Chen, J., & Igarashi, T. (2023). Unequal but not separate: Emergence of rich–poor cooperation in resource exchange. *Asian Journal of Social Psychology*. https://doi.org/10.1111/ajsp.12569

Unequal but Not Separate:

Emergence of Rich-Poor Cooperation in Resource Exchange

Running Title: Rich-poor cooperation in resource exchange

Jiayu Chen[1] and Tasuku Igarashi[2]

[1]Graduate School of Education and Human Development, Nagoya University;

kagyokuchen@gmail.com

[2]Graduate School of Education and Human Development, Nagoya University;

igarashi.tasuku.n6@f.mail.nagoya-u.ac.jp

Author Note

Jiayu Chen https://orcid.org/0000-0002-7521-6717

Tasuku Igarashi https://orcid.org/0000-0001-9432-4425

Correspondence concerning this article should be addressed to Jiayu Chen, Graduate School of Education and Human Development, Nagoya University, Furo-cho, Chikusa-ku, Nagoya, AICHI 464-8601, Japan. Email: kagyokuchen@gmail.com.

Acknowledgments

We thank Haruhiko Mitsunaga for his helpful advice in utilizing Bayesian models to analyze the two-step behavioral data.

Data availability statement

The data supporting the conclusion of this article will be made available at https://osf.io/ac3sz/.

Funding

This study did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Conflict of interest disclosure

The authors declare that this research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Research materials availability statement

The research materials supporting the conclusion of this article will be made available at https://osf.io/ac3sz/.

Pre-registration statement

The authors hereby state that the research project plan was not preregistered to this journal, other journals, or any public repositories.

Ethics approval statement

Studies 1 and 2 were approved by the Ethical Review Board of the Graduate School of Education and Human Development, Nagoya University (18-1223, 19-1328).

Abstract

Addressing inequality is a critical challenge for society as a whole and requires sustained efforts to promote fairness and opportunity for all. Filling in the resource gap across social classes is essential in reducing inequality. Previous studies have revealed that ingroup favoritism hinders the rich from cooperating with the poor and expands the wealth gap. Nevertheless, ways of narrowing the gap between the rich and the poor remain an open question. Inducing rich–poor cooperation could be effective in eliciting resource flow across classes. In this study, two experiments using a modified Prisoner's Dilemma game were conducted in Japan (*N* = 213) and China (*N* = 150) to examine whether highlighting partners' cooperativeness under permeable group boundaries induces rich–poor cooperation. All participants were allocated to the rich group and participated in the game with programmed rich- or poor-group partner bots, whose cooperation rates were manipulated. Despite the initial resource disparities between participants and the partner bots, participants were more likely to select and cooperate with cooperative poor-group partners than with non-cooperative rich-group partners. Generalized trust played an important role in the enhancement of rich–poor cooperation. The findings shed light on the possibility of reducing inequality and promoting social mobility in society.

Keywords: cross-cultural study, generalized trust, inequality, Prisoner's Dilemma game, rich–poor cooperation, selective play

Introduction

Eradicating inequality through persistent and targeted efforts to increase fairness and opportunities for all members is crucial for building a more equitable and inclusive society. Given the worldwide rise of inequality, there is a global need to find remedies to this problem. One possible solution is the facilitation of resource sharing between the “haves” and “have-nots.” However, this is difficult because human social preference lies in similarity, which is well documented as the status homophily principle and ingroup favoritism. The status homophily principle (Lazarsfeld & Merton, 1954), known as the preference for interacting with others of similar status or social class, shows that social characteristics strongly determine social selection. Correspondingly, ingroup favoritism, which is the tendency of favoring others with shared group identities, indicates that a similarity in social identities shapes people’s preference in allocating resources. Both the status homophily principle and ingroup favoritism emerge under inequality. Exposed to wealth disparities, resource-rich people are likely to avoid social connection and resource sharing with the poor, resulting in rich–poor segregation (Nishi et al., 2015).

In the following sections, we first introduced a social identity perspective to explain the preference for homophilous social selection and cooperation in resource exchange. We then discuss the possibility of overcoming it from the bounded generalized reciprocity perspective.

Social identity and homophily in resource exchange

The social identity theory (SIT) posits that people tend to establish their social identities through the cognitive categorization of social groups and similarity or homogeneity between themselves and other group members (Tajfel & Turner, 2001; Turner et al., 1987). People generally show strong ingroup favoritism in resource sharing (see Balliet et al., 2014 for review). A recent study (Melamed et al., 2020) conducted a repeated Prisoner’s Dilemma game (PDG) across two universities and found that prospective PDG partners were more likely to be selected based on their group category (i.e., whether or not the partners belong to the same university as participants) than on their cooperativeness. This suggests the emergence of category-based segregation in the cooperation network.

Recent psychological research has unpacked homophilous preference under inequality from the perspective of SIT (Aksoy, 2019; Jetten et al., 2021). People incline to categorize "us" versus "them" based on similarity in wealth (Jetten et al., 2017). Furthermore, they are likely to describe themselves and others by wealth-related words in a highly unequal social system (Peters et al., 2021). Regarding action strategies rooted in wealth categorization, a theoretical perspective of homophily suggests that homophily increased predictability of another person's behavior, thereby fostering reciprocity and the formation of instrumental relationships (Ibarra, 1992). People utilize wealth categories as information to distinguish social partners who are likely to adopt similar strategies; they have an inclination to choose similar social partners and exchange resources with them (Johnson & Smirnov, 2018). Additionally, initial disparities may induce payoff asymmetry between rich and poor groups (Aksoy, 2019). In other words, cooperation between two rich individuals yields larger benefits than cooperation between a rich and a poor individual. If the rich need to select potential interaction partners based only on their resources, it would be reasonable to nominate one who has relatively rich resources; thus, the rich (upper class) are often privileged in the allocation of resources. Accordingly, we argue that the key to facilitating resource sharing between the "haves" and "have-nots" lies in inducing the rich to overcome wealth homophily and proactively share their resources with the poor. Thus, the current study explored the rich's behavioral strategies under resource disparities.

In the real world, wealth serves as social class signals, inducing cross-class prejudice and stereotypes (Connor et al., 2021). For instance, the poor (in low socioeconomic status) is generally perceived as parasitic (e.g., opportunistic, exploitative) and incompetent (Cuddy et al., 2008). These social class stereotypes further affect people's judgment in resource exchange (Russell & Fiske, 2008). People spontaneously categorize themselves as relatively rich or poor in comparison with others (Kraus et al., 2017). The relatively rich are likely to share more resources with other ingroup (rich) members than with outgroup (poor) members (Martinangeli & Martinsson, 2020); meanwhile, the poor show strong implicit evaluative preference towards rich people (Rudman et al., 2002). Recent literature on the social selection theory has indicated that aspiration serves as an essential mechanism for explaining people's tendency to connect with high-status targets (Snijders & Lomi, 2019). Compared with the rich, the poor, being driven by aspiration, may show a stronger willingness to cooperate with the rich. Furthermore, neither rich–poor segregation nor wealth homophily always holds true. People tend to show a greater preference for others relatively low in ability but are willing to help others over those relatively high in ability but are ungenerous (Dhaliwal et al., 2022). These findings imply that the rich–poor boundary in real society is not universally impermeable.

Cooperativeness in resource exchange

Considering the flexibility of cognitive group boundary, the nature of ingroup favoritism can be interpreted as a consequence of cooperative interactions with others pursuing mutual benefits. This view was theorized from the perspective of bounded generalized reciprocity (BGR; Yamagishi, et al., 1999), which argues that mutual outcome interdependence, rather than mere category commonalities, triggers resource sharing with other members. In other words, a group boundary only emerges when people decide whether to cooperate with others through the expectation of mutual cooperation (Yamagishi & Kiyonari, 2000). In line with this argument, people embedded in dynamic social networks in repeated PDG tend to selectively form social ties with partners who have good reputations (Rand et al., 2011; Wang et al., 2012). A meta-analysis on ingroup favoritism revealed that the mechanism of benefiting ingroup over outgroup members is better explained by BGR than SIT perspectives (Balliet et al., 2014). These findings suggest that cooperativeness-based preference can override group boundaries and promote resource exchange among cooperators regardless of their social categories.

However, to the best of our knowledge, a conclusion on whether SIT or BGR is more appropriate in explaining dominant strategies for rich–poor partner selection has not yet been reached. In this study, the selective play paradigm (Hayashi & Yamagishi, 1998) was applied to test whether people make category-based partner selections (rooted in SIT) or cooperativeness-based partner selections (rooted in BGR), in a situation where relatively rich and poor group categories are manipulated as salient. In the selective play paradigm, players employ both selection (to select whom to interact with) and action strategies (cooperation or defection) in repeated interactions. The paradigm incorporates the cost-benefit structure in real-world resource exchanges and highlights the importance of cooperativeness for players in finding better partners to achieve of mutual benefits.

Pivotal role of generalized trust in the generalized exchange system

Individuals' sensitivity to others' cooperativeness differs according to generalized trust. Generalized trust is a belief on human benevolence grounded in an expectation toward others' cooperativeness; it plays an essential role in obtaining resources under social uncertainty (Yamagishi et al., 1995). According to the emancipation theory of trust (Yamagishi & Yamagishi, 1994), generalized trust serves as an incentive for relationship extension. In other words, generalized trust is a sort of cognitive bias on risk-proneness when people cultivate new social relationships for better outcomes (Yamagishi, 2011). For resource exchanges, individuals with high generalized trust (high trusters) are more sensitive to opportunity costs (i.e., the value of what is lost by making a certain choice) than those with low generalized trust (low trusters). Hayashi and Yamagishi (1998) indicated the essential role of generalized trust in the selective play paradigm through the promotion of the selective tie-formation strategy for better outcomes. A longitudinal study on the formation and termination of social relationships revealed that high trusters tend to pursue access to valuable information sources in advice-seeking networks (Igarashi & Hirashima, 2021).

Generalized trust is positively related to social class in wealthy countries (Hamamura, 2012). Under inequality, generalized trust could facilitate cross-class encounters from the middle and upper classes to the lower classes (Fiske & Markus, 2012). If the cooperativeness-based partner selection is more plausible than the category-based partner selection, generalized trust would trigger tie-formation from the resource rich to the cooperative poor beyond social class homophily.

Current Study

The current study aims to scrutinize ways of overcoming social class homophily and achieving cross-class cooperative interactions. We used the framework of an experimental economic game. Experimental economic games such as the Prisoner's Dilemma Game (PDG) and Public Goods Game (PGG) are powerful tools to observe people's social preferences for selecting partners and investing resources for future outcomes, especially when participants are allowed to update their partners in repeated interactions (Van Dijk & De Dreu, 2021).

Two studies were utilized to examine whether cooperativeness (BGR perspective) or categorical membership (SIT perspective) is preferred when players differ in their resource amounts in the experimental setting. In the real world, people categorize others as rich or poor through multiple clues including residential and occupational status. However, these clues are not available in a standard online experimental economic game. Therefore, we introduced an explicit rich–poor group label to elicit the perceived wealth disparities among players in the experiment. Potential interaction partners' cooperativeness (selfish or cooperative) was manipulated by programmed bots based on their categorical memberships (rich or poor). Bots with programmed responses are used to examine people's responses toward specific behaviors and have been found to be effective (Shirado & Christakis, 2020). We examined whether participants' partner selection and cooperation strategies vary according to player bots' cooperation rates and their categorical memberships.

This study examined three hypotheses. First, when cooperativeness is equal among potential partners, people (rich-group players) are more likely to choose the rich (ingroup) than the poor (outgroup) partners (Hypothesis 1a) and to cooperate with the former (Hypothesis 1b). Second, when the poor (outgroup) partners are more cooperative than the rich (ingroup), people are more likely to choose the poor (outgroup) than the rich (ingroup) partners (Hypothesis 2a) and cooperate with the former (Hypothesis 2b). Finally, people with high generalized trust tend to choose cooperative partners regardless of their categorical memberships (Hypothesis 3). These hypotheses were tested in Japan (Study 1) and China (Study 2), as these countries have relatively low and high generalized trust (Steinhardt, 2011; Yamagishi & Yamagishi, 1994).

Study 1

Method

Participants and design

The experiment was conducted on June 15, 2019. We recruited 254 Japanese participants from an online crowdsourcing service (Lancers). Each participant received 300 yen (approximately $2) as remuneration. After the survey was completed, the top five participants were selected as the winners based on the points they earned in the game and were given another 1000 yen (approximately $8) as bonus. This study uses a between-participant design. Participants were randomly assigned to either control or poor-cooperator-rich-defector (PCRD) condition.

Modified selective play paradigm

A modified repeated PDG incorporating the selective play paradigm was utilized (Hayashi & Yamagishi, 1998). At the beginning of the game, participants were informed that the experiment was a multi-player online experiment including paired activities and that all players would play the game with a unique ID to ensure anonymity. Participants were told that they would be allocated to either the rich or the poor group based on the initial points randomly given to them. The cut-off value of rich and poor groups was 1000 points. All participants were allocated to the rich group with 1530 initial points. To emphasize the rich–poor group category, a badge (rich: large money bag, poor: small money bag) was shown above their IDs and points to present their current group status. Participants were told that their group would be determined according to the points at each round.

Then, participants (rich-group players) played PDG for 30 rounds. Each round involved a two-step decision-making process: (1) selecting a partner and (2) choosing whether to cooperate or defect. Participants were informed that at each round, they were privileged to choose a partner from either the rich or poor groups. The points of the potential partners varied and ranged from P / 10 + 100 to P / 10 + 300 for potential poor-group partners, and from P - 300 to P + 300 for potential rich-group partners, where P represents the participants' points at each round. The potential partners were different across the 30 rounds; they were all programmed player bots, although participants did not know about them. After choosing a partner from the rich or poor group, participants played PDG with that partner. In addition to the standard PDG, payoffs in the game were based on the mutual decisions of the pair. If both players chose to cooperate, each player received 50 points. If both chose to defect, the pair received no points. If one player chose to cooperate and the other chose to defect, the cooperator lost 50 points and the defector received 100 points. At the end of each round, the decisions and the points earned by each player were displayed.

Participants (rich-group players) were randomly assigned to either the control or PCRD condition. In the control condition (N = 107), both rich and poor partner bots cooperated with participants randomly (at a 50% probability). In the PCRD condition (N = 106), poor-group partner bots cooperated with participants with an 80% probability, whereas rich-group partner bots cooperated with a 20% probability.

Generalized trust

Generalized trust was measured by the six-item General Trust Scale (Yamagishi & Yamagishi, 1994) using a five-point Likert scale from 1 (completely disagree) to 5 (completely agree). The items are "Most people are trustworthy," "Most people will respond in kind when they are trusted by others," "Most people are trustful of others," "Most people are basically honest," "I am trustful," and "Most people are basically good and kind." Cronbach's α was .86.

Procedure

The experiment was programmed in oTree (Chen et al., 2016). At the beginning, participants were instructed to play a resource distribution game with multiple online players. After being given the instruction and completing a practice session, participants took part in the game in either the control or PCRD conditions. Participants did not know about the total number of rounds in the game. Upon completion of the 30-round game, participants answered generalized trust and demographic questions (age, gender, education, and occupation), followed by a debriefing[1].

Results

Data from 30 participants who did not complete the task, three participants who withdrew their consents for analysis, and five participants whose experimental manipulation failed[2] were excluded. Consequently, data from 213 participants (M_{age} = 40.88, *SD* = 9.82, 132 males and 81 females) were used in the analysis.

Trend in partner choice

As the game involved two-step decision-making (partner choice and cooperation/defection) at each round, participants' (rich-group players') strategic behaviors were defined as a combination of the behavior at each step and classified into four types: (1) choose a poor-group partner and cooperate (CP [cooperate with the poor] strategy); (2) choose a poor-group partner and defect (DP [defect the poor] strategy); (3) choose a rich-group partner and

[1] We also measured participants' subjective social status (Adler et al., 2000) and self-esteem (Rosenberg, 1965). However, because we were primarily interested in the effect of generalized trust on rich-poor cooperation, we did not include these variables in the main analysis.

[2] Due to programming errors, the five participants had a round (1) in which they had belonged to the poor group because they decreased their points and/or (2) in which they needed to select one from two poor-group partners.

cooperate (CR [cooperate with the rich] strategy); and (4) choose a rich-group partner and defect (DR [defect the rich] strategy). Of those, we were more interested in the preference for CP strategy than the others. Participants' behavioral patterns, including the choice of and cooperation with poor-group partners, are presented in Figures 1 and 2.

A proportion test was used to compare the preference for poor- over rich-group partners across the 30 rounds. Participants (rich-group players) in the PCRD condition were more likely to choose the poor-group partners across the 30 rounds than those in the control condition, χ^2 (1) = 290.59, $p < .001$. One-sample proportion tests in each condition also indicated that the proportion of poor-group partners chosen was significantly lower than 50% in the control condition (43.36%), χ^2 (1) = 56.27, $p < .001$, but higher than 50% in the PCRD condition (64.65%), χ^2 (1) = 272.57, $p < .001$. These results revealed that participants preferred cooperative poor-group partners over selfish rich-group partners.

Two-step decision-making and the role of generalized trust

Figure 1 shows the descriptive statistics of participants' behavioral strategies. The proportion of poor-group partner (bot) choices were positively related to the cooperation ratio in both conditions (control: $r = .32$, $p = .002$; PCRD: $r = .36$, $p < .001$; see Figure 1-a). In the control condition, participants were more likely to adopt the DR (choosing a rich partner and defecting) strategy (36.9%). In the PCRD condition, participants tended to use the CP (choosing a poor partner and cooperating) strategy (39.9%) over the other strategies (see Figure 1-b). Participants in the PCRD condition were more likely to choose poor-group partner bots than those in the control condition (see Figure 1-c). A greater number of participants adopted the CP strategy in the PCRD condition than in the control condition (see Figure 1-d). Figure 2 shows the distribution of the poor-group partner (bot) choice ratio in the control and PCRD conditions, respectively.

We then fitted a Bayesian multinominal regression model including the experimental condition, generalized trust (centered), and their interaction effects as explanatory variables to estimate the preferences for the four strategies (CP, DP, CR, and DR) across the 30 rounds. CP strategy was set as the baseline for comparison with other strategies (for more details see Supplementary Study 1).

Table 1 presents the parameter estimates. Calculated values based on the combinations of the parameter estimates in each condition are presented in Figures 3a (showing the preferences for each strategy) and 3b (showing the effect of generalized trust on the preferences for each strategy). Note that all participants were allocated to the rich group.

In the control condition, DR strategy was preferred over other strategies; participants (rich-group players) were more likely to choose and defect rich-group partners when the cooperativeness of rich- and poor-group partners was equal. Therefore, Hypothesis 1a was supported but 1b was not. In contrast, CP strategy was preferred over other strategies in the PCRD condition. Participants were more likely to choose and cooperate with poor-group partners when they were cooperative. Therefore, Hypotheses 2a and 2b were supported.

In addition, the preference for CP strategy over other strategies was boosted by generalized trust. This indicates that participants with high generalized trust were more likely to choose and cooperate with cooperative poor-group partners. Meanwhile, participants with high generalized trust also showed a tendency to choose and cooperate with rich-group partners in the control condition where partners' cooperativeness did not differ across the groups. Therefore, Hypothesis 3 was only supported in the PCRD condition.

Discussion

Study 1 investigated rich-group players' partner choice and cooperation strategies in the modified selective play paradigm including rich- and poor-group partner bots. Participants (rich-group players) showed a strong tendency to choose other rich-group partners but defected them when their cooperativeness was equivalent to that of poor-group partners. In contrast, participants showed a clear tendency to choose and cooperate with poor-group over rich-group partners when the former was more cooperative than the latter.

The findings suggest that cooperativeness has a stronger impact on partner selection than rich–poor group categories. Although the rich-group identification is known to induce cooperation with the same rich-group (ingroup) players (Martinangeli & Martinsson, 2020), the current findings are consistent with the theorization of groups in BGR, wherein group boundaries are not determined based on mere category membership but on cooperative interactions among members in the same social network (Yamagishi et al., 1999). Furthermore, the current findings extend the scope of this theory by stipulating that the ingroup/outgroup boundary of the generalized exchange system could spontaneously emerge through the expectations of others' cooperativeness.

Generalized trust facilitated the preference for cooperative outgroup (poor) partners. High trusters are superior in social intelligence or processing social information about potential partners' cooperativeness (Yamagishi, et al., 1999). In the current experiment, once rich-group players who had high generalized trust exchanged resources with cooperative poor-group partners, they would realize the counterparts' trustworthiness and easily achieve cross-class resource exchanges.

The relationship between poor choice ratio and cooperation rate was positive and significant in both the control and PCRD conditions. This finding indicates that participants were less likely to exploit poor partners regardless of their cooperativeness. However, the current experimental design could not distinguish strategic cooperative behavior with cooperative others from mere charity giving or pure altruism to "kind-hearted but poor" players. Another caveat is that participants were forced to choose their partner in the PCRD condition from poor cooperators or rich defectors. In this research design, the rich–poor partner selection was confounded with cooperator preference and defector aversion. Therefore, Study 2 examined the same hypotheses by adding the rich-cooperator-poor-defector (RCPD) condition, in which poor-group partners behaved selfishly while rich-group partners behaved cooperatively. We assume that players allocated to the rich-group are more likely to choose and cooperate with cooperative rich-group partners compared to selfish poor-group partners.

In Study 1, generalized trust was related to the choice of and cooperation with ingroup (rich) partners when ingroup and outgroup partners' cooperativeness did not differ. This was not what we originally expected, so further examination is necessary to determine if the trend is robust. We also conducted the second experiment in China to test the robustness and universality of the current findings.

Study 2

Method

The experiment was conducted between November 15 and 20, 2019. Two faculty members of a department of Jilin University in China asked 496 Chinese undergraduate and graduate students to participate in the study through the department's student social networking service group. Participants took part in the online experiment by clicking a link and completing the task between 8 am and 10 pm. A total of 170 participants completed the task. Each participant received 15 Yuan (approximately $2) as remuneration. After all the experiments were completed, the top five participants were selected as the winners based on their performance and received 60 Yuan (approximately $8) as a bonus.

The experimental procedure was similar to that in Study 1 except for the addition of the RCPD condition. Participants played a 30-round PDG based on the modified selective play paradigm. In the control condition (N = 42), both rich- and poor-group partner bots cooperated with participants (rich-group players) at a 50% probability. In the PCRD condition (N = 49), poor-group partner bots cooperated with participants at an 80% probability, and rich-group player bots cooperated with participants at a 20% probability. In the RCPD condition (N = 59), rich-group partner bots cooperated with participants at an 80% probability and poor-group partner bots cooperated with participants at a 20% probability. Additionally, the money bag badges were presented to each player. Generalized trust was measured by the Chinese version of the 6-item General Trust Scale (Wang & Yamagishi, 1999), using a five-point Likert scale from 1 (completely disagree) to 5 (completely agree). Cronbach's α was .86.

Results

Data from three participants who withdrew their consent and 17 participants whose experimental manipulation failed[3] were excluded. The final sample contained responses from 150 participants (M_{age} = 21.62, *SD* = 2.49, 94 males and 56 females).

Trend in partner choice

A proportion test was used to compare the preference for poor- over rich-group players across 30 rounds among the three conditions. A significant difference was evident in the preference for poor-group players among the control condition (46.98%), the PCRD condition (67.14%), and the RCPD condition ((18.64%), χ^2 (2) = 788.23, $p < .001$). Residual tests revealed the significant differences across the three conditions (all *p*s < .001); compared to the control and RCPD conditions, participants (rich-group players) in the PCRD condition were more likely to choose the poor-group over rich-group players as a partner across the 30 rounds. One-sample proportion tests also indicated that the proportion of poor-group players chosen as a partner was significantly lower than 50% in the control condition ((46.98%), χ^2 (1) = 4.46, $p = .035$) and in the RCPD condition ((18.64%), χ^2 (1) = 694.85, $p < .001$), but higher than 50% in the PCRD condition ((67.14%), χ^2 (1) = 172.11, $p < .001$). These results revealed that participants preferred poor-group players as partners if they were cooperative.

[3] Similarly, in Study 1, 17 participants had a round in which: (1) they belonged to the poor group because they had decreased their points and/or (2) they needed to select one from two poor-group partners because of programming errors.

Two-step decision-making and the role of generalized trust

The behavioral strategies of Chinese participants (rich-group players) are shown in Figure 4. The proportion of poor-group partner (bot) choices were positively related to participants' cooperation ratio in the PCRD condition ($r = .52$, $p < .001$; see Figure 4-a). Participants were most likely to adopt the CP strategy in the control (36.7%) and PCRD (48.6%) conditions, and the CR strategy (55.1%) in the RCPD condition (see Figure 4-b). Participants in the PCRD condition showed an increasing trend of selecting a poor-group partner across the rounds, compared to those in the RCPD condition who showed a decreasing trend (see Figure 4-c). Participants in the RCPD condition were less likely to adopt the CP strategy compared to those in the control or PCRD conditions. A greater proportion of participants adopted the CP strategy in the PCRD condition than in the RCPD condition (see Figure 4-d). Figure 5 shows the distribution of the poor-group partner (bot) choice ratio in the control, PCRD, and RCPD conditions.

As in Study 1, a Bayesian multinomial regression model was used to estimate the preferences for four (CP (baseline), DP, CR, and DR) strategies across the 30 rounds. The results are shown in Table 2. Calculated values based on the combinations of the parameter estimates in each condition are presented in Figures 6a (showing the preferences for each strategy) and 6b (showing the effect of generalized trust on the preferences for each strategy). Note that all participants were allocated to the rich group.

No substantial difference was identified in the preference for CP and CR strategies in the control condition (see Figure 6a). Therefore, Hypotheses 1a and 1b were not supported. In the other conditions, participants (rich-group players) preferred to select and cooperate with cooperative partners. Participants in the PCRD condition were more likely to employ CP over CR strategy, while participants in the RCPD condition were more likely to employ CR over CP strategy. Therefore, Hypotheses 2a and 2b were supported.

Participants with high generalized trust were more likely to employ CP strategy in the PCRD condition and employ CR strategy in the RCPD condition (see Figure 6b). This indicated that participants (rich-group players) with high generalized trust were more likely to choose and cooperate with cooperative players. However, participants with high generalized trust also tended to employ CP strategy in the control condition where poor and rich group players did not differ in their cooperativeness. Therefore, Hypothesis 3 was partially supported.

Cross-cultural comparison

The cooperation rates in PDG were compared across the 30 rounds between Japanese (Study 1) and Chinese (Study 2) participants in the control and PCRD conditions. Chinese participants were more cooperative than Japanese participants in the control condition ((Chinese: 54.05%, Japanese: 32.46%), χ^2 (1) = 168.12, p < .001) and in the PCRD condition ((Chinese: 50.94%, Japanese: 38.64%), χ^2 (1) = 60.59, p < .001). In terms of generalized trust, Chinese participants (M = 21.26, SD = 4.44) were more trustful than Japanese participants ((M = 17.62, SD = 4.35), t (317.11) = 7.77, p < .001, Cohen's d = 0.83).

Discussion

A strong preference for cooperative partners was observed regardless of their categorical membership in the PCRD and RCPD conditions. In the RCPD condition, a significant positive relationship was observed between the cooperative-rich choice ratio and the cooperation ratio. The trend is interpreted as defector aversion by comparing selfish poor-group partners with cooperative rich-group counterparts to pursue better outcomes rather than mere charity giving or pure altruism for poor-group partners. Specifically, high trusters were more likely to select and cooperate with interaction partners based on their cooperativeness.

Participants preferred both poor- and rich-group partners and cooperated with them in the control condition. However, this finding was difficult to interpret because all participants belonged to the same department; consequently, they might have thought that they knew each other and had concerns about their reputations during the online experiment, even while being aware of their anonymity. Additionally, participants (rich-group players) might have been motivated to lend a hand to others randomly allocated to the poor group (as a savior of the "poor" students). If this was the case, cooperative behavior should have been found indiscriminately across rich- and poor-group partner players when cooperativeness did not work as a source of normative partner selection.

General Discussion

The current study examined whether a partner's cooperativeness in PDG induced a cooperative strategy beyond the rich–poor boundary and whether generalized trust facilitated cross-class cooperation. The findings of the two online experiments in Japan and China showed a consistent pattern indicating that rich-group players prefer to select and cooperate with cooperative partners regardless of their rich–poor categorical membership. Generalized trust also facilitated this tendency. The cross-cultural comparison for the current sample suggests that Chinese individuals are more cooperative and trustful than Japanese individuals.

When selecting a partner and deciding whether or not to cooperate in PDG, rich-group players focused more on their partner's cooperativeness than on their rich–poor categorical memberships. These findings provide supportive evidence for cooperativeness-based partner selection rooted in BGR. Some may wonder if the results are inconsistent with previous literature (Melamed et al., 2020) that revealed ingroup favoritism as group-based homophilous partner selections in PDG. This may be due to the permeability of the group boundary. The current study determined the rich and poor groups according to the random number of resources among participants and instructed them to consider the boundary as changeable according to the points they would earn in the game. Therefore, the boundary of a generalized exchange system could emerge based on the expectation of mutual cooperation and its consequences rather than on initial group categories.

Meanwhile, the evidence that visible wealth disparities hinder rich individuals from serving social connections to poor individuals (Nishi et al., 2015) poses a question of how to shift the focus from rich–poor group categories to the cooperative nature of individuals. The current findings provide a hint for narrowing the resource gap between the rich and the poor, motivating people to focus more on others' cooperativeness than on their categorical membership to acquire better outcomes. In reality, wealthy individuals can take risks to benefit those who are cooperative but poor in resources. This is a meritocratic and prospective investment for the future to fill the skill-success gap (Sornette et al., 2019), as exemplified in entrepreneur-venture capitalist relationships for mutual gain (Cable & Shane, 1997). Highlighting one's cooperativeness through reputation or other social systems under high social mobility could be an effective intervention to promote the cross-class resource-flow mechanism. Currently, this study targeted only resource-rich people in the experimental setting. Future research should extend the current findings by complementing the preference of resource-poor people for cooperative or resource-rich partners to fully address the rich–poor resource gap.

The current study also revealed the moderating role of generalized trust in cooperativeness-based over category-based social selection and cooperation. Aside from ingroup favoritism, the rich–poor social category serves as a cue for impression formation, particularly for negative stereotypes in the competence domain for the poor (Cuddy et al., 2008). The risk-tolerance and social-intelligence nature of generalized trust might help people overcome negative stereotypes and lead to the selection of and cooperation with cooperative poor partners. However, we measured generalized trust before PDG. The design cannot reject the possibility that the PDG experience changed the level of generalized trust. The measurement order should be reversed in future research.

The current experiments were conducted in two Asian countries, Japan and China. Japan is relatively wealthy and ranks sixth in terms of GDP (Gross Domestic Product) per capita among Asian countries in 2019 (IMF, 2019). As Hamamura (2012) pointed out, social class and generalized trust show a positive association only in wealthy countries where the social and economic environments endorse ample resources for rich people, allowing them to be less hesitant in trusting strangers for their own benefit. The effect of generalized trust on motivating people to serve social ties and cooperate with cooperative poor partners was also found among university students in China, where GDP per capita is not very high in the mainland. This is interpreted by existing evidence that higher education is related to higher social trust (Charron & Rothstein, 2016), and that longer years of schooling predict higher generalized trust (Kim, 2021). In addition, both countries are in East Asia, where people develop social connections and trust others from a networked-intragroup perspective (Yuki, 2003). It is important to confirm the universality of the current findings in Western societies, in which relationship formation and maintenance are generally made through category-based ingroup conceptualizations.

Chinese participants showed higher levels of generalized trust than Japanese participants. This result can be interpreted in line with previous evidence suggesting that Japanese collectivism is based on long-term social networks of assurance, whereas Chinese collectivism has its essence in building new social networks based on broader, personal connections (Takahashi et al., 2008). In the current experiment, Chinese participants also showed higher overall cooperation rates than Japanese participants (crowdsourcing workers). This pattern might be observed due to the concerns for acquaintanceship among Chinese participants who belonged to the same department, as discussed earlier. Therefore, it is premature to conclude that Japanese individuals are more uncooperative than Chinese individuals. Further investigation into the cross-cultural differences in cross-class cooperation should control for these factors.

It is also unknown if the motivation for rewarding cooperative partners exceeds that for sanctioning non-cooperative ones. Invisible wealth disparities in PGG implementing sanction systems lead people to favor the rich and punish the poor; this is because perceived generosity and reciprocal expectations may derive from sole resource amounts rather than cooperativeness

(Hauser et al., 2019). Social network dynamics in the real world are often modeled based on these two opposite mechanisms.

Additionally, the prediction of partner selection based on categorical membership was not fully supported in the control condition. In other words, some participants might have an exploitative strategy toward any partner regardless of their categorical membership. This might be because the rich–poor membership in the experiment was ambiguous and less meaningful. It would be desirable to conduct partner selection-cooperation experiments between the upper and lower classes in the real world.

The current study also did not implement a public reputation system that shares participants' cooperativeness with other players. Recently, BGR was extended to a more general reputation-driven mechanism for cooperation regardless of group categories (Romano et al., 2017). The applicability of this idea was confirmed under the traditional minimal group paradigm (Tajfel et al., 1971), in which categorical memberships are not changeable and no stereotype is attached to the category. In the real world, the poor can become rich, and the rich can become poor, depending on the changes in the resources they have. Future research should include the reputation system in the permeable group setting and determine how it influences the current findings.

Conclusion

Socioeconomic inequality has come to the fore in recent years. Understanding how the gap between the rich and the poor can be filled from a psychological perspective is essential not only for social scientists but also for policymakers. This study demonstrates that focusing on the cooperativeness of partners is essential in building bridges between the rich and the poor and cultivating a new boundary for mutual cooperation. For the common good, one's cooperativeness should be evaluated independently from their social category. We believe our research sheds light on reducing socioeconomic inequality and removing the barriers to upward social mobility.

References

Aksoy, O. (2019). Crosscutting circles in a social dilemma: Effects of social identity and inequality on cooperation. *Social Science Research*, *82*, 148–163. https://doi.org/10.1016/j.ssresearch.2019.04.009

Adler, N., ES, E., Castellazzo, G., & Ickovics, J. (2000). Relationship of subjective and objective social status with psychological and physiological functioning: preliminary data in healthy white women. *Health Psychology*, *19*(6), 586–592. https://doi.org/10.1037//0278-6133.19.6.586

Balliet, D., Wu, J., & De Dreu, C. K. W. (2014). Ingroup favoritism in cooperation: a meta-analysis. *Psychological Bulletin*, *140*(6), 1556–1581. https://doi.org/10.1037/a0037737

Cable, D. M., & Shane, S. (1997). A prisoner's dilemma approach to entrepreneur-venture capitalist relationships. *The Academy of Management Review*, *22*(1), 142. https://doi.org/10.2307/259227

Charron, N., & Rothstein, B. (2016). Does education lead to higher generalized trust? The importance of quality of government. *International Journal of Educational Development*, *50*, 59–73. https://doi.org/10.1016/j.ijedudev.2016.05.009

Chen, D. L., Schonger, M., & Wickens, C. (2016). oTree-An open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, *9*, 88–97. https://doi.org/10.1016/j.jbef.2015.12.001

Connor, P., Varney, J., Keltner, D., & Chen, S. (2021). Social class competence stereotypes are amplified by socially signaled economic Inequality. *Personality and Social Psychology Bulletin*, *47*(1), 89–105. https://doi.org/10.1177/0146167220916640

Cuddy, A. J. C., Fiske, S. T., & Glick, P. (2008). Warmth and competence as universal dimensions of social perception: The stereotype content model and the BIAS Map. *Advances in Experimental Social Psychology*, *40*, 61–149. https://doi.org/10.1016/S0065-2601(07)00002-0

Dhaliwal, N. A., Martin, J. W., Barclay, P., & Young, L. L. (2022). Signaling benefits of partner choice decisions. *Journal of Experimental Psychology: General, 151*(6)*,* 1446–1472*.* https://doi.org/10.1037/xge0001137

Fiske, S. T., & Markus, H. R. (Eds.). (2012). *Facing social class: How societal rank influences interaction*. Russell Sage Foundation.

Hamamura, T. (2012). Social class predicts generalized trust but only in wealthy societies. *Journal of Cross-Cultural Psychology*, *43*(3), 498–509. https://doi.org/10.1177/0022022111399649

Hauser, O. P., Kraft-Todd, G. T., Rand, D. G., Nowak, M. A., & Norton, M. I. (2021). Invisible inequality leads to punishing the poor and rewarding the rich. *Behavioural Public Policy*, *5*(3), 333–353. https://doi.org/10.1017/bpp.2019.4

Hayashi, N., & Yamagishi, T. (1998). Selective play: choosing partners in an uncertain world. *Personality and Social Psychology Review*, *2*(4), 276–289. https://doi.org/10.1207/s15327957pspr0204_4

Igarashi, T., & Hirashima, T. (2021). Generalized trust and social selection process. *Frontiers in Communication, 6*:667082. https://doi.org/10.3389/fcomm.2021.667082

GDP per capita, current prices (2019, October). *World Economic Outlook.* International Monetary Fund. https://www.imf.org/external/datamapper/datasets/WEO

Jetten, J., Peters, K., Álvarez, B., Casara, B.G.S., Dare, M., Kirkland, K., Sánchez- Rodríguez, Á., Selvanathan, H.P., Sprong, S., Tanjitpiyanond, P., Wang, Z. and Mols, F. (2021).

Consequences of economic inequality for the social and political vitality of society: A social identity analysis. *Political Psychology*, *42*, 241-266. https://doi.org/10.1111/pops.12800

Jetten, J., Wang, Z., Steffens, N. K., Mols, F., Peters, K., & Verkuyten, M. (2017). A social identity analysis of responses to economic inequality. *Current Opinion in Psychology*, *18*, 1–5. https://doi.org/10.1016/j.copsyc.2017.05.011

Johnson, T., & Smirnov, O. (2018). Inequality as information: Wealth homophily facilitates the evolution of cooperation. *Scientific Reports*, *8*(1), 1–10. https://doi.org/10.1038/s41598-018-30052-1

Kim J. (2021). Class position and general trust : an analysis using relative class position. *The Doshisha Shakaigakukenkyu (Doshisha review of sociology)*, *25*, 97–108. https://doi.org/10.14988/00028266

Kraus, M. W., Park, J. W., & Tan, J. J. X. (2017). Signs of social class: The experience of economic inequality in everyday life. *Perspectives on Psychological Science*, *12*(3), 422–435. https://doi.org/10.1177/1745691616673192

Lazarsfeld, P. F., & Merton, R. K. (1954). Friendship as a social process: A substantive and methodological analysis. *Freedom and control in modern society*, *18*(1), 18–66.

Martinangeli, A. F. M., & Martinsson, P. (2020). We, the rich: Inequality, identity and cooperation. *Journal of Economic Behavior and Organization*, *178*, 249–266. https://doi.org/10.1016/j.jebo.2020.07.013

Melamed, D., Munn, C. W., Simpson, B., Abernathy, J. Z., Harrell, A., & Sweitzer, M. (2020). Homophily and segregation in cooperative networks. *American Journal of Sociology*, *125*(4), 1084–1127. https://doi.org/10.1086/708142

Nishi, A., Shirado, H., Rand, D. G., & Christakis, N. A. (2015). Inequality and visibility of wealth in experimental social networks. *Nature*, *526*(7573), 426–429. https://doi.org/10.1038/nature15392

Peters, K., Jetten, J., Tanjitpiyanond, P., Wang, Z., Mols, F., & Verkuyten, M. (2021). The language of inequality: Evidence economic inequality increases wealth category salience. *Personality and Social Psychology Bulletin, 48*(8)*,* 1204–1219. https://doi.org/10.1177/01461672211036627

Rand, D. G., Arbesman, S., & Christakis, N. A. (2011). Dynamic social networks promote cooperation in experiments with humans. *Proceedings of the National Academy of Sciences of the United States of America*, *108*(48), 19193–19198. https://doi.org/10.1073/pnas.1108243108

Rosenberg, M. (1965). *Society and the Adolescent Self-Image*. Princeton University Press.

Romano, A., Balliet, D., & Wu, J. (2017). Unbounded indirect reciprocity: Is reputation-based cooperation bounded by group membership? *Journal of Experimental Social Psychology*, *71*, 59–67. https://doi.org/10.1016/j.jesp.2017.02.008

Rudman, L. A., Feinberg, J., & Fairchild, K. (2002). Minority members' implicit attitudes: Automatic ingroup bias as a function of group status. *Social Cognition*, *20*(4), 294–320. https://doi.org/10.1521/soco.20.4.294.19908

Russell, A. M. T., & Fiske, S. T. (2008). It's all relative: Competition and status drive interpersonal perception. *European Journal of Social Psychology*, *38*(7), 1193–1201. https://doi.org/10.1002/EJSP.539

Shirado, H., & Christakis, N. A. (2020). Network engineering using autonomous agents increases cooperation in human groups. *IScience*, *23*(9). https://doi.org/10.1016/J.ISCI.2020.101438

Snijders, T. A. B., & Lomi, A. (2019). Beyond homophily: Incorporating actor variables in statistical network models. *Network Science*, *7*(1), 1–19. https://doi.org/10.1017/nws.2018.30

Sornette, D., Wheatley, S., & Cauwels, P. (2019). The fair reward problem: The illusion of success and how to solve It. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3377177

Steinhardt, H. C. (2011). How is high trust in China possible? Comparing the origins of generalized trust in three Chinese societies. *Political Studies*, *60*(2), 434–454. https://doi.org/10.1111/j.1467-9248.2011.00909.x

Tajfel, H., Billig, M. G., Bundy, R. P., & Flament, C. (1971). Social categorization and intergroup behaviour. *European Journal of Social Psychology*, *1*(2), 149–178.

Tajfel, H., & Turner, J. (2001). An integrative theory of intergroup conflict. In M. A. Hogg & D. Abrams (Eds.), *Intergroup relations: Essential readings* (pp. 94–109). Psychology Press.

Takahashi, C., Yamagishi, T., Liu, J. H., Wang, F., Lin, Y., & Yu, S. (2008). The intercultural trust paradigm: Studying joint cultural interaction and social exchange in real time over the Internet. *International Journal of Intercultural Relations*, *32*(3), 215–228. https://doi.org/10.1016/j.ijintrel.2007.11.003

Turner, J. C., Hogg, M. A., Oakes, P. J., Reicher, S. D., & Wetherell, M. S. (1987). *Rediscovering the social group: A self-categorization theory.* Basil Blackwell.

van Dijk, E., & De Dreu, C. K. W. (2021). Experimental games and social decision making. *Annual Review of Psychology*, *72*(1), 415–438. https://doi.org/10.1146/annurev-psych-081420-110718

Wang, F., & Yamagishi, T. (1999). A comparative study on trust in China, Japan, and America. *Sociological Research*, *80*(2), 67–82.

Wang, J., Suri, S., & Watts, D. J. (2012). Cooperation and assortativity with dynamic partner updating. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(36), 14363–14368. https://doi.org/10.1073/PNAS.1120867109

Wilkinson, R. G., & Pickett, K. (2010). *The spirit level : Why equality is better for everyone*. Penguin UK.

Yamagishi, T. (2011). *Trust: The evolutionary game of mind and society*. Springer Science & Business Media.

Yamagishi, T., Jin, N., & Kiyonari, T. (1999). Bounded generalized reciprocity: Ingroup boasting and ingroup favoritism. *Advances in Group Processes*, *16*(1), 161–197.

Yamagishi, T., Kikuchi, M., & Kosugi, M. (1999). Trust, gullibility, and social intelligence. *Asian Journal of Social Psychology*, *2*(1), 145–161. https://doi.org/10.1111/1467-839X.00030

Yamagishi, T., & Kiyonari, T. (2000). The group as the container of generalized reciprocity. *Social Psychology Quarterly*, *63*(2), 116–132. https://doi.org/10.2307/2695887

Yamagishi, T., & Yamagishi, M. (1994). Trust and commitment in the United States and Japan. *Motivation and Emotion*, *18*(2), 129–166. https://doi.org/10.1007/BF02249397

Yamagishi, T., Yamagishi, M., Takahashi, N., Hayashi, N., & Watabe, M. (1995). Trust and commitment formation. *The Japanese Journal of Experimental Social Psychology*, *35*(1), 23–34. https://doi.org/10.2130/jjesp.35.23

Yuki, M. (2003). Intergroup comparison versus intragroup relationships: A cross-cultural examination of social identity theory in North American and East Asian cultural contexts. *Social Psychology Quarterly, 66*(2), 166–183. https://doi.org/10.2307/1519846

Figure Captions

Figure 1

Descriptive statistics of participants' behavioral patterns in Study 1 (N = 213)

Note. (a) Scatterplots of poor-group partner (bot) choice ratio and participants' cooperation ratio in control (n = 107) and poor-cooperator-rich-defector (PCRD) condition (n = 106). (b) Distribution of each behavioral strategy across 30 rounds among 213 participants. CP = choose a poor-group partner and cooperate; DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect. (c) Proportion of participants who chose a poor-group partner in each round. (d) Proportion of participants who cooperated with a poor-group partner in each round.

Figure 2

Descriptive statistics of participants' partner choice in Study 1 (N = 213)

Note. Distribution of the poor-group partner (bot) choice ratio in the control condition (n = 107) and the poor-cooperator-rich-defector (PCRD) condition (n = 106) in Study 1.

Figure 3

Patterns of two-step decision-making (partner choice and cooperation/defection) and the effect of generalized trust (Study 1, Japan)

Note. (a) Probability of occurrence of four strategies in the control (*n* = 107) and poor-cooperator-rich-defector (PCRD) conditions (*n* = 106). (b) Conditional effect of generalized trust on triggering each strategy in each condition. CP = choose a poor-group partner and cooperate (baseline); DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect. Generalized trust was mean centered. All participants were allocated to the rich group. The figures are depicted based on the estimates in Table 1. Error bars and borders indicate 95% credible intervals. *N* = 213.

Figure 4

Descriptive statistics of participants' behavioral patterns in Study 2 (N = 150)

Note. (a) Scatterplots of poor-group partner (bot) choice ratio and participants' cooperation ratio in the control (*n* = 42), poor-cooperator-rich-defector (PCRD) (*n* = 49), and rich-cooperator-poor-defector (RCPD) (*n* = 59) conditions. (b) Distribution of each behavioral strategy across 30 rounds among 150 participants. CP = choose a poor-group partner and cooperate; DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect. (c) Proportion of participants who chose a poor-group partner in each round. (d) Proportion of participants who cooperated with a poor-group partner in each round.

Figure 5

Descriptive statistics of participants' partner choice in Study 2 (N = 150)

Note. Distributions of poor-group partner (bot) choice ratio in the control (n = 42), poor-cooperator-rich-defector (PCRD) (n = 49), and rich-cooperator-poor-defector (RCPD) (n = 59) conditions in Study 2.

Figure 6

Patterns of two-step decision-making (partner choice and cooperation/defection) and the effect of generalized trust (Study 2, China)

Note. (a) Probability of occurrence of four strategies in the control (*n* = 42), poor-cooperator-rich-defector (PCRD) (*n* = 49), and rich-cooperator-poor-defector (RCPD) conditions (*n* = 59). (b) Conditional effect of generalized trust on triggering each strategy in each condition. CP = choose a poor-group partner and cooperate (baseline); DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect. Generalized trust was mean centered. All participants were allocated to the rich group. The figures are depicted based on the estimates in Table 2. Error bars and borders indicate 95% credible intervals. *N* = 150.

Table Legends

Table 1

Preference for partner choice and cooperation/defection strategies in the selective play paradigm (Study 1, Japan)

Note. CI = credible interval. The Bayesian Multinomial regression model was estimated with a logit link including four chains (5000 warm-up and 10000 iterations in each chain). The estimation was based on 852 observations from 213 respondents, including the frequency distributions of four strategies (CP = choose a poor-group partner and cooperate (baseline); DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect) across 30 rounds. Generalized trust was mean centered. Boldface indicates estimates for which the 95% CI do not overlap zero.

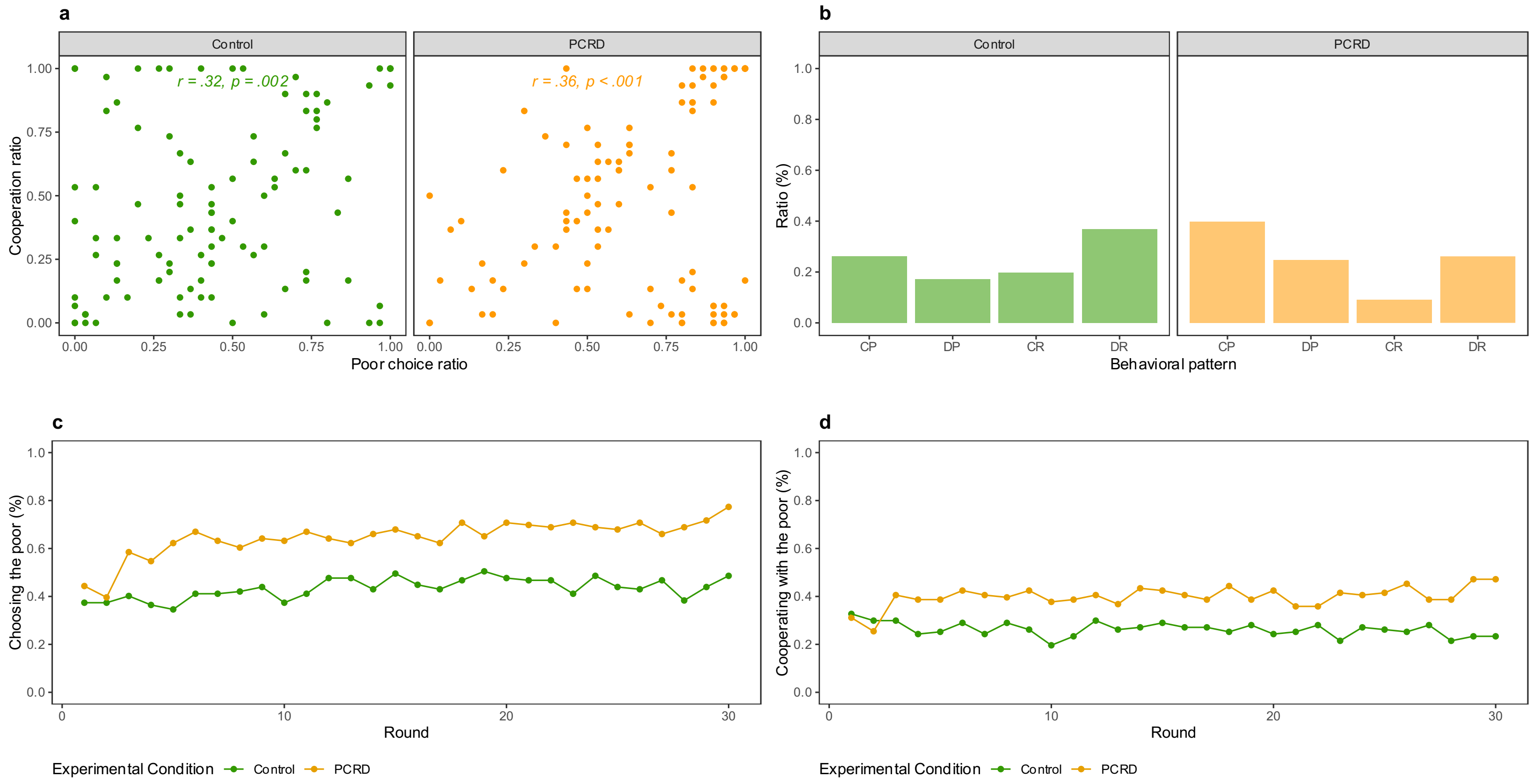
Table 2

Preference for partner choice and cooperation/defection strategies in the selective play paradigm (Study 2, China)

Note. CI = credible interval. The Bayesian Multinomial regression model was estimated with a logit link including four chains (5000 warm-up and 10000 iterations in each chain). The estimation was based on 600 observations from 150 respondents, including the frequency distributions of four strategies (CP = choose a poor-group partner and cooperate (baseline); DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect) across 30 rounds. Generalized trust was mean centered. Boldface indicates estimates for which the 95% CI do not overlap zero.

Figure 1

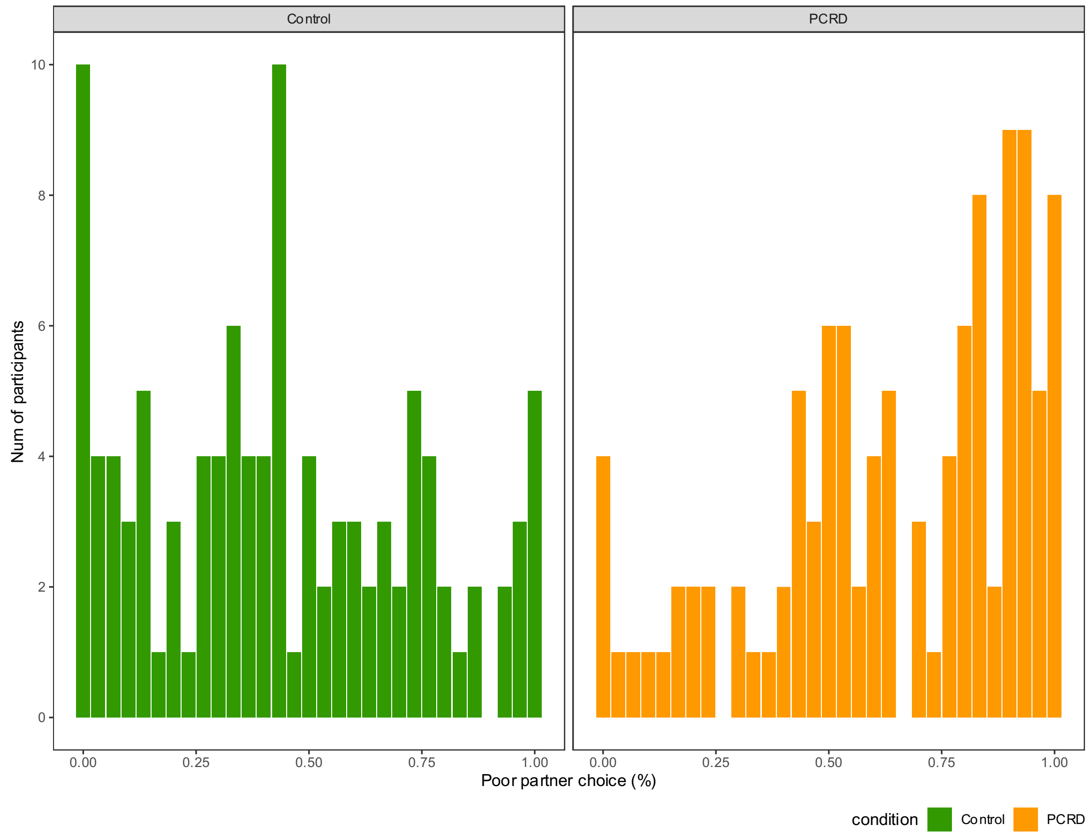
Descriptive statistics of participants' behavioral patterns in Study 1 (N = 213)



Note. **(a)** Scatterplots of poor-group partner (bot) choice ratio and participants' cooperation ratio in control (n = 107) and poor-cooperator-rich-defector (PCRD) condition (n = 106). **(b)** Distribution of each behavioral strategy across 30 rounds among 213 participants. CP = choose a poor-group partner and cooperate; DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect. **(c)** Proportion of participants who chose a poor-group partner in each round. **(d)** Proportion of participants who cooperated with a poor-group partner in each round.

Figure 2

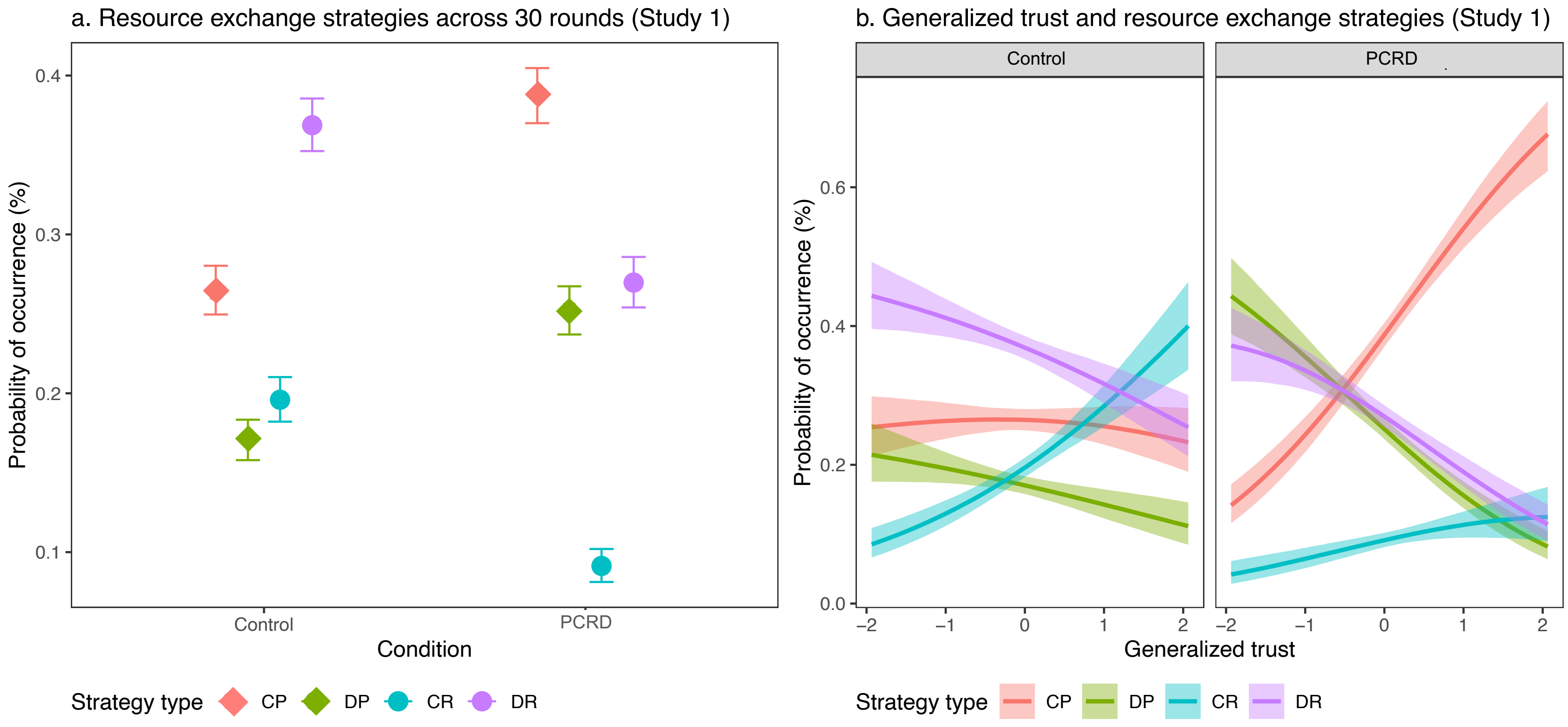
Descriptive statistics of participants' partner choice in Study 1 (N = 213)



Note. Distribution of the poor-group partner (bot) choice ratio in the control condition (n = 107) and the poor-cooperator-rich-defector (PCRD) condition (n = 106) in Study 1.

Figure 3

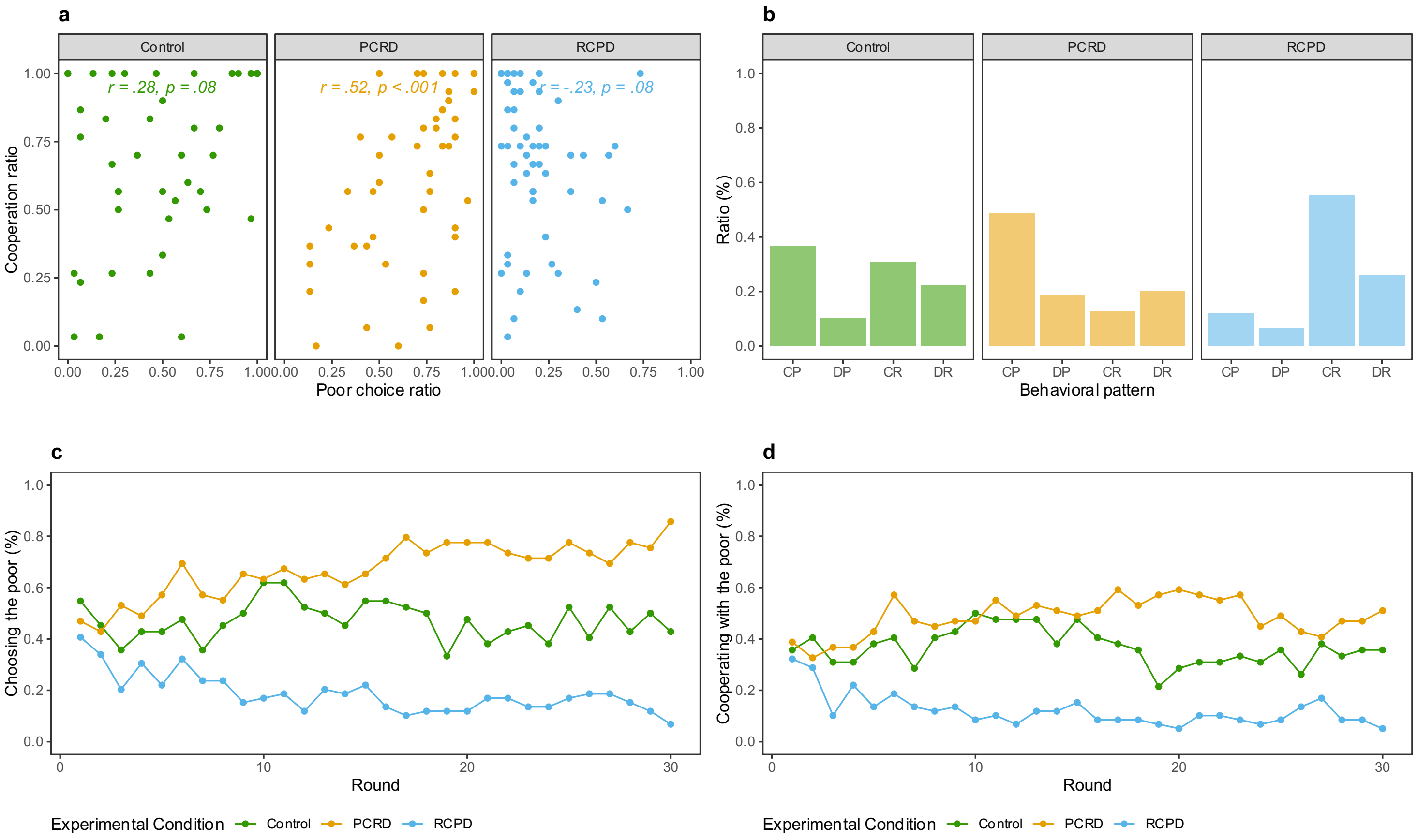
Patterns of two-step decision-making (partner choice and cooperation/defection) and the effect of generalized trust (Study 1, Japan)



Note. (a) Probability of occurrence of four strategies in the control (n = 107) and poor-cooperator-rich-defector (PCRD) conditions (n = 106). (b) Conditional effect of generalized trust on triggering each strategy in each condition. CP = choose a poor-group partner and cooperate (baseline); DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect. Generalized trust was mean centered. All participants were allocated to the rich group. The figures are depicted based on the estimates in Table 1. Error bars and borders indicate 95% credible intervals. N = 213.

Figure 4

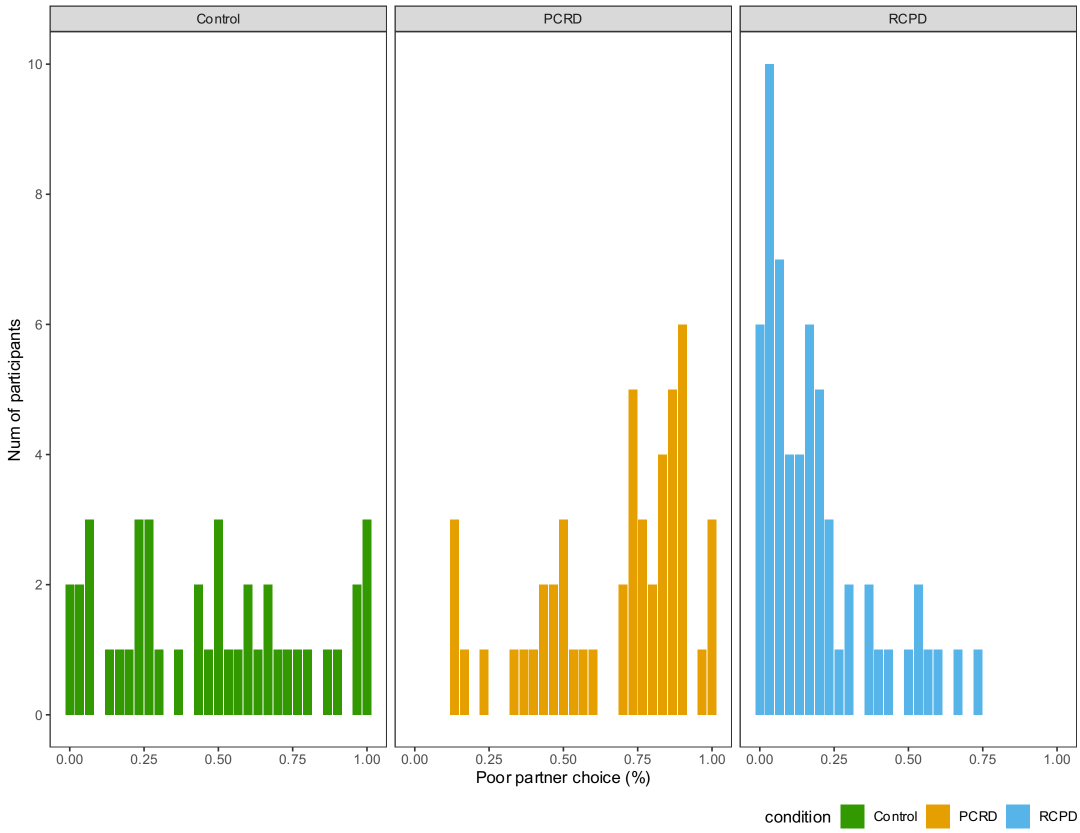
Descriptive statistics of participants' behavioral patterns in Study 2 (N = 150)



Note. (a) Scatterplots of poor-group partner (bot) choice ratio and participants' cooperation ratio in the control (n = 42), poor-cooperator-rich-defector (PCRD) (n = 49), and rich-cooperator-poor-defector (RCPD) (n = 59) conditions. (b) Distribution of each behavioral strategy across 30 rounds among 150 participants. CP = choose a poor-group partner and cooperate; DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect. (c) Proportion of participants who chose a poor-group partner in each round. (d) Proportion of participants who cooperated with a poor-group partner in each round.

Figure 5

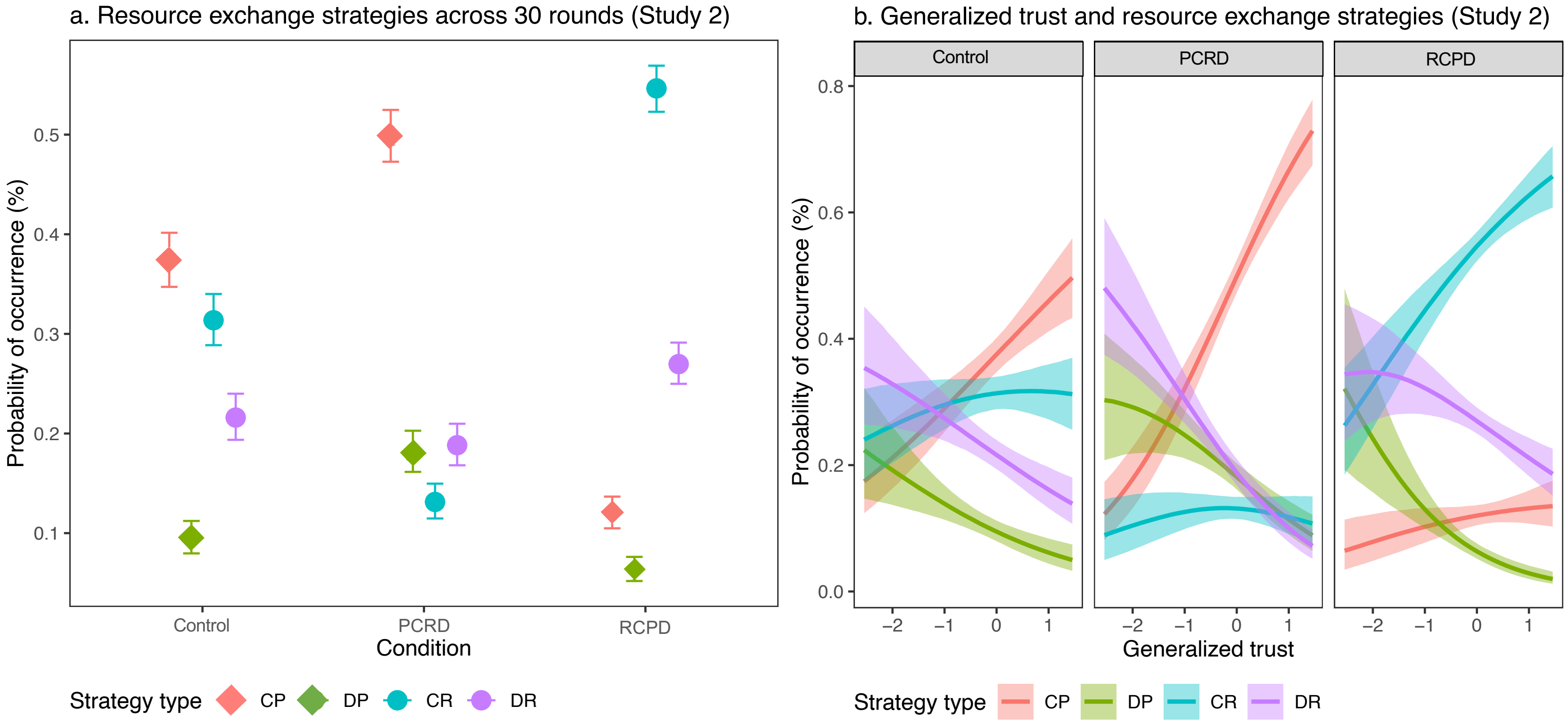
Descriptive statistics of participants' partner choice in Study 2 (N = 150)



Note. Distributions of poor-group partner (bot) choice ratio in the control (n = 42), poor-cooperator-rich-defector (PCRD) (n = 49), and rich-cooperator-poor-defector (RCPD) (n = 59) conditions in Study 2.

Figure 6

Patterns of two-step decision-making (partner choice and cooperation/defection) and the effect of generalized trust (Study 2, China)



Note. (a) Probability of occurrence of four strategies in the control (*n* = 42), poor-cooperator-rich-defector (PCRD) (*n* = 49), and rich-cooperator-poor-defector (RCPD) conditions (*n* = 59). (b) Conditional effect of generalized trust on triggering each strategy in each condition. CP = choose a poor-group partner and cooperate (baseline); DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect. Generalized trust was mean centered. All participants were allocated to the rich group. The figures are depicted based on the estimates in Table 2. Error bars and borders indicate 95% credible intervals. *N* = 150.

Table 1

Preference for partner choice and cooperation/defection strategies in the selective play paradigm (Study 1, Japan)

	Estimate	Posterior SD	95% CI
DP strategy: Intercept (Control condition)	**-0.44**	0.06	[-0.55, -0.33]
CR strategy: Intercept (Control condition)	**-0.30**	0.05	[-0.40, -0.20]
DR strategy: Intercept (Control condition)	**0.33**	0.05	[0.24, 0.42]
DP strategy: PCRD condition	0.01	0.07	[-0.14, 0.15]
CR strategy: PCRD condition	-0.14	0.08	[-0.29, 0.01]
DR strategy: PCRD condition	**-0.67**	0.1	[-0.87, -0.47]
DP strategy: Generalized trust (Control condition)	**-1.14**	0.09	[-1.32, -0.98]
CR strategy: Generalized trust (Control condition)	**0.41**	0.08	[0.26, 0.56]
DR strategy: Generalized trust (Control condition)	**-0.52**	0.12	[-0.76, -0.29]
DP strategy: PCRD condition × Generalized trust	**-0.69**	0.07	[-0.82, -0.57]
CR strategy: PCRD condition × Generalized trust	-0.12	0.06	[-0.24, 0.01]
DR strategy: PCRD condition × Generalized trust	**-0.57**	0.09	[-0.75, -0.39]

Note. CI = credible interval. The Bayesian Multinomial regression model was estimated with a logit link including four chains (5000 warm-up and 10000 iterations in each chain). The estimation was based on 852 observations from 213 respondents, including the frequency distributions of four strategies (CP = choose a poor-group partner and cooperate (baseline); DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect) across 30 rounds. Generalized trust was mean centered. Boldface indicates estimates for which the 95% CI do not overlap zero.

Table 2

Preference for partner choice and cooperation/defection strategies in the selective play paradigm (Study 2, China)

	Estimate	Posterior SD	95% CI
DP strategy: Intercept (Control condition)	**-1.38**	0.11	[-1.59, -1.17]
CR strategy: Intercept (Control condition)	**-0.18**	0.07	[-0.31, -0.04]
DR strategy: Intercept (Control condition)	**-0.55**	0.08	[-0.71, -0.4]
DP strategy: PCRD condition	**0.36**	0.13	[0.11, 0.62]
CR strategy: PCRD condition	**-1.16**	0.11	[-1.37, -0.95]
DR strategy: PCRD condition	**-0.42**	0.11	[-0.63, -0.22]
DP strategy: RCPD condition	**0.74**	0.16	[0.42, 1.05]
CR strategy: RCPD condition	**1.69**	0.10	[1.49, 1.9]
DR strategy: RCPD condition	**1.36**	0.12	[1.14, 1.59]
DP strategy: Generalized trust (Control condition)	**-0.64**	0.12	[-0.88, -0.41]
CR strategy: Generalized trust (Control condition)	**-0.20**	0.09	[-0.38, -0.02]
DR strategy: Generalized trust (Control condition)	**-0.49**	0.10	[-0.69, -0.31]
DP strategy: PCRD condition × Generalized trust	-0.11	0.16	[-0.43, 0.21]
CR strategy: PCRD condition × Generalized trust	-0.21	0.15	[-0.51, 0.1]
DR strategy: PCRD condition × Generalized trust	**-0.43**	0.14	[-0.71, -0.15]
DP strategy: RCPD condition × Generalized trust	-0.23	0.20	[-0.64, 0.18]
CR strategy: RCPD condition × Generalized trust	0.24	0.14	[-0.04, 0.53]
DR strategy: RCPD condition × Generalized trust	0.16	0.15	[-0.15, 0.47]

Note. CI = credible interval. The Bayesian Multinomial regression model was estimated with a logit link including four chains (5000 warm-up and 10000 iterations in each chain). The estimation was based on 600 observations from 150 respondents, including the frequency distributions of four strategies (CP = choose a poor-group partner and cooperate (baseline); DP = choose a poor-group partner and defect; CR = choose a rich-group partner and cooperate; and DR = choose a rich-group partner and defect) across 30 rounds. Generalized trust was mean centered. Boldface indicates estimates for which the 95% CI do not overlap zero.

Supplementary Materials

Study 1

Bayesian modeling

The data were analyzed in R 4.2.0 (R Core Team, 2022). We applied the Bayesian multinominal logistic regression models (four chains with 10000 iterations, 5000 warm-ups, thin = 1, and 20000 post-warmup draws) using the *brms* package version 2.17.0 (Bürkner, 2017). The *brms* package fits Bayesian models using Stan (Carpenter et al., 2017). We reported the following results based on the Bayesian analysis reporting guidelines (Kruschke, 2021).

The dependent variable was the occurrence of the four strategies (CP strategy [choose a poor-group partner and cooperate]; DP strategy [choose a poor-group partner and defect]; CR strategy [choose a rich-group partner and cooperate]; and DR strategy [choose a rich-group partner and defect]) in each participant across 30 rounds in PDG. For example, if the first participant employs the CP strategy 9 times, the DP strategy 6 times, the CR strategy 7 times, and the DR strategy 8 times, the first row of the matrix is [9, 6, 7, 8]. Predictors were dummy variables of the experimental conditions (0: control condition, 1: poor-cooperator-rich-defector [PCRD] condition) and generalized trust (mean-centered). We used weakly informative priors, relying on the default priors set by the *brms* package (intercepts for dummy variables: Student's *t* distribution with df = 3, M = 0 and SD = 2.5; and other parameters (shown as b): uniform distributions). The model formula and prior distribution settings in Study 1 are shown below:

```
# Bayesian multinominal logistic regression model
mod <- brm(strategy | trials(round) ~ condition * generalized_trust,
      family = multinomial(),
      seed = 1234,
      chains = 4,
      iter = 10000,
      data = dat)
```

Priors set by brms in Study 1 were as follows:

prior	class	coef	group	resp	dpar	nlpar	lb	ub	source
(flat)	b								default
(flat)	Intercept								default
(flat)	b				muCR				default
(flat)	b	conditionPoorcooperator			muCR				(vectorized)
(flat)	b	conditionPoorcooperator:generalized_trust			muCR				(vectorized)
(flat)	b	generalized_trust			muCR				(vectorized)
student_t(3,0,2.5)	Intercept				muCR				default
(flat)	b				muDP				default
(flat)	b	conditionPoorcooperator			muDP				(vectorized)
(flat)	b	conditionPoorcooperator:generalized_trust			muDP				(vectorized)
(flat)	b	generalized_trust			muDP				(vectorized)
student_t(3,0,2.5)	Intercept				muDP				default
(flat)	b				muDR				default
(flat)	b	conditionPoorcooperator			muDR				(vectorized)
(flat)	b	conditionPoorcooperator:generalized_trust			muDR				(vectorized)
(flat)	b	generalized_trust			muDR				(vectorized)
student_t(3,0,2.5)	Intercept				muDR				default

Below is the Stan code generated by *brms in Study 1:*

```
  // generated with brms 2.17.0
functions {
  /* multinomial-logit log-PMF
   * Args:
   *   y: array of integer response values
   *   mu: vector of category logit probabilities
   * Returns:
   *   a scalar to be added to the log posterior
   */
   real multinomial_logit2_lpmf(int[] y, vector mu) {
     return multinomial_lpmf(y | softmax(mu));
   }
}
data {
  int<lower=1> N;  // total number of observations
  int<lower=2> ncat;  // number of categories
  int Y[N, ncat];  // response array
  int trials[N];  // number of trials
  int<lower=1> K_muDP;  // number of population-level effects
  matrix[N, K_muDP] X_muDP;  // population-level design matrix
  int<lower=1> K_muCR;  // number of population-level effects
  matrix[N, K_muCR] X_muCR;  // population-level design matrix
  int<lower=1> K_muDR;  // number of population-level effects
  matrix[N, K_muDR] X_muDR;  // population-level design matrix
  int prior_only;  // should the likelihood be ignored?
}
transformed data {
  int Kc_muDP = K_muDP - 1;
  matrix[N, Kc_muDP] Xc_muDP;  // centered version of X_muDP without an intercept
  vector[Kc_muDP] means_X_muDP;  // column means of X_muDP before centering
  int Kc_muCR = K_muCR - 1;
  matrix[N, Kc_muCR] Xc_muCR;  // centered version of X_muCR without an intercept
  vector[Kc_muCR] means_X_muCR;  // column means of X_muCR before centering
  int Kc_muDR = K_muDR - 1;
  matrix[N, Kc_muDR] Xc_muDR;  // centered version of X_muDR without an intercept
  vector[Kc_muDR] means_X_muDR;  // column means of X_muDR before centering
  for (i in 2:K_muDP) {
    means_X_muDP[i - 1] = mean(X_muDP[, i]);
    Xc_muDP[, i - 1] = X_muDP[, i] - means_X_muDP[i - 1];
  }
  for (i in 2:K_muCR) {
    means_X_muCR[i - 1] = mean(X_muCR[, i]);
    Xc_muCR[, i - 1] = X_muCR[, i] - means_X_muCR[i - 1];
  }
  for (i in 2:K_muDR) {
    means_X_muDR[i - 1] = mean(X_muDR[, i]);
    Xc_muDR[, i - 1] = X_muDR[, i] - means_X_muDR[i - 1];
  }
}
parameters {
  vector[Kc_muDP] b_muDP;  // population-level effects
  real Intercept_muDP;  // temporary intercept for centered predictors
  vector[Kc_muCR] b_muCR;  // population-level effects
  real Intercept_muCR;  // temporary intercept for centered predictors
  vector[Kc_muDR] b_muDR;  // population-level effects
  real Intercept_muDR;  // temporary intercept for centered predictors
}
transformed parameters {
  real lprior = 0;  // prior contributions to the log posterior
  lprior += student_t_lpdf(Intercept_muDP | 3, 0, 2.5);
  lprior += student_t_lpdf(Intercept_muCR | 3, 0, 2.5);
  lprior += student_t_lpdf(Intercept_muDR | 3, 0, 2.5);
}
model {
  // likelihood including constants
  if (!prior_only) {
    // initialize linear predictor term
    vector[N] muDP = Intercept_muDP + Xc_muDP * b_muDP;
```

```
      // initialize linear predictor term
      vector[N] muCR = Intercept_muCR + Xc_muCR * b_muCR;
      // initialize linear predictor term
      vector[N] muDR = Intercept_muDR + Xc_muDR * b_muDR;
      // linear predictor matrix
      vector[ncat] mu[N];
      for (n in 1:N) {
        mu[n] = transpose([0, muDP[n], muCR[n], muDR[n]]);
      }
      for (n in 1:N) {
        target += multinomial_logit2_lpmf(Y[n] | mu[n]);
      }
    }
    // priors including constants
    target += lprior;
  }
  generated quantities {
    // actual population-level intercept
    real b_muDP_Intercept = Intercept_muDP - dot_product(means_X_muDP, b_muDP);
    // actual population-level intercept
    real b_muCR_Intercept = Intercept_muCR - dot_product(means_X_muCR, b_muCR);
    // actual population-level intercept
    real b_muDR_Intercept = Intercept_muDR - dot_product(means_X_muDR, b_muDR);
}
```

We performed general Markov chain Monte Carlo (MCMC) diagnostics based on the model fitting. Rhat values were below 1.05, indicating that no convergence was encountered during sampling (Figure S1). Additionally, all values of N_{eff} / N were above 0.1, suggesting an effective sample size (Figure S2). Figure S3 indicates a 95% posterior distribution of parameters fitted in the Bayesian model.

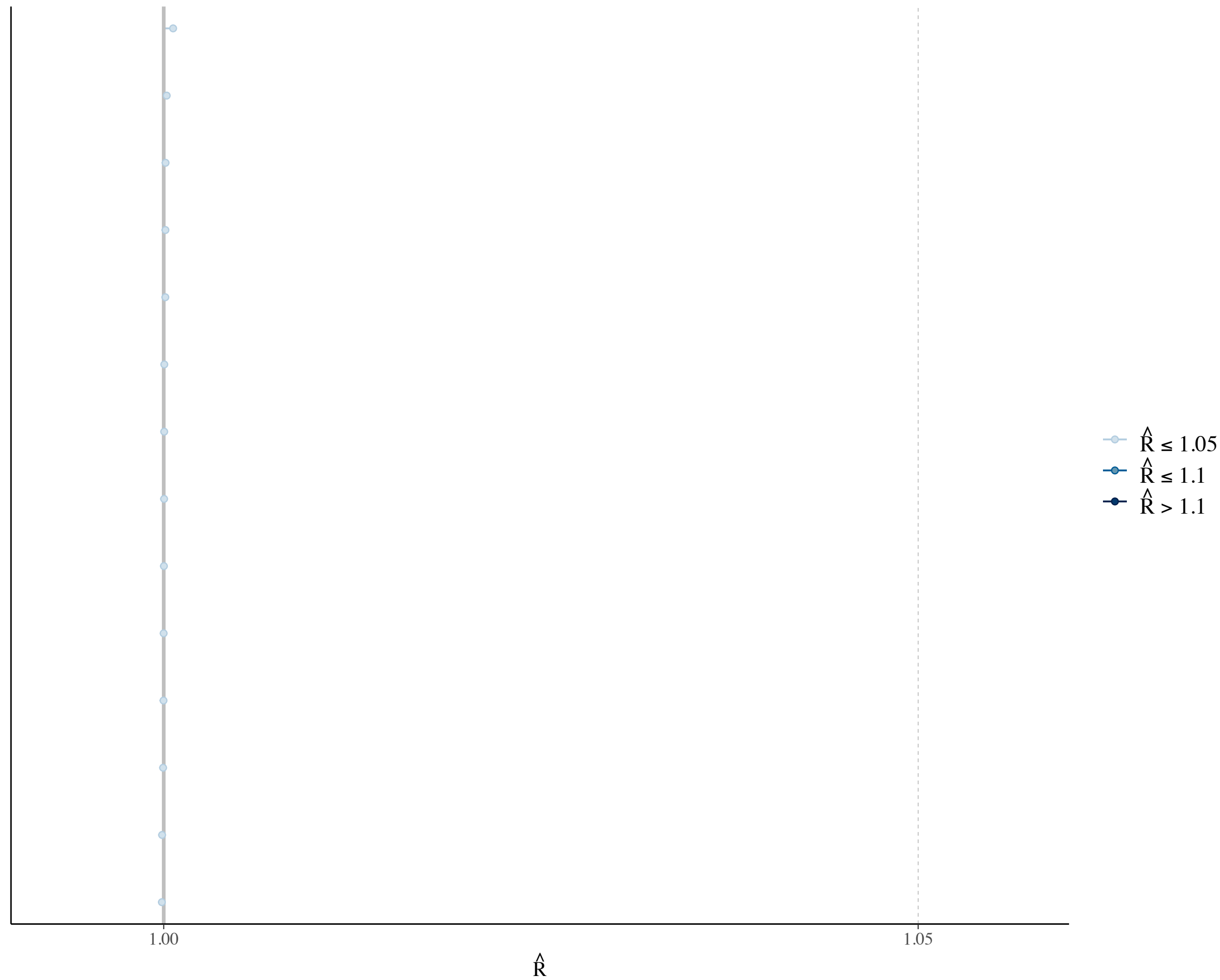


Figure S1. MCMC diagnostics for a Rhat convergence statistic in Study 1 (N = 213). Rhat values of each parameter were below 1.05, indicating a good convergence.

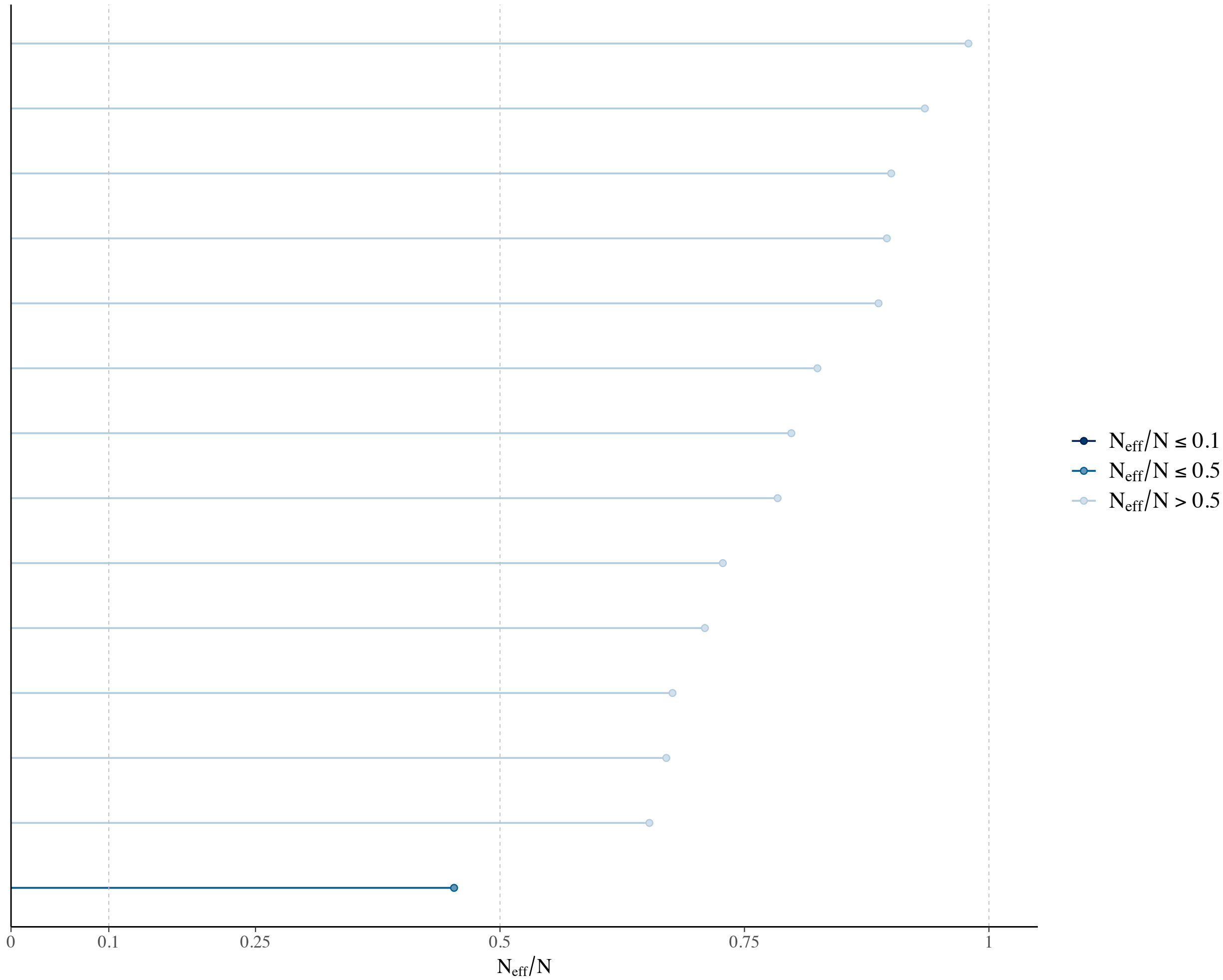


Figure S2*.* MCMC diagnostics for effective sample size statistic in Study 1 (*N* = 213). Ratios of effective sample size to total sample size were above 0.1, indicating an effective sample size.

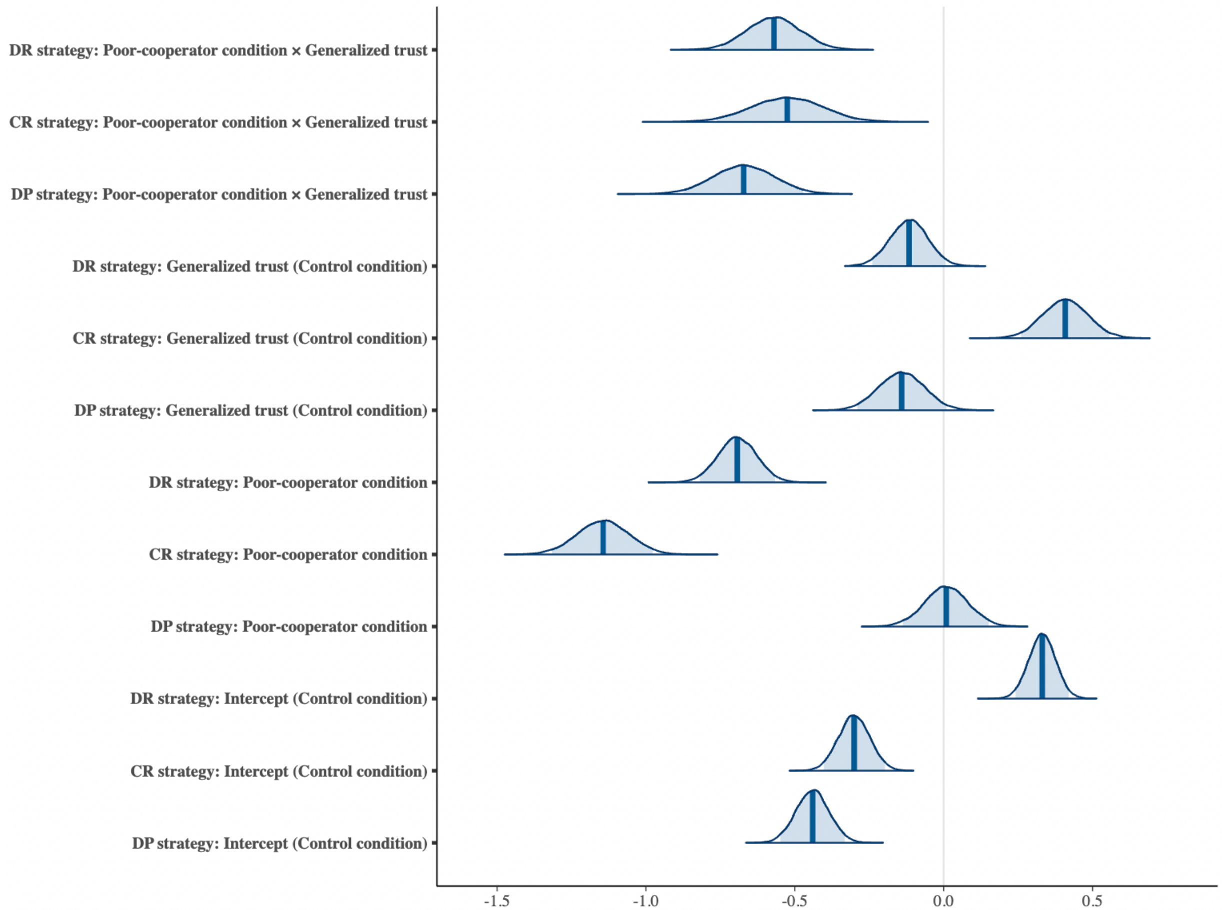


Figure S3. Posterior distributions of predictors with medians and 95% intervals. The blue points and bars represent calculated coefficients with 95%confidence intervals. Generalized trust was centralized.

Study 2

Bayesian modeling

As in Study 1, the dependent variable in Study 2 was the occurrence of the four strategies (CP, DP, CR, and DR) in each participant across 30 rounds in PDG. Predictors were dummy variables of the experimental conditions (0: control condition, 1: PCRD condition, 2: rich-cooperator-poor-defector (RCPD) condition) and generalized trust (mean-centered). We used the default priors set by the *brms* package (intercepts for dummy variables: Student's *t* distribution with *df* = 3, *M* = 0, and *SD* = 2.5; and other parameters (shown as *b*): uniform distributions). The model formula and prior distribution settings in Study 2 are shown below:

```
# Bayesian multinominal logistic regression model
mod <- brm(strategy | trials(round) ~ condition * generalized_trust,
      family = multinomial(),
      seed = 1234,
      chains = 4,
      iter = 10000,
      data = dat)
```

Priors set by brms in Study 2 were as follows:

prior	class	coef	group	resp	dpar	nlpar	lb	ub	source
(flat)	b								default
(flat)	Intercept								default
(flat)	b				muCR				default
(flat)	b	conditionPoorcooperator			muCR				(vectorized)
(flat)	b	conditionPoorcooperator:generalized_trust			muCR				(vectorized)
(flat)	b	conditionRichcooperator			muCR				(vectorized)
(flat)	b	conditionRichcooperator:generalized_trust			muCR				(vectorized)
(flat)	b	generalized_trust			muCR				(vectorized)
student_t(3,0,2.5)	Intercept				muCR				default
(flat)	b				muDP				default
(flat)	b	conditionPoorcooperator			muDP				(vectorized)
(flat)	b	conditionPoorcooperator:generalized_trust			muDP				(vectorized)
(flat)	b	conditionRichcooperator			muDP				(vectorized)
(flat)	b	conditionRichcooperator:generalized_trust			muDP				(vectorized)
(flat)	b	generalized_trust			muDP				(vectorized)
student_t(3,0,2.5)	Intercept				muDP				default
(flat)	b				muDR				default
(flat)	b	conditionPoorcooperator			muDR				(vectorized)
(flat)	b	conditionPoorcooperator:generalized_trust			muDR				(vectorized)
(flat)	b	conditionRichcooperator			muDR				(vectorized)
(flat)	b	conditionRichcooperator:generalized_trust			muDR				(vectorized)
(flat)	b	generalized_trust			muDR				(vectorized)
student_t(3,0,2.5)	Intercept				muDR				default

Below is the Stan code generated by *brms in Study 2:*

```
  // generated with brms 2.17.0
functions {
  /* multinomial-logit log-PMF
   * Args:
   *   y: array of integer response values
   *   mu: vector of category logit probabilities
   * Returns:
   *   a scalar to be added to the log posterior
   */
   real multinomial_logit2_lpmf(int[] y, vector mu) {
     return multinomial_lpmf(y | softmax(mu));
   }
}
data {
  int<lower=1> N;  // total number of observations
  int<lower=2> ncat;  // number of categories
  int Y[N, ncat];  // response array
  int trials[N];  // number of trials
  int<lower=1> K_muDP;  // number of population-level effects
  matrix[N, K_muDP] X_muDP;  // population-level design matrix
  int<lower=1> K_muCR;  // number of population-level effects
  matrix[N, K_muCR] X_muCR;  // population-level design matrix
  int<lower=1> K_muDR;  // number of population-level effects
  matrix[N, K_muDR] X_muDR;  // population-level design matrix
  int prior_only;  // should the likelihood be ignored?
}
transformed data {
  int Kc_muDP = K_muDP - 1;
  matrix[N, Kc_muDP] Xc_muDP;  // centered version of X_muDP without an intercept
  vector[Kc_muDP] means_X_muDP;  // column means of X_muDP before centering
  int Kc_muCR = K_muCR - 1;
  matrix[N, Kc_muCR] Xc_muCR;  // centered version of X_muCR without an intercept
  vector[Kc_muCR] means_X_muCR;  // column means of X_muCR before centering
  int Kc_muDR = K_muDR - 1;
  matrix[N, Kc_muDR] Xc_muDR;  // centered version of X_muDR without an intercept
  vector[Kc_muDR] means_X_muDR;  // column means of X_muDR before centering
  for (i in 2:K_muDP) {
    means_X_muDP[i - 1] = mean(X_muDP[, i]);
    Xc_muDP[, i - 1] = X_muDP[, i] - means_X_muDP[i - 1];
  }
  for (i in 2:K_muCR) {
    means_X_muCR[i - 1] = mean(X_muCR[, i]);
    Xc_muCR[, i - 1] = X_muCR[, i] - means_X_muCR[i - 1];
  }
  for (i in 2:K_muDR) {
    means_X_muDR[i - 1] = mean(X_muDR[, i]);
    Xc_muDR[, i - 1] = X_muDR[, i] - means_X_muDR[i - 1];
  }
}
parameters {
  vector[Kc_muDP] b_muDP;  // population-level effects
  real Intercept_muDP;  // temporary intercept for centered predictors
  vector[Kc_muCR] b_muCR;  // population-level effects
  real Intercept_muCR;  // temporary intercept for centered predictors
  vector[Kc_muDR] b_muDR;  // population-level effects
  real Intercept_muDR;  // temporary intercept for centered predictors
}
transformed parameters {
  real lprior = 0;  // prior contributions to the log posterior
  lprior += student_t_lpdf(Intercept_muDP | 3, 0, 2.5);
  lprior += student_t_lpdf(Intercept_muCR | 3, 0, 2.5);
  lprior += student_t_lpdf(Intercept_muDR | 3, 0, 2.5);
}
model {
  // likelihood including constants
  if (!prior_only) {
    // initialize linear predictor term
    vector[N] muDP = Intercept_muDP + Xc_muDP * b_muDP;
    // initialize linear predictor term
```

```
    vector[N] muCR = Intercept_muCR + Xc_muCR * b_muCR;
    // initialize linear predictor term
    vector[N] muDR = Intercept_muDR + Xc_muDR * b_muDR;
    // linear predictor matrix
    vector[ncat] mu[N];
    for (n in 1:N) {
      mu[n] = transpose([0, muDP[n], muCR[n], muDR[n]]);
    }
    for (n in 1:N) {
      target += multinomial_logit2_lpmf(Y[n] | mu[n]);
    }
  }
  // priors including constants
  target += lprior;
 }
 generated quantities {
  // actual population-level intercept
  real b_muDP_Intercept = Intercept_muDP - dot_product(means_X_muDP, b_muDP);
  // actual population-level intercept
  real b_muCR_Intercept = Intercept_muCR - dot_product(means_X_muCR, b_muCR);
  // actual population-level intercept
  real b_muDR_Intercept = Intercept_muDR - dot_product(means_X_muDR, b_muDR);
}
```

We performed general Markov chain Monte Carlo (MCMC) diagnostics based on the Bayesian model fitting. All Rhat values were below 1.05, indicating that no convergence was encountered during sampling (Figure S4). Also, all values of N_{eff} / N were above 0.1, suggesting an effective sample size (Figure S5). Figure S6 indicates a 95% posterior distribution of parameters fitted in the Bayesian model.

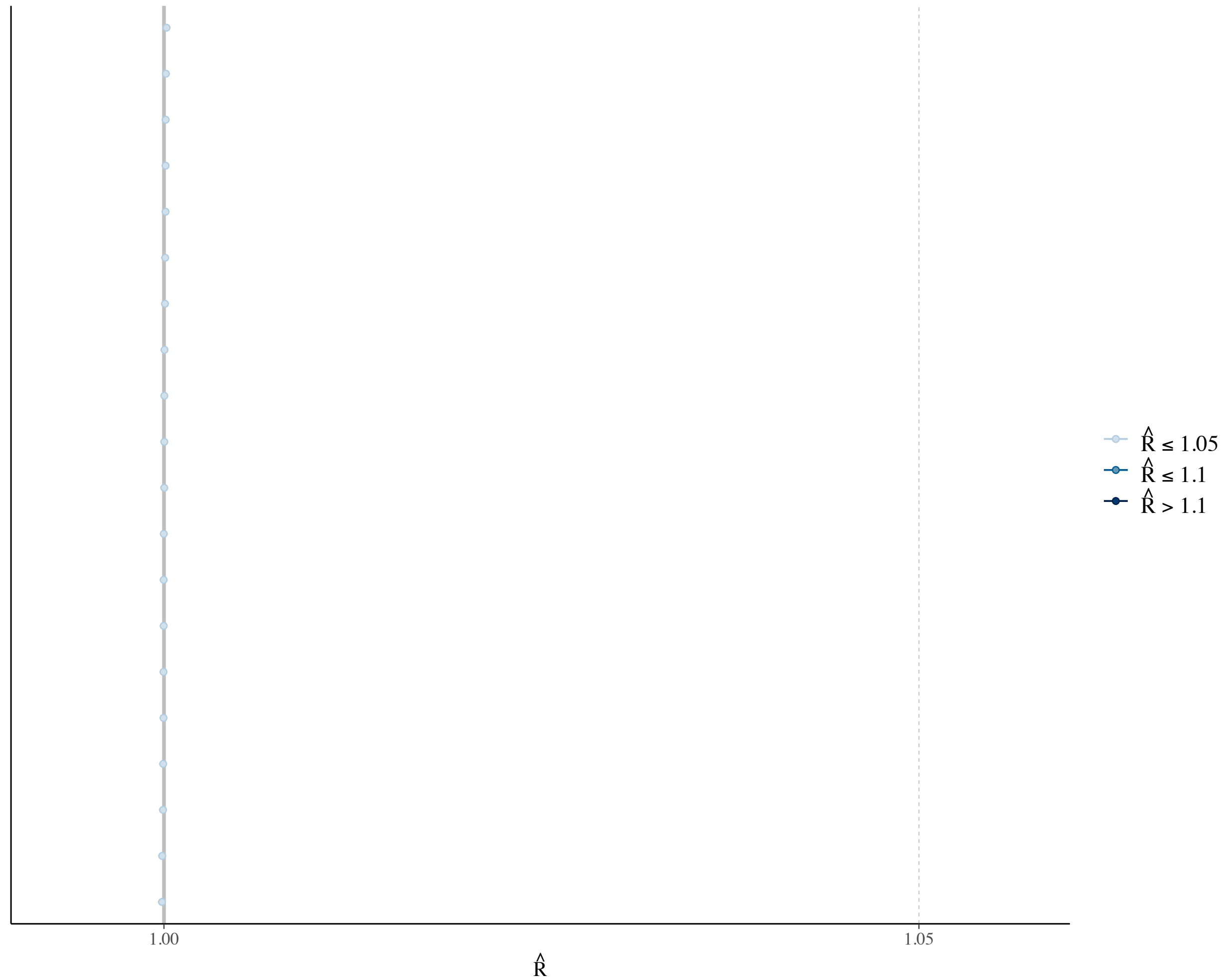


Figure S4. MCMC diagnostics for a Rhat convergence statistic in Study 2 (*N* = 150). Rhat values of each parameter were below 1.05, indicating a good convergence.

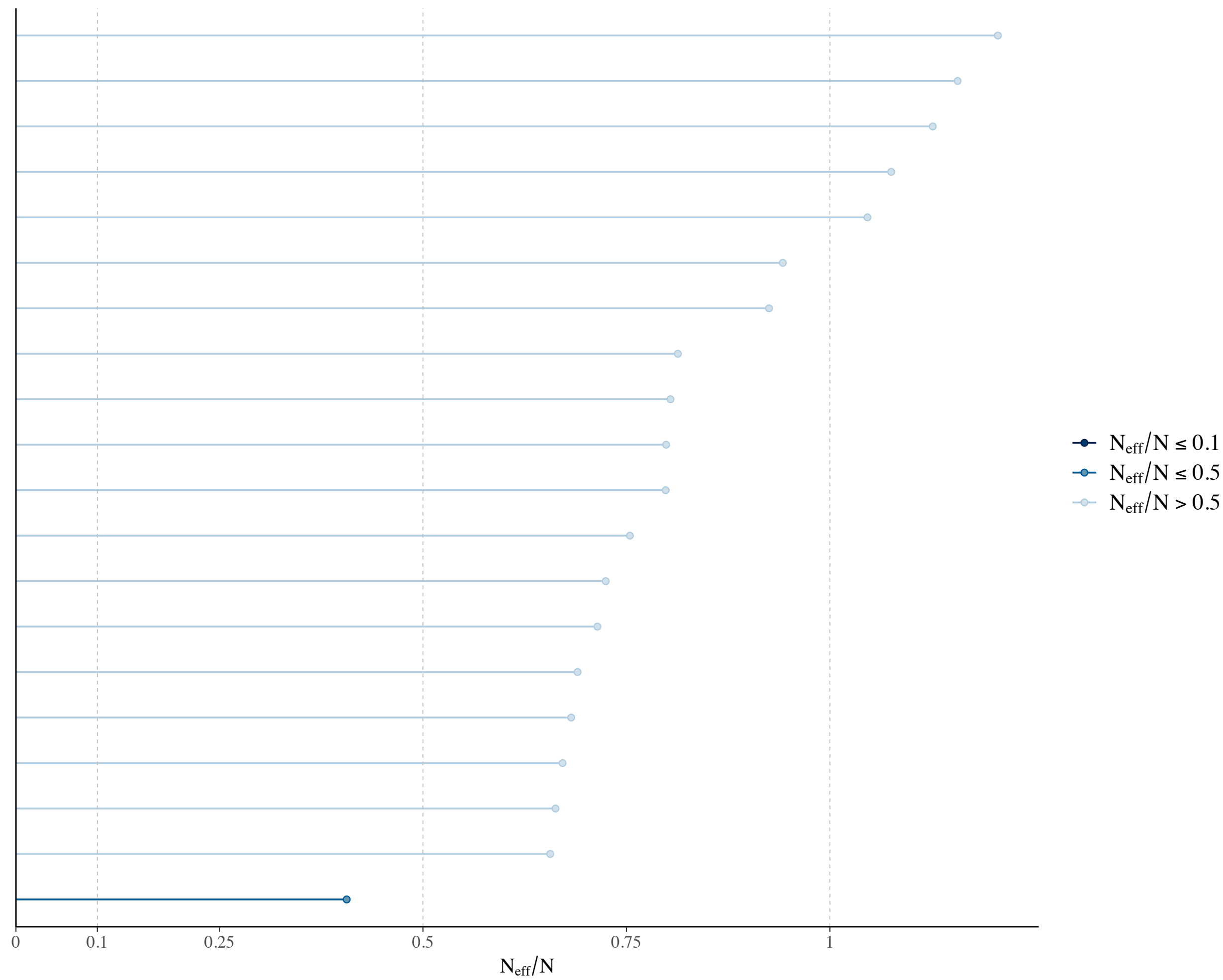


Figure S5. MCMC diagnostics for effective sample size statistic in Study 2 (*N* = 150). Ratios of effective sample size to total sample size were above 0.1, indicating an effective sample size.

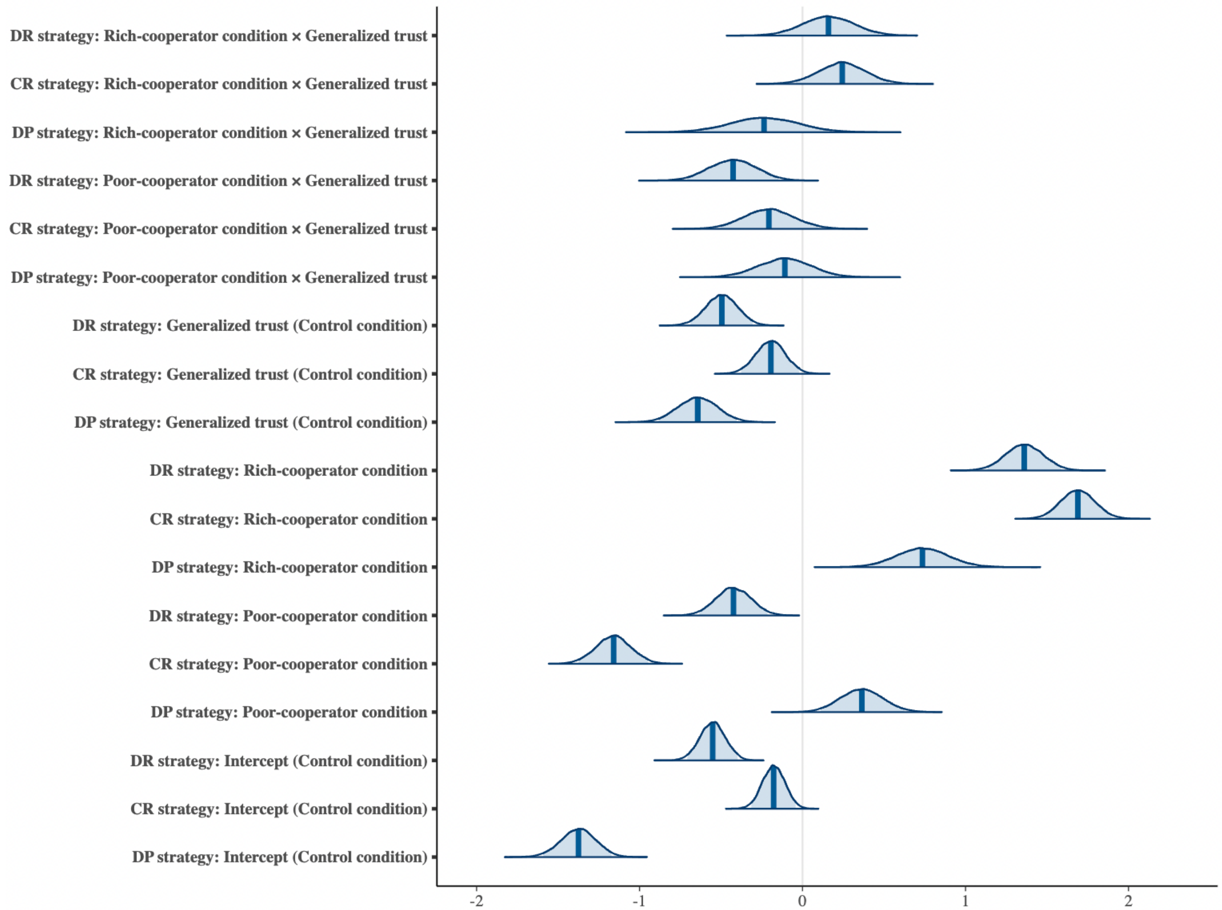


Figure S6. Posterior distributions of predictors with medians and 95% intervals in Study 2 (N = 150). The blue points and bars represent calculated coefficients with 95%confidence intervals. Generalized trust was centralized.

References

Bürkner, P.-C. (2017). brms: An R Package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*(1). 1–28. https://doi.org/10.18637/jss.v080.i01

Carpenter, B., Gelman, A., Hoffman, M. D., Lee, D., Goodrich, B., Betancourt, M., Brubaker, M., Guo, J., Li, P., & Riddell, A. (2017). Stan: A probabilistic programming language. *Journal of Statistical Software*, *76*(1), 1–32. https://doi.org/10.18637/jss.v076.i01

Kruschke, J. K. (2021). Bayesian analysis reporting guidelines. *Nature Human Behaviour.* https://doi.org/10.1038/s41562-021-01177-7

R Core Team. (2022). R: A language and environment for statistical computing, R Foundation for Statistical Computing, Vienna, Austria. https://www.R-project.org/