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The dynamic emergence of cooperative norms in a social dilemma

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A B S T R A C T

This paper addresses the formation of social norms of cooperation through interaction in repeated Public Goods Games, using novel multilevel techniques. Cooperation has traditionally been understood as the interplay of static factors such as shared social identity and pre-existing norms. This study investigates the dynamic emergence of cooperative norms in the presence or absence of social categorization. A small effect of categorization was found: Categorization helps initiate and maintain higher levels of cooperation. However, the differences in emergent cooperation between small groups were much stronger than the differences between the Categorization and Non-Categorization conditions. Using explorative analyses, three distinct classes of groups were found. Within groups, group members follow nearly identical rules for their choice of cooperative behavior. We argue that individual behavior converged because of the social interactions within these groups. Overall, the development of cooperation is best predicted by the process of norm formation that occurs when social identities emerge.

1. Introduction

How does cooperation in small groups emerge? This paper takes a dynamic perspective on the formation of social norms for cooperation. We also consider how social categorization can influence this norm formation. We seek to understand how cooperation arises and is maintained in a social dilemma: drawing on advances both in experimental software and in multilevel latent class Markov models, we can analyze decision rules for cooperation and the emergence of individual behavioral patterns in conjunction with group norms.

The formation of cooperative norms in a small community, or society at large, has at least one fundamental hurdle: When there are collective goods – whether it be collective action, public television, farming collective lands, etc. (Katz, Lazer, Arrow, & Contractor, 2004; Shankar & Pavitt, 2002) – there may be free riding because collective goods are shared equally, regardless of personal contribution (Samuelson, 1954). Therefore, traditional game theory argues that in order to maximize one's (economic) self-interest, it is rational not to cooperate. For example, Hardin (1968) argued in the "Tragedy of the Commons" that everyone has an individual predisposition to take advantage of a common-pool resource, such as the environment, and therefore people are destined to undermine it – for example, through overgrazing or polluting. If this were true, all attempts at cooperation are ultimately doomed to fail or falter.

Such social dilemmas are commonly studied in Public Goods Games (PGG) (Olson, 1965). A PGG is essentially a simulated society in which participants decide how much to contribute to the Public Good – the socially optimal outcome is universal cooperation, the best individual outcome is defection while all others cooperate. Contrary to classic rational actor expectations, however, research suggests that cooperation in social dilemmas tends to be "irrationally" high: in the range of 40–60% of what one can contribute (for example, see Ledyard, 1995).

Why is "rational defection" so rare in these experiments? In his seminal work on the Prisoner's Dilemma, Robert Axelrod (1984) found that the most sustainable and profitable strategy in repeated interaction is tit-for-tat rather than self-interested defection. Tit-for-tat entails that people begin interaction by cooperating and then copy their interactant's subsequent behavior – i.e., conditional cooperation. Tit-for-tat was seen as: a) nice, as it starts with cooperation; b) forgiving, as one will cooperate again when the other player stops defecting; c) retaliatory, as it punishes non-cooperation; and d) clear, as it is easy to discern the interaction pattern. Tit-for-tat was thought to be evolutionary robust and could emerge in an environment of egoist players, optimizing each player's payoff. However, in reality one's payoff is not

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necessarily instrumental (i.e., maximizing points) but might also have a relational value.

Building on the ideas of game theory, the interdependence perspective (Kelley et al., 2003; Kelley & Thibaut, 1978; Rusbult & Van Lange, 2008; Thibaut & Kelley, 1959) provides a framework to look at the effect of between-person processes on collective outcomes, where one's optimal outcome has strong relational considerations. These considerations are determined by personal characteristics and situational factors. Whether exchanges are seen as rewarding or not, depends not only on instrumental payoff but also on one's individually fixed preferences and expectations. Furthermore, interdependence theory assumes that an individual's behavior will – to greater or lesser extent – be influenced by the actions of others, given a particular interdependence structure. Examples of these structures include situations in which an individual has unilateral control over another's outcomes, or vice versa; or where both partners' actions have an effect on outcomes for both. In other words, the situation structure influences an individual's behavior in relation to those to whom one's outcome is tied. If levels of "rational defection" are rare in PGG's, interdependence theory suggests this may be because certain individuals value good relations more than profit. However, one potential issue for interdependence theory is that most research in this tradition focuses on dyads, which is quite far removed from the more complex dynamics of groups.

Nevertheless, Public Goods research has revealed many static factors that contribute to higher levels of cooperation. Of particular interest to social scientists are a shared social identity (e.g., Brewer & Kramer, 1986; Simpson, 2006) and differences in preferences and beliefs (e.g., social value orientation, Messick & McClintock, 1968).

1.1. Static views on cooperation and social identity

Much of the traditional research using PGGs examines cooperation in one-shot experiments. There is an extensive literature on situational and personal factors that influence decisions to cooperate or defect in such settings. We refer to these as "static" factors, in the sense that their effects are assumed independent of (or exogenous to) the social interactions or exchanges within the PGG.

For example, cooperation tends to be high in groups that share a social identity. Shared social identities can be formed "deductively", whereby group members infer a joint category membership because they exhibit shared characteristics or prototypical traits (Postmes, Spears, Lee, & Novak, 2005; Tajfel, Billig, Bundy, & Flament, 1971; Turner, 1985). In other words, group identity can form from the top down. Belonging to a shared social category (gender, race, nationality etc.) or even "minimal" groups without meaning (Tajfel et al., 1971) can, for example, increase the sense of belonging and group cohesion (Turner, Hogg, Oakes, Reicher, & Wetherell, 1987) and promote ingroup favoritism (Tajfel et al., 1971).

Higher social identification with one's group not only alters expectations about the behaviors of others: greater cooperation is mediated by one's sense of self as a group member (De Cremer, Van Knippenberg, Van Dijk, & Van Leeuwen, 2008). Having a shared social identity appears to transform the goals of selfish individuals so that they cooperate rather than defect (De Cremer & Van Vugt, 1999; Turner, 1991). Accordingly, one can increase cooperation by categorizing people at the collective, rather than subgroup or individual level (Brewer & Kramer, 1986; Wit & Kerr, 2002; but see Jetten, Postmes, & McAuliffe, 2002, for exceptions). Group members, when they identify as a group and hence when shared identity is salient, tend to optimize ingroup outcomes and minimize ingroup inequalities (Simpson, 2006), both of which happen when all group members contribute maximally to the Public Good.

A large body of literature shows that levels of cooperation also depend on personal preferences. In interdependence theory, a personality difference that has received much attention is the distinction between those who are more individualistic, competitive and "proself" versus those who are more altruistic, cooperative and "prosocial" (social value orientation, SVO, Messick & McClintock, 1968; Van Lange, 1999). This explains about 9% of the variation in cooperation in social dilemmas (Balliet, Parks, & Joireman, 2009). Approaches to SVO tend to treat these preferences for cooperation or selfishness as fairly stable response styles (Messick, 1999). With respect to exchange decisions, these response styles may operate as social heuristics for behaviors that have become automated and intuitive because they were rewarding in the past (Jordan, Peysakhovich, & Rand, 2014) and therefore may spill over into novel situations (Peysakhovich & Rand, 2016). To our knowledge, how these personal response styles play out in dynamic settings, where individuals with different social heuristics interact for a prolonged series of exchanges, has not yet been explored.

Above the individual level, the decision whether or not to cooperate can also be influenced by the overarching goal frame salient in a particular context (Lindenberg, 2015a, b), which also informs the social heuristics drawn on by the individual. Notably, Lindenberg (2015a, b) draws a distinction between personal preferences and overarching goals, arguing that the latter are determined by the social environment. According to Lindenberg (2015a, b), particular social situations activate certain goal frames to a greater extent than others (although others may still operate in the background). This explains why the social framing of cooperation dilemmas can have different outcomes for cooperative or competitive behavior (see for example Liberman, Samuels, & Ross, 2004; Van Lange, Joireman, Parks, & Van Dijk, 2013). For example, framing a social dilemma in cooperative terms ("Community game"), versus competitive terms ("Wall Street game"), can increase cooperation by providing a normative goal frame (where collective gain is salient) versus a gains goal frame (where individual gain is salient). Beyond these situational goal frames, the level of within-game cooperation is also likely to be affected by the quality of interactions within the game. Here we might see the emergence of norms of an entirely different kind.

1.2. Dynamic views on cooperation and social identity

The emergence of cooperation is increasingly being studied through iterative social dilemmas. Naturally, this shift in interest in the field focuses on how relations (or even societies) form that are more or less cooperative. This is highly relevant: variability in the levels of cooperation between societies tends to be high (e.g., Henrich et al., 2001), so it is important to understand what makes a society promote high levels of cooperation. As an overall trend, research suggests that cooperation is usually higher when there is a higher probability of interacting again in the future (Dal Bó, 2005), possibly due to the role of direct and indirect reciprocity where one expects present cooperative behavior to be returned in the future (Lindenberg, 2015b; Molm, Schaefer, & Collett, 2007). Factors that enhance the effect of reciprocity in cooperative situations include: homogeneity, smallness and stability of the group and its membership (Diekmann & Lindenberg, 2015).

Most findings from iterative PGGs show that contributions often start at around 50% of what one can possibly contribute and, although they tend to decline over time, the average contribution remains above zero (Barrera, 2014). Additional research considers factors preventing this tendency of declining cooperation. For example, studies have found that implementing a sanctioning system can mitigate a decline in cooperation (e.g., Barrera, 2014; van Miltenburg, Buskens, Barrera, & Raub, 2014). Sanctioning is a form of negative feedback in response to defection, which ideally discourages future defection and encourages cooperation. Sanctioning can occur in multiple ways, through material or symbolic means – for example, monetary penalties or the communication of social disapproval (Barrera, 2014; Van Miltenburg et al., 2014).

Although cooperation can increase through learning and experience in some infinitely repeated games, this is not the case in all games (e.g., Dal Bó, 2005): the exact conditions that account for these group differences are not well understood. Therefore, it is valuable to study dynamic factors – rather than static factors only – that may increase cooperation. One of these is the effect of communication in cooperation dilemmas. Communication increases cooperation (Chen & Komorita, 1994; Dawes, McTavish, & Shaklee, 1977) presumably because it provides the ability to: 1) enhance understanding of the PG situation; 2) coordinate actions; 3) create cooperative social norms; 4) form strategic agreements; 5) enhance trust in others; and 6) establish a social identity (Chen, 1996; Shankar & Pavitt, 2002). Communication is thus interactive and can help people to coordinate and support higher levels of cooperation within groups.

Another dynamic component is the in-game formation of either positive or negative social ties which depends on the nature of interaction with other players rather than exclusively on one's pre-interaction social value orientation. For example, Van Dijk, Sonnemans, and Van Winden (2002) found direct evidence for social ties (i.e., the extent to which two people care about the well-being of one another) forming over time in interaction. Once positive social ties are formed, it seems likely that they would have implications for future cooperation.

According to the Interactive Model of Social Identity Formation (Postmes, Haslam, & Swaab, 2005; Postmes, Spears, et al., 2005), communication and the formation of social ties both play a role in the induction of a shared identity. Research suggests that social interaction, the formation of personal relations, and coordinated action can all contribute to the emergence of group bonds. In this process, social identity is formed inductively (from the bottom up), rather than just deductively (inferred top-down based on predefined social categories). This is naturally a more emergent view of social identification, consistent with arguments that the agency of an individual in the group can promote identification (Reicher & Haslam, 2013); and that interpersonal network interactions foster group belonging and well-being (Easterbrook & Vignoles, 2013).

One study has shown some evidence that cooperation may be higher in groups that have formed a shared identity through induction (Jans, Postmes, & Van der Zee, 2012), but only for heterogeneous rather than homogenous groups. The actual process of forming a shared identity during social exchange, and how this in turn influences cooperation over time, has not been studied as far as we know.

In sum, while prior research has often explored static factors that influence cooperation (e.g. categorization, personal preferences, social heuristics, goal frames), more recently attention has turned to dynamic factors accounting for the emergence and maintenance of cooperation over time (e.g. induction, communication, social tie formation). There are many dynamic factors operating at the group and individual level that all seem to be heavily influenced by the social environment. One approach to further this line of research is to determine how these factors operate together and arise simultaneously.

1.3. The present research

How do within-game cooperative norms emerge over time *in tandem* with dynamic factors, such as the induction of a shared identity? We introduce some methodological advances – in terms of experimental design and software, as well as statistical techniques – that enable us to study the emergence of groups and cooperative norms within groups over time. The study presented here is an experimental Public Goods Game where social interaction over time was possible and where we manipulated the presence or absence of social categorization.

2. Method

2.1. Participants and design

Psychology students (N = 240, 164 female, 74 male, two undeclared, M_{age} = 20.32) participated in return for course credit. Groups of six interacted for 1.5 h. There were 2 conditions, Categorized versus Non- Categorized, with 20 groups each. For multilevel studies, power calculations require approximate knowledge not only of effect sizes, but also of intraclass correlation coefficients and other parameters (Snijders & Bosker, 2012). Given the novelty of the present research and thus not knowing which parameter values to expect, we had no reliable grounds for sample size calculations and decided to use what we expected would be a relatively high sample size at the experimental group level. The study was approved by the departmental Ethics Committee. We report all measures, manipulations, and exclusions in this study.

2.2. Procedure

A Public Goods game with communication was created on the experimental platform, the Virtual Interaction Application (VIAPPL, see viappl.org). Participants came to the lab in groups of 6. They were connected through the server and all interaction took place over VIAPPL, while they were physically present in the same room with screens partitioning individual computers. The game had four stages: 1) dyadic exchange and group formation; 2) Public Goods Game; 3) group reformation and, finally, 4) a second PGG. Before the experiment, the general rules of the PGG were explained (via instruction manuals) and a brief demonstration of the software was given.

To introduce dynamic interaction and to make the emergence of groups possible, participants were given the opportunity to build their own social psychological stimulus through interaction in the first stages of the experiment. A settler's metaphor was used for this: participants were asked to imagine that they had arrived on a newly discovered island where they would settle and farm the land. They were informed that there are other new arrivals on this island with whom they could communicate, interact, and form “farming co-operatives” in order to build their farms and start cultivating the land.

2.2.1. Dyadic exchange

In order for participants to form farming co-operatives (or co-ops), participants could interact with each other beforehand. After the background story was presented, participants began a dyadic exchange task where they exchanged building materials with other participants to build their farmhouse. Each participant possessed one unique building material and there were six in total. They were asked to accumulate three additional materials during the task. Participants could message one another in order to coordinate their exchanges.[1]

The outcome of dyadic exchange was symbolic as the ‘houses’ built had no carry-over into the following phases of the game. However, this task did provide participants with a history of interaction that could be a basis for forming co-ops. The feedback at the end of the task was identical for all participants – “*Well done! You built your farm as best you could. Now organize - through discussion - which co-op you want to join!*”. The message appeared regardless of how many materials the participant ended up with.

2.2.2. Group formation

At this stage participants were given the opportunity to join one of three co-ops after communicating via instant messaging for 3 min.[2] The

[1] Since communication itself could not bind players to their choices, strategic patterns of behaviors had the potential to emerge – for example a player could promise to exchange with another player in order to get the second player's resource but then not follow through in the action round. We are interested not in these strategic patterns themselves (and therefore do not analyze them here), but rather how participants could use this information in their interactions in order to form the co-ops in the following phase of the game.

[2] Due to a limitation in the software at the time, participants had to indicate their choice twice. The second time they did so, the co-ops were set for the PGG. This was necessary to give participants who discovered they had not coordinated their selections well the opportunity to change their choices.

choice of three co-ops instead of two, reflects the idea that groups often exist in complex formations, not purely in dichotomous terms (Kerr, Durrheim, & Dixon, 2017). Furthermore, we felt that two groups would make the choice for the Categorized condition too obvious so we allowed room for participants to make alternate groups, not simply recreate the assigned categories/groups (although they could form two groups and leave the third co-op empty). The only rule was that each co-op could have a maximum of 4 members; the 5th person who tried to join would be asked to make a different selection.

2.2.3. Public goods game

Two Public Goods Games were played. The first followed directly after group formation and lasted 12 rounds.[3] The second game (10 rounds) was played after participants were allowed to reform co-ops (this time without making exchanges beforehand). Following general rules of PGGs (Olson, 1965), participants received an endowment of 10 tokens at the beginning of each round of the game. They then communicated for a short period of time (40 s) before individually deciding whether to contribute anything from 0 to 10 tokens to their co-op (they could not contribute to other co-ops). Unallocated tokens were automatically added to one's ‘personal account’. At the end of each round, participants were paid out from their co-op; whereby the total funds in the co-op were multiplied by 1.2 and divided equally among the co-op members, regardless of how many tokens they had personally contributed. At the end of each round, each participant received an updated token balance: a 2 token increase per round + tokens not contributed to their co-op + their share of the co-op profit. The tokens had a symbolic value and did not relate to any payment at the end of the experiment but we encouraged participants to “*Try to collect 45 tokens or more!*”.

This set up presents a classic social dilemma where the socially optimal outcome – where all co-op members benefit equally and the total is maximal – is obtained if all members invest their entire endowment in their co-op at every round. However, individuals could potentially earn more tokens if the others in their co-op made high contributions and they would defect by investing less or nothing. Participants were provided with payoff examples in the instruction manual (see Fig. 1).

Participants were able to see how many tokens each other participant contributed to their co-op in the previous round. This was presented through a visual summary image at the end of each round (see Fig. 2).

In addition, all other participants' token balances were visible during the entire game. Participants could also see the amounts contributed in other co-ops.

2.2.4. Post-experimental questionnaire

This was administered after completion of the second PGG. The questions referred to the second co-op that a participant had joined. We did not ask questions about the first co-ops to avoid priming effects in the second PGG.

2.2.5. Experimental manipulation

There were two experimental conditions: Categorized and Non-Categorized. In the Categorized condition, participants were randomly assigned to one of two groups – the Purple or Green group – at the beginning of the experiment. Each group was asked to imagine that they had arrived on the island as a group, on the same ship. The metaphor of common ships was meant to provide an abstract and minimal social category from which participants could deduce who should be in their co-ops. Group homogeneity was made salient by coloring the avatars, representing participants onscreen, purple or green. In minimal group studies such categorizations promote in-group bias (Tajfel et al., 1971). We expected categorization to influence the choice of co-op as well as subsequent cooperative behavior. In line with the Interactive Model of Social Identity Formation (Postmes, Haslam, & Swaab, 2005; Postmes, Spears, et al., 2005), this is a process in which group identity is deduced from a shared “history” of the group, group homogeneity and/or the presence of a distinct outgroup.

In the Non-Categorized condition, participants imagined that each had individually arrived on a different ship from a unique land. Individual heterogeneity was made salient by using uniquely colored avatars. By not providing a pre-assigned category, we reasoned that any groups that formed could only be “induced”– that is, formed only based on communication in the dyadic exchange stage. We assumed that the Non-Categorized condition offered more scope for an inductive group formation process in which personal value to the group may be acknowledged (here, through individual heterogeneity) and the co-ops are formed through interpersonal interaction. In addition, there is no distinct outgroup from the beginning of the manipulation, unlike in the Categorized condition.

In both conditions, participants were free to choose to form any co-ops they wished.

2.3. Dependent variables

2.3.1. Co-op formation and change

This DV was measured by an individual's choice of co-op membership, before the first and second PGG respectively. With it we could test 1) whether individuals in the Categorized condition were more likely to form a co-op with their categorical group (Green or Purple) and 2) the degree of change in co-op membership between PGGs (for both conditions).

2.3.2. Cooperation/amount contributed to the PG

The behavioral data from both PGGs represented the degree of cooperation with one's co-op. This was operationalized by the number of tokens contributed to the co-op at each round (an integer from 0 to 10).

2.3.3. Social psychological measures

To better understand why participants cooperated or not, we included several variables which are of theoretical interest and which could be linked to the behavioral data. Items were measured on a 7 point Likert scale from 1 = “strongly disagree” to 7 = “strongly agree”. The primary constructs we measured were: social identification (e.g., “During the game, I identified with other members of my co-operative”; adapted from Leach et al., 2008; 6 items, $\alpha = 0.82$); belongingness (e.g., “During the game I felt connected with one or more members in my co-operative”; Van Beest & Williams, 2006; 4 items, $\alpha = 0.86$) and the entitativity of the co-op (e.g., “This co-operative acted as a unit”; Brooke, Postmes, Jetten, & Dyson, 2009; Jans, Postmes, & Van der Zee, 2011; 4 items; $\alpha = 0.89$). We also measured perceived trust (e.g., “I trusted that other members of my co-operative would follow through on what they said in their messages”; 2 items, $\alpha = 0.75$) and satisfaction with the co-op (e.g., “I wanted to exit my co-operative”, reverse scored; 4 items, $\alpha = 0.85$). To avoid interrupting the game or priming participants, these were all measured after the second PGG and thus referred to the second co-op only.

In addition, identification with (4 items, $\alpha = 0.84$) and perceived entitativity of (4 items, $\alpha = 0.90$) the entire group of participants was measured because a game-like experience could bond all participants, regardless of co-op membership. By including these measures we could distinguish ‘game feelings’ from feelings toward the co-op, which we were interested in. Items for game social identification include, for example: “I identified with all the other participants in the game”; and for game entitativity: “All the participants of this game were in agreement on how to behave”. Social identification with, and perceived

[3] To avoid end-game effects we did not inform the participants how many rounds there were in each PGG but rather told them that the computer would randomly determine the number.

Example 1:
You are in a co-op with 3 people. You start with 10 tokens. You decide to invest 8 in your co-op. The other co-op members invest 8 and 8 respectively.
The share that everyone gets would be: ((8 + 8 + 8) x 1.2)/3 = 9.6
It's pay-out time! You get:
2 + 2 **+** 9.6 = **13.6 (14)** and so do the others

Example 2:
You are in a co-op with 4 people. You start with 10 tokens. You decide to invest 5 in your co-op. The other co-op members invest 2, 5 and 8 respectively.
The share that everyone gets would be: ((5+2+ 5+8) x 1.2)/4 = 6
It's pay-out time! You get:
2 + 5 + 6 = **13**
The others get **16, 13** and **10** respectively.

Fig. 1. Examples of payoff calculations given to participants.

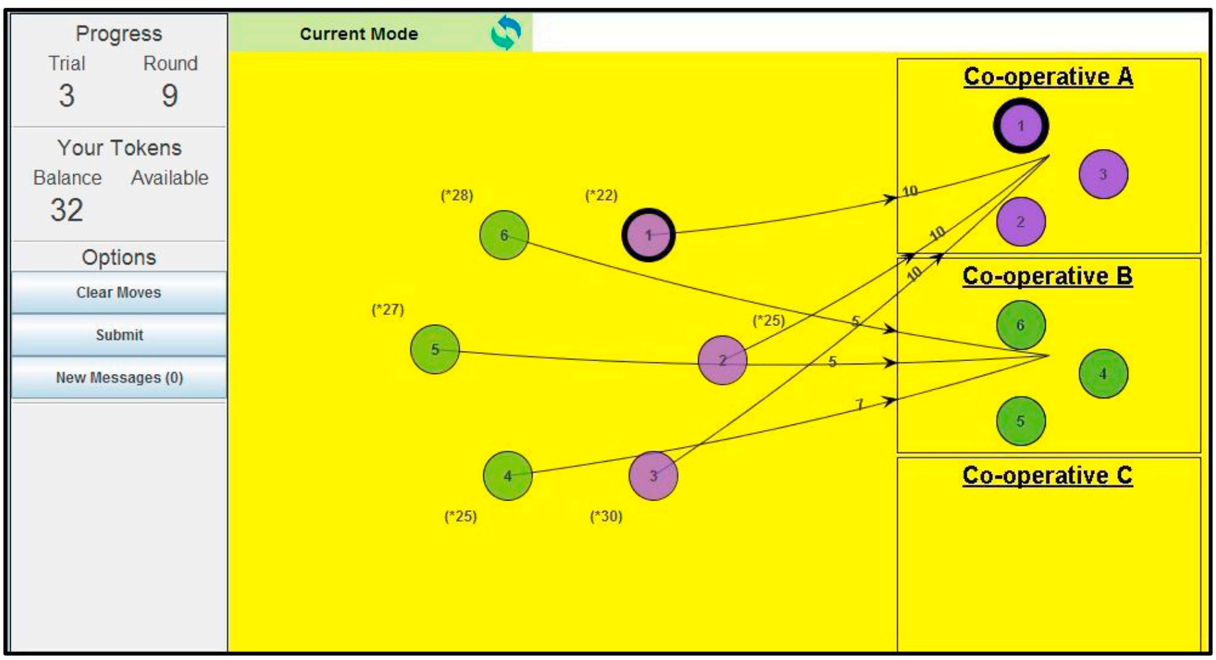

Fig. 2. Visual summary image taken from one experimental group in the categorized condition.
Note: The avatar with the darker outline around it represented the individual player onscreen.

entitativity of the co-op were only slightly correlated with the game experience (r = 0.30 and 0.36 respectively). This weak correlation rules out the possibility that bonding within the game as a whole could account for effects within co-ops. Game identification and entitativity are not used in further analysis.

Finally to tap into inductive identity we measured personal value to the group (e.g., "My co-op could not have functioned without me"; adapted from Koudenburg, Postmes, Gordijn, & Van Mourik Broekman, 2015); however, the scale had low reliability (3 items, α = 0.55) and was not used in the analysis. We also measured ingroup bias toward the other co-ops in the game but the low reliability (3 items, α = 0.57) also excluded this measure from further analysis. The descriptive statistics for each measure can be found in Table A1 in the Supplementary Information.

2.3.4. Discussion content

In this paper, we do not analyze the content of the messages as it is beyond the scope of this article and will be the subject of future work. However, we would like to provide some relevant descriptive information. Messages were no longer than 100 characters, although an unlimited number of messages could be sent between contribution rounds. Across the two PGGs, 224 out of 240 participants sent at least one message to their co-op. Across the 224, the mean number of messages sent was 15.3 and 12.3 in the first and second PGG, respectively. The mean number of characters per message was 21 and 24, with a maximum of 48 and 37 messages sent per PGG. There were no differences in the quantity of communication between conditions.

2.4. Hypotheses

Hypothesis 1. For the Categorized condition, participants on the same "ship" (representing a social category) have a higher probability of being in the same co-op, compared to random selection. Since no one in the Non-Categorized condition shared a ship, this condition is not a suitable comparison and so we test this hypothesis through simulations for the Categorized condition. Of course, if this hypothesis is supported, this logically implies differences between experimental conditions.

Hypothesis 2. At the end of the cooperation, co-ops in the Categorized

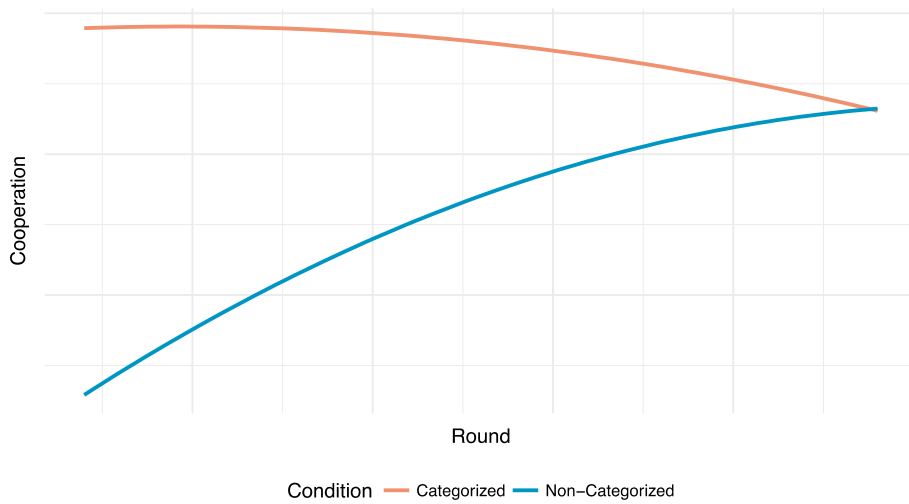

Fig. 3. Expected levels of cooperation over time.

and Non-Categorized condition will have similar levels of social identification, entitativity, belongingness etc. This expectation is based on the theory that shared identities and solidarity emerge through cooperative interactions, even in the absence of a priori social categorizations (Jans et al., 2012; Postmes, Spears, et al., 2005). Note that this research hypothesis of "no difference" is a statistical null hypothesis.

Hypothesis 3. On average, contributions to the co-op will be higher in the Categorized compared to the Non-Categorized condition. Differences between conditions will be stronger in earlier phases of the game. Cooperation within co-ops in the Non-Categorized condition is expected to emerge over time, in line with Interactive Model of Social Identity Formation (Postmes, Haslam, & Swaab, 2005; Postmes, Spears, et al., 2005) (see Fig. 3).

3. Analysis approach and results

3.1. Co-op formation and change: Hypothesis 1

3.1.1. Method

Were participants in the Categorized condition more likely to form co-ops with their category (Green or Purple group)? We tested independence between pre-assigned categories and co-ops in this condition to find out.

We calculated the Jaccard similarity coefficient[4] between the adjacency matrices for belonging to the same category and belonging to the same co-op (Batagelj & Bren, 1995; Jaccard, 1900). A coefficient of 1 indicates complete overlap (i.e., social categories are identical to co-ops), while 0 indicates that every pair in the same social category is in different co-ops. The null hypothesis was tested by a permutation test, comparing the observed Jaccard coefficient with the distribution of Jaccard coefficients between the observed co-ops and randomly chosen, equally sized groups.[5] If the observed Jaccard value is significantly high in this comparison, this is a sign that individuals were more likely to join a co-op with their own category members rather than with other category members.

Stability of the co-ops (in both conditions) over the course of the experiment was also tested. Participants selected co-ops before the first PGG and before the second PGG, therefore co-op membership could change. Stability was likewise measured by Jaccard's similarity index and a permutation test, described above. Higher Jaccard indices for co-op change over time indicate that co-op members tended to stick together, while indices of 0 mean that co-ops changed completely.

3.1.2. Results

First, we tested whether in the Categorized condition, participants in the same pre-assigned categorical group are more likely to be in the same co-op. The results from the permutation test showed that participants were more likely to form co-ops with their categorical group members compared to random choice, in both Co-op Formation phases ($p < .001$ for both, see Table 1). Therefore Hypothesis 1 is supported.

As an illustration: if, for example, in the Categorized condition the first co-op is formed by all members of one category and one member of the other category, and the second co-op by the remaining two members of the second category, then $J = 4/9 = 0.44$. Note that the proportions of games in which categories were exactly the same as co-ops were 0.10 and 0.15, for the first and second PGG respectively.

Next, we tested the degree of change in co-ops between PGGs for both conditions.

As shown in Table 2, the observed mean Jaccard coefficients were around 0.5 for both conditions – meaning that about 50–60% of the pairs stayed together. The results of the permutation tests for both conditions were significant ($p < .001$), indicating significant similarity in co-op membership between the two PGGs.

3.2. Social psychological effects: Hypothesis 2

3.2.1. Method

To test for differences between the Categorized and Non-Categorized condition in the measured social psychological variables, we ran a multilevel, multivariate model (Snijders & Bosker, 2012) using runMlwin in R (Version 2.36) (Leckie & Charlton, 2013; Rasbash, Charlton, Browne, Healy, & Cameron, 2009). We examined the effect of experimental condition (Categorized vs. Non-Categorized) on several dependent variables: social identification, belonging, entitativity, trust and satisfaction with the co-op. Correlations are reported in Table A2 of the Supplementary Information.

This model takes into account the dependencies between measured variables (i.e. responses, Level 1), as well as possible similarities among participants (Level 2) in the same co-op (Level 3). Co-ops from the second PGG define the nesting level at Level 3. Adding a fourth level (i.e., experimental group) caused convergence issues and was dropped from the final model.

[4] This coefficient is defined as the proportion of the pairs that are linked in both categories and co-ops, among the pairs that are linked in at least one of these.

[5] Note that the Green and Purple groups also were of equal size.

Table 1
Co-op selection: categorized condition.

Co-op formation phase	Random mean Jaccard (with s.e.)	Observed mean Jaccard
First PGG	0.27 (0.04)	0.53
Second PGG	0.28 (0.05)	0.56

Table 2
Co-op change between PGGs: Both conditions.

Condition	Random mean Jaccard (with s.e.)	Observed mean Jaccard
Categorized	0.28 (0.04)	0.56
Non-categorized	0.25 (0.04)	0.54

3.2.2. Results

We had not expected notable differences between conditions and the results largely support this expectation (Hypothesis 2). Comparing the null model to the model with the experimental condition, showed the multivariate test was significant ($\chi^2(5) = 13.9$, $p = .02$), therefore the univariate results are considered. However, there were no significant univariate differences at all. There were no significant differences between conditions for social identification (β = −0.250, SD = 0.197, z = −1.27, 95% CI (−0.637, 0.136), $p = .20$), entitativity (β = −0.133, SD = 0.219, z = −0.60, 95% CI (−0.564, 0.299), $p = .55$), trust (β = −0.217, SD = 0.191, z = −1.14, 95% CI (−0.592, 0.157), $p = .25$), satisfaction with the co-op (β = 0.002, SD = 0.222, z = 0.01, 95% CI (−0.432, 0.0437), $p = .99$) or sense of belonging to the co-op (β = −0.323, SD = 0.181, z = −1.79, 95% CI (−0.7677, 0.031), $p = .07$). The null findings make the multivariate significance difficult to interpret.

3.3. The effect of categorization versus non-categorization on cooperative behavior: Hypothesis 3

3.3.1. Method

Changes in the level of cooperation – as inferred from the amount contributed to the co-op at each round – was analyzed by two different methods. First, we present longitudinal multilevel models, followed by a more detailed analysis using a dynamic latent class model. The former method is more traditional and easier to grasp, giving important descriptive insights. However, it also revealed that model assumptions of heteroscedasticity were not met; therefore, it cannot conclusively test hypotheses. We do present model-based standard errors here to give readers an indication of the uncertainty in the estimates. The second analysis gives more fine-grained results.

First, we tested a longitudinal, polynomial multilevel model (Snijders & Bosker, 2012) in which rounds/time (Level 1) is nested in participants (Level 2), in co-ops (Level 3), in experimental groups (Level 4). Splines – i.e., functions that allows for the pattern of growth to change direction or speed at specified points – improved model fit (Snijders & Bosker, 2012). Analyses were conducted using the lme4 package (Bates, Mächler, Bolker, & Walker, 2015) in R (R Core Team, 2016). Data from the first and second PGG were modelled separately since co-op membership (and therefore the nesting structure) could change from the first to the second PGG. We base our reported model on model-building criteria and did not use hypothesis testing. The assumption of homoscedasticity of the residual variance is not tenable for this dataset as many people repeated their behavior from round to round. Nevertheless, this model gives good descriptive insights.

3.3.2. Results

3.3.2.1. Cooperation in the first PGG. We investigated the difference in cooperation over time between the two conditions. The intra-class correlation showed that 37% of the unexplained variation in cooperation lies at the co-op level; 59% at the round level; only 4% lies at the experimental group level and 0% at the individual level. The best fitting model was a quadratic model with a spline function[6] and random slopes for round at the co-op level. Details can be found in Table A3 in the Supplementary Information.

Results suggest a negative effect of condition on cooperation (β = −0.77, SE = 0.42) with slightly higher cooperation in the Categorized compared to the Non-Categorized condition. There was also a negative interaction between round and condition (β = −0.10, SE = 0.06). The corresponding curves of model predictions for both conditions over time are shown in Fig. 4: Cooperation increases over time in both conditions until round 4, after which cooperation in the Categorized condition continues to increase slightly whereas cooperation in the Non-Categorized condition declines slightly. Higher overall cooperation in the Categorized condition is in line with Hypothesis 3, however the time pattern is not (see Fig. 3) since cooperation in the Non-Categorized condition declined after round 4. As seen in Fig. 5, most of the variation occurred between individual co-ops, much more so than between conditions.

3.3.2.2. Cooperation in the second PGG. For the interested reader, and to avoid too much repetition, full results for the second PGG can be found in the Supplementary Information. The overall pattern of results was similar: overall cooperation was slightly higher in the Categorized compared to the Non-Categorized condition, although in both conditions cooperation started higher and dipped slightly toward the end.

In summary, overall cooperation was rather high in both conditions, and the condition did not have a strong effect on cooperation. Descriptively, there were higher levels of cooperation in the Categorized compared to the Non-Categorized condition, in both PGGs. This is in line with Hypothesis 3. However, the variance components and the plots suggest much variability between co-ops in the degree to which cooperation emerged. This variability is further investigated after the interim discussion.

3.4. Interim discussion: the role of categorization on cooperation

The discussion of this paper is in two parts. In this section, co-op formation and the role of categorization on overall cooperation are discussed. In the next section, we elaborate on the results from the second half of our analyses and make concluding remarks.

First, in reference to co-ops formed in the Categorized condition, we found that participants mostly self-selected their co-ops along category lines. While nothing in the experimental set-up forbade participants from forming any co-op they liked, perhaps with minimal information in a novel setting, they did what they thought was expected by the experimenter. However, the dyadic exchange rounds with communication before the PGG did provide interaction with all other participants (not just categorical group members). In addition, participants could join one of three co-ops, instead of two – designed to reduce the perceived demand that participants should form co-ops along category lines (20% of the time, three co-ops were formed). Although some co-ops formed exactly according to their pre-assigned categories (12.5% of the time), most did not. Therefore, the formation of groups was likely a considered choice on the part of participants, although not purely cued by categorization. Nevertheless, since categorization did significantly impact co-op selection, this implies a logical difference between experimental conditions, although perhaps not very strong.

Following group formation, cooperation in the first PGG was high in both conditions – even higher than the usual 40–60% of cooperation

[6] The spline has a node at round 4. This means that the function is quadratic for rounds up to 4, as well as quadratic from round 4 onward, and smooth, but the coefficient for the squared term changes value at round 4.

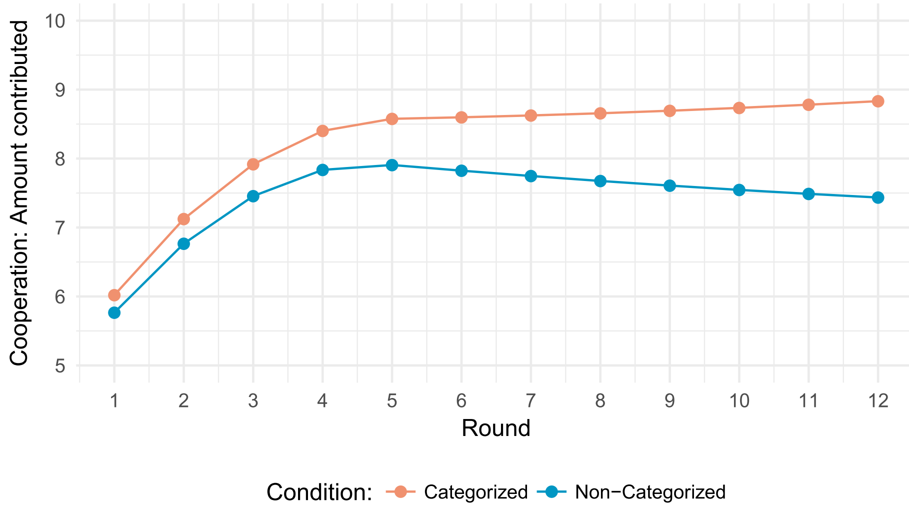

Fig. 4. Average cooperation over time.

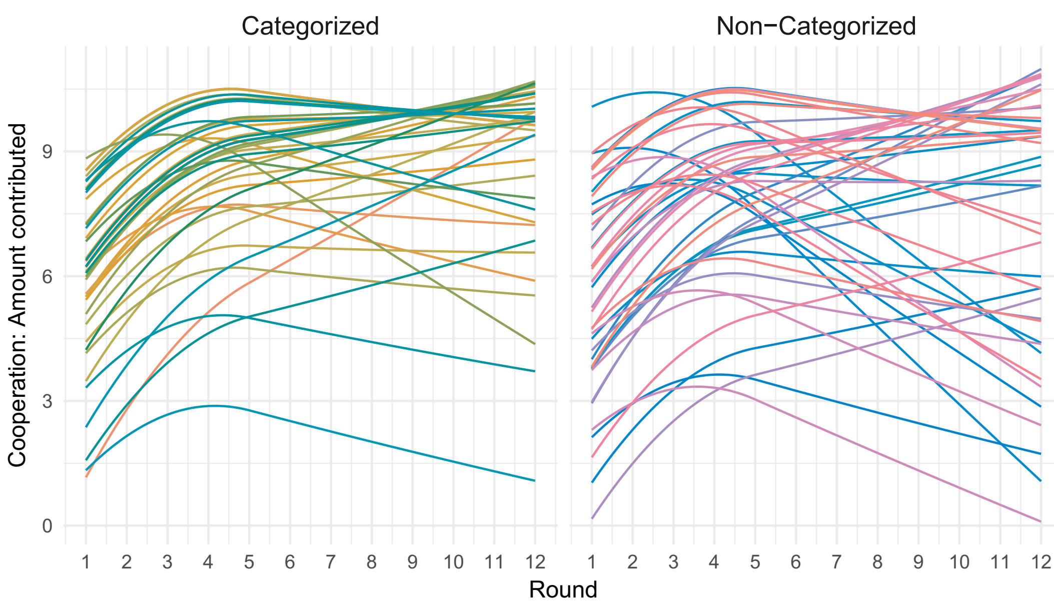

Fig. 5. Co-op cooperation over time.

found in most public goods research (Ledyard, 1995). High levels of cooperation were probably due to the framing of the experiment – as building a community of farmers, after arriving on a deserted island –, repeated interaction, and the ability to communicate (allowing organisation, pledging, sanctioning, etc.).

In the Categorized condition, we see that overall, there are slightly higher levels of cooperation that increase over time. Deductive groups, formed in a top-down manner by emphasizing category similarity (here via shared avatar color and background story), may have an easier time cooperating at higher levels from the beginning of interaction, thus cooperation has a stronger basis for growing over time, with little indication of decline. We initially expected that cooperation in categorized groups, starting at a higher level, would eventually decline as time went on (see Fig. 3) but found that categorization seems to prevent decline, in the first PGG at least. This suggests that for sustainable cooperation, having a group categorization could be beneficial.

In the Non-Categorized condition, although cooperation is still relatively high, and increases for a time, the trend toward the end of the interaction in the first PGG is downward. We expected that once non-categorized groups were given time to interact, cooperation would increase steadily rather than decrease. Previous research has shown that inductively formed groups – in which heterogeneity is salient and personal value highlighted – show equally high levels of social identification and solidarity as deductive groups, even though the pathway to identification and solidarity may be different (Jans et al., 2012; Koudenburg et al., 2015; Postmes, Spears, et al., 2005). However, by looking closely at the between-group variation of cooperation at the co-op level, we see that while some co-ops in the Non-Categorized condition did continuously increase in cooperation over time, there was a set of others that did not, and there appears to be more variation between co-ops in this condition compared to the Categorized condition. Thus cooperation appears to depend more strongly on within-group processes in the Non-Categorized than in the Categorized condition. Perhaps inductive groups have a harder time maintaining cooperation compared to groups with a shared social category, but this largely depends on how the inductive group processes unfold.

Finally, in both conditions, there was little change in co-op membership between the first and second PGG – which makes sense considering the high levels of cooperation. Evidently, there is no need to leave a co-op that is collaborating well together. Furthermore, the slight decrease in cooperation in the Non-Categorized condition, toward the end of the first PGG, was not stark enough for participants to change co-ops more compared to the Categorized condition, suggesting that co-operation can still reach high levels in inductive groups. Related to this finding, there were no ultimate differences in one's sense of identification, group belonging and entitativity between experimental conditions at the end of interaction (i.e., end of the second PGG). This supports the Interactive Model of Social Identity Formation (Postmes, Haslam, & Swaab, 2005; Postmes, Spears, et al., 2005) which posits that inductively formed groups can develop the same social psychological outcomes as deductively formed groups, although the pathway may be different.

The multilevel growth model, reported above and discussed here, provides a good description of how cooperation develops in the Categorized and Non-Categorized conditions. But for the purpose of testing hypotheses, it is not reliable because our data violated the assumption of homoscedasticity. Specifically, a sizeable proportion of individuals gave the same contribution round after round (i.e., repetition) while others hit the ceiling of cooperation; and this tended to be a shared behavior in some co-ops. These "zero variance" behaviors are a meaningful feature of the kinds of cooperative behaviors we are seeking to describe; but having a high proportion of them is extremely unlikely under the assumptions of the multilevel model. Therefore, the standard errors of these results cannot be trusted entirely. More importantly, our analysis revealed a considerable amount of between-co-op variability in cooperation *within* conditions that could not be well represented by a standard longitudinal multilevel model. To address these issues, we present the results of a more statistically complex model below. This model allows us to classify similar kinds of decision rules; individuals; and co-ops, regardless of the experimental conditions and comprises a more fine-grained exploratory approach to analyzing these data.

3.5. Classifying cooperative behavior, types of individuals, and types of co-ops

3.5.1. Method

The second analysis of amount contributed to the Pubic Good over time regards these amounts as resulting from a process of decisions made by participants. Technically, we use multilevel latent class Markov models (Lukočiene, Varriale, & Vermunt, 2010; Paas, Vermunt, & Bijmolt, 2007; Van de Pol & Langeheine, 1990; Vermunt, Tran, & Magidson, 2008) implemented in Latent Gold (Version 5.1) (Vermunt & Magidson, 2016).

In the model specified, decisions about the contributions are represented as regression models, operating round by round, where the amount contributed is the dependent variable and the explanatory variables are the participant's own contribution in the previous round and the mean contribution of the participant's co-op in the previous round. It is assumed that participants' decision rules can be classified in a few types ("latent classes"), and each type embodies one decision rule, defined by the regression coefficients and the residual variance in the regression model. The type of decision rule followed by any given participant may change over time. Because of the experimental design, the model has three levels of latent classes, as follows.

1. The first level is round, with a regression model for the amount contributed. The explanatory variables are the lagged contributions of self and co-op, and a dummy for the first round, necessary because then there are no lagged contributions. The parameters of this regression model embody the decision rule about cooperative behavior and are selected from K_1 latent classes. These classes are dynamic, meaning that they can change from round to round.
2. The second level is the individual, which is also in a latent class selected from K_2 latent classes of individuals. These are constant over time. The latent class of the individual probabilistically determines the latent classes at the round level.
3. The third level is the co-op, in a latent class selected from K_3 latent classes of co-ops, likewise constant over time. The latent class of the co-op probabilistically determines the latent classes of the individual.

To specify the dynamic classes at Level 1, we need initial probabilities and the transition probability matrix specifying the probabilities p_{hk} that in round $t + 1$ the class is k, given that in round t it was h. These initial probabilities and transition matrices depend on the latent class of the individual and are estimated from the data.

The numbers of latent classes K_1, K_2, and K_3 at the three levels are determined by a combination of goodness of fit and interpretability. Results of the estimation then include the set of decision rules employed (latent classes of regression models), the estimated class of each individual (determining the decision rules they generally employ), and the estimated class of the co-ops (determining their composition of classes of individuals). For a more technical treatment of the method, the interested reader is referred to the Supplementary Information where we provide more detailed background to the latent class Markov model, provide model specifications, further discuss our predictors and covariates for the model, as well as outline the process of model development.

3.5.2. Results

Separate models were applied to the first PGG and the second PGG data as the nesting factor (i.e., co-op) could be different between games. We selected labels to describe the classes at each level, to aid with interpretation.

3.5.2.1. Cooperation in the first PGG

The estimated model (see Supplementary Information for model building details) specified 4 classes of decision rules (Level 1) that participants drew on to decide how much to cooperate in a given round. Furthermore, individual participants could be classified into three classes (Level 2) which overlapped almost perfectly with three classes of co-ops (Level 3).

3.5.2.1.1. Level 1: decision rules for cooperation. We labelled the four decision rules as: Maximum Cooperation (the ceiling of cooperation), Nearly-There (close to Maximum Cooperation), Repetition (repeating one's behavior from the previous round) and Reaction (responding to the contributions of the co-op), named in accordance with the interpretation below. Table 3 presents for each decision rule the overall relative frequency with which it is applied, the mean amount that resulted from its application, and the parameters of its linear regression model. The history of the game was found to be an important predictor in the decision regarding how much to cooperate with one's co-op. Both own lagged amount and the lagged amount of the co-op can significantly distinguish among decision rules (own lag: χ^2 (3) = 88,820.06, $p < .001$; co-op lag: χ^2 (3) = 126.11, $p < .001$). The four decision rules are significantly different from one another for

Table 3
Decision rules: regression results for first PGG.

	Maximum cooperation	Nearly-there	Repetition	Reaction
Overall relative frequency	56%	8%	11%	26%
Mean amount	10	8.23	6.89	4.95
Intercept	10	6.740	0	3.093
First round[a]	0	0.224	0	−0.791
Lagged amount (own)	0	0.017	1	−0.364
Lagged amount (co-op)	0	0.185	0	0.631
Residual variance	0.001	0.239	0.007	4.914

Note: The numbers reported in rows 3–6 are regression coefficients.
[a] The dummy for time was a binary variable 1 at the first round and 0 for all other rounds. The results of the dummy are not discussed here.

Table 4
Transition probability matrices of the decision rules.

		Decision rule			
		Maximum cooperation	Nearly-there	Repetition	Reaction
Previous decision rule	Maximum cooperation	0.86	0.05	0.00	0.09
	Nearly there	0.59	0.07	0.22	0.12
	Repetition	0.19	0.18	0.28	0.35
	Reaction	0.19	0.08	0.15	0.58

Note: The numbers presented in the table are the probabilities of each decision rule transitioning into each of the other decision rules in the following round. Row sums are 1.000, because these are the total probabilities of the previous decision rule transitioning into anything.

the first round of the game, predicting different levels of cooperation from the outset (χ^2 (3) = 16.02, p = .001). The four transition probability matrices are also significantly different (χ^2 (12) = 153.28, p < .001). The transition probabilities themselves are given in Table 4. We now discuss the four decision rules.

The first decision rule, Maximum Cooperation, was the most common, guiding participant decisions on how much to cooperate 56% of the time. If someone applied this decision rule they would contribute the full endowment of 10 tokens to the PG. Due to this ceiling effect, the amount to contribute when using this decision rule could not be predicted by the history of the game (b = 0, for both own lag and co-op lag, Table 3) and the residual variation is almost nil (σ^2 = 0.001), meaning that the rule – when used – was almost deterministic. In terms of stability, Maximum Cooperation was likely to remain the participant's decision rule in the following round, with an 86% probability (see Table 4).

The second most common decision rule, occurring 26% of the time, was Reaction (M_{amount} = 4.95). To give some insight into the coefficients, the regression model can be roughly approximated, for rounds 2 and further, by (1/3) ∗ 7 + (1/3) ∗ self-lagged + (1/3) ∗ (2 ∗ (co-op-lagged − self-lagged)). Interpreting this, the value of 7 and the own previous contribution may be regarded as providing reference values, and the third contribution is a reward for the co-op or a punishment – as the case may be – for the deviation between the contributions of co-op and self. If, in the previous round, the co-op average was higher than own contribution, it is a reward – the new amount contributed is higher than the reference value. If the co-op average was lower, then punishment follows – the new amount contributed is less than the reference value. In this decision rule the residual variation was highest (σ^2 = 4.91, Table 3). Reaction was more likely to remain the decision rule in the following round (58%) rather than transitioning to other decision rules, although it was less stable than Maximum Cooperation (see Table 4).

Although not part of the definition of this decision rule, it is interesting to see descriptively in which situations it was applied. The frequency of applying Reaction was a decreasing function of the previous average contribution by the co-op, decreasing from about 64% for low contributions (0–5 tokens) to 3% for very high contributions (10 tokens). Participants were more likely to be reactive to contributions by fellow co-op members, and base their behavior on a comparison between own and others' contributions, in stages where the contributions by others were relatively low.

Repetition (M_{amount} = 6.89) occurred 11% of the time. This decision rule consisted of repeating what one did in the previous round[7] (own lagged amount: b = 1.00, Table 3). Residual variance in this rule was low (σ^2 = 0.007). From the transition probabilities in Table 4, it appears that Repetition was the most unstable decision rule, with no clear pattern for transitioning to one of the other rules.

The least frequent decision rule was Nearly-There (M_{amount} = 8.23), occurring 8% of the time. The contribution was quite high on average, with some variation explained mostly by the average co-op contribution in the previous round (b = 0.185, Table 3) and very slightly by one's own previous contribution (b = 0.017). Residual variance was still rather low (σ^2 = 0.24). The label was chosen in view of the high probability of an individual switching to Maximum Cooperation in the next round (60% of the time, Table 4).

Fig. 6 above visualizes the tendency for Maximum Cooperation to increase over time, while Reaction decreases.

3.5.2.1.2. Level 2: individual classes. Based on the four decision rules of behavior, the model distinguished among three classes of participants, which we labelled: Committed Cooperators (M_{amount} = 9.19, 47% of participants), Responsive Players (M_{amount} = 8.05, 36%) and Reactive Players (M_{amount} = 5.99; 17%). It will become clear below that we interpret these classes as mainly emerging from group processes: we can rule out that a priori individual differences are involved.

The strongest difference among the three classes are in the probability matrices of transitioning from one to another decision rule (χ^2 (24) = 184.89, p < .001). There were less strong differences guiding the decision rule at the start of the game (χ^2 (6) = 13.51, p = .04). The probability matrices for initial decision rules and transition probabilities per individual class are found in Table 5 and the findings of interest will be discussed further.

Throughout the game, Committed Cooperators were much more likely to choose Maximum Cooperation over other decision rules, with a 79% probability. However, in the first round of the game (Table 5), they had a relatively low chance of using it (25%). This suggests that Committed Cooperators did not necessarily start off by contributing the highest amount, rather their cooperation developed over time. Furthermore, once they chose Maximum Cooperation, these players had a 97% chance of continuing with it in the subsequent round.

Responsive Players drew on all decision rules but were most likely to be guided by Maximum Cooperation (49%) and Reaction (27%) during the game. In the first round, they had a 16% and 26% chance of choosing Maximum Cooperation and Reaction respectively (see Table 5). In comparison to Committed Cooperators, Responsive Players had a lower probability of sticking to Maximum Cooperation once they begun to use it (69% compared to 97%).

Finally, Reactive Players were most likely to choose Reaction (66%) and Repetition (21%) throughout the game, and they were the least likely class to select Maximum Cooperation (6%). In addition, they tended to begin the game with the lowest amount of cooperation – with a 63% chance of choosing Reaction[8] and zero probability of choosing Maximum Cooperation. In the unlikely case that Reactive Players chose Maximum Cooperation in one round, they only had a 6% chance of continuing to use it in the following round.

3.5.2.1.3. Level 3: co-op classes. A total of 86 co-ops formed in the first PGG, across the experimental groups. The model categorized these co-ops into three classes. Strikingly, the three co-op classes strongly overlap with the three individual classes (99.3–99.6%). This means that the probabilities of the decision rules for cooperative behavior were: 1) consistent among all individuals *within* co-ops and 2) different *between* co-ops. This high correspondence of co-op and individual classes is best explained by the formation of within-co-op social norms, which we will come back to in the discussion.

The three co-op classes were labelled: Committed Co-ops (M_{amount} = 9.19), Responsive Co-ops (M_{amount} = 8.04) and Reactive Co-ops (M_{amount} = 6.01); see Fig. 7 for their trajectories of amounts

[7] Notably, Repetition is higher in the first round of Fig. 6, and in this case it means a contribution of 5.

[8] Of course, in the first round, participants are not reacting to anything. However Reaction is labelled as such according to its general pattern.

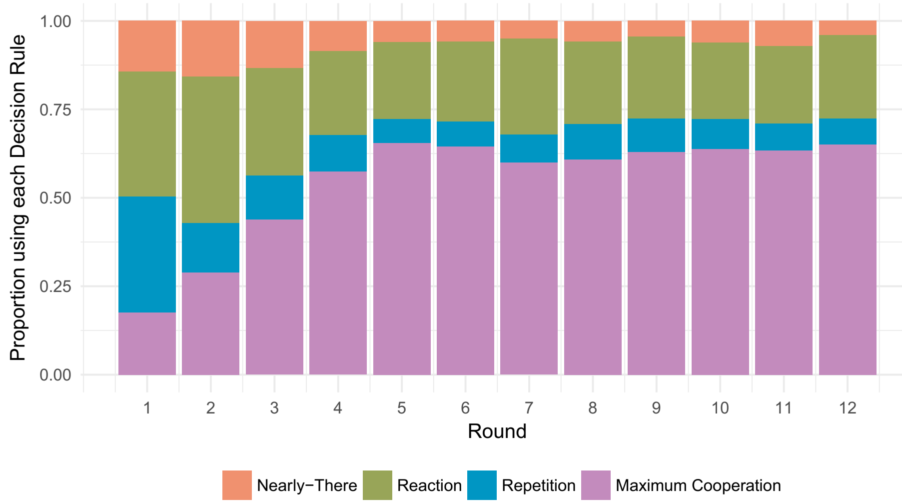

Fig. 6. Proportion of individuals using each decision rule at each round: First PGG.

Table 5
Transition probabilities for individual classes in first PGG.

Individual class	Starting decision rule			
	Maximum cooperation	Nearly-there	Repetition	Reaction
Committed	0.26	0.13	0.29	0.32
Responsive	0.16	0.19	0.38	0.26
Reactive	0.00	0.07	0.29	0.64

Individual class	Previous decision rule	Present decision rule			
		Maximum cooperation	Nearly-there	Repetition	Reaction
Committed	Maximum cooperation	0.97	0.03	0.00	0.00
	Nearly-there	0.68	0.04	0.25	0.03
	Repetition	0.31	0.21	0.06	0.42
	Reaction	0.21	0.26	0.07	0.46
Responsive	Maximum cooperation	0.69	0.09	0.00	0.21
	Nearly-there	0.62	0.01	0.21	0.15
	Repetition	0.26	0.19	0.33	0.22
	Reaction	0.29	0.09	0.16	0.46
Reactive	Maximum cooperation	0.06	0.00	0.00	0.94
	Nearly-there	0.14	0.39	0.18	0.29
	Repetition	0.02	0.14	0.36	0.48
	Reaction	0.09	0.00	0.18	0.73

contributed over time.

In a final model, the experimental condition (Categorized versus Non-Categorized) was included as a covariate at the co-op level to determine whether it affected the type of co-op formed in the PGG. However, the overall main effect of condition was only marginally significant (χ^2 (2) = 4.88, p = .09). For interest, exploration of the paired comparisons suggests that categorization can perhaps, to a small extent, predict the difference between the presence of Committed and Reactive Co-ops between conditions (χ^2 (1) = 4.22, p = .04). There were more Committed Co-ops in the Categorized condition (55% versus 32%) and more Reactive Co-ops in the Non-Categorized condition (24% versus 10%).

3.5.2.2. Cooperation in the second PGG. The results from the second PGG were very similar to the first. We found the same four decision rules, three individual classes and three co-op classes, as well as the same overlap between individual and co-op classes. To avoid repetition, full results are in the Supplementary Information. To summarize these findings: The same classifications were found in the second PGG, but the overall level of cooperation was higher. Specifically: 1) the mean amounts contributed, predicted by the decision rules, were higher; 2) there was a higher proportion of individuals using Maximum Cooperation in each individual class; 3) more individuals could now be classified as Committed Cooperators and 4) more co-ops could be classified as Committed Co-ops. Therefore, these findings suggest that cooperation is learned and transferred from the first PGG into the second. Cooperative behavior seems to spill over from one stage of the experiment to the next and interestingly, the type of cooperator one is classified as at one time, can change – since there was a higher proportion of Committed Cooperators (13% more) in the second PGG, even though the participants were the same.

4. Discussion: cooperative norms develop within groups

In this paper, we aimed to study the emergence of cooperative norms over time, following group formation. Furthermore, we aimed to compare the processes of group formation and cooperation in categorized and non-categorized groups. In the first Discussion section, we elaborated on the findings from the more traditional approach to data analysis. In the present section we focus on findings from the dynamic latent class model, with some additional discussion on the experimental method and overall study limitations.

While our first analysis provided a good description about how cooperation generally emerges over time for categorized and non-categorized groups; our second approach, using dynamic latent class models, allowed us to study the emergence of particular classes of individuals and co-ops, and the types of decision rules that they apply. This second method lends itself for modelling inductive processes: we did not explicitly predict or test for particular classes of co-ops or individuals but were able to explore the emergence of these within the context of this game.

We found that co-op members, in a given round, were likely to employ one of four decision rules – Maximum Cooperation, Nearly-There, Repetition and Reaction – which determined the amount contributed to the Public Good. The emergence of some of the decision rules used by participants in this study is in line with previous research. For example, Repetition, in which players simply repeat what they did the previous round, predicted an average contribution within the range of the 40–60% contribution often found in one-shot PGGs (Ledyard, 1995). This decision rule seems to be a "safe" and common strategy and is thus repeated. In addition, the decision rule of Reaction closely

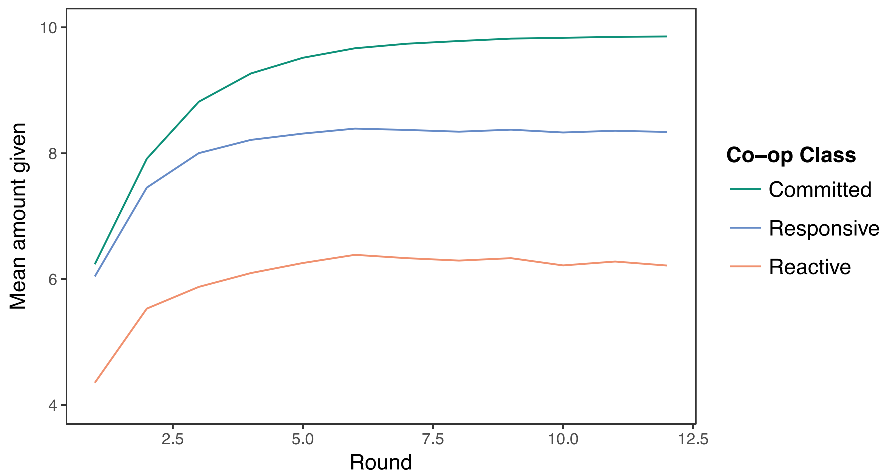

Fig. 7. The average amount contributed to the co-op over time: First PGG.

mimics what one finds with conditional cooperation – i.e., one cooperates when the group does and defects when the group does (Axelrod, 1984; Fischbacher, Gächter, & Fehr, 2001). All four decision rules were consistent across both PGGs. The decision rule itself used (a) the particular amount one personally contributed to the PG in the previous round and (b) the average level of cooperation shown by one's co-op members. The probability of choosing a given decision rule depended on (c) the decision rule one had previously chosen, and (d) the type of individual one could be classified as – Committed Cooperator, Responsive Cooperator or Reactive Player. These decision rules and the classes of individuals that emerged through interaction in the PGG, help to explain the findings from the first set of analyses – cooperation emerges over time through interaction with others. As an illustration, Committed Cooperators mostly did not start off by hitting the ceiling for cooperation. Their commitment level and high contributions developed over time as they established Committed Co-ops together. These findings indicate that further progress in understanding how to support cooperation can be made by studying the reasons why maximum cooperation emerges, as well as the contexts (i.e., the particular types of groups) in which it flourishes.

One possible key to maximizing cooperation is how a group establishes its shared identity and normative patterns of behavior. We found almost perfect overlap between the individual and co-op classes, meaning that co-ops consisted of people of the same individual class. We interpret this to mean that cooperation depends highly on one's group and that learning occurs within the group. We believe that we can rule out the alternative explanation for this finding because it is too improbable that across all 86 co-ops, people with the same preferences for cooperation happened to find one another after very limited interaction. Therefore, our finding suggests the formation of group norms, which, in turn, influences the kind of cooperator one 'becomes'. As additional support for this interpretation, there was also a change in the overall relative frequency of individual classes from the first to the second PGG (although the participants remained the same), meaning that some participants changed the type of person they were classified as. For example, more people were classified as Committed Cooperators in the second PGG. Therefore it would seem that people can learn to become more cooperative when exposed to cooperative groups and also, that cooperative groups emerge in the process of interaction.

This finding is quite different to traditional research findings in the interdependence literature, in which people are usually assumed to have fixed personal preferences for cooperation or selfishness (e.g., Messick & McClintock, 1968; Van Lange, 1999). In this study, we find strong evidence that the type of cooperation that is prevalent in the group as a whole determines the type of cooperator one becomes (see also Peysakhovich & Rand, 2016).

4.1. *Studying emergent social phenomena*

This study shows that individual classes, group norms, and stable co-ops (perhaps with a shared social identification) form in tandem, through interaction. We found that within a short period of interaction, group members aligned their decision making behavior regarding cooperation and, even under the same experimental conditions of the PGG, different types of groups emerged. The key question of this study about the emergence of cooperation could not be answered without our methodological approach: To study the emergent nature of any social behavior (including, but not exclusively, cooperation) it is important to account for complex social interdependencies, beyond dyads. In this study, we used the experimental platform VIAPPL through which we could monitor interaction over time to follow the emergence of cooperation and address issues of causality. While this approach may limit external validity, it has the strong advantage of allowing us to study complex emergent phenomena in a carefully controlled environment. A potential challenge for research such as this, is the interdependent nature of the data – which needs to be accounted for in the statistical analysis. With multilevel latent class Markov models, we were able to learn from these interdependencies – distilling patterns of behaviors, classes of individuals and classes of co-ops. Without this approach, we would not have seen that individual preferences appear emergent through interaction with the group and are collectively established in a short period of interaction. We imagine many cases in which this type of group analysis could be used to study emergent phenomena and will be useful to those interested in group processes research.

4.2. *Implications*

In this paper, we were able to clearly distinguish three types of cooperators: Committed, Responsive and Reactive. These "cooperators" emerged together in interaction and collectively established social norms regarding decision making on cooperation. Recent research has also uncovered the existence of Consistent Contributors (Weber & Murnighan, 2008) and Resilient Cooperators (Mao, Dworkin, Suri, & Watts, 2017), albeit in lower numbers than this study, and only making up a minority of their group. Nevertheless, even a single Consistent Contributor can change the social norms of cooperation, leading to higher contributions by group members (Weber & Murnighan, 2008); and a small minority of Resilient Cooperators are able to stabilize unravelling (i.e., prevent progressively earlier defection), thus sustaining high levels of cooperation for longer, at personal cost (Mao et al., 2017). Similarly, we imagine that Maximum Cooperators, could influence Responsive Players especially, but Reactive Players too. Future research could determine the optimal ratio of these types of cooperators to players who defect regularly, for maximal cooperation to emerge. Perhaps introducing clusters of these cooperators can be effective (see Axelrod, 1984). A challenge here may be that the cooperators in this study emerged together in a short period of interaction but we do not know how, as individuals, they might influence a pre-existing non-cooperative group over time.

Under what conditions do these cooperators emerge? Maximum Cooperators were slightly more common when social categories were salient, suggesting that if social identification is activated early on – rather than later, through induction – more of these cooperator types can emerge. Further, cooperation-friendly environments (e.g., experiments with a higher marginal per capita return) seem to result in the emergence of Consistent Contributors (Weber & Murnighan, 2008). Likewise, the cooperation-friendly framing of this experiment (as a community game) possibly activated a normative goal frame (Lindenberg, 2015a, b) thus supporting the emergence of many Maximum Cooperators. On the other hand, Reactive Players, or "rational actors", may emerge in greater numbers than we found when competitiveness is more salient. Future research could further explore conditions under which different types of cooperators may emerge; what motivates these types of players under what conditions; and how many of them are required to influence others in the group, thus shaping norms of cooperative or uncooperative behavior.

4.3. Limitations

According to the Interactive Model of Social Identity Formation (Postmes, Haslam, & Swaab, 2005; Postmes, Spears, et al., 2005), social identification with a group is often an interplay between deductive and inductive processes. In many natural groups, these processes are quite difficult to completely tease apart. In our study, as with natural groups, it was also difficult to completely separate these processes in a way that still maintained experimental equivalence between conditions. While our pre-assigned categorized groups were signaled through group homogeneity (visually, through color) and a history of the group was presented to participants (with the story of having arrived from the same country together, an attempt to mimic nationality as a categorical identity), there was no actual history and the groups were minimal and small. Furthermore, categorized individuals could interact with their entire group and choose their own co-ops, which were not always perfectly aligned with their pre-assigned categorical groups.

On the other hand, participants in co-ops in the Non-Categorized condition – co-ops which were indeed small, interactive and heterogeneous – were still faced with the task of choosing their co-ops early on in the game, limiting the organic emergence of these groups. In addition, the other one or two co-ops could be seen on screen by participants during the game. These other groups could have served as comparison outgroups. Therefore, one may argue that non-categorized, inductive groups here function as social categories as soon as participants select their co-ops. Perhaps this could explain why there was not a large difference between conditions in terms of cooperation. However, some differences did still emerge (although often marginally significant). For example, the pattern of decline in cooperation in the first PGG for non-categorized groups, and the fact that more Reactive co-ops were likely to form in the Non-Categorized condition and more Committed Co-ops in the Categorized condition. So, the manipulation appears to have been effective in tapping into different processes. Nevertheless, the small differences between conditions were less impressive than the variability between co-ops within conditions. This variability to us seems more important in understanding cooperation within groups. In other words, any prior categorization effect was overshadowed by the emergent social norms within groups. Therefore, the dynamic process of emergent social norms appears more influential than the static framing of the group, at least in this experiment.

Another potential limitation is that we did not incentivize participants according to the outcome of the experiment. While this is common practice in psychological experiments, it is not the standard economic approach. This may lead to the question whether participants were sufficiently motivated to engage in a meaningful way in the experiment: We believe that indeed they were motivated. Descriptions of the number of messages sent suggest that participants were engaged with one another – allowing for communication over time likely made the relational value of interaction more important than self-interest (i.e., maximizing tokens). Furthermore, not all co-ops reached the highest levels of cooperation therefore, not incentivizing clearly did not have a uniform (positive) effect on the groups. However, it would be interesting for future research to study how incentives might change the number of Committed Co-ops that form under different goal frames.

From this study, we know that interaction over time is important in the development of cooperative people and groups; however we have not yet examined what it is about the quality of the interaction itself that promotes the emergence of maximally cooperative groups rather than reactive groups. Categorization appears to be only a part of the story in fostering cooperative groups. Our results seem to suggest that people can change and adapt depending on the social context of interaction, and become more cooperative together if they can develop the right learning environment as a group. Some groups, however, are more successful than others at forming cooperative norms.

4.4. Conclusion

The results from this study show that collaboration is not a static given, but rather cooperation within groups is emergent over time through social interaction. There are large differences among groups to the extent in which they can achieve maximum cooperation, and while some of this appears to be accounted for by shared category membership, most of it emerges through interaction. In that process of emergence, individual types and co-op types arise in tandem, shaping (and being shaped by) emergent group norms. The emergent properties of the "personality" of the individual cannot be seen independently of the emergent properties of group as a whole (in fact there is almost perfect overlap between the two). At the end of the day, this means that at least some of the static factors discussed at the start of this paper are shaped collectively, through social interactions.

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Appendix A. Supplementary data

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