

Normative Equivalence in Human–AI Cooperation: Behaviour, Not Identity, Drives Cooperation in Mixed-Agent Groups

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Abstract

The introduction of artificial intelligence (AI) agents into human group settings raises essential questions about how these novel participants influence cooperative social norms. While previous studies on human–AI cooperation have primarily focused on dyadic interactions, little is known about how integrating AI agents affects the emergence and maintenance of cooperative norms in small groups. This study addresses this gap through an online experiment using a repeated four-player Public Goods Game (PGG). Each group consisted of three human participants and one bot, which was framed either as human or AI and followed one of three predefined decision strategies: unconditional cooperation, conditional cooperation, or free-riding. In our sample of 236 participants, we found that reciprocal group dynamics and behavioural inertia primarily drove cooperation. These normative mechanisms operated identically across conditions, resulting in cooperation levels that did not differ significantly between human and AI labels. Furthermore, we found no evidence of differences in norm persistence in a follow-up Prisoner’s Dilemma, or in participants’ normative perceptions. Participants’ behaviour followed the same normative logic across human and AI conditions, indicating that cooperation depended on group behaviour rather than partner identity. This supports a pattern of normative equivalence, in which the mechanisms that sustain cooperation function similarly in mixed human–AI and all-human groups. These findings suggest that cooperative norms are flexible enough to extend to artificial agents, blurring the boundary between humans and AI in collective decision-making.

1 Introduction

Finding solutions to climate change, geopolitical instability, and widening resource inequality represents a fundamental challenge: addressing social problems involving public goods often requires cooperation among actors with heterogeneous incentives and information. At the same time, rapid advances in artificial intelligence are reshaping how people solve a wide range of problems by inserting autonomous agents into domains once reserved for humans. Nine out of 10 organisations already report the regular use of AI in their operations ([McKinsey Report, 2025](#)) and two-thirds of people worldwide believe that AI products and services will significantly impact daily life within the next three to five years ([Nestor et al., 2025](#)). In this study, the term artificial intelligence (AI) is used broadly to refer to autonomous or semi-autonomous decision-making agents that perform tasks or make strategic choices that typically require human judgment. This conceptualization encompasses AI systems that participate in shared decision processes, such as software agents allocating energy across smart grids, algorithms coordinating traffic or resource flows, or automated trading systems making cooperative or competitive moves in markets. As these agents increasingly participate in joint decision-making situations, understanding how humans cooperate with and respond to AI partners becomes an essential social question ([Tsvetkova et al., 2024](#)).

Research shows that humans often treat AI as social actors, and that willingness to cooperate with AI depends on framing, perceived warmth, competence, and trust (Nass et al., 1994; de Melo et al., 2011; McKee et al., 2024; Chong et al., 2022; Zhang et al., 2023). This tendency aligns with the Social Heuristics Hypothesis (Rand et al., 2014), which posits that cooperation is often an intuitive, automated response generalized from daily social interactions. If humans default to these internalized cooperative scripts, they may extend them to artificial partners unless motivated to deliberate. At the same time, studies consistently find that cooperation with AI partners tends to be lower than with human counterparts, a phenomenon recently formalized as the 'machine penalty' (Makovi et al., 2025). This pattern is often linked to algorithm aversion or the strategic exploitation of AI agents perceived as less sensitive to social cues and sanctions than humans (Dietvorst et al., 2015; Karpus et al., 2021; Bazazi et al., 2025). Yet this literature is overwhelmingly based on dyadic designs, emphasizing partner-to-partner reciprocity while omitting the group processes that generate emergent norm expectations. Groups structures can diffuse attention and accountability, highlight social influence, and create shared expectations that shape behaviour. Accordingly, the open question is not simply whether people cooperate with AI, but whether mechanisms that sustain group cooperation change when one member is perceived as an AI (Reinecke et al., 2025; Eng et al., 2023).

To address this question, we turn to social norms: the shared expectations that guide behaviour and sustain cooperation in groups. In repeated group interaction, individuals adapt conditionally to others, aligning choices with empirical expectations (what others do) and injunctive expectations (what others think one ought to do), two expectation types that jointly define a social norm (Bicchieri et al., 2018; Young, 2015; Kölle and Quercia, 2021). When these coincide, cooperation is sustained; when they diverge, cooperation erodes (Fehr and Fischbacher, 2004; Baronchelli, 2024). Classic experiments in public-goods settings show that individuals tend to condition their contributions on those of others, increasing cooperation when others contribute and withdrawing when they do not, an effect known as conditional cooperation (Fischbacher et al., 2001; Keser and van Winden, 2000; Thöni and Volk, 2018). These findings highlight that cooperation in groups depends on shared expectations and social influence, mechanisms that may also extend to mixed human–AI groups. Despite recent calls for further research on these relational norms in human–AI collectives (Reinecke et al., 2025), there is a paucity of empirical evidence at the group level through the lens of social norms.

Building on this human evidence, recent research has begun to examine how artificial agents themselves participate in or influence these normative dynamics. AI can shape norms positively by reinforcing fairness, reciprocity, and trust (Taddeo and Floridi, 2018; McCannon, 2024) or negatively by normalizing free-riding and moral disengagement (Köbis et al., 2021; Eng et al., 2023). Computational and multi-agent studies likewise show how artificial agents can seed, amplify, or stabilize cooperative norms (Shi et al., 2024; Kulkarni and Brunswicker, 2024; Ren et al., 2024; Hintze and Adami, 2024). Together, these strands suggest that AI can mediate, amplify, or dampen the normative forces that sustain cooperation, while leaving open whether the process of norm-guided cooperation itself changes when an AI joins the group. Yet despite this growing body of work, we still lack systematic behavioural evidence on how humans respond when AI agents become part of their cooperative networks. Specifically, it remains unknown whether the processes of norm formation and adherence that sustain cooperation among human groups operate equivalently when an AI joins the group. This creates a theoretical tension: Does the specific identity of an agent disrupt social cohesion (differentiation), or do the functional mechanics of group norms render the agent's identity irrelevant (normative equivalence)?

To test this, we conducted a between-subjects 2×3 group experiment based on established behavioural economic games that capture cooperation and norm formation in groups. Participants (three humans and one programmed agent) played ten rounds of a linear Public Goods Game (PGG). The PGG captures how individual incentives conflict with collective welfare, requiring participants to decide how much of their endowment to allocate to a shared group account (Chaudhuri, 2011; Fehr and Gächter, 2000). The fourth player was framed as either human or AI and followed one of three predefined strategies: unconditional cooperator (always contributes the full endowment), conditional cooperator (matches the group's average contribution from the previous round), or free-rider (always contributes zero). To assess norm persistence beyond the group context, participants then completed a one-shot Prisoner's Dilemma (PD) with a group partner (Nemeth, 1972; Doebeli and Hauert, 2005; Peysakhovich and Rand, 2016; Stagnaro et al., 2017; Arechar et al., 2018). Finally, we elicited participants' norm perceptions through a coordination measure of social appropriateness for contribution levels (Krupka

and Weber, 2013), along with empirical and injunctive norm expectations (Wang et al., 2024). This combined design allows us to test whether the normative dynamics of cooperation operate equivalently when one group member is AI-labelled, and whether such norms persist beyond the immediate group context.

Based on the theoretical framework outlined above, specific hypotheses were preregistered before data collection (AsPredicted #234846). Theoretically, the introduction of AI agents creates a tension between two outcomes. On the one hand, a differentiation effect suggests that the artificiality of an agent will dampen reciprocity, consistent with algorithm aversion. On the other hand, normative equivalence implies that the group’s strong behavioural signals may override the agent’s identity, rendering the distinction irrelevant. Despite this competing possibility, we prioritized the differentiation perspective given the robust evidence for algorithm aversion in dyadic settings. Consequently, we hypothesised lower overall cooperation and weaker normative influence when the fourth member was AI-labelled rather than human-labelled (H1). Beyond this label effect and the groups’ collective contribution, we anticipated that the bots’ individual behavioural strategy itself would shape cooperation, such that an unconditional cooperator would reinforce cooperative norms (H1a), a conditional cooperator would sustain intermediate levels of cooperation (H1b), and a free-rider would erode them (H1c). Finally, we examined whether cooperative norms established in the group context would persist when participants made subsequent one-on-one decisions. If AI-labelled members evoke weaker social identification and diminished norm pressure, these dynamics should also reduce the internalization and carry over of cooperative norms beyond the group interaction. Accordingly, we predicted that norm persistence would be stronger in human groups compared to human-AI hybrid groups (H2).

Results show that group behaviour is the strongest driver of individual cooperation, regardless of whether the bot is labelled as human or AI, or of its strategy. Differences among the bots’ cooperation strategies were small to negligible, and the one-shot Prisoner’s Dilemma revealed no systematic differences by label or strategy concerning norm persistence. Across all conditions, post-task norm perceptions and expectations were closely aligned, and contributions followed the same behavioural regularities: responsiveness to others’ contributions, inertia in individual behaviour, and a gradual decline over time. Together, these results point to a form of normative equivalence, where the same processes that sustain cooperation among humans operate unchanged when an AI-labelled agent is introduced to the group. This conclusion advances research on human–AI interaction by providing group-level evidence that cooperative norms extend seamlessly to artificial partners. When social presence and communication are minimal, behavioural signals and shared expectations, rather than categorical identity cues, govern cooperation. The study thereby establishes a theoretical and methodological baseline for future work that introduces adaptive, communicative, or higher-presence AI agents to test when and how this equivalence breaks. Practical implications for the design of AI systems in teams and institutions suggest that transparent, norm-consistent behaviour may foster social integration more effectively than anthropomorphic design or human-like labelling.

2 Methods

2.1 Experimental Design

The experiment employed a between-subjects design, in which each participant played ten rounds of a Public Goods Game (PGG) followed by a single Prisoner’s Dilemma (PD) decision. In the PGG, participants were randomly assigned to one of six experimental conditions in a 2×3 factorial design, crossing agent label (human vs. AI) with bot strategy (Unconditional Cooperator, Conditional Cooperator, or Free-Rider), see Figure 1. In all conditions, groups consisted of three human participants and one computer-controlled player (bot). The interaction structure was identical across treatments; the only differences were (a) the label displayed to participants for the fourth player (human or AI), and (b) the bot’s programmed cooperation strategy. The bot strategies consisted of: 1) Unconditional Cooperator: Always contributes their full endowment in every round, 2) Conditional Cooperator: Matched the average contribution from the previous round and 3) Free-Rider: Always contributes nothing. The bots’ cooperation strategies were not disclosed to the participants. By holding interaction structure constant and varying only the label and cooperation strategy of one agent, we can test whether the normative dynamics of cooperation, namely reciprocity, conformity to group contributions, and norm

alignment, remain stable across human and AI conditions. The experiment was implemented in oTree (Chen et al., 2016), an open-source platform for online interactive economic games.

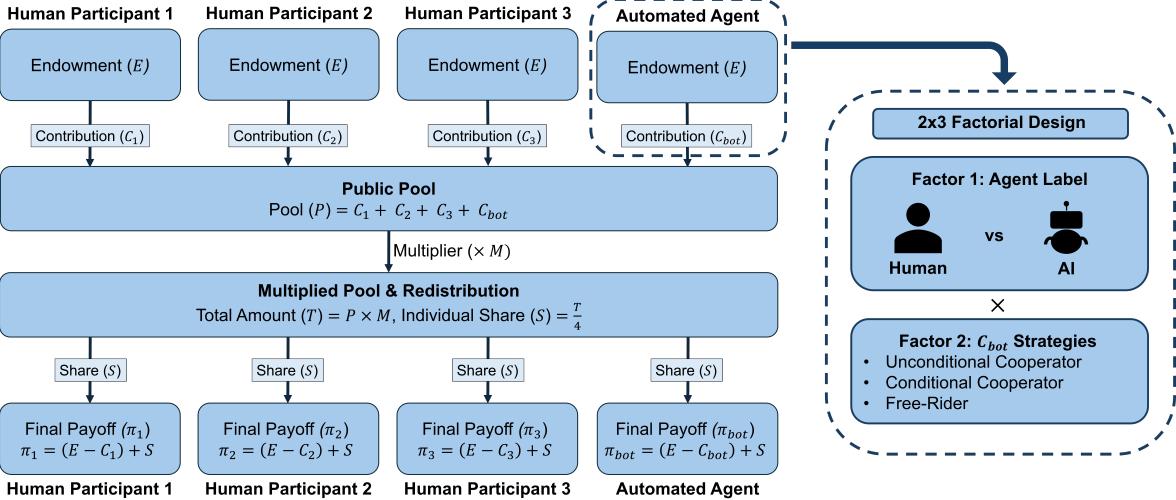


Figure 1: Schematic representation of the experimental design and PGG mechanics

2.2 Procedure

Participants first viewed an information page outlining study participation and data protection, followed by an informed consent form. After providing consent, they received detailed instructions on the experimental procedure and completed a short comprehension test. Participants who failed this test on three consecutive attempts were excluded from the study. After passing the comprehension check, participants were randomly assigned to four-player groups consisting of either four humans or three humans and one AI-labelled bot. In both conditions, the fourth player was a computer-controlled agent following one of three predefined cooperation strategies described earlier. Groups then played ten rounds of a linear PGG. In each round, participants received an endowment of 100 tokens and decided how much to contribute to a shared group account. After each round, participants viewed a results page displaying the aggregate group contribution and their individual payoffs. Crucially, to mimic the opacity of large-scale collective action, participants did not see the individual contributions of specific group members. Total contributions were multiplied by 1.5 and evenly redistributed among all four players. Group composition remained constant across rounds. To maintain consistency of group interaction, the session was terminated for all members if any participant dropped out; in such cases, participants were informed that the game had ended and received only the fixed participation fee. Following the PGG, participants completed a one-shot Prisoner’s Dilemma (PD) framed as a new interaction with another member of their previous group. In reality, partner responses were always simulated to reflect cooperation, providing an unobtrusive measure of norm persistence after the group interaction. Finally, participants completed a norm elicitation task, rating the social acceptability of various PGG contribution levels. This was followed by a post-experiment survey measuring trust, fairness, group cohesion, normative pressure, and, if applicable, measures pertaining to the AI group member. The session concluded with a debrief, during which participants reported their perceived group composition (human vs. AI) and any suspicions regarding the identity of other group members.

2.3 Participants

Participants were recruited via Prolific, an established online platform for behavioural research that offers greater participant diversity, more precise screening, and higher data quality than alternative crowdsourcing platforms (Peer et al., 2017; Palan and Schitter, 2018; Germine et al., 2012; Paolacci and Chandler, 2014). Five experimental sessions were conducted across three days at varying times to account for potential time-of-day effects. Participants received a fixed payment of £6 per hour plus a performance-based bonus at a rate of 1,500 tokens = £1, resulting in an average effective hourly payment of £8.95 for the average 17 minutes it took complete the study. All participants provided

informed consent, and the study protocol was approved by the Ethics Committee of University College Dublin (Approval No. 128-LS-C-25-Yasseri).

A total of 366 individuals entered the study. Thirty-seven did not consent, five left during the instructions, and fourteen failed the comprehension check, leaving 310 who began the experiment. Due to the group-based design, attrition in any group required terminating the session for all members, yielding 246 participants who completed the PGG and 240 who finished the whole experiment. Four additional participants failed the manipulation check, resulting in a final sample of 236. To validate the effectiveness of the group composition manipulation, we asked participants in the post-experiment debrief: "At any point, did you doubt whether the group composition was exactly as described?" Forty-four participants (18.6%) answered affirmatively. To ensure that these suspicions did not drive the observed lack of treatment effects, we conducted a robustness check excluding these participants. As detailed in Section 3.2, excluding these participants did not alter the substantive findings. Consistent with our preregistered analysis plan, we retained the full sample for the primary analysis to avoid post-hoc selection bias and preserve randomization. Participants were distributed near-equally across the human ($n = 114$) and AI ($n = 122$) treatment conditions and across the three bot strategies within each label. The sociodemographic profile of the sample was broadly balanced: the modal age groups were 28–37 (41 percent) and 18–27 (29 percent); sex was evenly split; and the sample showed substantial ethnic and national diversity. Most participants were employed full-time or part-time, with roughly one-third identifying as students.

2.4 Pre-registration and Sample Deviations

The study design, hypotheses, and analysis plan were preregistered on AsPredicted (registration #234846). The study design and hypotheses remained identical to those specified in the preregistration. Regarding sample size, the preregistration stated that it would be determined by an a priori power analysis based on pilot effect sizes. However, pilot data revealed effect sizes close to zero. Because standard power analyses for near-zero effects yield unrealistically large sample requirements, we could not proceed with the pre-specified power calculation. Instead, we targeted a sample size sufficient to detect substantively meaningful deviations in cooperation. The final sample of 236 complete group interactions yields approximately 40 independent observations per cell for the main strategy comparisons. Post-hoc sensitivity analysis confirms that this yields high precision for our primary investigation: the 90% confidence interval for the label effect allows us to rule out label effects larger than approximately 4 tokens. While the design is less powered to detect subtle interaction effects among bot strategies, the confidence intervals are sufficiently narrow to exclude large, disruptive behavioural shifts. All deviations from the preregistration are fully reported here, and the complete preregistration document is available at [<https://aspredicted.org/wd7j-jyg5.pdf>].

2.5 Measures

The primary dependent variables were derived from participants' decisions in the PGG and the Prisoner's Dilemma (PD). In the PGG, participants made contribution decisions ranging from 0 to 100 tokens over ten rounds. These contributions were analysed both as repeated measures in mixed-effects regressions and as mean contributions across rounds in linear regressions. The PD provided a binary outcome as either cooperate or defect, which was coded accordingly and analysed using logistic regression models. Beyond behavioural outcomes, we also measured participants' normative perceptions following the two decision tasks. Building on Krupka and Weber (2013), participants rated the social appropriateness of five possible contribution levels (0, 25, 50, 75, and 100 tokens) not bound to specific to human or AI agents contributions, on a Likert scale ranging from very socially inappropriate to very socially appropriate. These ratings were used to compute an overall norm score and a norm slope, indicating the extent to which perceived appropriateness increased with contribution size. We additionally measured two complementary norm expectations: the empirical norm, capturing participants' perceptions of others' actual contributions, and the injunctive norm, capturing their beliefs about how much others thought one should contribute (Wang et al., 2024). Together, these three measures provided quantitative indicators of normative expectations and their relationship to both treatment conditions and cooperative behaviour.

Following the behavioural tasks, participants completed a post-experiment survey assessing perceived trust, fairness, group cohesion, and normative pressure during the game. Participants in the AI

treatment received additional items on the AI player's social perception, accountability, representation, and fairness. Each construct was measured with two to three items and aggregated into index scores. These exploratory measures were designed to identify potential mechanisms underlying variation in cooperation and norm perception across conditions.

3 Results

3.1 Experiment Descriptive Results

Figure 2 shows that average contributions in the PGG were very similar across human and AI groups. Across all conditions, contributions started at roughly 40–50 tokens and declined modestly over the ten rounds to around 30–40 tokens, consistent with the typical downward trend in repeated public-goods interactions. Groups paired with the unconditional cooperator bot tended to sit at the upper end of this narrow range, conditional cooperators at the lower end, and free-riders in between, but the trajectories largely overlapped and followed the same gradual decline. Human-labelled groups contributed slightly more than AI-labelled groups, yet these gaps were only a few tokens. Overall, the descriptive patterns suggest that neither the human-AI label nor the specific bot strategy produced caused differences in cooperation dynamics.

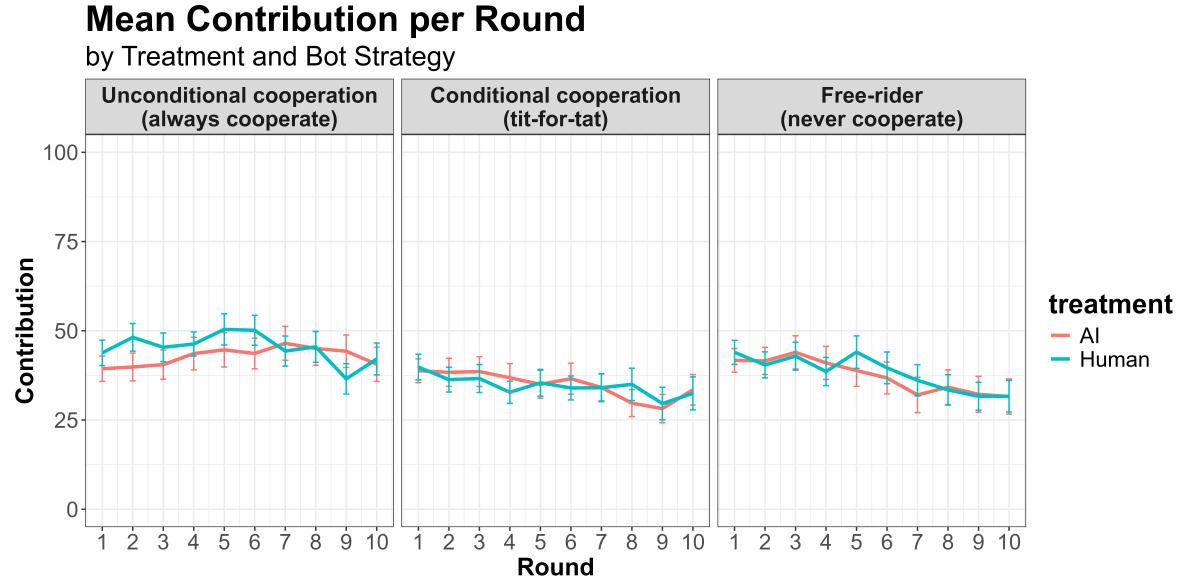


Figure 2: Mean Contribution per Round by Treatment and Bot Strategy.

Figure 3 shows cooperation and defection rates in the one-shot Prisoner's Dilemma. Across both human and AI treatments, cooperation was slightly more common than defection, and overall rates were similar. In the AI-conditional cooperation condition, about two-thirds of participants cooperated, whereas in the human treatment cooperation rates clustered around 50 percent across strategies. Despite these small variations, the confidence intervals overlapped widely, indicating no meaningful differences across labels or bot strategies.

Prisoner's Dilemma Choices

by Bot Strategy and Treatment

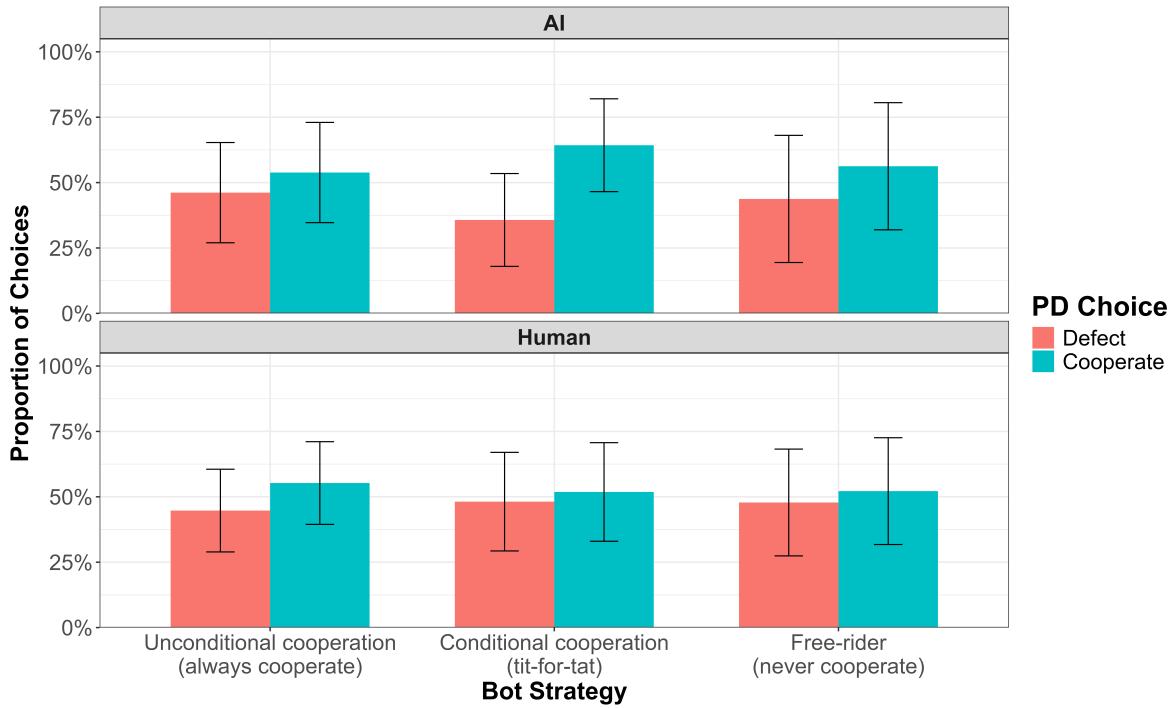


Figure 3: Prisoner's Dilemma choices by treatment and bot strategy. The first letter denotes the prediction of the partner's behaviour, and the second letter denotes the participant's choice.

Figure 4 shows the distribution of participants' Prisoner's Dilemma decisions by the expectation of their partner's choice. The most common pattern was CC (mutual cooperation), accounting for nearly half of all cases in both treatment, although being slightly more frequent in the AI condition. On the other side, around a quarter of participants fell into the category of DD (mutual defection), expecting defection and defecting themselves, somewhat more frequent in the human condition. Less common were CD (exploitation), in which participants predicted their partner's cooperation but defected, and DC (altruistic cooperation), in which participants predicted defection but cooperated anyway. Both occurred relatively rarely at around 10-20%. Overall, the distribution of the profiles suggest that participants were more inclined towards mutuality, either in cooperation and defecting, compared to exploitation or altruism.

Prediction vs Actual Cooperation in PD

by Treatment

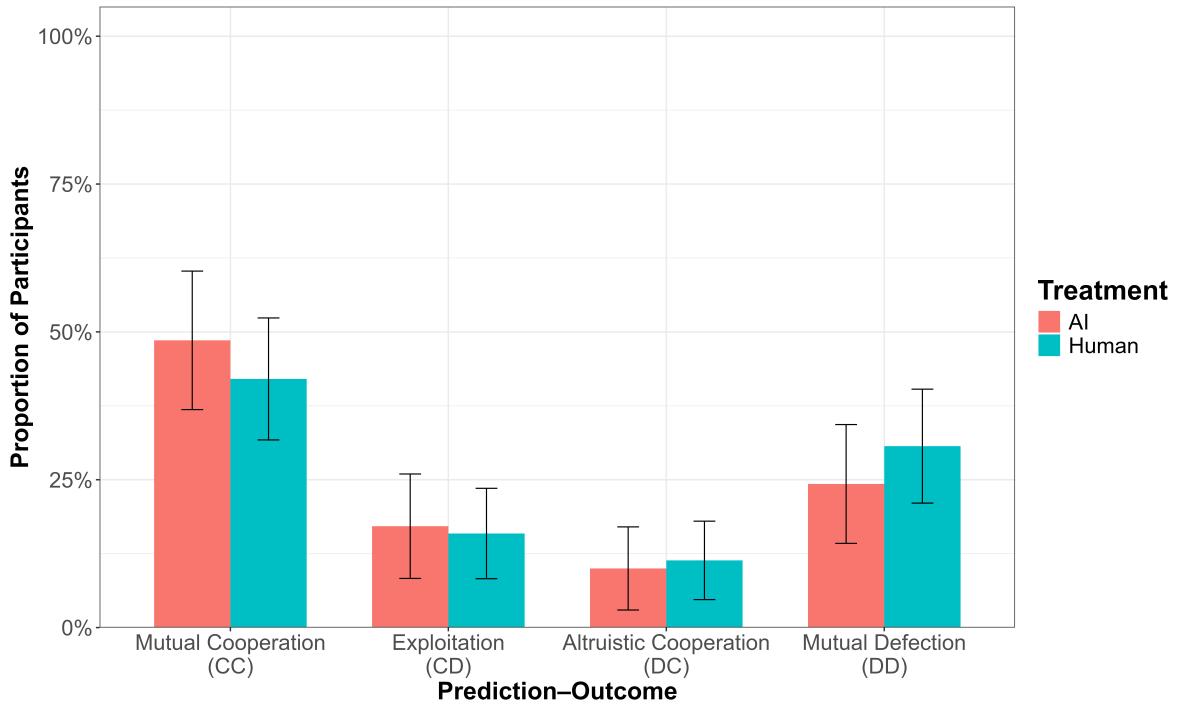


Figure 4: Prisoner’s Dilemma choices by treatment and bot strategy.

3.2 Model-based Results

3.2.1 PGG

To gain insight into the mechanisms through which the presence AI Agents can change cooperation decisions, we estimate a series of statistical models across the PGG, the prisoners dilemma, as well as the norm expectations elicited from participants. The models allow us to disentangle how perceptions of agent type and bot strategies interact with normative pressures on cooperation decisions in a group (PGG), how cooperation persists in subsequent interactions (PD), and how normative expectations and perceptions might mediate these dynamics.

First, we examine the main effect of our treatments on cooperation decisions using a linear mixed-effects regression model. To this end, we include the treatment and bot strategies, the contributions of others in previous rounds (group pressure), their own contributions in the previous round (individual inertia), and time trends across rounds. To account for the heterogeneity and nested structure of the decisions, we include person-level random slopes and random slopes for both normative pressure (others’ contribution) and round trend. This allows us to capture both baseline differences in contribution levels as well as variation in participants’ susceptibility to social pressure and rounding effects.

Our primary hypothesis (H1) predicted a "differentiation effect," where the presence of an AI-labelled agent would reduce overall cooperation and normative pressure. Contrary to this prediction, the mixed-effects model (see Table 1) reveals no significant effect of the AI label on contribution levels (human vs. AI; $b = 1.09, p = .738$). Consequently, we reject H1; participants did not penalize the group for the presence of an AI agent, supporting the alternative perspective of normative equivalence. The regression further reveals that participants’ behaviour was strongly shaped by both their own and others’ prior contributions. They contributed significantly more when others had contributed highly in the previous round ($b = 0.14, p = .006$) and when they have contributed more in the previous round themselves ($\beta = 0.28, p < .001$). We also observe a round effect, with the typical decline in cooperation in the repeated game ($b = -0.59, p = .001$).

We further hypothesized that the specific strategy of the agent would shape group norms: unconditional cooperation would raise contributions (H1a), conditional cooperation would sustain them

(H1b), and free-riding would erode them (H1c). The results offer little support for these specific predictions. While groups with unconditional cooperators trended slightly higher and free-riders slightly lower (see Figure 2), these differences were not statistically significant in the regression model. The lack of substantial differentiation among bot strategies suggests that the presence of two other human moderators buffered the group against the extreme behaviours (0 or 100 tokens) exhibited by the single automated agent. This finding is robust to participant suspicion: Excluding the 44 participants who expressed doubt about the group composition, the treatment effect remained statistically non-significant ($\beta = 3.05, p = .396$) and the primary behavioral drivers (inertia, conditional cooperation) remained stable. These results indicate that we find the same behavioural rules which govern conditional cooperation, namely sensitivity to others' contributions, individual inertia, and decline across rounds, equally in both human and AI groups.

Table 1: Public Goods Game Contributions (Linear Mixed-Effects Regression Model

Predictors	Estimates	CI	p
<i>Fixed effects</i>			
(Intercept)	25.07	18.06 – 32.08	<0.001
Others' lagged contrib.	0.14	0.04 – 0.24	0.006
human (vs. AI)	1.09	-5.31 – 7.49	0.738
Conditional Cooperation (vs. Unconditional)	-2.82	-8.24 – 2.59	0.307
Free-Rider (vs. Unconditional)	1.10	-4.54 – 6.73	0.703
Own lagged contrib.	0.28	0.23 – 0.32	<0.001
Round (centered)	-0.59	-0.92 – -0.26	0.001
human × Others' lagged contrib.	-0.02	-0.14 – 0.11	0.803
<i>Random Effects (variance)</i>			
σ^2 (Residual)	272.51		
τ_{00} id	139.48		
τ_{11} id.Others lagged contrib.	0.02		
τ_{11} id.Round (centered)	1.99		
ICC	0.34		
N_{id}	236		
Observations	2,124		
Marginal R^2 / Conditional R^2	0.165 / 0.448		

Notes. Linear mixed model (REML) with random intercepts and random slopes for *others* and *round* by participant. Confidence intervals are 95%. Reference categories: Partner label = *AI*; Bot strategy = *Always coop*. Model: `player ~ others * treatment + bot_strategy + lagp + round + (1 | unique_id) + (0 + others, | unique_id) + (0 + round, | unique_id)`.

Precision and Range of Treatment Effects: While the mixed-effects model revealed no significant treatment effect ($b = 1.09, p = .738$), we further examined the precision of this estimate to determine the smallest effect size that the data could meaningfully detect. Using estimated marginal means from the model, we calculated the pairwise contrast between human- and AI-labelled conditions and its 90 % confidence interval (AI – human = -0.49, CI [-3.92, 2.94]). This interval indicates that any true difference in mean contributions is unlikely to exceed approximately ± 4 tokens. Thus, although we cannot claim formal statistical equivalence, the analysis indicates that any plausible treatment difference is small and well below the magnitude typically considered meaningful. Participants, therefore, appeared to approach the cooperation task under a shared normative logic, regardless of whether one group member was labelled as human or AI.

3.2.2 Prisoner's Dilemma

Hypothesis H2 predicted that cooperative norms formed in human-only groups would be more robust, leading to higher norm persistence (cooperation in the one-shot PD) compared to mixed groups. However, the logistic regression analysis contradicts this prediction. As illustrated in Figures 5a and 5b, while the probability of cooperating in the PD increases with prior contributions at both the

individual (Panel a) and group levels (Panel b), the regression lines for human and AI treatments overlap almost perfectly. This visual convergence confirms that the likelihood of cooperating was not significantly predicted by the previous group composition . The norm persistence of the group experience, therefore, did not differ by agent type. Consequently, H2 is not supported; the normative inertia carried over into the subsequent interaction regardless of whether the previous group included an AI.

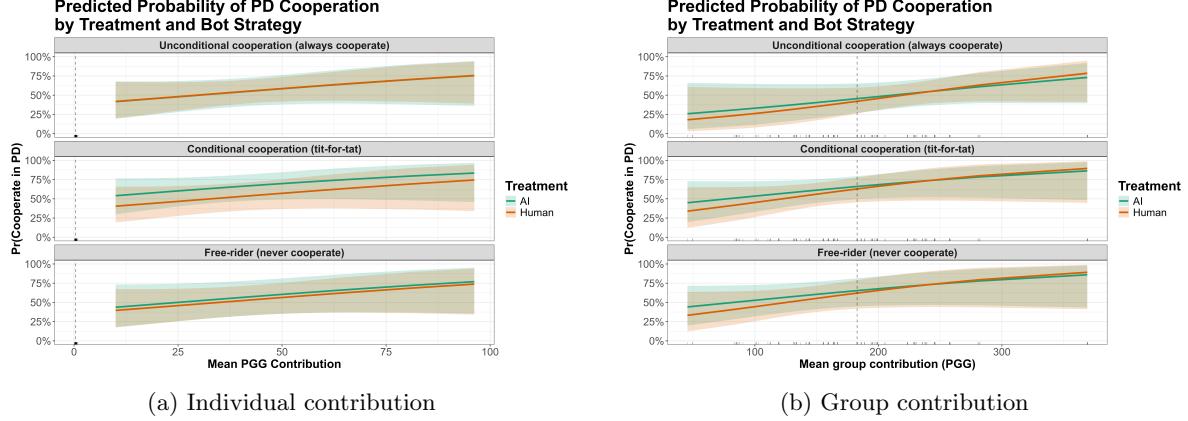


Figure 5: Predicted probability of PD cooperation by prior PGG contributions at the (a) individual and (b) group level.

3.3 Additional Results

3.3.1 Norm Attitudes

We asked participants a few questions about perceptions of cooperative norms. After the two games they were asked to rate different contribution levels (0,25,50,75,100) and their social acceptability of those contributions. Further, they were asked what they believed other people in their group contributed (empirical expectation) and what they thought they were expected to contribute (normative expectation), allowing us to test normative pressures across conditions.

Participants' social acceptability ratings closely aligned with contribution levels. Contributions of 0 were judged as very unacceptable ($M = 1.3$), whereas acceptability rose sharply between 25 ($M = 2.38$) and 50 ($M = 3.21$). We then see a plateauing of ratings with almost identical ratings for contributions of 75 and 100 ($M = 3.45$). Importantly, Figure 6 as well as a regression analysis show no significant differences emerged between human and AI groups, with acceptability ratings closely aligning, and only slightly diverging at the contribution level of 75, although the difference is not statistically significant.

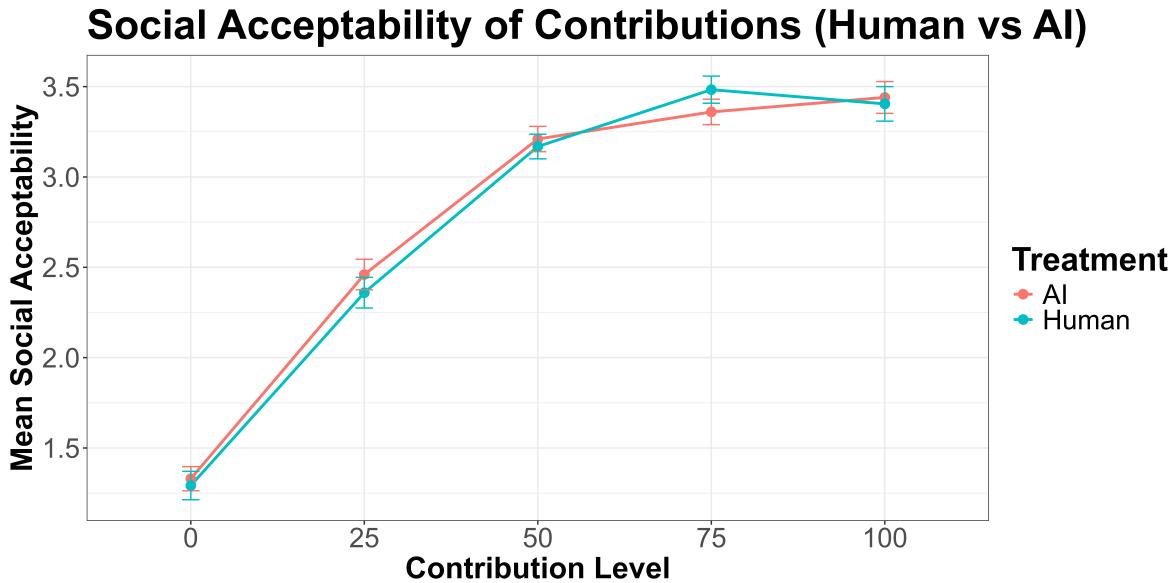


Figure 6: Social acceptability of different contribution levels by treatment

Participants' empirical expectations closely matched actual group contributions (Median Expectation = 40.8, median Actual = 41.0), indicating overall accurate beliefs about others' cooperation. Differences between treatments were negligible: participants slightly overestimated others in the AI condition (+0.3) and slightly underestimated them in the human condition (-0.8). As shown in Figure 7, expectations rose linearly with actual contributions, with nearly identical slopes across treatments.

Participants' injunctive norm expectations exceeded the group's actual contributions (Median Expectation = 45.6, Median Actual = 41.0), indicating that they believed others should contribute slightly more than they did. Figure 7 shows that this pattern was consistent across treatments: both AI ($\Delta = +4.3$) and human ($\Delta = +4.8$) groups showed similar positive gaps, with largely overlapping regression lines. Overall, participants' normative beliefs aligned with actual cooperation levels but reflected modestly higher expectations regarding contributions. Since normative expectation patterns mirrored actual contributions and were nearly identical across treatments, this further supports the idea that the group's normative environment operated similarly regardless of the AI label.

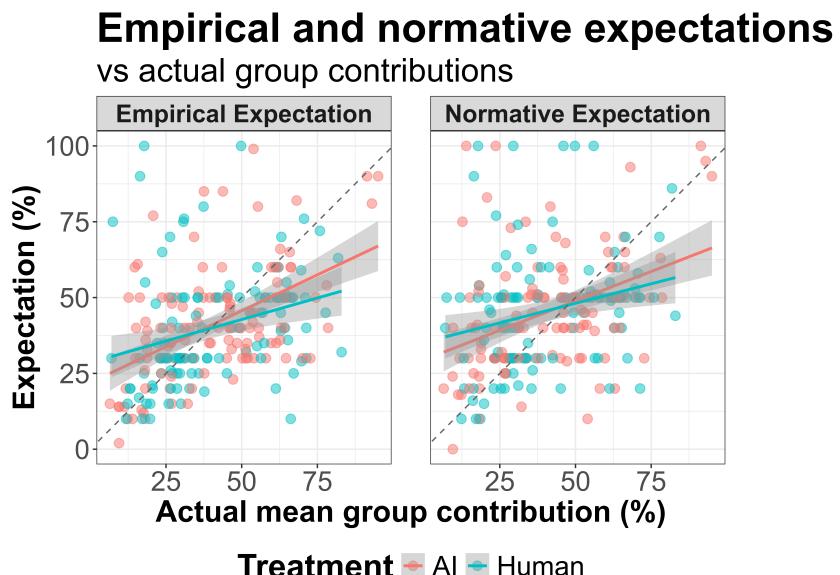


Figure 7: Norm Expectations by Treatment

3.3.2 Post Experiment Survey

Several indicators focused on trust, perceptions and acceptability were elicited from participants to gain a deeper understanding of their motivations within the games. The results indicate positive group perceptions across both treatments (Figure 8 & Figure 9). Participants in both treatments agreed that their teammates were fair, trustworthy and cooperative, while responses were more mixed regarding normative pressures. Mean responses for trust, fairness, cohesion, and normative pressure items did not differ significantly across treatments (all $p > .10$), except for the statement “I aligned my behaviour with what I thought the rest of the group expected of me”. Here we find a marginally lower response in the AI condition ($b = -2.17, p = .031$). This suggests that participants interacting with an AI-labelled teammate felt slightly less alignment pressure, while general perceptions of fairness and trust remained comparable across treatments. The participants in the AI treatment found AI to be trustworthy, fair, and part of the team, although its role was seen a bit more as that of a tool than a teammate. Interestingly, most participants thought that AI contributed positively to the group’s success and wouldn’t blame AI for failures.

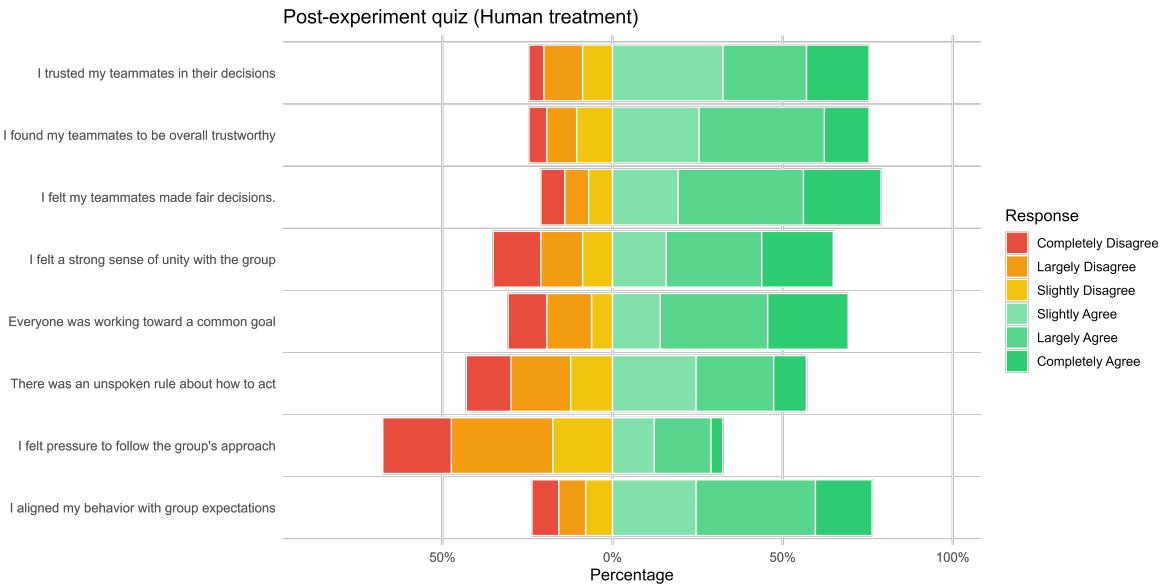


Figure 8: Post Experiment Survey human Treatment

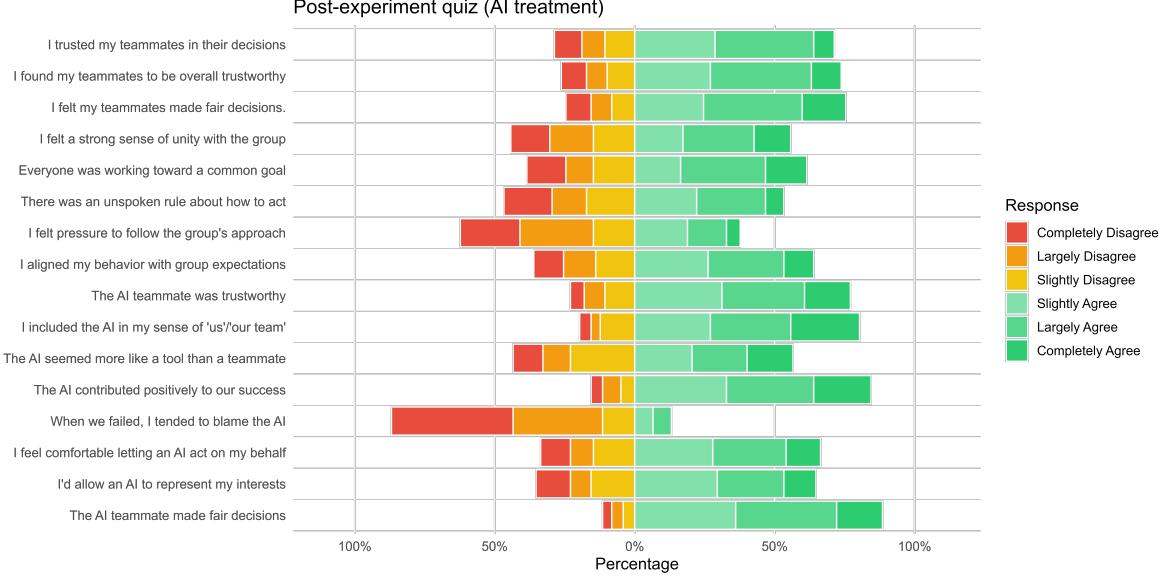


Figure 9: Post Experiment Survey AI Treatment

To test whether any of these attitudes and perceptions influenced cooperative behaviour in the PGG, we estimated two regression models. For the general statements asked of both treatments, we found that trust was the only significant predictor of higher contributions ($b = 3.71, p = .046$). Among the AI treatment variables, we found that cooperation increased with trust ($\beta = 7.33, p = .006$) and with normative pressure ($b = 4.86, p = .008$). Yet we found that overall AI acceptance would be associated with lower contribution levels ($b = -5.76, p = .001$). Together, these findings suggest that participants who trusted their group and perceived stronger normative expectations contributed more. In contrast, in the AI group we found that algorithm aversion can have an adverse effect on contributions.

4 Discussion

Our study examined whether the inclusion of an AI-labelled teammate alters the social dynamics of group cooperation. Contrary to our hypothesis (H1) derived from the algorithm aversion and exploitation literature, we found no systematic behavioural differences between human- and AI-labelled conditions. Participants' contributions were shaped along familiar normative mechanisms such as conditional cooperation, sensitivity to others' past behaviour, and gradual decline over time. These processes operated almost identically across treatments and strategies. This pattern mirrors findings from prior dyadic studies (Ng, 2023; Makovi et al., 2023) showing that trust and reciprocity can generalize to AI partners. Once the AI was embedded within a collective context, its artificial label ceased to influence cooperative behaviour: participants appeared to respond to social cues and group signals rather than to agent identity.

4.1 Normative Equivalence

These results point to a form of normative equivalence, in which the mechanisms that sustain cooperation function similarly in mixed human–AI and all-human groups. We introduce the term 'normative equivalence' to describe the observed process-level similarity in how social norms guide cooperation behaviour. By normative equivalence, we do not argue that humans perceive AI as morally equivalent to, equally trustworthy as, or socially interchangeable with human partners. Rather, the concept refers explicitly to a form of norm adherence, the mechanism by which individuals align their cooperation with empirical and injunctive expectations (Bicchieri et al., 2018). It denotes that the same behavioural regularities of reciprocity and conditional cooperation emerged regardless of the partner's label. We distinguish this from norm enforcement. Since our design excluded peer punishment, our

findings establish that humans comply with cooperative norms similarly in mixed groups. However, enforcement mechanisms appear necessary when the human social buffer is removed. [Makovi et al. \(2025\)](#) demonstrate that while punishment alone increases cooperation with AI, it does not eliminate the machine penalty; only the combination of peer rewards and punishment successfully closes the gap. This suggests that while normative equivalence in compliance emerges automatically in mixed groups, achieving equivalence in cooperation levels within AI dominated contexts requires explicit and combined enforcement mechanisms.

These findings challenge the ‘differentiation’ perspective often found in human-AI interaction research, particularly assumptions regarding algorithm aversion and moral disengagement ([Karpus et al., 2021](#); [Mutzner et al., 2023](#)). This aligns with recent experimental work using the Prisoner’s Dilemma, which similarly found no significant differences in cooperation rates between human and AI partners ([Bazazi et al., 2025](#)). However, this equivalence may depend on the social density of the group: while [Makovi et al. \(2025\)](#) observed a ‘machine penalty’ in groups where participants believed all partners were machines, our results suggest that in mixed groups where humans remain the majority, the presence of human peers buffers against this effect. Contrary to predictions derived from Social Identity Theory or Mind Perception ([Oudah et al., 2024](#)), which suggest reduced obligation toward non-human agent participants, participants did not exploit AI teammates, withhold trust, or display weaker norm alignment. This indicates that normative equivalence represents a distinct mechanism from surface-level social responses described by the Computers Are Social Actors (CASA) paradigm ([Nass et al., 1994](#)). While CASA focuses on unconscious reactions to anthropomorphic cues, normative equivalence denotes a deeper behavioural alignment in which the group’s functional logic (reciprocity) overrides the partner’s ontological category. In essence, once cooperative norms are activated, the ‘AI’ label becomes a distinction without a difference; participants rely on observable behaviour as the primary normative cue rather than the agent’s identity.

This dominance of behavioural signals over ontological categories aligns with the Social Heuristics Hypothesis ([Rand et al., 2014](#)), which posits that cooperation is often an intuitive, automated response generalized from daily social life. In this view, ‘Normative Equivalence’ may emerge because participants default to a cooperative heuristic when interacting with any agent that reciprocates, regardless of its nature. Inhibiting this response to exploit a ‘mindless’ bot strategically would require overriding these internalized norms—a cognitive effort that participants in our study appeared unmotivated to make. This suggests that unless an AI explicitly violates local norms (e.g., by engaging in erratic or hyper-competitive behaviour), human partners will default to treating it as a socially valid member of the group.

4.2 Theoretical and Methodological Implications

The absence of strong treatment effects across both labels and strategies also provides a methodological insight. Because participants received feedback on the group’s total contribution rather than individual actions, the specific strategy of the single AI agent was likely diluted by the behaviour of the other two humans. Our results indicate that such minimal cues may be insufficient to meaningfully shift behaviour in group contexts, where cooperation is driven by dynamic collective expectations rather than isolated actions or categorical visual distinctions. The experiment thus establishes a useful baseline where cooperative dynamics remain normatively equivalent across human and AI labels under conditions of minimal social presence and no communication. However, these dynamics may change as the group’s composition shifts. For instance, [Makovi et al. \(2025\)](#) observe a clear ‘machine penalty’ when participants believe all partners are machines, suggesting that the presence of a human majority in our study may have buffered against such effects. Increasing the proportion of AI agents could therefore alter perceived social balance, responsibility diffusion, or majority influence, potentially amplifying or diminishing normative pressures. Future studies can build on this baseline by introducing adaptive, communicative, or emotionally expressive AI agents, and by systematically varying their proportions within groups. This would allow testing of when, and through which mechanisms, normative equivalence might begin to break.

From a broader perspective, these findings speak to the integration of AI into human collectives. It further fits into the emerging field of Machine Behaviour ([Rahwan et al., 2019](#)), illustrating how artificial agents can be functionally integrated into human collectives without requiring complex social intelligence. The stability of the hybrid groups suggests that ‘socialness’ in a system is not solely a property of agents’ minds but an emergent property of the rules and feedback loops governing their

interactions. Social norms governing cooperation might therefore be more elastic than might initially be assumed. Individuals readily apply the same cooperative logic to heterogeneous groups that include artificial actors. This elasticity may prove beneficial as AI systems become routine participants in work teams and online communities and are more involved in decision-making processes. Yet it also raises new questions about accountability and transparency. If cooperative norms extend seamlessly to AI systems, it should be considered whether responsibility for outcomes may diffuse equally seamlessly among human and non-human participants.

4.3 Limitations

Based on our experiments and results, several limitations should be acknowledged. First, as with many online experiments involving deception, there remains a risk that some participants did not fully believe in the group composition. Although most correctly identified their condition, a minority of participants (18.6%) expressed doubt regarding the group's composition. However, our robustness check indicated that these suspicions did not significantly alter the main findings, suggesting that the observed normative equivalence holds even among participants who fully accepted the cover story. Yet, this highlights the inherent difficulty of creating credible mixed-agent group settings in online environments, where subtle cues of artificiality or repetition can influence perceived realism. Second, our design focused on short-term, anonymous interactions. Without extended histories or reputation-building, participants' behaviour may have reflected situational cooperation rather than deeper norm internalization. Real-world human–AI collaboration can involve ongoing relationships, feedback which cannot be fully captured in brief experimental sessions. Third, while our treatments varied both the agent label and strategy, the AI's behaviour was scripted rather than adaptive. This limits the ecological validity of our findings, as real AI systems increasingly learn and respond dynamically to human input. Future studies could incorporate adaptive agents to examine whether evolving responsiveness strengthens or weakens normative alignment over time. Specifically adaptations involving communication or punishment mechanisms, which heighten the perception of complex interaction, might change treatment differences. Finally, the impact of the bot's strategy was likely dampened by the aggregate feedback mechanism. Future research should examine whether AI strategies have a more pronounced effect in settings with transparent individual feedback, in which human participants can clearly identify and respond to the AI agent's specific contributions.

5 Conclusion

This study examined how cooperative norms function in hybrid human–AI groups. Using a repeated Public Goods Game followed by a one-shot Prisoner's Dilemma, we found that cooperation patterns and normative expectations were virtually identical whether one group member was labelled as human or as AI. These results indicate a form of normative equivalence where mechanisms that sustain cooperation, such as reciprocity, conditionality, and responsiveness to group behaviour operate unchanged when artificial agents are introduced. Rather than demonstrating algorithm aversion or moral disengagement, our findings highlight the stability and generality of cooperative norms in hybrid groups. When behaviour is transparent, individuals appear to rely on shared group signals rather than categorical distinctions between humans and AI. This baseline of normative equivalence provides a foundation for future research examining when such stability persists and when it breaks. This is particularly true in richer, more communicative, or more adaptive human–AI interactions, where moral agency, responsibility, trust, and transparency must be negotiated more actively.

CRediT authorship contribution statement

Nico Mutzner: Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Writing - Review & Editing.

Taha Yasseri: Conceptualization, Methodology, Resources, Writing - Review & Editing, Supervision.

Heiko Rauhut: Methodology, Resources, Writing - Review & Editing, Supervision, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

The authors used ChatGPT-4o/5 & Gemini 3 for (a) language-related tasks such as proofreading, improving grammar and style, rephrasing sentences for clarity, and translation, and (b) for optimizing code used in statistical analyses (e.g., syntax correction, code efficiency, formatting). After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the article's content.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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A Appendix 1: Sociodemographics

Table 2: Sociodemographic characteristics of participants (N = 236)

Characteristic	Category	n (%)
Age (years)	18–27	67 (29.0)
	28–37	96 (40.7)
	38–47	33 (14.0)
	48–57	22 (9.4)
	58–67	11 (4.7)
	68–70	5 (2.1)
Sex	Female	117 (49.6)
	Male	116 (49.2)
	Prefer not to say	1 (0.4)
Ethnicity	White	111 (47.0)
	Black	100 (42.4)
	Mixed	11 (4.7)
	Asian	10 (4.3)
	Other	1 (0.4)
Top 5 Nationalities	South Africa	84 (35.6)
	United Kingdom	46 (19.5)
	United States	35 (14.8)
	Poland	12 (5.1)
	Kenya	8 (3.4)
Student status	Yes	70 (29.7)
	No	132 (55.9)
	Missing	32 (13.6)
Employment status	Full-time	131 (55.5)
	Part-time	37 (15.7)
	Unemployed	15 (6.4)
	Other	22 (9.3)
	Missing	29 (12.3)