Applied Mathematics and Computation 410 (2021) 126445

Contents lists available at ScienceDirect

Applied Mathematics and Computation

journal homepage: www.elsevier.com/locate/amc

Reducing the bystander effect via decreasing group size to solve the collective-risk social dilemma

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ARTICLE INFO

Article history:
Received 8 April 2021
Revised 3 June 2021
Accepted 7 June 2021

Keywords:
Collective cooperation
Bystander effect
Climate change
Risk
Group size
Social dilemma
Games

ABSTRACT

Collective cooperation is essential to human society, and it exists in many social dilemmas. In the scenario of a collective-risk social dilemma, a group of players have to collectively contribute to a public fund to prevent the tragedy of the commons, such as dangerous climate change, because everybody will lose all their remaining money when the damage happens with a certain probability if the group fails to reach a fixed fundraising target. Yet, it remains largely unclear how the group size affects the probability of reaching the collective target and the mechanism that drives different outcomes of the collective cooperation. Here, we contribute to the literature by exploring the role of group size in the collective-risk social dilemma and the potential underlying mechanism using both model simulations and human experiments. Through simulations we found that the rate of failure for collective cooperation increases for larger groups, along with the arising of bystander effect and a decrease in average contributions, which are confirmed by our experimental observations. We further analyze the patterns of investment behaviors in the experiment setting by categorizing players into cooperators, altruists, and free riders using both a clustering method and a golden standard. We found that altruists who tend to contribute more, rather than cooperators who prefer contributing a fair-share investment, play a crucial role in groups with success outcome in early and/or middle stages of the game. Our results indicate that bystanders are dynamic and their amount depends on the contribution of others. When others contribute less, bystanders also contribute less. If the collective goal is unlikely to achieve, more players choose to be bystanders who strategically contribute less, intriguing the failure of the collective goal. Our findings suggest a potentially effective way to solve the collective-risk social dilemma by reducing the bystander effect through the mechanism design of forming small groups.

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https://doi.org/10.1016/j.amc.2021.126445

1. Introduction

Cooperation in social dilemmas is essential for the human society, from small groups of individuals to large organizations of countries [1]. However, the optimal choice for players is defective according to Darwin's theory where everyone is tempted to be a free-rider on others' efforts [2,3]. The instinctive drive for cooperation has attracted increasing attentions from scientists, since it may provide a key to solve the tragedy of the commons. It has been found that individuals cooperate for various reasons, such as direct and indirect reciprocity [4,5], group selection [6,7], network reciprocity [8,9], and avoiding punishment [10], etc. Recently, collective cooperation in social scenarios of risk dilemma has been a topic of interest owing to its importance in the human society. For example, a globally challenging problem is to prevent dangerous climate change. To this end, different countries have to create plans and set targets to lower greenhouse gas emissions. Indeed, a naturally arising question is what are the main factors that affect collective actions on climate change. To answer this question, Milinski et al. [11,12] conducted a controlled experiment with simulated dangerous climate change where subjects face a collective-risk social dilemma [13–15]: reaching a fixed target sum through successive monetary contributions, or losing all their remaining money with a certain probability when the target sum could not be achieved. They found that the high risk of simulated dangerous climate change and improved reputation with inherent benefits promote collective cooperation to achieve the goal. In addition, cooperation is also known to be influenced by the group size [16–22]. However, little is known about the effect of group size on cooperation under risk.

Some recent works presented that cooperation is more efficient in large groups when the game dynamics are governed by group interactions [16–19]. For example, large groups can deploy the resources which small groups often lack, thus enhance the enforcement of collective action [22]. However, to date scholars have not yet reached a consensus, since there exists factors which influence or are influenced by the group size and further affect cooperation [22]. Some others suggested that cooperation could be harder in larger groups if the increasing number of players induces a decrease in individual gains relative to the cost of cooperation [23]. Such a scenario happens, for example, when the common good is sufficiently rival [24]. Negative effects of group size on cooperation may lie on the fact that social pressure and social incentives are more effective in small groups [20,21]. Besides, the bystander response [25,26], where bystanders prefer contributing less or none when others contribute less, may also play an important role in hindering cooperation in larger groups, since the help expected from others is more unlikely obtained. Indeed, individuals in a group may play different roles in achieving a collective goal. Some behave as altruists who tend to contribute more to guarantee that the collective goal is achieved. Some prefer to be cooperators who are likely to contribute a fair-share investment. And there are also free riders who enjoy group benefits and are reluctant to pay for the costs. Several studies indicate that individuals tend to be free riders when group size increases [27]. As a result, larger groups may fail to achieve the collective goal because of more free riders [12,22]. In contrast, how and why a group could succeed in achieving the goal is not yet fully understood, especially the role of altruists in such success.

In this paper, we explore whether a large group or a small group can easily reach collective cooperation in the scenario of a collective-risk social dilemma where a group of players has to collectively contribute to a public fund to prevent dangerous climate change because everybody will lose all their remaining money when the damage happens with a certain probability if the group fails to reach a fixed fundraising target. We first investigate the bystander effect using a simulation model [12] under different group sizes. We find that large groups are more likely to fail while small groups are more likely to succeed. Then we present evidence from experimental observations, and further discuss the influence of altruists and bystanders on cooperation. Our approach in public goods experiments with risk captures the essential factors in social dilemma. We find that altruists in a group play a crucial role in leading to the success of the group achieving the goal. Our results further indicate that bystanders are dynamic and affect average contribution at the early rounds of the game. When others contribute less, bystanders also contribute less. Nevertheless different from free riders, bystanders strategically choose to contribute less in larger groups, leading to the failure of the collective cooperation.

2. Methods

The process of evolutionary dynamics in real world is admittedly complex. On understanding the nature of collective cooperation, literature has focused on two major features, namely, social collective-risk dilemma and strategy learning [11,12]. Specifically, the social collective-risk dilemma suggests that, on the one hand, individuals are motivated to contribute more during the game by the collective-risk of losing everything if they are unable to achieve the goal in the end. On the other hand, individuals attempt to reduce their contributions during the game in order to maximize their net profits if they achieve the goal. By comparison, the strategy learning suggests that the strategy set with higher payoffs has higher fitness, which may lead to the spreading of cheats. For example, in the dangerous climate change game, people aim to reach a fixed level of target sum through successive monetary contributions, and lose all their remaining money with a certain probability (collective-risk) if the goal is failed to achieve. Here, we will introduce the evolutionary dynamics of collective-risk social dilemma in both the human experiment and simulation model to study the effects of group size on collective cooperation and the potential mechanism of investment behavioral patterns.

Human experiments. The human-subjects–based collective risk game, which is motivated from the global social dilemma of climate change, was conducted from March 2013 to December 2014 with a total of 80 freshmen and sophomores majoring in mathematics, physics, computer science, economics, as well as different areas of social sciences at Wenzhou University.

The study protocol was approved by the Wenzhou University's Institutional Review Board. In the experiment, participants provided assent in the following way. Before the experiment, each participant was randomly allocated an isolated computer cubicle to avoid communication among participants. When participants were seated, they were required to view the instructional slide that explained the design of the experiment. Then, within the given time, they needed to finish questionnaires related to the experiment. The consent of participation was given only after they accurately answered the questionnaires. For this game, each section required simultaneous participation of 20 members, who were further randomly divided into several groups (i.e., the setup was completely anonymous). Importantly, the size of the group M (the number of members in a group) was kept constant during the entire experiment.

Within each group, the members finished 10 independent rounds of the games together. Each players are given 20 scores at the beginning of the game. At reach round, each player has to decide the amount of the investment (a value in $\{0, 1, 2\}$) to the public fund. The targeted amount of total investment for a group is $10 \times M$, meaning that each player is expected to invest on average 1 score per round. After finishing all decision-making processes in the present round, every subject was notified of (*i*) the individual contribution (0, 1, or 2 scores), (*ii*) the total investment of his/her group in the current round, and (*iii*) the remaining gap between the total contribution and the required sum of the group (i.e., the collective target) on the screen for 20 seconds. The entire investment in the public fund would be used to control CO_2 emission, as this is beneficial for avoiding extreme weather events.

On finishing 10 rounds, the total investment of one group was required to reach the sum $10M$ (equivalent to 1 score per subject per round on average). If the overall contribution was not less than the required investment target $10M$, extreme weather could be certainly avoided and the subjects would earn the money left. For example, in a $M = 2$ group, whose total investment exceeds the required sum, the subject investing 12 scores to the public fund could surely get $10 \times 2 - 12 = 8$ scores after the experiment. On the contrary, if the overall investment did not reach the required target, the extreme weather would be excited with a risk probability (for simplicity, but without loss of generality, this probability was fixed to 0.5 at all sessions). For the case where extreme weather was avoided, each subject in the given group could earn their remaining money; otherwise, all subjects of that group got nothing. It is evident that, in this climate game with risk-averse strategies, there always exists a conflict between short- and long-term interests. At the end of the game (i.e., after 10 rounds), players will save the rest of the money if they succeed, and lose it with a probability of r if they fail.

To provide participants with an incentive, the final remaining scores at the end of the experiment were translated into real monetary payouts ranging from 20–40 RMB (Chinese money). The conversion rate used was 1 score = 1 RMB. Our experiments consisted of 44 groups (the numbers of $M = 2$ and $M = 20$ groups are 40 and 4, respectively). The instructions and questionnaires took 5–10 min and the entire game took 25–35 min for 10 rounds. All participants earned an average of 32.2 RMB.

Simulation model. Similar to the experiment, individuals are divided into groups with M members from a total of N individuals, ($M \geq 2$, $N > 2$, and $M \leq N$). Players can opt for three strategies in a round (investment with 0, 1, or 2 scores) in the simulation model. Individuals play the collective-risk game with others in the same group. In the simulation model, each time step contains two stages: (i) playing the game for 10 rounds before getting payoffs, and (ii) updating the strategy set. There are two points that are different from the experiments: strategy selection (deciding the contribution to the public fund in every round) and strategy updating (renewing strategies in the framework of evolution). Thus, players have a strategy set with random selections from three strategies; an individual follows the strategy set of the randomly selected person if his/her payoff is lower than that of the randomly selected person at the end of a time step. Here, 10 rounds are defined as a time step. In addition, we simulate the evolutional process where the person with the lowest payoff among N individuals at the end of each time step is replaced by a new person. Because each individual is given 20 scores at the beginning of the time step, the payoff involves the money left and risk r. The payoff is equal to the money left if the target sum is $10M$ after 10 rounds, whereas individuals lose the money left with risk r if the sum of the collective investment in the group is below the target sum.

In our model, individuals have random strategies at the beginning of the simulation, i.e., the endowment strategy set is initialized by 0, 1, or 2 with the same probability. Before the game, every player is initialized with 20 scores, which can be contributed to the public fund or reserved as fortune. In each of the 10 rounds, a player contributes to the common fund according to the endowment strategy set $\{s_1, s_2, \ldots, s_{10}\}$, where s_i is the amount of investment at the i-th time step (round). After the 10-round game, the total endowment of an individual is $\alpha_j = \sum_{i=1}^{10} s_i$. And the collective endowment of a group k is $\Omega_k = \sum_{j=1}^{M} \alpha_j$. If Ω_k is below the target sum (collective goal) $T = 10 \times M$, players in group k lose all their scores with a probability of r no matter how many scores they currently hold. If otherwise, player j in group k gets a payoff of $20 - \alpha_j$, a score the player currently holds. To sum up, a player j gets an average payoff of $20 - \alpha_j$ if the goal is achieved, and an average payoff of $(1 - r) \times (20 - \alpha_j)$ otherwise. After each time step (round), all players have an opportunity to update their investing strategy set as follows. Player k compares its payoff with a randomly selected player l. If player l's payoff is higher, player k will adopt player l's investing strategy set. In this manner, the evolutionary dynamics can be modeled as a selection process: players play games with members in the same group, while adopting strategy sets with higher payoffs by learning from the whole population with size N. At the same time, our model has a mutation process that occurs with a small probability ε (set as 0.05 in our simulations), where a randomly selected element of the strategy set is reset as 0, 1, or 2 with an equal chance.

Although we do not know on what basis individuals decide to contribute to the public fund at each round, the real prospect can be reflected by updating the strategy in the model based on the learning process that is widely used in evo-

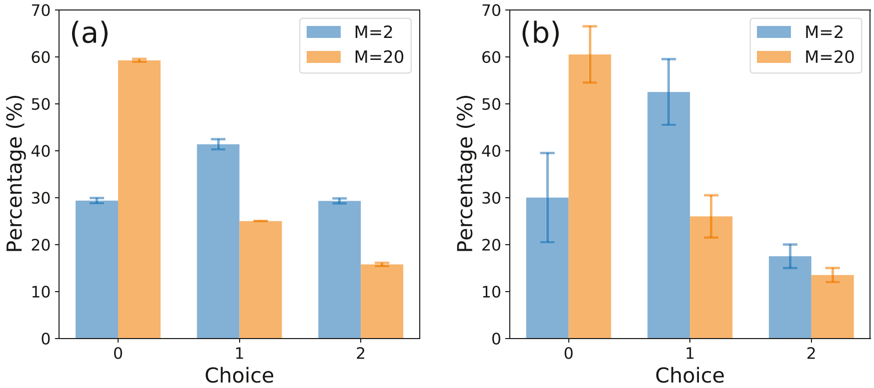

Fig. 1. Percentage of choices in the collective-risk game. (a) Results from the simulations. The system employs 1000 agents for the simulation. The probability of getting no payoffs when the group fails is set as $r = 0.9$. The blue and orange bars correspond to the $M = 2$ and $M = 20$ groups, respectively. (b) Results from the human experiments. There are in total 80 individuals who participated the experiments. Error bars indicate standard error of mean. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

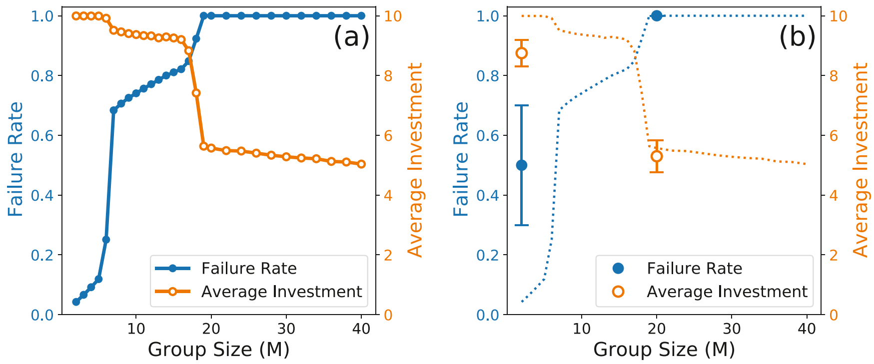

Fig. 2. The failure rate of groups and the average investment of players under different group sizes. (a) Results from the simulation model, where a range of group sizes are considered. (b) Results from the human experiment, where group sizes M=2 and M=20 are two observations. Dashed lines show the corresponding model results. Error bars indicate standard error of mean.

lutionary game models. Therefore, we can gain insight into the evolutionary process similar to that of the experiment. Our simulation results were obtained for a system that reaches the stable state and the size of system N was fixed size ranking from 1000 to 1026 (the number of N is multiple of group size M). As expected and we show below, the simulation results are in agreement with our experimental results that larger size groups have more difficulties in collective cooperation.

3. Results

Fig. 1 (a) presents the simulation results from the model. We find that players in larger groups ($M = 20$) have a larger probability to invest less than those in smaller groups ($M = 2$). In particular, most of players in $M = 2$ groups invest 1, a fair endowment beneficial to achieve the goal, while players in $M = 20$ groups mostly do not contribute during the game. The simulation result of our model suggests that the increase of group size may hinder individual's willingness of making contributions to the group. We further conducted an experiment of collective-risk social dilemma to validate our model. Fig. 1(b) shows the empirical results from the human experiment, which are qualitatively consistent with our observations from the simulation in Fig. 1(a). Specifically, the most frequent choice is 1 for $M = 2$ groups (42.4%), while the most frequent choice is 0 for $M = 20$ groups (59.5%). The consistency between simulations and empirical results supports the validation of our model in simulating the complex process of collective cooperation.

We further explore how the group size M affects the individual investing behaviors and the probability of achieving the collective goal. We first present our results of the simulation model using a large range of group size M. From Fig. 2(a) we find that the failure rate (in blue) of the group outcome increases with M. Interestingly, the failure rate exhibits an abrupt jump from about 0.1 to about 0.7 when M increased from 5 to 7. The failure rate increases gradually afterward and experiences another rapid increase when M is around 19, after which the failure rate remains 1. Meanwhile, we find that the average investment (in orange) of players decreases as the increase of M, showing that players in larger groups invest on average less than their counterparts in smaller groups. In particular, the average investment is almost halved from

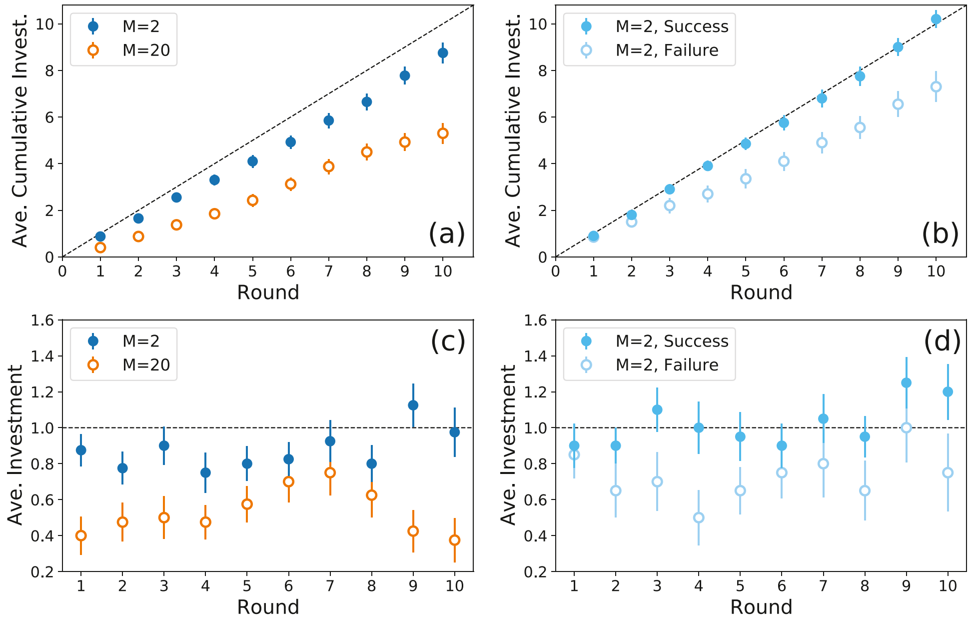

Fig. 3. The average investment at each round of the human experiments. (a) The average cumulative investment for group sizes M=2 and M=20. (b) The average cumulative investment for M=2 groups, breaking down by success and failure outcomes of the game. (c) and (d) show the corresponding results for the average step investment at each round. Error bars indicate standard error of mean.

about 9 to about 5 when M increases from 17 to 19. These observations are aligned with the bystander effect [26], a social psychological theory stating that one's likelihood of helping decreases with the number of onlookers.

We test these simulation results in our human experiments using $M = 2$ and $M = 20$ as two representing data points. As shown in Fig. 2(b), the empirical results show a great consistency with the simulation results, where the failure rate increases and the average investment decreases with the group size. Specifically, we find that half of the groups failed to reach the goal when $M = 2$, and no group succeeded when $M = 20$. The average investment is significantly smaller under $M = 20$ (at about 5.4) than under $M = 2$ (at about 8.8). In short, these empirical results are qualitatively in support of the simulation results and thus provide a validation of our model in understanding the effects of group sizes on collective cooperation.

We have observed the decrease of average investment as the group size M increases (Fig. 2). Next, we further break down this observation into different rounds and explore the temporal trend of individual investing behaviors during the game. Figs. 3(a) and 3(c) respectively show the cumulative investments and the step investment of players at each round for both $M = 2$ and $M = 20$ groups. The dashed line indicates the expected investment to achieve the collective goal. Though there are variations, players in $M = 2$ groups on average invest close to the expectation (i.e., value 1) at each round, and they invest more than those in $M = 20$ groups. Moreover, we find that the step investment under $M = 20$ exhibits an inverted-U shape (Fig. 3(c)), implying that players were trying to reach the goal by strategically investing more right after the middle round of the game. However, when the goal is less likely to be achieved in the end (all $M = 20$ groups failed in the experiments), the step investment in last two rounds drops remarkably, suggesting that players are strategically investing less to maximize their payoffs.

Next, we focus on the temporal trends of investment behaviors for both succeeded and failed groups under the group size $M = 2$. When examining the cumulative investments in Fig. 3(b), we find that the investments of the succeeded groups are perfectly aligned with the expectations (dashed line), while the investments of the failed groups are much less and are deviated from the expectations. Fig. 3(d) shows that succeeded groups have on average larger investments than failed groups during the game. In particular, their investments in last two rounds are disproportionately larger in order to achieve the goal and to avoid possible loss due to the risk. Interestingly, we notice an early signal that can largely distinguish the two groups, where failed groups invest much less than succeeded groups since the very beginning of the game. More specifically, Fig. 3(d) shows a clear visual difference between the two types of groups since the second round. The lack of collective cooperation at the beginning of the game leads the failed group into a different evolving trajectory and results in the miss of the collective cooperation goal in the end.

To better understand the evolution dynamics, we further explore how individuals behave differently over time in the human experiment. According to the step investment, individuals can be grouped into three categories: cooperator, altruist, and free rider. Specifically, at each round of the game, cooperators are likely to contribute a fair-share investment (1 score), altruists tend to contribute more than enough investments (2 scores) to help achieve the collective goal, and free riders behave more selfish by investing less than others (0 score).

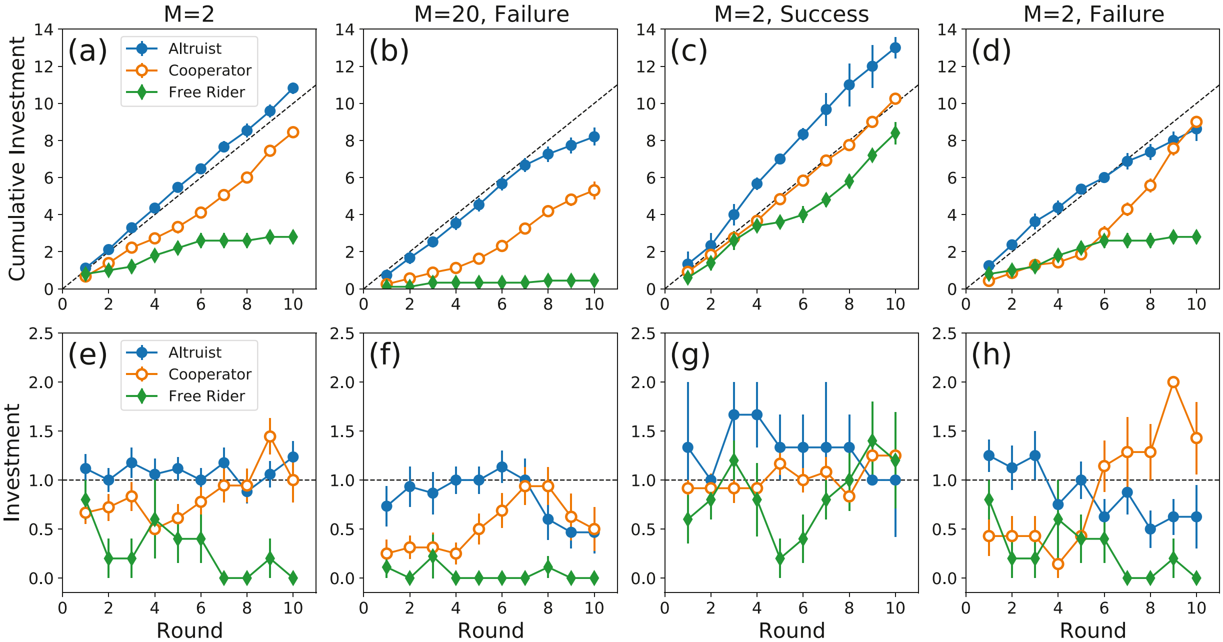

Fig. 4. Three behavioral clusters in the human experiment. (a) and (b) show the cumulative investment of each behavioral cluster under group size M=2 and M=20, respectively. (c) and (d) show the cumulative investment of each behavioral cluster for M=2 groups with success and failure outcomes, respectively. (e-h) show the corresponding results for the step investment. Note that no success outcome was observed for the group size M=20 in the experiment. Error bars indicate standard error of mean.

Using the experiment data, we first apply the K-means method to cluster all individuals in three groups based on their cumulative investments. Then, according to the patterns of cumulative investments, we manually label each cluster as altruist, cooperator, and free rider based on the overall behaviors of all players in a cluster relative to other clusters. In Figs 4(a) and 4(e) we show the cumulative investment and the step investment respectively for each behavioral cluster when the group size $M = 2$. In Figs. 4(b) and 4(f) we show similar results when the group size $M = 20$. We notice that all $M = 20$ groups are with failure outcomes in the experiment, showing that it is harder for larger groups to reach the collective goal. To better understand the behavioral patterns under different outcomes and their dependence on the group size, we further break down the $M = 2$ groups by success and failure outcomes. The results for groups with success outcome are shown in Figs. 4(c) and 4(g), while the results for groups with failure outcome are shown in Figs. 4(d) and 4(h). Lastly, we notice that the above three behavioral clusters are separated at a relative scale. Nevertheless, the success and failure outcomes of the groups are determined at an absolute scale set by the target sum. We thus also performed a similar analyses where three behavioral clusters are identified under the (absolute) golden standard (i.e., by definition, cooperator, altruist, and free rider invest on average larger than 1, equal to 1, and less than 1 at each round across the game). The results are shown in Fig. 5.

Interestingly, in Figs. 4 (a) and (b) for both $M = 2$ and $M = 20$ we observe that only altruists make a fair contribution close to the expected investment line to achieve the goal during early and middle stages of the game. Meanwhile, both cooperators and free riders contribute much less than the expectation to the public fund. However, when we break down individuals and observe only those in groups with success outcome, we find that the cooperators invest closely following the expected investment line (Fig. 4(c)). Most remarkably, in groups with success outcome, we find that both altruists shown in Fig. 4(c) and absolute altruists under the golden standard shown in Fig. 5(c) make great contributions during middle stages of the game, which are crucial to compensate the less contributions from free riders. At the later stage of process, all players in these groups anticipate high probability of the goal achieved, and they get consensus on more contributions. On the contrary, altruists in groups with failure outcome tend to decrease their investments when the collective goal is unlikely to achieve in late rounds (Figs. 4(b) and (d)). At the later stage, the free rides, cooperators and altruists become bystanders. In addition, the average step investment of cooperators in these groups increases from middle stages of the game (Figs. 4(f) and (h)). Nevertheless, these groups still fail to achieve the goal. For free riders in these groups, we find that they gradually decreases their investments and rely on others to make contributions under small group size $M = 2$ (Fig. 4(h)). Under large group size $M = 20$, they contributes significantly less since the very beginning and throughout the game (Fig. 4(f)). Actually, comparing the results for small groups of the size $M = 2$ with the results for larger groups of the size $M = 20$ in Figs. 4(e) and 4(f), we observe that all players in the larger groups of the size $M = 20$ invest less even in the first half rounds. Interestingly in the second half rounds, we find stronger effect of bystanders in larger groups by inducing lower investment, as shown in Fig. 4(f). This phenomenon is more pronounced for altruist and cooperators as they have contributed disproportionately more and expected others to contribute as well [28].

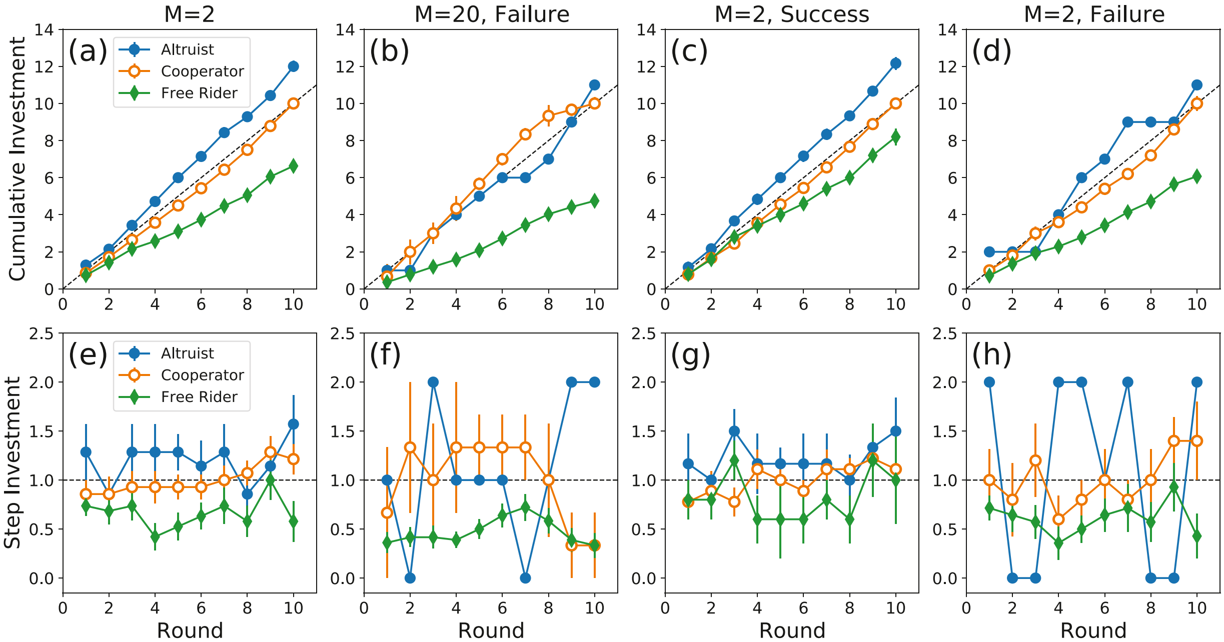

Fig. 5. Three behavioral clusters identified using the golden standard in the human experiment. (a) and (b) show the cumulative investment of each behavioral cluster under group size M=2 and M=20, respectively. (c) and (d) show the cumulative investment of each behavioral cluster for M=2 groups with success and failure outcomes, respectively. (e-h) show the corresponding results for the step investment. Note that no success outcome was observed for the group size M=20 in the experiment. Under the golden standard, cooperator, altruist, and free rider invest on average larger than 1, equal to 1, and less than 1 at each round across the game. Error bars indicate standard error of mean.

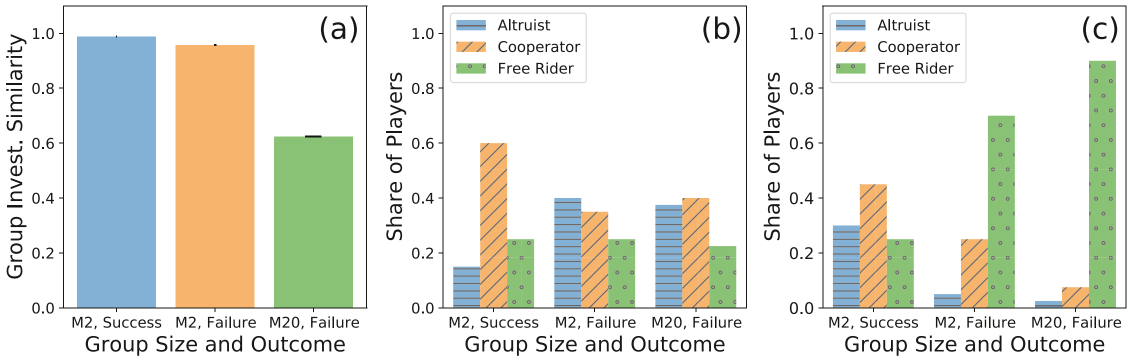

Fig. 6. Investment similarity and share of behavioral clusters from experiments. (a) The average similarity of within-group players' investment under different group sizes and outcomes. (b) The share of players in the three behavioral clusters identified by relatively investment patterns corresponding to Fig. 4. (c) The share of players in the three behavioral clusters identified by the golden standard, where cooperator, altruist, and free rider invest on average larger than 1, equal to 1, and less than 1 at each round across the game. Note that no success outcome was observed for the group size M=20 in the experiment.

We further explore the collective behaviors of players and the outcomes of the game in more detail. First, we consider the similarity of players in groups with different sizes and outcomes. Specifically, we calculate the cosine similarity of each pair of players in a group based on their cumulative investment vectors and then take an average for all players. Fig 6(a) shows the average similarity of player's investment behaviors in the human experiments. We find that the investment behaviors of players in succeeded groups (M2, Success) are very similar to those in failed groups (M2, Failure) under small group size $M = 2$. The within-group similarities in these two types of groups are very close to 1, implying that the coordination has achieved within the group. However, we observe distinctly different outcomes. Moreover, the similarity in large groups (M20, Failure) is much smaller than that in small groups (M2, Failure), indicating that it is more difficult to achieve within-group coordination as the group size increases. A similar failure outcome with a varying level of coordination under different group sizes implies that opposite to the common impression, cooperators by themselves are not a decisive contributor to the success outcome of a group. We thus attribute more the success outcome of the groups (M2, Success) to the overwhelming contributions from altruists as shown in Fig. 4(c) and Fig. 5(c).

Next, we look at the share of three clusters of players under different group sizes and outcomes. When identifying the three clusters using relative investment behaviors, as shown in Fig. 6(b), we find that all groups including succeeded small groups (M2, Success) and failed groups (M2, Failure; M20, Failure) have a similar share of free riders. Notice that the average investments of the same type of players are different in this case, for instance, free riders invest much more in succeeded groups (Fig. 4(c)) than in failed groups (Fig. 4(d)). By comparison, when identifying the three clusters using the golden standard, as shown in Fig. 6(c), we find that the shares of altruists and cooperators largely drop, while the share of free riders increases when the group size increases. Moreover, failed groups have a much larger share of free riders than succeeded groups when they have the same group size. The increasing share of free riders may lead to the higher failure rate in collective cooperation as the group size grows (Fig. 2). Our results also confirm Milinski's observation again that the more free riders the more failures of achieving collective goals [12].

4. Discussion

The achievement of a collective goal requires the efforts from all group members. The dilemma is that how to motivate members to cherish collective interests instead of their own payoffs, even though they are aware of the risk of not achieving the collective goal. This has attracted lots of attentions from scientists in different fields. Our results provide the following scenario in collective-risk dilemma games [12]. The bystander who always expects others to contribute more leads to failure. If the collective goal is found difficult to achieve, even the altruist does not want to contribute more. Thus, at the end of the process, altruists become bystanders, which induces inevitable failure. On the contrary, when altruists play the leading role at the beginning or middle stage of the process, everyone sees the light of hope for the achievement of the goal. As a result, free riders change their positions of the bystander. In this way, free riders, cooperators and altruists reach a consensus to contribute more throughout of the process, guaranteeing the collective goal achieved successfully.

Our results of experiments and simulations of the collective-risk dilemma game suggest that reducing bystander effect is a promising way to overcome the collective dilemma of climate changing. In this way, the altruistic dividend can be obtained because all players easily get consensus on more contributions in small groups where altruists play a key role in the expectation to achieve the collective goal. Otherwise, even altruists are more willing to change their position to bystanders. It is also worth mentioning that players tend to act as altruists if individuals are able to choose members freely to form groups in certain unequal way, such as blocking defector invasion and leaving bads [29–32]. In current study we provide practical insights for controlling dangerous climate changes [33,34]. We argue that the mechanism design is important to avoid dangerous climate changes, since the appearance of bystanders in a large group is harmful for collective cooperation owing to breakage of weak cooperation [35,36] as well as communication, migration and education [37–42] on consensus of collective cooperation. Our method also provides a possible road map to solve the problem of dangerous climate changes: few large nations reach a consensus first, then others nations join.

Acknowledgment

This paper is supported by Natural Science Foundation of Zhejiang Province (Grant No. LY17F030005), Youth Foundation of Social Science and Humanity, Ministry of Education of China (Grant No. 20YJCZH077), and Educational Commission of Zhejiang Province (Grant No. Y201942464). J. Kurths was financed by the Ministry of Science and Higher Education of the Russian Federation within the framework of state support for the creation and development of World-Class Research Centers "Digital biodesign and personalized healthcare" No. 075-15-2020-926.

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