated individuals in a social vacuum, without considering their relationship in social networks. For example, a large body of past work elicits rejection using a paradigm called the "cyberball game" (Williams et al., 2000). In this game, participants toss a ball around with two other players, who at some point started passing the ball between each other while ignoring the participants. While this paradigm has proved useful for eliciting emotions that are essential to rejection, such as “hurt feelings” (Eisenberger et al., 2003; MacDonald and Leary, 2005), the rejectors are almost always presented to participants as anonymous strangers and thus lack information on their social relationships. Moreover, this paradigm fails to capture the real-world dynamics of *learning* who tends to reject us by choosing our own interaction partners (Fazio et al., 2004).

More recently, research has started to incorporate social networks into the study of rejection by examining how rejection affects people’s social network position and structure. Consistent with the reconnection hypothesis, Bayer and colleagues (2018) found that people who are highly rejection-sensitive tend to report denser friendship networks on Facebook, suggesting a greater need for security and social support. Similarly, Pauksztat and Salin (2020) found that employees who had been bullied subsequently reported more friendship relationships at work—which likely arises as a coping strategy for rejection. These results are further supported by lab studies, which found that rejection (as opposed to inclusion) not only biases people’s memory for novel networks (O’Connor and Gladstone, 2015) but also expands the scope of their personal networks, by facilitating self-disclosure to close friends (Bayer et al., 2019). However, most of these works focus on the social network of the *target* of rejection, and it remains unclear how rejection shapes people’s perception of and response to the *rejector’s* social network.

In the current research, we address the limitations of prior work by testing the dynamics of rejection in social networks using a novel paradigm. Participants learn who tends to reject and accept them through an instrumental learning game (Cho and Hackel, 2022) and then learn the friendship networks of the rejector and accepter. Next, participants choose to interact with novel members of these networks. By measuring participants' choices, we can test if their prior social rejection experiences generalize to other people in the rejector's friendship network, whom participants have not interacted with. We expect that responses to rejection *generalize* across network ties. To the extent that people are motivated to avoid the rejector, they should also show an avoidance tendency towards the rejector's friends in the social network.

The psychological bases of generalization in social networks

Generalization of rejection in social networks could arise from at least three psychological mechanisms—*homophily*, *associative learning*, and *cognitive balance*. First, generalization in social networks can be driven by explicit inferences based on homophily—that similar people tend to interact with each other (McPherson et al., 2001). Homophily beliefs allow people to make inferences about novel targets in social networks. To the extent that a rejector and their friends are inferred to possess similar traits, and to the extent that people are motivated to avoid the rejector because of those traits, people might show generalized avoidance of the rejector's friends. In line with this possibility, theoretical work argues that indirect network ties are essential for the transmission of information and cooperation in both animal and human communities (Brent, 2015; Smith and Colins., 2009). Empirical studies further show that reputations can be generalized across individuals through friendship ties (Martinez et al., 2016; Jolly and Chang, 2021; Schwyck et al., *in prep*). In addition, research shows that people use knowledge about social network structure to make inferences about unencountered targets (Son et al., 2021). Moreover, people tend to see two people as less similar as their distance in the friendship network increases (Parkinson et al., 2017). Collectively, past research suggests that the impression formed of a rejector can spread to their network neighbors based on belief about homophily, which in turn could drive generalized avoidant behaviors after rejection. Specifically, there is reason to expect that people do not avoid all members of the rejector's social network to the same extent, but instead show decreased generalization for targets who are farther from the rejector.

Second, generalized response to rejection might arise from associative learning. Associative learning refers to the process through which a neutral object acquires positive or negative valence through spatiotemporal co-occurrence with positively or negatively valenced cues (De Houwer et al., 2001). Research finds that value can transfer between stimuli that have been arbitrarily associated with one another (Wimmer and Shohamy, 2012) and this mechanism can explain the formation and update of attitude in the *social* domain (Walther et al., 2005; FeldmanHall and Dunsmoor, 2019; FeldmanHall et al., 2017). In such cases, neutral targets (the conditioned stimuli) who appear alongside a rejector (the unconditioned stimulus) might be perceived in a negative light, even if they are not friends with the rejector and do not share their traits. Thus, the negative value of a rejector might generalize to their friends not necessarily because they are similar but merely because friends tend to hang out with each other and thus become automatically paired in people's minds. Moreover, associative learning theory posits that value can transfer between stimuli that are perceptually similar—a phenomenon termed stimulus generalization (Rescorla, 1976)—and the extent of generalization tracks the extent of similarity between stimuli (Fazio et al., 2004; FeldmanHall et al., 2018). Therefore, like homophily, stimulus generalization also predicts that the generalized response to rejection will be strongest among targets who are closest to the rejector in the network, assuming that network distance is a proxy for similarity.

Third, generalization from rejection is also supported by the theory of cognitive balance. According to this theory, attitude towards one target can transfer to another if the former has a positive evaluative relationship with the latter (Heider, 1958; Gawronski et al., 2005; Rambaran et al., 2015). Thus, negative values associated with the rejector might generalize to their neighbors in the social network, to the extent that they are believed to be connected by positive relationships (e.g. friendship).

In summary, all three accounts—homophily, associative learning, and cognitive balance—suggest that the negative value associated with a rejector can spread to members of the rejector's social network. In addition, both the homophily and associative learning accounts suggest that the *strength* of generalization should decrease as a function of *network distance*. By the same logic, generalization should also happen for social *acceptance*. That is, targets who are connected to the accepter in a social network should be seen in a positive light. Accordingly, we also expect that people, after being accepted, will show a preference for targets who are closer to the accepter in the social network.

Importantly, the three accounts also make different predictions about the pattern of generalization and thus can be potentially disentangled. While both the homophily and cognitive balance accounts suggest that positive social ties (e.g. friendships) are required for generalization, the associative learning account posits that it can happen based on entirely arbitrary associations. Therefore, in the current research, we not only test *whether* generalization happens but also examine *how* it happens. Specifically, we take an initial step towards this question by testing whether generalization depends on an explicit inference about homophily.

Overview of studies

We conducted three studies to test the generalization of rejection and acceptance in social networks and its underlying mechanisms. In all studies, participants interacted with two members of a novel social group and received feedback on whether these targets tend to reject or accept them. Participants also learned the friendship relationships among all group members. Finally, participants chose which group members to interact with, including novel members whom they have not received feedback from. By testing participants' likelihood of interacting with *novel* group members as a function of their distance to the original rejector/accepter in the network, we can measure the extent to which participants generalize from rejection/acceptance.

In Study 1, we tested *whether* generalization happens by having participants learn about a novel social network with both a rejector and an accepter in it. We hypothesized that participants would show a preference for targets who are farther away from the rejector and closer to the accepter in the network. In Study 2, we dissociated the generalization of rejection and acceptance, asking whether generalization occurs for each type of feedback. Participants learned about a novel network with *either* a rejector *or* an accepter in it. We hypothesized that participants would show generalized responses to both rejection and acceptance.

In Study 3, we aimed to better understand the mechanisms underlying generalization of rejection. We manipulated whether the network ties were based on friendship or arbitrary pairings. If associative processes are able to elicit generalization, then we should observe generalization regardless of whether the network ties are based on friendship or arbitrarily defined. In addition, if generalization also depends on the explicit inference that friends have similar rejection tendencies, then we should observe a *stronger* generalization effect when the network is based on friendship.

Study 1 was conducted as an exploratory study and was not pre-registered. Studies 2 and 3 were pre-registered, including sample size, measures, exclusion criteria, and analysis plan. Pre-registration documents are available at: https://aspredicted.org/y43cj.pdf, https://aspredicted.org/cw2ad.pdf. For each experiment, we report all conditions, manipulations, and measures. We distinguish between planned and unplanned (exploratory) data analyses, and we note departures from planned analyses where appropriate.

Study 1

`In Study 1, we asked whether people generalize from rejection and acceptance. Participants completed a trust-based game where they learned whether two members of a social group tended to reject or accept them. Then, participants learned the friendship relationships among all members of the group. Finally, we asked participants to continue choosing novel partners within the group, without receiving feedback. Unbeknownst to the participants, the network structure of the group and the behaviors of its members were pre-programmed. This allowed us to test whether participants' likelihood of choosing a target depends on the target's distance from the rejector and accepter in the friendship network. We predicted that participants would generalize by preferring targets who are farther away from the rejector and closer to the accepter.

Method

Overview. The study used a similar design as a recent study (Cho and Hackel, 2022) and consisted of two sessions. In Session 1, participants answered questions about themselves, with the expectation that their responses would be evaluated by another group of participants. A week later, participants were invited back for Session 2, in which they learned about previous participants ("Deciders") who had supposedly read their responses, along with the responses of other new participants, in order to form impressions and make decisions about who to play an economic game with. In reality, the Deciders' decisions were pre-programmed by the experimenters (described in detail below).

`In Session 2, participants completed a computer task consisting of three phases (Figure 1). In Phase 1, participants repeatedly chose between two group members (i.e. Deciders) to learn whether those Deciders tended to accept versus reject them. In Phase 2, participants learned the friendship relationships among all group members and were tested for their memory accuracy. Finally, in Phase 3, participants continued choosing Deciders without feedback. By examining participants' choice of novel Deciders in Phase 3, we were able to assess the extent to which participants generalized from prior rejection and acceptance by avoiding Deciders close to the original rejector and approaching those close to the accepter.

Participants. In Study 1, 60 participants were recruited through the Amazon Mechanical Turk (MTurk) platform for Session 1, and 46 returned for Session 2 (22 women, 23 men, 1 non-binary; mean age = 40.2, range = 22 to 70). To ensure data quality, we only recruited MTurk participants with more than 95% approval rate on Cloud Research. Only participants who completed both Session 1 and Session 2 were included in the data analysis. To ensure participants' engagement in the task, we removed data from those who either 1) failed to respond in at least 20% of the Instrumental Learning trials, or 2) failed to reach at least 60% accuracy in the friendship memory test (with 50% being chance level). These criteria resulted in 13 participants being excluded, leaving 36 participants for analysis. This sample size is comparable to other studies using a similar within-subject design with multiple learning and generalization trails (e.g. Martinez et al., 2016; Hackel et al., 2022). Informed consent was obtained from all participants in accordance with approval from the USC Office for Protection of Human Subjects.

`Stimuli. The Deciders were represented by face avatars (created on the website pickaface.net) and pseudo-names (e.g. John D., created on the website random-name-generator.info). Both the avatars and names were half male and half female (in order to allow generalization across gender within subjects). Each avatar was also randomly paired with a name of the corresponding gender category to minimize any effect of a particular combination on the results.

Procedure. In Session 1, participants were told that they would be playing a game that involves learning about groups. Participants answered 6 questions about themselves, particularly focused on their trustworthiness (e.g., "When was a time when you were honest, even though you didn't have to be?"), which they were told would then be sent to other participants to read (see Table 1 for a full list of questions). Afterwards, participants completed questionnaires assessing individual differences that may be relevant to responses to social rejection, including trait loneliness (measured by the UCLA loneliness scale, Russell et al., 1978) and rejection sensitivity (measured by the ARSQ, Berenson et al., 2009).

A week later, participants were invited back for Session 2. In this session, they were told that eight USC students enrolled in the same class had read their responses and the responses of a few other MTurkers. The eight students were in a "Player A" role (the "Deciders") and the participants were in a "Player B" role (the "Responders").

We told participants that the Deciders picked partners from this group of Responders for a trust game (Berg et al., 1995) after reading their responses from Session 1. For every round of the game, a Decider could choose to send points worth money to one of two Responders. Points would be tripled, and the Responders would then choose whether to return half of the points to that Decider or keep all of them.

To play the game in a given round, participants needed to match with a Decider. Participants were informed that each Decider saw a random subset of two Responders in each round and chose whom they wanted to play with. In the Instrumental Learning phase, participants repeatedly chose to match with two of the eight Deciders and learn the choices they had ostensibly made. This design should help us capture the dynamics of social rejection and acceptance as people learn about others by choosing to interact with them and receiving feedback (Cho and Hackel, 2022).

Instrumental learning phase. Across 60 trials, participants learned about the two Deciders and were never exposed to anyone else in the group (Figure 1). In each trial, the two Deciders were presented side by side on the screen and participants had two seconds to choose who to match with by pressing either “E” (left) or “I” (right) on the keyboard. The locations of the Deciders were counterbalanced. If participants did not make a choice within two seconds, they saw a screen that said “NO RESPONSE” for half a second, followed by a three-second delay before moving on to the next trial. The timing of each trial was the same whether participants responded or not.

After choosing a Decider, participants received three seconds of feedback about whether the Decider chose them or another participant. A figure appeared below the Decider with two avatars representing the participants themselves and another participant. A green box surrounded the person that was chosen. Unbeknownst to the participants, in each round, one Decider (the “rejector”) had a 20% probability of choosing them over another participant, whereas the other Decider (the “accepter”) had an 80% probability of choosing them.

If a Decider chose the participants, then they were matched and would play one round of the trust game. Participants were shown a number of points worth money sent from that Decider that had been tripled (ranging from 6 to 24 points). They had three seconds to press a key to decide whether to keep all or return half of the points to the Decider. If the Decider did not choose the participants, then they couldn’t play the game and instead had to wait 3 seconds before moving on to the next trial. These trust games served to fulfill the cover story, motivating participants to try to match with a Decider. The number of points participants kept during the trust game was converted to a small bonus compensation at the end of the study, averaged at $.25.

Network learning phase. Following instrumental learning, participants learned about the friendship relationships among the eight Deciders, who were described as students enrolled in the same class at USC. Participants were told that prior to the study, the students completed a survey to indicate who they considered friends among their classmates, and only people who nominated each other were recorded as friends. Participants then learned who was friends with whom, while being told that they would be tested for memory accuracy later.

To learn the friendship relationships, participants repeatedly saw pairs of Deciders on the screen (see Figure 1). In each round, participants saw the name and avatar of two Deciders, along with the text "[Name 1] is friends with [Name 2]". Participants could take as long as they needed to memorize each pair of friends before pressing the spacebar to continue to the next trial. Each pair of friends were presented a total of 20 times, with their positions counter-balanced. We also told participants that if two students were never presented on the screen together, then they were not friends.

We used this paradigm because past work shows that people can successfully learn social network structures through sequential presentations of pairwise relationships (Lynn and Bassett, 2020; Thompson et al., 2018; Dziura and Thompson, 2019). In addition, this paradigm mimics how network relationships are often learned in real life, where an observer tends to see only a subset of individuals together at a time and rarely has access to the entire group's relationships at once.

Unbeknownst to participants, the Deciders' network had a ring structure, such that each node was connected to exactly two other nodes and nodes were structurally equivalent to each other (Figure 2, left). Notably, we arranged the accepter and rejector to be maximally distant from each other (i.e. separated by four degrees), so that we could maximally disentangle the effects of generalization from rejection versus acceptance.

After learning the friendship relationships, participants were tested for their memory accuracy. They were shown pairs of faces and asked to indicate whether each pair were friends. They saw a total of 32 pairs, 16 of which were true friends (each friendship tie appearing twice) while 16 were Deciders who were two degrees apart in the network (who were not friends and never presented together). Participants were asked to press either "up" ("yes") or "down" ("no") to indicate the friendship status of each pair of faces. Participants with 60 percent accuracy or above were included for further analyses (*M_accuracy* = 74.2%*, SD* = 18.1%*, Range* = 37.5% - 100%; *N* excluded based on memory accuracy = 13).

Test phase. After participants learned the friendship relationships among the Deciders, we assessed the generalization effects by measuring their partner choices among all eight Deciders (Figure 1). Participants were told that they would continue to try to match and play trust games with the Deciders, just like they did during the instrumental learning phase. However, they would no longer receive immediate feedback following their choices but would instead see the matching outcomes and play the games at the end of the study.

In each round, participants saw two of the eight Deciders side by side on the screen and had four seconds to choose who to match with by pressing either "E" (left) or "I" (right) on the keyboard. Every possible pair of Deciders appeared twice, with their positions counterbalanced. Thus, participants made A_8^2 = 56 choices in total. Following participants' response was an inter-trial interval (ITI) of one second. If participants failed to respond within four seconds, they would see a screen that said "NO RESPONSE" for half a second, followed by a one-second ITI.

This task allowed us to measure to what extent participants generalize from acceptance and rejection by avoiding targets who are close to the rejector and approaching targets close to the accepter, even when they had no prior interaction with those targets.

All three phases above (instrumental Learning, network learning, and test phase) were presented to participants using PsychoPy version 2021.2.3 via Pavlovia.org (Peirce, 2007).

Results

Choice of original rejector and accepter (manipulation check). We first asked whether participants successfully learned during the instrumental learning phase that one Decider (the 'accepter') tended to accept them while another (the 'rejector') tended to reject them. To test whether these manipulations worked, we calculated each participant's average probabilities of choosing the original rejector and the accepter during the test phase and compared them using paired samples t-test. Participants were more likely to choose the accepter (M_choice = 71.2%, SE = .05) than the rejector (M_choice = 26.6%, SE = .04; Δ = .45, 95% CI = [.28, .61], $t(35)$ = 5.43, $p < .001$, d = 1.57), indicating that they successfully learned about the two Deciders.

Choices between novel targets. We next asked whether people generalize from rejection and acceptance by approaching targets that are close to the accepter and avoiding targets close to the rejector in the friendship network.

To test this hypothesis, we used mixed-effects logistic regression (implemented with the *lmer* function in the lme4 library and the lmerTest library, R 4.2; Bates et al., 2014; Kuznetsova et al., 2017) to model trial-by-trial choices during the test phase. Because generalization, by definition, only occurs for *novel* targets, we excluded trials involving either the original rejector or the original accepter. The model predicted whether the novel target on the left side of the screen was chosen (1: Yes, 0: No) as a function of the left target's distance to the rejector in the friendship network *relative to* the right target (i.e., left target's distance minus right target's distance). (The left side of the screen was arbitrarily chosen; this analysis examined whether participants choose a target based on which target was closer to the rejector). Given the way we set up the network, greater distance to rejector means smaller distance to accepter, so we only included the former in our analysis. We included a random intercept for participant and a by-participant random slope for relative distance to the rejector.

As hypothesized, participants showed evidence for generalization, choosing the left target more often when they were further away from the rejector relative to the right target ($b = .28$, $SE = .09$, $z = 3.12$, $p = 0.02$, 95% CI = [.11, .46]) (Figure 3). Participants thus avoided novel individuals who were closer to the rejector and approached novel individuals closer to the accepter.

***Individual differences* measures**. We next examined whether individuals who are more sensitive to rejection (Berenson et al., 2009) or lonelier (Russell et al., 1978) generalize rejection to a greater extent. We added rejection sensitivity and loneliness as moderators that interacted with left target's relative distance in the mixed-effects model above. However, neither measure significantly moderated the generalization effect (ps > .09). Generalization appeared to occur broadly rather than only for lonely or rejection-sensitive individuals (see Table 1).

Discussion

In Study 1, we investigated how people respond to social rejection and acceptance within a social network. Consistent with prior work, we found that participants tended to approach the accepter and avoid the rejector. However, participants also generalized from acceptance and rejection by approaching novel targets who were close to the accepter and avoiding those who were close to the rejector in the social network. These results provide initial evidence that social acceptance and rejection can be generalized based on social network ties.

However, Study 1 has three main limitations. First, because participants in Study 1 were rejected and accepted by members of the same network, it remains unclear whether the generalization effect was primarily driven by 1) a tendency to approach targets close to the accepter, 2) a tendency to avoid targets close to the rejector, or 3) a combination of both motivations. Second, participants in Study 1 were forced to choose between two Deciders during the test phase. This design failed to capture situations where people *avoid social interaction altogether* following social rejection. Third, due to its small sample size ($N = 36$), Study 1 had limited power to assess how individual differences moderate generalization. We addressed these limitations in Study 2.

Study 2

In Study 2, we aimed to replicate the findings in Study 1 while addressing its limitations. First, to disentangle the effects of acceptance and rejection on generalization, we used a between-subject design, where participants were either accepted or rejected by one person in the Deciders' social network. Second, to measure participants' tendency to avoid *social interaction*, we gave participants the opportunity to choose a non-social interaction with slot machines, instead of human Deciders, during both the instrumental learning and test phases. Third, to increase the power to detect moderation effects by individual differences measures, we recruited 300 participants for Session 1. We tested fear of negative evaluation (FNE) as an alternative moderator of the generalization effect. Past research has found that FNE is a key moderator determining whether people approach or avoid social interaction after rejection (Maner et al., 2007). Thus, we hypothesized that people with higher FNE will show *stronger* generalization from rejection, such that they are more likely to choose targets further away from the rejector, compared with people low on FNE.

Finally, we measured participants' meta-perception of how much each target likes them. Past research shows that the meta-perception that other people like and value us predicts partner choice (Cho and Hackel, 2022). We thus examine whether generalized responses to rejection and acceptance are manifested in participants' explicit beliefs about the targets, in addition to their partner choice behaviors.

Method

Participants. In Study 2, we recruited 300 participants on MTurk for Session 1 (using the same criteria as in Study 1), 228 of whom returned for Session 2 (100 women, 111 men, 2 non-binary, 15 did not report; mean age = 39.2, range = 20 - 69). Only participants who completed both Sessions 1 and 2 were included in the data analysis. We administered a pre-registered exclusion rule to remove data from those who either 1) failed to respond in at least 20% of the Instrumental Learning trials, or 2) failed to reach at least 60% accuracy in the friendship memory test (with 50% being chance level). These criteria resulted in 77 participants being excluded, leaving 151 participants for analyses. According to power analysis for mixed-effects generalized linear models using the *simR* package, 151 participants would give us 83% power to detect effect size of .20, and 96% power to detect effect size of .25. Informed consent was obtained from all participants in accordance with approval from the USC Office for Protection of Human Subjects.

Procedure. The procedure for Session 1 was identical to that of Study 1, except that in Study 2 we additionally measured participants' fear of negative evaluation (FNE) using the Brief Fear of Negative Evaluation (BFNE) scale (Leary, 1983). Session 2, like Study 1, consisted of three phases (instrumental learning, network learning, and test phases). However, there were a few key differences.

Instrumental learning phase. During the instrumental learning phase, participants tried to match with one Decider and were randomly assigned to one of two conditions. In the *rejection* condition, the Decider rejected participants with 80% probability whereas in the *acceptance* condition, the Decider accepted participants with 80% probability. In addition, to simplify the game, when matched, participants always received 60 points from the Decider, of which they could then decide to either "keep all" or "return half".

In order to measure participants' avoidance of *social* interactions, we also added two non-human targets to the instrumental learning phase, which participants could learn about through choices. In each round, participants had to choose between the Decider and one of two slot machines. The "generous" slot machine, if chosen, had an 80 percent probability of paying 30 points to participants and a 20 percent probability of paying nothing. The "stingy" slot machine, when chosen, only had a 20 percent probability of paying 30 points. Thus, on average, the generous slot machine paid out the same amount as the accepter, while the stingy slot machine paid out the same amount as the rejector, if participants always chose to keep all points from the Decider.

Network learning phase. We changed the layout of the Deciders' network during the Network Learning phase (Figure 2, right). We shrank the size of the network from eight to six. Given that participants learned only about one Decider, a network of six targets was sufficient to create a relatively wide range of network distance (from one to three degrees of separation) for generalization to happen. Therefore, a larger network was unnecessary. Meanwhile, this change could alleviate participants' cognitive burden during learning as the number of relationships to memorize was reduced from 8 to 6. Each friendship relationship was presented 28 times to participants. After learning the network structure, participants were tested for their memory accuracy, following the same procedures as Study 1 (*M_accuracy* = 73.4%*, SD* = 19.1%*, Range* = 25% - 100%, *N* excluded based on memory accuracy = 77). Everything else in the Network Learning phase was identical to Study 1.

Test phase. During the test phase, we incorporated three trial types. One trial type was identical to the test phase in Study 1: participants chose between two human targets (i.e. Deciders). However, in a second trial type, participants sometimes chose between a human target and a slot machine. This design allowed us to test whether social rejection affects people's tendency to interact with novel human targets at all. If generalization occurs, then participants should avoid interaction more often (by choosing slot machines against humans) after rejection, compared with acceptance. Finally, in a third trial type, participants chose between two slot machines in order to ensure they learned which slot machine was generous and which was stingy. Everything else in the instrumental learning and test phases was identical to Study 1.

After the test phase, participants completed two additional measures. First, to measure whether the meta-perception of being liked by the original Decider generalizes to novel Deciders in the network, we asked participants the extent to which they think each Decider likes them, on a scale from 1 (not at all) to 7 (very much). In addition, we asked participants how much they liked the Deciders' group on a scale from 1 (not at all) to 7 (very much).

Results

Choices of original Decider and slot machines (manipulation check). We first tested whether participants successfully learned about the original Decider by comparing their likelihood of choosing the original Decider between the acceptance and rejection conditions.

Replicating the results in Study 1, participants in the acceptance condition (*M_choice* = 75.1%, *SE* = .02) were significantly more likely to choose the original Decider than participants in the rejection condition (*M_choice* = 22.5%, *SE* = .02; Δ = .53, 95% CI = [.45, .60], $t(145.6) = 13.30$, $p < .001$, $d = 2.16$). We then compared participants' likelihood of choosing both slot machines. Collapsing across both conditions, participants were significantly more likely to choose the generous slot machine (*M_choice* = 56.6%, *SE* = .03) than the stingy slot machine (*M_choice* = 37.0%, *SE* = .03; Δ = .20, 95% CI = [.14, .25], $t(150) = 6.93$, $p < .001$, $d = .61$). These results suggest that our manipulations during the Instrumental Learning phase were successful, such that participants learned who tended to reject/accept them and which slot machine tended to offer payment.

Choices between two Deciders (exploratory analysis). We then tested the generalization effects, that is, whether participants were more likely to choose novel Deciders close to the original accepter but less likely to choose those close to the original rejector. We first examined participants' choices between two novel Deciders during the test phase. We recoded each target's distance to the original rejector/accepter into a "positivity score". For example, Deciders have a positivity score of 1 if they are 1-degree apart from the rejector or 3-degrees apart from the accepter. If generalization happens, then participants should be more likely to choose targets with relatively higher positivity scores. Moreover, recoding distance into positivity score allowed us to compare the strength of generalization between the rejection and acceptance conditions. If the gradient of generalization is stronger in one condition, then the slope of positivity score should accordingly be steeper. We ran a mixed-effects logistic regression predicting whether participants chose the left Decider (1: Yes, 0: No) using 1) the left Decider's positivity score relative to the right Decider, 2) condition (rejection vs. acceptance), and 3) their interaction. We included a random intercept for participant and a by-participant random slope for positivity score.

We found a significant effect of positivity on choice (b = .39, 95% CI = [.19, .59], z = 3.88, p < .001). In both conditions, participants were more likely to choose a Decider as their positivity increased *relative to* the other Decider available onscreen. There was no main effect of condition or interaction between positivity and condition (ps > .21), suggesting that participants generalized to similar extents across rejection and acceptance (see Figure 4 and Table 3).

Choices between Decider and slot machine (planned analysis). To further test the generalization effects, we ran our pre-registered analysis by examining participants' choices between a Decider and a slot machine. This analysis asked whether participants were more likely to interact with human targets with higher positivity scores as opposed to slot machines. We recoded participants' choices in each trial based on whether the human target (Decider) was chosen (1: Yes; 0: No) and ran a mixed-effects logistic regression predicting choice in each trial using 1) the Decider's positivity score, 2) condition, and 3) their interaction, while controlling for which slot machine was presented (1: generous, -1: stingy). Positivity did not significantly predict participants' probability of choosing novel Deciders (b = .11, CI = [-.21, .42], z = .65, p = .52). However, condition had a significant effect on choice such that participants in the rejection condition were less likely to prefer novel Deciders to the slot machines throughout the test phase (b = -1.08, CI = [-1.93, -.22], t = -2.47, p = .01) (see Figure 4 and Table 1). Thus, when choosing between social and non-social interactions, participants did not show a gradient of generalization based on the human target's positivity, but instead appeared to generalize to the human target's group *as a whole*, avoiding *all* novel human targets more following rejection than acceptance.

Comparing generalization from rejection and acceptance (exploratory analysis). The analyses above indicate that generalization happens for both rejection and acceptance. Visual inspection of the data further suggests that there might be an asymmetry in generalization between the two conditions. Whereas the probability of choosing a novel Decider increases roughly linearly as the Decider moves away from the rejector, choice probability seems to vary non-linearly with distance in the acceptance condition (see Figure 4). This suggests that people might generalize rejection farther than acceptance, consistent with the well-documented phenomenon of negativity bias (Rozin and Royzman, 2001; Fazio et al., 2004).

To formally evaluate this apparent asymmetry, we fit a piecewise growth model for the choices between two novel human Deciders. In this model, we created three phases based on the novel Deciders' positivity (phase 1: positivity score = 1 – 2 for rejection, 0 – 1 for acceptance; phase 2: positivity score = 2 – 3 for rejection, 1 – 2 for acceptance). Then, we predicted participants' probability of choosing each novel Decider using 1) the three phases, 2) condition and 3) the interaction between condition and each phase. The model included random intercept and by-participant random slope for all phases. The model thus allowed us to separately estimate the generalization effects for novel targets located at different positions of the social network and assess whether these effects differed in strength.

Contrary to the visual patterns, condition did not interact with either phase 1 ($b = .05$, $p = .23$) or phase 2 ($b = -.07$, $p = .12$), so it is unclear whether the pattern of generalization differed between the rejection and acceptance conditions. That said, there is reason to believe that an asymmetry might in fact exist for generalization, a point we will return to in the discussion section.

Individual differences measures (exploratory analysis). Finally, we examined whether the generalization effects are moderated by individual differences measures. We focused on whether fear of negative evaluation (FNE) amplifies generalization of rejection. We built upon our original mixed-effects logistic regressions by adding FNE (mean centered across participants) and its interaction with positivity and condition as additional predictors.

For choices between two novel Deciders, we found a significant three-way interaction among positivity, condition, and FNE, such that higher FNE amplifies the generalization effect in the rejection condition compared with the acceptance condition (b = .28, 95% CI = [.04, .51], z = 2.33, p = .02; see Figure 5 and Table 4). After rejection, participants who strongly feared negative evaluation were less likely to interact with targets who were closer to the rejector. However, participants who showed weak fear of negative evaluation did not show this pattern of generalization.

For choices between a novel Decider and a slot machine, we observed a significant two-way interaction effect between FNE and condition, such that the effect of condition on choice is greater among participants higher in FNE (b = -.98, 95% CI = [-1.71, -.24], z = -2.60, p = .009, see Figure 5 and Table 4). Individuals who feared negative evaluation were more likely to avoid social interactions with all group members after rejection. In contrast, FNE did not moderate the effect of distance on choice of Decider in either condition (ps > .18); notably, however, we did not observe a significant effect of distance in this trial type, as reported above. Thus, fear of negative evaluation exacerbated both patterns of generalization we observed—a gradient of approach or avoidance in trials featuring two humans, and an overall tendency to avoid social interactions in trials featuring a human and a slot machine.

***Meta-perception of liking (exploratory analysis)*.** To test whether the meta-perception of liking by the original Decider generalizes to the novel Deciders, we ran a mixed-effects linear regression predicting participants' perceived liking by each novel Decider using the Decider's positivity score, with a random intercept for participant and a by-participant random slope for positivity score. Target positivity positively predicted perceived liking (b = .13, 95% CI = [.01, .24], t = 2.22, p = .03), such that participants believed targets who were farther away from the rejector or closer to the accepter liked them better. Thus, the generalization effects were manifested not only in people's partner choices but also in their explicit beliefs.

Liking (planned analysis). Finally, we tested whether social acceptance by one group member (i.e. the accepter) leads to greater liking of the group. Consistent with this idea, participants in the acceptance condition liked the Deciders' group significantly better than those in the rejection condition (M_accept = 5.49, SE = .13; M_reject = 4.70, SE = .15; Δ = .79, 95%CI = [.38, 1.19], t(149.0) = 3.87, p < .001, d = .62). Social rejection and acceptance influence not only how we treat individuals, but also how we evaluate groups.

Discussion

Study 2 aimed to disentangle generalizations from rejection and acceptance. We found that participants generalized from both rejection and acceptance when they only received feedback from one Decider in the network. When choosing between two novel Deciders, participants that had been rejected preferred the Decider that was farther away from the original rejector, whereas participants that had been accepted preferred the Decider that was closer to the original accepter. In other words, participants' partner choices between two novel humans show a pattern of gradient based on network distance.

In Study 2, we also let participants choose between a novel Decider and a slot machine—a design that allowed us to test participants' general tendency towards any *social* interaction after rejection and acceptance. While participants' choices in these trials did not significantly depend on the novel Decider's distance to the original rejector/accepter, participants were significantly less likely to choose humans (as opposed to slot machines) following rejection. Although these findings do not support the idea that the *strength* of generalization depends on network distance, they nevertheless provide evidence for generalization in a broad sense—that is, values attached to one member of a group can influence how people behave towards other members of the same group (Hackel et al., 2022). To summarize, after rejection, people try to distance themselves from the rejector, whether by avoiding *social* interaction altogether or by interacting with targets far from the rejector, if complete avoidance is impossible.

We also noted an interesting, albeit statistically non-significant, difference in the pattern of generalization between rejection and acceptance. Generalization of rejection traveled farther across network ties and thus appeared stronger than the generalization of acceptance. There is reason to believe that this asymmetry in fact exists because it fits well with the definition of negativity bias. One key feature of negativity bias is a "steeper gradient" for negative events, such that the negativity of an event increases more rapidly as an observer approaches it in space and time (Rozin and Royzman, 2001). Moreover, the same phenomenon has been observed in associative learning, where the generalization of value across similar objects is stronger for negative than positive values (Fazio et al., 2004). Thus, it is likely that the generalization of social value in human networks follows a similar law, though we might have had insufficient power to detect it.

In addition, we found evidence that fear of negative evaluation moderated generalization from rejection, but not acceptance. This result aligns well with past literature finding that people who fear negative valuation tend to avoid social interaction rather than reconnect after rejection (Maner et al., 2007). Our finding serves as a proof of concept for our manipulation by demonstrating that participants in the rejection condition indeed felt *rejected*. Moreover, it posits FNE as a potential factor that interacts with generalization to shape people's social network position and psychological wellbeing. We will return to this point in the General Discussion.

Finally, we found that generalization also happens for people's meta-perception. Participants perceived less liking by novel targets who were close to the rejector or far away from the accepter. This mechanism can explain the generalization of rejection: people might infer that targets close to a rejector in a social network have high rejection tendencies and thus should be avoided. In other words, generalization might emerge from explicit inferences based on one's social network knowledge, rather than association alone. We tested this possibility directly in Study 3.

Study 3

Collectively, Studies 1 and 2 showed that generalization from rejection and acceptance is consequential to interpersonal connections in social networks—it influences not only *whom* we connect with, but also *whether* we seek social interaction.

However, it remains unclear what mechanisms drove the generalization effects. As mentioned earlier, at least three mechanisms can account for our findings in Studies 1 and 2. Participants' avoidance of people close to the rejector could have resulted from either 1) the explicit inference that the rejector and their friends possessed similar traits (*homophily*), 2) the spread of negativity from the rejector to their network neighbors through mental association (*associative learning*), or 3) the motivation to form a balanced representation of the rejector, their friends, and oneself (*cognitive balance*). Importantly, these three accounts make different predictions about how people respond to rejection. Whereas the homophily and cognitive balance mechanisms require explicit knowledge about the rejector's social relationships, the associative learning mechanism can operate based on arbitrary association and without conscious awareness (Wimmer and Shohamy, 2012).

Therefore, in Study 3 we further disentangled these mechanisms by asking whether generalization of rejection depends on explicit inferences of homophily based on friendship knowledge. We used the same paradigm as in Studies 1 and 2, while manipulating the nature of the social network ties, framing them as based on either *friendship* or *random-pairing*. Accordingly, participants in the friendship condition, but not the random-paring condition, should hold the explicit belief that the novel Deciders who are closer to the rejector in the network are more likely to reject them.

We hypothesized that participants in both conditions would generalize rejection by avoiding novel Deciders close to the rejector because both explicit inference and association likely contribute to generalization. However, we expected the effect to be stronger in the friendship condition (which evokes both mechanisms) than in the random-paring condition (which only evokes the association mechanism).

Method

Participants. We conducted *a priori* power analysis by using the *simR* package in R and determined that 200 participants would give us 92% power to detect the equivalent generalization effect as in Study 2 (effect size = .25), and 80% power to detect the equivalent moderation effect of FNE (effect size = .15). Based on the retention and exclusion rates from

Studies 1 and 2, we recruited 400 participants for Session 1 using MTurk, 264 of whom returned for Session 2 (131 women, 120 men, 5 non-binary, 8 did not report; mean age = 39.7, range = 19 - 76). Given the large proportions of exclusion based on memory in Studies 1 and 2, we pre-registered a more liberal exclusion rule in Study 3 by removing data from those who either 1) failed to respond in at least 20% of the Instrumental Learning trials, or 2) failed to reach at least 50% (instead of 60%) accuracy in the network memory test. Although the 50% (i.e. chance level) threshold is more liberal, we consider it to be justified because it has been used in previous studies with a similar design (Hackel et al., 2022) and our main findings held when using the more conservative threshold. These criteria resulted in 52 participants being excluded, leaving 212 participants for analyses. Informed consent was obtained from all participants in accordance with approval from the USC Office for Protection of Human Subjects.

Procedure. Session 1 remained the same except that we made changes to the individual difference measures. We removed the rejection-sensitivity and loneliness scales because they had no effect on the generalization effects in either Study 1 or 2. Meanwhile, we added a novel measure for belief about homophily, which included five items: 1) "If two people are similar, then they are more likely to become friends", 2) "People who are friends tend to like or dislike the same things", 3) "People who are friends tend to have similar opinions to one another", 4) "Friendships between dissimilar people are more likely to dissolve over time", 5) "'Birds of a feather flock together' accurately describe the nature of friendship" (*Cronbach's alpha* = .78). Recent work suggests that people hold beliefs about homophily, and these beliefs shape the extent to which they generalize trust decisions based on friendship (Schwyck et al. *in prep*). Thus, we included the belief about homophily as an exploratory factor that might modulate the generalization effect.

Session 2 remained largely the same, where participants first instrumentally learned about one Decider in the network and then learned the network structure, before making the generalization choices. However, we made two major changes.

Instrumental learning phase. During the instrumental learning phase, we removed the acceptance condition so that all participants encountered a rejector. This change allowed us greater power for testing a moderating effect of FNE. In addition, to shorten the task, we reduced the instrumental learning trial number from 60 to 45

Network learning phase. During the network learning phase, we manipulated the nature of the network ties by randomly assigning participants to one of two conditions. In the *friendship condition*, participants saw the same instructions as in Studies 1 and 2, whereas in the *random-paring* condition, they saw the following instructions:

> "In this part, we are interested in how well you can memorize information about the group of students. We randomly assigned the students to pairs of two. In this part, you will learn who has been paired with whom. Please note that each student could be paired with more than one other student."

Throughout the rest of the task, we replaced the language about friendship with random-pairing for participants in the random pairing condition.

`The timing of the network learning task was the same as Studies 1 and 2. Each network tie was presented 20 times. Following network learning, participants were tested for their memory following the same procedures as Studies 1 and 2 ($M\_accuracy$ = 73.0%, SD = 19.3%, N excluded based on memory accuracy = 50).

Test phase. The test phase followed the same procedures as Study 2, where participants continued choosing partners for the trust game, without receiving immediate feedback. Half of the trials were choices between two novel Deciders while the other half were choices between one novel Decider and one slot machine. The two trial types were intermixed.

`***Post-task measures***. Following the Test phase, we measured participants' perceived likelihood of acceptance by each Decider; "How likely is it that this person has chosen to match with you for the game?" 1 (Not at all) – 7 (Very much). Next, we measured participants' attitudes toward the network using the same measure as in Study 2: "How much do you like the student group?", 1 (Not at all) – 7 (Very much). In addition, we checked participants' comprehension of the task by asking them to indicate whether the pairings during the network learning phase were based on 1) friendship, 2) random-pairing, or 3) something else. Finally, participants answered demographic questions and were debriefed.

Results

Task comprehension (manipulation check). We first checked whether participants understood the task by examining their answers to the comprehension check question. It turned out that 91.0% (101 out of 111) of the participants in the friendship condition and 87.1% (88 out of 101) of those in the random-pairing condition correctly reported the nature of the Decider's network ties, indicating that our between-subject manipulation (i.e. friendship vs. random-pairing) was successful.

Choices of original Decider and two slot machines (manipulation check). Next, we checked whether participants successfully learned the difference among the Deciders and between the two slot machines. We used paired samples t-tests to compare participants' likelihood of choosing the rejector and the two slot machines during the test phase. As expected, participants were more likely to choose the generous slot machine (M = 73.9%, SE = .02) than both the rejector (M_choice = 21.7%, SE = .02; Δ = .52, 95% CI = [.47, .58], $t(212) = 18.87$, $p < .001$, d = 1.83) and the stingy slot machine (M_choice = 48.5%, SE = .02; Δ = .25, 95% CI = [.19, .31], $t(211) = 8.26$, $p < .001$, d = .80). These results indicate that our within-subject manipulation was successful. Participants preferred the novel Deciders to the rejector and preferred the generous slot machine to the stingy one.

Choices between two Deciders (planned analysis). We next examined whether and to what degree rejection was generalized in the friendship and random-pairing conditions. We first tested the generalization effect for choices between two novel Deciders using the same mixed-effects logistic regression model in Study 2. This model predicted trial-by-trial choices of the left-side Decider (1: Yes, 0: No) using 1) the left-side Decider's distance to the rejector relative to the right-side Decider, 2) condition and 3) their interaction, while adding a random intercept for participant and a by-participant random slope for distance to rejector.

In support of generalization, participants were more likely to choose a Decider as their distance to rejector increased *relative to* the other Decider available onscreen ($b = .29$, 95% CI = [.13, .45], $z = 3.57$, $p < .001$). In addition, consistent with our prediction that the generalization effect is stronger in the friendship condition than in the random-pairing condition, we found a marginally significant interaction between distance and condition, such that the slope of distance from rejector on partner choice is steeper in the friendship condition ($b = .22$, 95% CI = [-.01, .45], $z = 1.89$, $p = .06$, see Figure 6 and Table 5). These effects were significant after we controlled for participants' memory accuracy during the network learning phase, suggesting that the asymmetry in generalization between conditions was not due to differences in memory ($b = .30$, $p < .001$; $b = .23$, $p = .05$, respectively) (see Figure 6 and Table 5).

Choices between Decider and slot machine (exploratory analysis). Next, we examined whether generalization happened for choices involving only one human target. We fitted the same corresponding model as in Study 2, predicting the choice of human target (as opposed to slot machine) using the human target's distance from the rejector, condition, and their interaction, while controlling for which slot machine was present (1: generous machine, -1: stingy machine). As expected, participants were more likely to choose the human targets that were farther from the rejector (b = .30, 95% CI = [.13, .48], z = 3.36, p < .001). Importantly, this generalization effect was also stronger in the friendship condition, as manifested by a significant two-way interaction between distance and condition (b = .36, 95% CI = [.11, .61], z = 2.85, p = .004, see Figure 6 and Table 5). These effects remained significant after we controlled for memory accuracy (b = .30, p < .001; b = .36, p = .004, respectively) (see Figure 6 and Table 5).

To better understand the significant interaction effect and determine whether generalization happened in both conditions, we further analyzed the simple effect of distance from rejector on partner choice in each condition and found that the interaction was driven by 1) a significant effect of distance on choice in the friendship condition (b = .36, 95% CI = [.12, .60], z = 2.90, p = .003), and 2) a non-significant effect of distance in the random-pairing condition (b = -.02, 95% CI = [-.23, .20], z = -.16, p = .87). Thus, contrary to our prediction, participants did not generalization rejection when the social network ties were arbitrarily determined, suggesting that association alone cannot give rise to generalization.

Meta-perception of acceptance (exploratory analysis). To further test whether participants generalized from rejection because they held the explicit belief that Deciders who were closer to the rejector in the friendship network were more likely to reject them, we ran a mixed-effects linear regression model, predicting participants' perceived acceptance by each novel Decider using 1) the Decider's distance from the rejector, 2) condition, and 3) their interaction, with a random intercept for participant and a by-participant random slope for distance. As expected, distance positively predicted perceived acceptance (b = .19, 95% CI = [.05, .33], t = 2.63, p = .009) but neither condition nor its interaction with distance had a significant effect (*p*s > .26). Thus, while participants inferred that Deciders closer to the rejector in the network were more likely to reject them, the strength of this effect did not seem to depend on the type of network ties.

Individual differences measures. Finally, we again tested whether our measures of individual differences (FNE and belief in homophily) moderated the generalization effects for both types of trials (Decider-Decider and Decider-Slot). Contrary to our expectation, we did not find a significant effect for either moderator (all *p*s > .39). Participants responded similarly to rejection, regardless of how much they feared negative evaluation or how much they believed in homophily.

Discussion

Study 3 asked whether generalization of rejection depends on the explicit belief that friends are similar to each other and thus have similar rejection tendencies. If so, then we should observe a stronger generalization effect when the network ties are based on friendship than when they are based on arbitrary pairing.

Our data support this hypothesis. Participants showed a steeper gradient when avoiding human targets who were close to the rejector in the friendship condition than in the random-pairing condition. Notably, the robustness of this effect depends on how we measure generalization. The asymmetry between the friendship and random-pairing conditions is most pronounced when participants were choosing between a human target and a slot machine (two-way interaction $b = .36$, $p = .004$). However, when we focus on the generalization choices between two human targets, this effect is only marginally significant ($b = .22$, $p = .06$). One possible explanation for this discrepancy is that the associative value of the human targets in the network (which can be formed in both the friendship and random-pairing conditions) is more salient when the human targets are juxtaposed than when they are presented individually. Thus, when choosing between two human targets, participants in the random-pairing condition might have a slight tendency towards generalization, which qualified the two-way interaction between distance and condition.

Meanwhile, like in Study 2, we found evidence for generalization not only in participants' partner choice, but also in their meta-perception. People who were closer to the rejector were perceived to have higher rejection tendencies. However, this effect did not differ between the friendship and random-pairing conditions, so it cannot be fully attributed to our manipulation, and it is unclear to what extent participants' generalized choices were due to their generalized meta-perception. That said, given the main finding on the asymmetry, Study 3 still supported a more general version of our hypothesis. That is, explicit knowledge about friendship in the rejector's social network *does contribute to* the generalization of rejection.

Finally, we had two unexpected findings in Study 3. First, we did not see generalization in the random-pairing condition, suggesting that associative learning alone is insufficient for the generalization of rejection. Second, we did not find a moderation effect of FNE as in Study 2. Given that the effect of FNE was small, it is possible that the study was underpowered to detect the relationship. Future versions of the study might benefit from manipulations that induce a stronger feeling of rejection, for example, using face-to-face interactions instead of computer-mediated economic games.

General discussion

Although social rejection is widely studied, relatively little is known about how it unfolds in social network contexts. Yet, rejection often happens in social networks, and people may incorporate knowledge of the social network to guide their response. The current research focuses on how people generalize from rejection and acceptance based on social network structure and the mechanisms underlying the generalization of rejection. Across three studies, we showed that people generalize from both acceptance and rejection by approaching novel targets who are close to the accepter and avoiding those close to the rejector. We also showed that generalized responses to rejection spread uniquely across *friendship* ties. In this section, we further elaborate on the nature of the generalization effects, their theoretical implications, the limitations of the present work, and its future directions.

The mechanisms of generalization

The pattern of generalization depends on how it is measured. We defined generalization as the tendency to avoid human targets who are closer to the rejector or farther from the accepter, and we measured this tendency in two ways. In Studies 2 and 3, participants completed two types of trials in the test phase. They either 1) chose between two novel human targets, or 2) chose *whether* to interact with a novel human target *or* a slot machine. Notably, in Study 2, we observed an asymmetry between these two trial types. When choosing between two human targets, participants consistently showed generalization by preferring targets that were closer to the accepter and farther away from the rejector (i.e. targets with higher positivity scores). However, this pattern no longer existed when participants chose whether or not to interact with one human target. Instead, participants who had been rejected were less likely to engage in social interaction *in general*, regardless of the positivity of the human target. One possible explanation for this asymmetry is that participants represented social value differently when making joint versus separate evaluations (Hsee et al., 1999). The juxtaposition of two targets (*joint evaluation*) might call for a direct comparison of their social values (Montague and Berns, 2002), thereby rendering their relative positivity salient. On the other hand, when a choice involved only one human target (*separate evaluation*), participants might base their choice more on whether they desired social interactions *in general*. In such cases, participants' choice would be less sensitive to the differences between targets but instead track how much they liked the targets' group as a whole. Notably, in Study 3, we did observe generalization in both trial types, so it is also possible that Study 2, with a smaller sample size, had insufficient power to detect this effect. Separate evaluation might have reduced the salience of each human target's positivity, without rendering it completely irrelevant to participants' decisions.

The different generalization effects between trial types also raise the question of how generalization should be defined. As Study 2 shows, the effects of generalization on people's social choices can be highly context-dependent, sensitive to factors such as how the choices are framed. When one has the option to avoid social interaction, it would be reasonable to define generalization as a general tendency to approach or avoid social interaction, which may be insensitive to the identity of each potential interaction partner. Future work could leverage insights from the contextual nature of generalization to create cognitive interventions that help rejection-sensitive individuals navigate their social environment.

The pattern of generalization depends on the nature of network ties. Study 2 suggests that the pattern of generalization depends on how it is measured. Study 3 further shows that generalization is stronger in some networks than others. Participants generalized more from rejection in friendship networks than in arbitrarily connected networks. This finding suggests that people's explicit knowledge of friendship leads them to generalize after rejection, possibly by helping them identify novel targets with high rejection tendencies.

In Study 3, we did not find generalization of rejection when the network was based on arbitrary connections. Given that most participants comprehended the task and memorized the networks well, it is likely that generalization of rejection *requires* knowledge of friendships and thus cannot arise from associative learning alone. Consistent with this idea, past research shows that the transfer of value from a person to their associates is stronger in social (e.g. friendship) versus non-social contexts (Martinez et al., 2016). However, one should not completely rule out the relevance of associative learning based on the null effect. For example, it is possible that participants in the random-pairing condition, knowing that the network ties were uninformative, deliberately *down-regulated* their negative affect towards targets associated with the rejector while choosing their partners. In this case, associative learning does affect people's *perception* of the targets, but this effect does not translate into their *decisions*. Future work should further probe the cognitive processes that help people incorporate network knowledge into social decision-making.

The consequences of generalization

Our findings also shed light on the consequences of generalization. At the individual level, people who generalized from rejection avoided social interaction with novel targets and formed fewer interpersonal connections (Study 2). Notably, we found evidence that these effects were moderated by individual differences in fear of negative evaluation (FNE). Specifically, after rejection, people who were higher on FNE were more likely to avoid interaction with targets who were closer to the rejector in the social network. This finding helps us understand factors that affect psychological wellbeing in network contexts. To the extent that people with higher FNE generalize more from social rejection, they may avoid social interaction to a greater extent and drift to more peripheral network positions across time. Generalization of rejection, therefore, can potentially explain how loneliness spreads in social networks (Cacioppo et al., 2009) and why lonely people ironically become lonelier across time, despite their desire for social connection. As a caveat, because the moderation effect of FNE was not replicated in Study 3, implications of this effect should be interpreted cautiously and left open to further investigation.

The current findings also suggest the consequences of generalization for collectives. Consistent with past work (Heine et al., 2016; Hackel et al., 2022), we showed that positive social feedback can lead people to form generalized positive attitudes towards out-groups (Study 2). This raises questions of how generalization might shape people's—especially newcomers'—attitudes towards their social *in-groups*, a question that remains underexplored in the literature. We believe our paradigm is well suited for this question, as we can experimentally manipulate both the rejection/acceptance experiences and the network structure of the groups that participants are joining.

Limitations and future directions.

The current research has a few limitations. First, although our findings strongly support that explicit knowledge about friendship contributes to the generalization of rejection, it is agnostic regarding the contribution of associative learning processes to this effect. Future work should address this issue by directly manipulating the presence and strength of association among the social targets.

Second, all three studies were lab experiments with an artificial design. This design allowed for careful experimental control of the social network and participants' rejection and acceptance experiences, but were unable to capture the full dynamic of real-world intragroup interactions. Nor could they reveal the longer-term health consequences of these processes. Future work should test how social rejection and acceptance unfold in the field, for example, by tracing college students' social ties as they join on-campus student clubs or by mapping out the psychological trajectory of employees as they navigate the workplace.

In conclusion, the present findings suggest that when responding to social rejection and acceptance, people not only rely on their memory from personal interactions but also utilize their knowledge of the rejector/accepter's social network. Importantly, people use social network information in a highly context-sensitive manner, generalizing primarily when the network ties are based on friendship. When choosing social partners in a novel environment, people integrate direct experiences from social learning with indirect inferences based on social network structure to guide their behavior.

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Table 1.

The self-related questions participants answered in Session 1 (Studies 1-3).

Question
What are 3 words a close friend would use to describe you?
For what in your life do you feel most grateful?
When was the last time you asked for forgiveness and what was it for?
What obstacles are you currently trying to overcome?
What was a time when you were honest, even though you didn't have to be?
What would you do if you were given credit for something that someone else actually did?

Table 2.

Mixed-effects logistic regression model on choice probability (Study 1).

Term	β	*SE*	*z*	*p*	95% CI
Model 1: Main effect of relative distance on choice					
(Intercept)	0.05	0.06	0.83	.409	[-0.07, 0.18]
left_relative_dist	0.28	0.09	3.12	**.002****	[0.11, 0.46]
Model 2: Loneliness as moderator					
(Intercept)	0.06	0.07	0.82	.413	[-0.08, 0.20]
left_relative_dist	0.27	0.09	3.04	**.002****	[0.09, 0.44]
loneliness.c	0.14	0.12	1.21	.227	[-0.09, 0.37]
left_relative_dist: loneliness.c	-0.24	0.14	-1.68	.093	[-0.52, 0.04]
Model 3: Rejection-sensitivity as moderator					
(Intercept)	0.04	0.07	0.61	.543	[-0.10, 0.18]
left_relative_dist	0.29	0.09	3.39	**.001*****	[0.12, 0.46]
RS_mean.c	0.02	0.01	1.22	.224	[-0.01, 0.04]
left_relative_dist: RS_mean.c	-0.03	0.02	-1.69	.092	[-0.06, 0.00]

Note. Results from linear mixed-effects models for the generalization effect. In the first model, the probability of choosing the left target is the dependent variable, with the left target's relative positivity being a fixed effect predictor. The second and third model included loneliness and rejection-sensitivity (centered) and their interactions with the left target's relative distance as predictors. For all three models, random intercepts and by-trial linear slopes were included for each participant.

* $p < .05$, ** $p < .01$, *** $p < .001$

Table 3.

Mixed-effects logistic regression model on choice probability (Study 2).

Term	β	*SE*	*z*	*p*	95% CI
Model 1: Choices between two human targets					
(Intercept)	-0.01	0.06	-0.29	.77	[-0.13, 0.09]
left_relative_positivity	0.39	0.10	3.88	**< .001*** **	[0.19, 0.59]
Condition (rejection)	0.10	0.08	1.24	.21	[-0.06, 0.25]
left_relative_positivity: condition (rejection)	-0.11	0.13	0.08	.40	[-0.38, .15]
Model 2: Choices between human target and slot machine					
(Intercept)	1.19	0.33	3.66	**< .001*** **	[0.55, 1.83]
positivity	0.11	0.16	0.65	.516	[-0.21, 0.42]
Condition (rejection)	-1.08	0.44	-2.47	**.014***	[-1.93, -0.22]
slot (generous)	-0.89	0.21	-4.27	**< .001*** **	[-1.29, -0.48]
positivity: condition (rejection)	0.15	0.20	0.76	.445	[-0.24, 0.54]
positivity: slot (generous)	0.10	0.13	0.74	.459	[-0.16, 0.35]
Condition (rejection): slot (generous)	-1.11	0.20	-5.40	**< .001*** **	[-1.51, -0.70]

Note. Results from linear mixed-effects models for the generalization effects. The first model is based on choices made between two targets, with the probability of choosing the left target as the dependent variable, the left target's relative positivity, condition, and their interaction as fixed effect predictors. The second model is based on choices made between one human target and one slot machine, with the probability of choosing the human target as the DV, the human target's positivity, condition, and their interaction as fixed effects predictors. For both models, random intercepts and by-trial linear slopes were included for each participant.

* p < .05, ** p < .01,*** p < .001

Table 4.

Mixed-effects logistic regression model on choice probability with FNE as moderator (Study 2).

Term	β	*SE*	*z*	*p*	95% CI
Model 1: Choices between two human targets					
(Intercept)	-0.02	0.06	-.33	.739	[-0.13, 0.10]
left_relative_dist	0.36	0.10	3.67	**< .001***	[0.17, 0.55]
condition (rejection)	0.10	0.08	1.31	.191	[-0.05, 0.26]
fne_mean.c	0.05	0.05	.91	.056	[-0.06, 0.15]
left_relative_dist: conditionrejection	-0.10	0.13	-.75	.456	[-0.36, 0.16]
left_relative_dist: fne_mean.c	-0.08	0.09	-.88	.380	[-0.25, 0.10]
conditionrejection: fne_mean.c	-0.10	0.07	-.15	.145	[-0.24, 0.04]
left_relative_dist: condition (rejection): fne_mean.c	0.28	0.12	2.33	**.020***	[0.04, 0.51]
Model 2: Choices between human target and slot machine					
(Intercept)	1.28	0.32	4.00	**< .001***	[0.65, 1.90]
distance_from_rejector	0.06	0.16	.39	.695	[-0.25, 0.38]
conditionrejection	-1.11	0.43	-2.61	**.009**	[-1.95, -0.28]
fne_mean.c	0.51	0.28	1.84	.066	[-0.03, 1.05]
slot (generous)	-0.85	0.21	-4.03	**< .001***	[-1.26, -0.44]
distance_from_rejector: conditionrejection	0.18	0.19	.92	.357	[-0.20, 0.56]
distance_from_rejector: fne_mean.c	-0.14	0.13	-1.03	.301	[-0.40, 0.12]
conditionrejection: fne_mean.c	-0.98	0.38	-2.60	**.009**	[-1.71, -0.24]

Table 4 (continued).

Mixed-effects logistic regression model on choice probability with FNE as moderator (Study 2).

Term	β	*SE*	*z*	*p*	95% CI
distance_from_rejector: slot (generous)	0.08	0.13	.64	.521	[-0.17, 0.34]
conditionrejection: slot (generous)	-1.14	0.21	-5.50	**< .001*** **	[-1.55, -0.74]
fne_mean.c: slot (generous)	0.20	0.09	2.25	**.024***	[-0.03, 0.37]
distance_from_rejector: conditionrejection: fne_mean.c	0.27	0.18	1.56	.192	[-0.07, 0.62]

Note. Results from linear mixed-effects models for moderation effect of FNE. The first model is based on choices made between two human targets. The second model is based on choices made between one human target and one slot machine. For both models, random intercepts and by-trial linear slopes were included for each participant.

* p < .05, ** p < .01, *** p < .001

Table 5.

*Mixed-effects logistic regression model on choice probability (Study 3)***.**

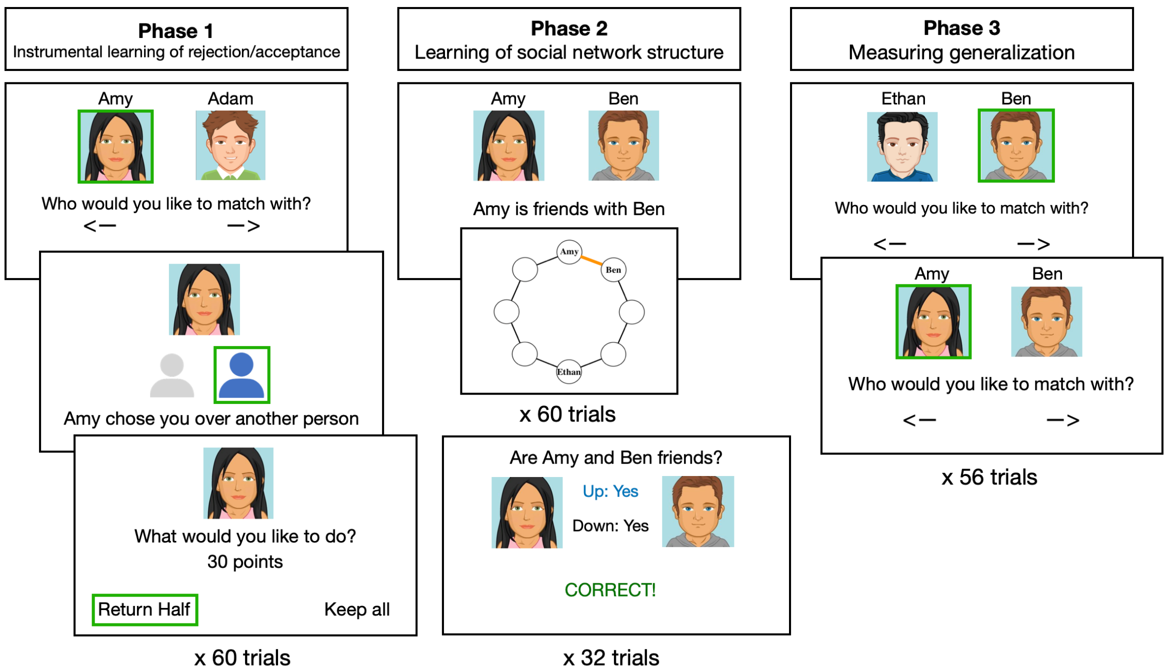
Term	β	*SE*	*z*	*p*	95% CI
Model 1: Choices between two human targets					
(Intercept)	0.03	0.05	.61	.540	[-0.07, 0.13]
left_relative_dist	0.29	0.08	3.57	**< .001*****	[0.13, 0.45]
conditionRandomPair	-0.06	0.07	-.87	.383	[-0.21, 0.08]
left_relative_dist: conditionRandomPair	-0.22	0.12	-1.89	.059	[-0.45, 0.01]
Model 2: Choices between human target and slot machine					
(Intercept)	-0.23	0.24	-.91	.363	[-0.73, 0.27]
distance_from_rejector	0.35	0.10	3.38	**<.001*****	[0.15, 0.56]
conditionRandomPair	0.50	0.34	1.46	.143	[-0.17, 1.16]
slot (generous)	-1.60	0.24	-6.67	**< .001*****	[-2.07, -1.13]
distance_from_rejector: conditionRandomPair	-0.37	0.13	-2.85	**.004****	[-0.62, -0.11]
distance_from_rejector: slot (generous)	-0.12	0.12	-1.00	.315	[-0.35, 0.11]
conditionRandomPair: slot (generous)	-0.03	0.17	-.15	.991	[-0.36, 0.31]

Note. Results from linear mixed-effects models for the generalization effects in Study 3. The first model is based on choices between two human targets, with probability of choosing the left target as the DV, left target's distance from rejector, condition, and their interaction as the fixed effect predictors. The second model is based on choices between one target and one slot machine, with probability of choosing the human target as the DV, the human target's distance from rejector, condition, and their interaction as the fixed effects predictors. For both models, random intercepts and by-trial linear slopes were included for each participant.

* $p < .05$, ** $p < .01$, *** $p < .001$

Figure 1.

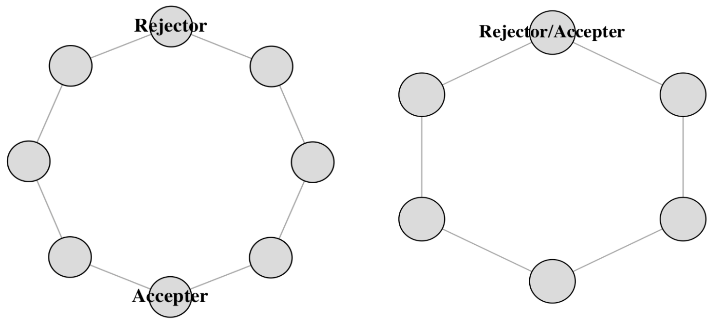
Schematic of Session 2, Study 1.



Note. Schematic of Session 2 of Study 1 testing generalization of social rejection and acceptance. **Phase 1:** In each round, participants choose one of two possible partners (“Deciders”) and received feedback indicating whether the Decider chose them (blue avatar) or a different participant (gray avatar) for a trust game. If matched, participants play a trust game where they choose whether to return points. To manipulate social rejection and acceptance, one Decider is programmed to choose participants 80% of the time and the other chooses them 20% of the time. **Phase 2:** Participants learn the social network structure by seeing which Deciders are friends and then complete a memory accuracy test, where they indicate whether each pair was friends, and receive feedback. **Phase 3:** Participants make further partner choices for trust games with no feedback. They now see network members with whom they did not interact in Phase 1.

Figure 2.

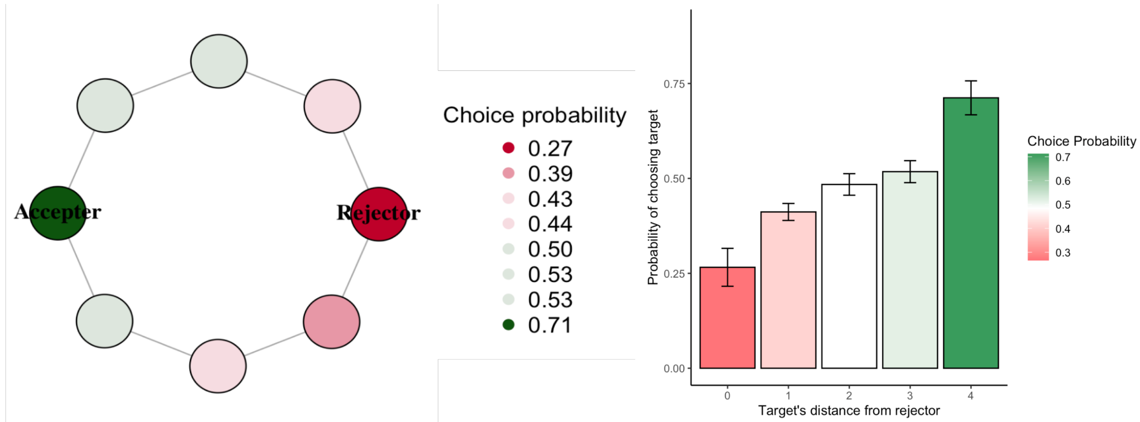
Social network structures in Studies 1 – 3.



Note. Social network structures in Studies 1 - 3. **Left**. In Study 1, participants learned about a group of eight students who are friends with each other in a ring-network. Participants started by learning about two targets (one rejector and one accepter) in the instrumental learning phase. The rejector and accepter are maximally distant from each other in the network (i.e. separated by 4 degrees). **Right**. In Studies 2 and 3, participants learned about a group of six students, only one of whom they interacted with in the instrumental learning phase. In Study 2, that interaction partner during instrumental learning was either a rejector or an accepter, depending on condition. In Study 3, the interaction partner was always a rejector. However, we manipulated the nature of the social network ties. In the friendship condition, participants were told that people who were connected in the network were friends, whereas in the random-pairing condition, they were told that the network connections were randomly determined.

Figure 3.

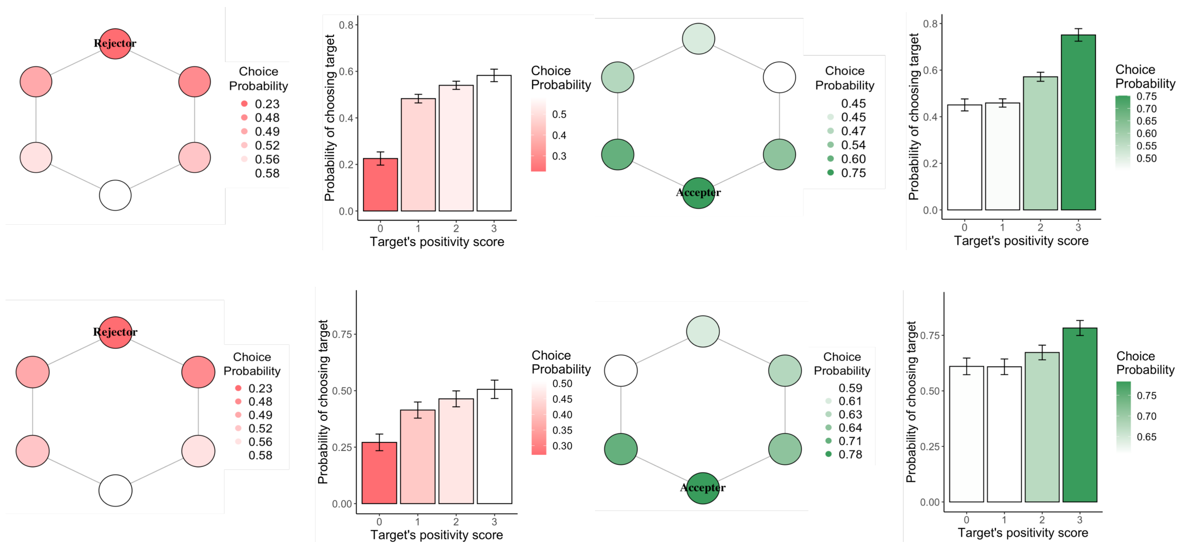
Generalization effects in Study 1.



Note. Generalization effect in Study 1. **Left**. Participants' likelihood of choosing each target during the Test phase depends on the target's distance to the rejector (i.e. closeness to the accepter) in the network. Participants were less likely to choose targets that were closer to the rejector (farther away from the accepter). **Right**. Participants' likelihood of choosing each target as a function of their distance to the rejector (closeness to the accepter). The rejector had distance of 0, and the rejector had distance of 4, while the novel targets had distance ranging from 1 to 3. Participants were more likely to choose a target as they move away from the rejector. Error bars represent 95% CI.

Figure 4.

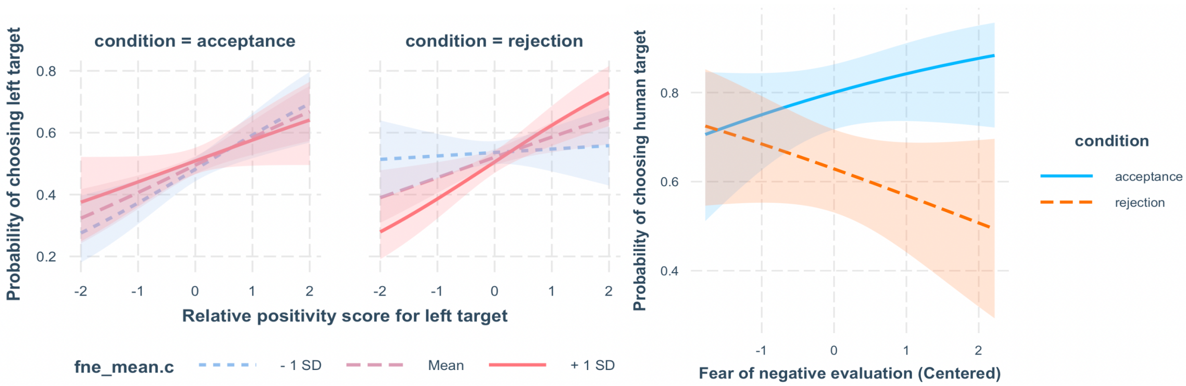
Generalization effects in Study 2.



Note. Generalization effects in Study 2. **Top row**. When choosing between two human targets, participants in both conditions were more likely to choose the target with higher positivity score, suggesting that generalization happens for both rejection and acceptance. **Bottom row**. When choosing between target and slot machine, participants also showed a trend of preferring targets with higher positivity scores. However, this trend did not reach statistical significance. That said, participants in the rejection condition were less likely to choose novel *human* targets than those in the acceptance condition. All error bars represent 95% CI.

Figure 5.

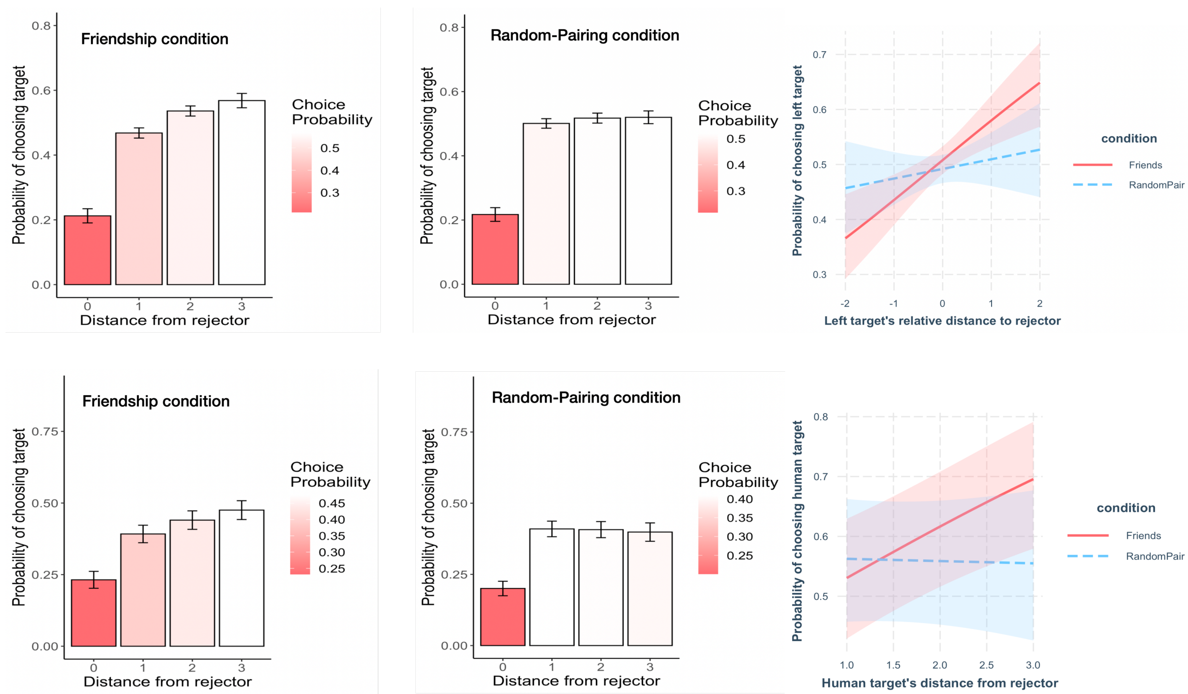
Moderation effects of FNE in Study 2.



Note. Moderation effects of FNE in Study 2. **Left**. For trials between two novel Deciders, FNE moderated generalization from rejection, but not generalization from acceptance, as revealed by a significant three-way interaction among FNE, positivity, and condition. The effect of positivity on choice in the rejection condition was stronger among participants high in FNE. This effect, however, did not hold in the acceptance condition. **Right**. For choices between Decider and slot machine, FNE moderate the main effect of condition on choice, such that after being rejected, participants high in FNE were less likely to choose human interaction compared with participants low in FNE. High and low FNE were defined as FNE scores at least one standard deviation above and below the mean, respectively. All shaded areas represent 95% CI.

Figure 6.

Generalization effects in Study 3.



Note. Generalization effects in Study 3. **Top row**. When choosing between two human targets, participants in the friendship, but not random-pairing, condition were more likely to choose the target who was relatively farther from the rejector, suggesting that generalization depends on friendship ties. **Bottom row**. When choosing between human and slot machine, participants also showed a similar trend, preferring human targets farther from the rejector in the friendship, but not the random-pairing condition. All error bars represent 95% CI.