Repairing cooperation through a cognitive intervention in the repeated Trust Game

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Abstract

Social trust is an important building block of strong social bonds, and its absence is a risk factor for social dysfunction. As such, interventions to foster and strengthen trust-based cooperation are highly desirable. Using the repeated Trust Game paradigm, we assess the effectiveness of a cognitive intervention aimed at repairing the potential breakdown of cooperation from a pre-programmed, one-off defection by the opponent. Over two games, participants are given the role of the trustee and face what they believe are two different players. In between games, they either receive a brief cognitive intervention or not. The intervention led to more cooperative behavior both pre and post defection by the opponent. HMM modelling of participants actions shows participants in the intervention group had a lower probability of transitioning to non cooperative states. Posterior latent state analysis also showed a higher proportion of players best described by more cooperative latent states in the intervention condition compared to the control condition.

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1   Introduction

Determining the other's goals, intentions, and decision-making process is fundamental to successful social interaction. This inference is however fraught with uncertainty, as we cannot directly observe these features, and may need extensive prior knowledge of the person. Absent a history of interaction, one may decide to trust the other's goals and intentions are aligned with one's own. The challenge of trust is that it is by construction a risky endeavour. If we deem a person trustworthy, we might take the risk of investing in the relationship, hoping for a collaborative outcome. If this trust is misplaced, it can come at a high cost. Not trusting others is also risky since opportunities for cooperation may be foregone.

Evidence from the literature emphasises the importance of social trust in determining why some people fare better than others physically and mentally (Giordano and Lindström 2016 ; Meng and Chen 2014). It affects the health status of individuals by reinforcing social support networks, maintaining community norms and facilitating collective action. Research into the determinants of psychopathology has linked trust-based constructs to the emergence of mental health disorders. Fonagy and Allison (2014) identified epistemic trust, or the belief in the authenticity and personal relevance of interpersonally transmitted knowledge, as an important function of early attachment relationships. It allows the individual receiving social information to let go of their natural self-protective vigilance, which can become a pathological hypervigilance frequently observed after traumatic experiences and a key factor for the emergence of multiple mental health disorders (Fonagy and Campbell 2017).

Since a lack of epistemic trust is a risk factor for social dysfunction (Fonagy and Campbell 2017), and given the importance of trust for building and maintaining strong social bonds, interventions to foster and strengthen trust-based cooperation would be highly beneficial to society. Such interventions would allow people to more easily repair broken relationships, and continue harvesting the benefits of cooperation even in the presence of accidental or intentional social norm violations.

A well-established paradigm in the study of trust is the repeated trust game (Joyce, Dickhaut, and McCabe 1995). In this game, the "investor" decides how much of an endowment to send to the other player (the "trustee"). The amount that is sent is tripled and the trustee decides, in return, how much of the tripled amount to send back to the investor. To encourage the emergence and maintenance of trust in this setting, some studies focused on modifying the game mechanism, for example by introducing a third-party who monitors the actions of the other players (Charness, Cobo-Reyes, and Jiménez 2008; Fiedler and Haruvy 2017). Others chose to intervene directly on the participants. For example, Drążkowski, Kaczmarek, and Kashdan (2017) found that trust was increased when participants were asked to think about and write down five things that they were grateful for. Burnham, McCabe, and Smith (2000) found that trust was also increased when participants were primed with the concepts of friend and foe.

Whilst these interventions show that it is possible to improve cooperative outcomes at the start of the game, they do not address how to repair a breakdown of trust that might occur due to intentional or accidental non-cooperative actions by the players. Cooperative play in the repeated trust game can easily break down when there is a transgressive behavior, such as a nil or very low investment by the investor or a return of the trustee below the investment sent (Bendor, Kramer, and Stout 1991). Such ruptures of cooperation appear frequently when the trustee suffers from social disorders such as Borderline Personality Disorder [BPD; Lieb et al. (2004)]. In theses situations, BPD trustees fail to engage in trust repairing behaviours such as coaxing the investor by signalling trustworthiness via sending high returns. This failure may be linked to the misperception that their low returns in the game are not violating social norms (King-Casas et al. 2008).

In devising potential interventions to repair trust, we can derive inspiration from the cognitive interventions championed by successful psychological therapies that aim to improve aspects of social dysfunction in BPD patients. Whilst there is no proven pharmacological therapy for BPD, psychotherapies such as Mentalisation Based Therapy (Allen and Fonagy 2006) and Dialectical Behavior Therapy (Linehan 1993) have been shown to improve various dysfunctional behaviors in BPD patients, including those related to social interaction (Gunderson et al. 2018). However, response to these treatments is highly variable, and determining which interventions are effective for particular patients is challenging (Rudge, Feigenbaum, and Fonagy 2020; Arch et al. 2012). One promising approach is the study of how specific components of psychotherapeutic treatment affect quantitative markers of behaviour such as those inferred through computational models (Huys, Maia, and Frank 2016; Reiter et al. 2021). Combining the use of specific cognitive probes inspired by therapeutic interventions and computational models of behaviour may allow us to uncover the cognitive mechanisms targeted by common forms of psychotherapy. In turn, this may provide the basis for choosing effective psychotherapeutic interventions for given individuals.

In this study, we assess the effectiveness of a cognitive intervention aimed at repairing the potential breakdown of cooperation from a one-off low investment sent by an computerised investor. The intervention focuses on explaining the potential harm from reciprocating non-cooperative actions and suggesting a non-impulsive course of action to coax the investor back into cooperation. Participants are given the role of the trustee and are randomly assigned to either a control or intervention group. They play two instances of the repeated trust game with two different investors. After the first instance of the game, they either receive a cognitive intervention (intervention condition) or perform an unrelated task solving anagrams (control condition). In reality, participants face the same computerised agent in both instances, which is programmed to play according to a hidden Markov model fitted to real players' data. We explore whether the intervention has an effect on the behaviour of the human trustee and whether this effect transfers to a different game (repeated Prisoner's Dilemma) and facing a seemingly new player.

2 Method

2.1 Participants and Design

A total of 318 participants were recruited on the Prolific Academic platform (prolific.co). The mean age of participants was 31.3 years. Participants were paid a fixed fee of £5 plus a bonus payment dependent on their performance that averaged £0.71. The experiment had a 2 (Condition: Intervention or Control) by 3 (Game: Trust-Game Pre Intervention, Trust-Game Post Intervention, Prisoner's Dilemma Post Intervention) design, with repeated measures on the second factor. Participants were randomly assigned to one of the two levels of the first factor.

2.2 Tasks and Measures

2.2.1 Repeated Trust Game

Participants played a 15-round repeated trust game (Joyce, Dickhaut, and McCabe 1995) in the trustee role against a computer-programmed investor. On each round the investor was endowed with 20 units and decided how much of that endowment to invest. This investment is tripled and the trustee then decides how to split this amount between them and the investor. If the trustee returns more than one third of the amount, the investor makes a gain. The Nash equilibrium for a single-round version is for the investor to send nothing. In the repeated version, rewards for both players are maximised if they build trust and share the benefits of the the investment multiplied by three. An investor who has been rewarded for taking the risk of sending an investment is more likely to invest more on future rounds. An investor obtaining a low return on their investment may choose to reduce future investment and thereby reduce both players' gains.
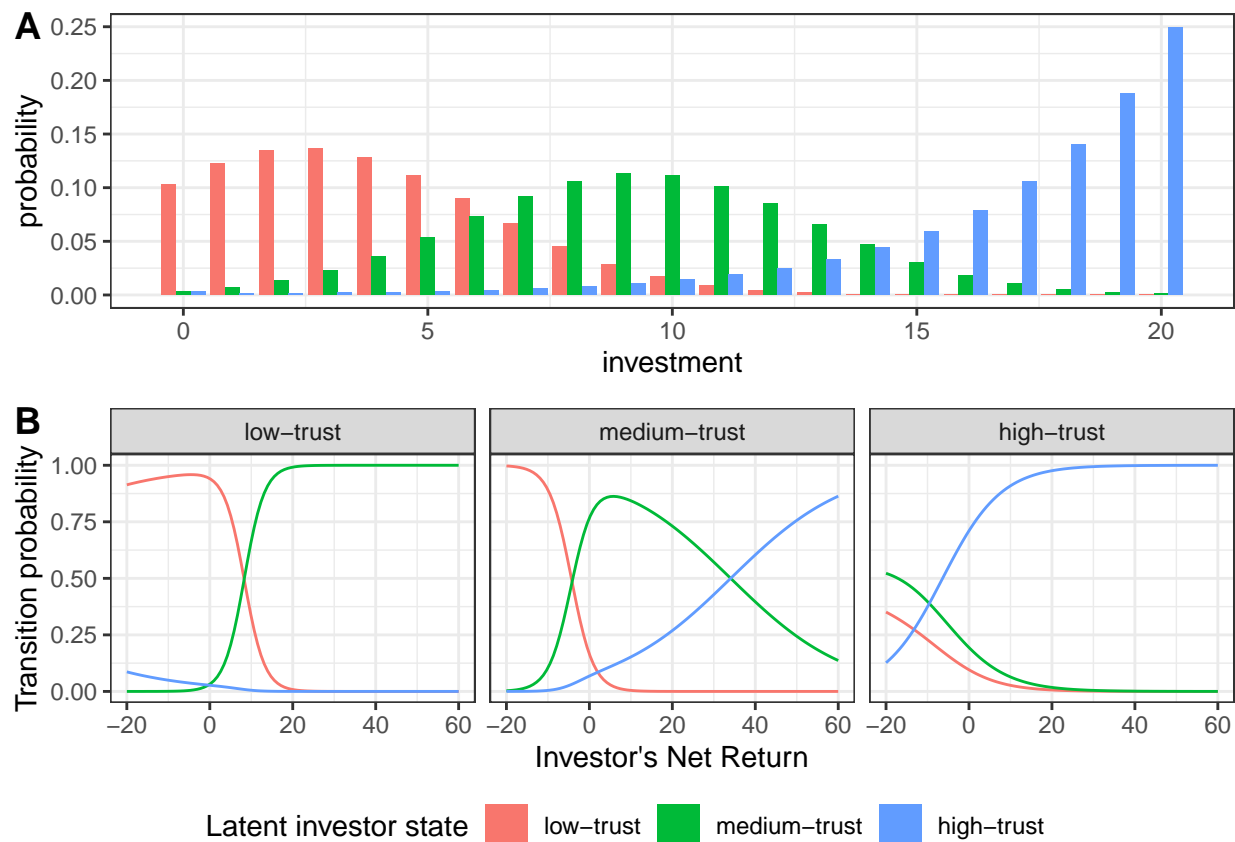

Figure 1: A: Distribution of investments by the artificial investor agent conditional on its latent state as estimated by a three state hidden Markov model fitted to human dyadic play dataset. B: Transition function for the HMM investor conditional on its current state and the net return from the previous round of play.

The strategy of the computerised investor was modelled on behaviour of human investors in a 10-round RTG (King-Casas et al. 2008). Using this data, we estimated a hidden Markov model (HMM) on investors' behaviour with three latent states, reflecting "low-trust", "medium-trust", or "high-trust". Each latent state was associated with a distribution over all possible investor actions (from 0 to 20 investment) that reflected the amount of trust (Figure 1.A). Over rounds, the investor can move between states, and the probability of these transitions was modelled as a function of the net return in the previous round (see Figure 1.B).

In order to probe efforts to repair trust, the computerised agent was programmed to provide a low investment on round 12 pre-intervention and 13 post-intervention. On all other rounds, the agent's actions were derived from the HMM (disregarding the participant's response on pre-programmed low investment rounds).

2.2.2 Repeated Prisoner's Dilemma

Participants played 7 rounds of a repeated Prisoner's Dilemma. In each round, participants could choose between: a cooperative action with a reward of 5 if the player also cooperated and a reward of 1 if not, or a non-cooperative action that would yield a 7 points if the other person chooses the cooperative action and 2 points if not. The Nash equilibrium for a single-round version is to choose the non-cooperative action.

The computerised agent was programmed to act according to a tit-for-tat strategy (Axelrod and Hamilton 1981), starting with a cooperative action and then mirroring what the other player chose in the preceding round. On round 4, the agent was pre-programmed to choose the defect action, regardless of the participant's preceding action.

2.3 Intervention

The intervention was built on interventions from DBT skills training, asking patients to reflect on the consequences of actions taken in emotional states (Linehan 2015). Specifically, participants were presented with a low investment and asked to indicate their response. They were then invited to consider what their ultimate aim in the game was and whether this response was most likely to achieve their aim. The intervention is detailed in the supplementary information.

In the control condition, participants were asked to solve five anagrams ("listen", "triangle", "deductions", "players", "care"). They provided their answers in a free-form text box. The time given to solve the anagrams was the same as that given to respond to questions in the intervention manipulation.
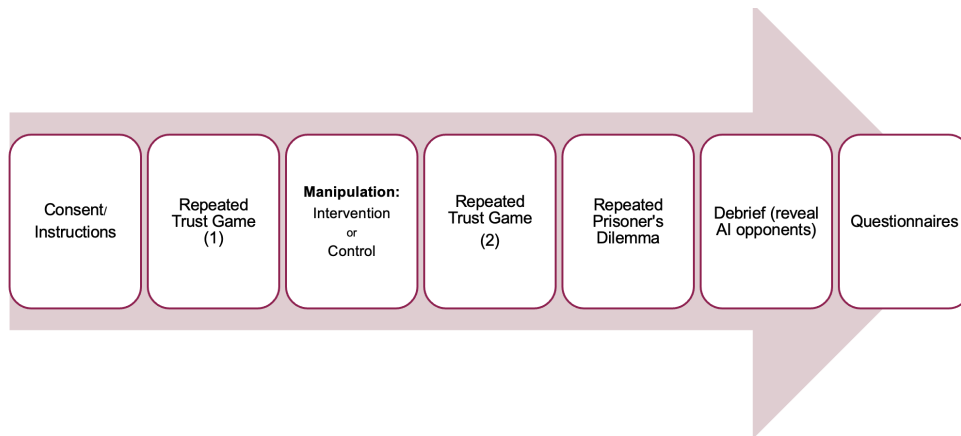
2.4 Procedure

Figure 2: Experiment overview. After playing 15 rounds of a repeated trust game (RTG) as trustee, participants were randomized to either receive the control or active intervention. They then played the second set of 15 rounds of RTG (again as trustee) to examine intervention effects, and 7 rounds of a repeated Prisoner's Dilemma to examine generalization of intervention effects. Finally, participants answered questionnaires and were debriefed.

At the start of the experiment (Figure 2), participants provided informed consent and were instructed the study would consist of three phases in which they would face a different other player. Participants were told their goal was to maximise the number of points in all phases. They were not told the number of rounds of each phase. Phase one was a 15 round repeated Trust Game (RTG) in which participants took the role of trustee, facing the same investor over all 15 rounds. On each round, after being informed about the amount sent by the investor, participants were asked to provide feedback, with participants in the Intervention condition rating their feeling in terms of valence (from negative to positive) and arousal (from low to high), and participants in the Control condition rating the investment in terms of speed (from slow to fast) and magnitude (from low to high). These ratings were made by indicating a point on a two-dimensional grid. Participants then decided on how much of the tripled investment to return to the investor, before continuing to the next round. After completing 15 rounds of the RTG, participants

rated how cooperative, selfish, trustworthy and friendly they perceived their interaction partner (all on a scale from 1 to 10). After phase one, participants in the intervention condition completed the intervention, and participants in the control condition solved anagrams. Subsequent phase two was similar to phase one, with participants being told they would face a new player. Phase three consisted of 7 rounds of the repeated prisoner's dilemma game (RPD), with participants informed they would face a third player. Participants then completed questionnaires related to mentalising abilities, emotion regulation, and BPD traits (see the supplement for details). They were then asked about the strategy in the games, as well as whether they thought the other players were human or computer agents. They were then debriefed and thanked for their participation.

2.5   Statistical analysis

To explore whether participants behaved differently after the intervention compared to the control group over all rounds, we estimate a linear-mixed effects model as implemented in the R package "afex" (Singmann et al. 2022), with fixed effects for Condition (intervention or control), Game-number (pre- or post-intervention) and Investment, as well as interactions between Condition and both Investment and Game-number, and participant-wise random intercepts and random slopes for Game-number. More complex models with additional random effects provided could not be estimated reliably. For the F-tests, we used the Kenward-Roger approximation to the degrees of freedom, as implemented in the R package "afex". We Z-transform the Investment variable as centering is beneficial to interpreting the main effects more easily in the presence of interactions.

To model participants' returns in the RTG across games and conditions, we fit various hidden Markov models to participants' returns using the depmixS4 package (Visser and Speekenbrink 2021) for R. The transition between latent states is assumed to depend on the investment received and a dummy variable to characterise the group that the participant belongs to. Details on how the models are constructed can be found in the supplement. We fit models with different numbers of hidden states, and use the Bayesian Information Criterion (Schwarz 1978) to select the best model.

3   Behavioural results

Average investments and returns prior to the "defection round" (Figure 3) were within the range of reported investments (40-60% of endowment) and returns (35-50% of total yield) in the literature (Charness, Cobo-Reyes, and Jiménez 2008; Fiedler, Haruvy, and Li 2011). Mixed-effects analysis on the returns shows a significant main effect of Condition (intervention vs. control), $F(1, 317.20) = 9.53$, $p = .002$, with higher percentage returns in the intervention compared to the control condition. Importantly, we also find an interaction between Condition and Game (RTG pre- vs. post-intervention), $F(1, 318.30) = 26.91$, $p < .001$. Post-hoc tests show an increase in the percentage returned in the intervention condition, pre - post, $\Delta M = -0.03$, 95% CI $[-0.05, -0.02]$, $t(316.54) = -4.85$, $p < .001$, but a decrease in the control condition, $\Delta M = 0.02$, 95% CI $[0.00, 0.03]$, $t(319.69) = 2.34$, $p = .020$ (see Figure 4.A). This indicates the intervention was effective in increasing cooperative behaviour. There was also a significant main effect of Investment, $F(1, 9, 208.68) = 373.23$, $p < .001$, such that higher investments were associated with higher percentage returns. An Investment by Condition interaction, $F(1, 9, 208.68) = 45.35$, $p < .001$, indicates the positive effect of investment on percentage returns was greater in the control than intervention condition. There was also an Investment by Game interaction, $F(1, 8, 990.38) = 4.31$, $p = .038$. Finally, we find a three way interaction between Game, Condition and Investment, $F(1, 8, 990.38) = 24.56$, $p < .001$, showing that the differentiated effect of the investment on the proportion returned by condition is itself moderated by the Game (pre- vs post intervention).

We next analysed HMM agent investments with a linear-mixed effects model with fixed effects for Condition (intervention vs control), Game (pre vs post intervention), as well as interaction between Condition and Game, and participant-wise random intercepts and random slopes for Game. This shows a main effect of Condition, $F(1, 317) = 8.72$, $p = .003$, and Game, $F(1, 317) = 8.32$, $p = .004$. As can be seen in Figure 4.B, investment was higher in the intervention compared to the control condition across games, and higher in the second game compared to first across conditions.

We next analysed returns separately for rounds prior to the pre-programmed transgression (rounds 1 to 11 pre-intervention and 1 to 12 post-intervention) and rounds after (rounds 12 to 15 pre-intervention and rounds 13 to 15 post-intervention). Applying the same mixed effects model as before to returns before the transgression largely replicates the results over all trials. Participants in the intervention condition increased their returns in the second game, $\Delta M = -0.04$, 95% CI $[-0.05, -0.02]$, $t(317.20) = -5.19$, $p < .001$. There was no evidence that participants in
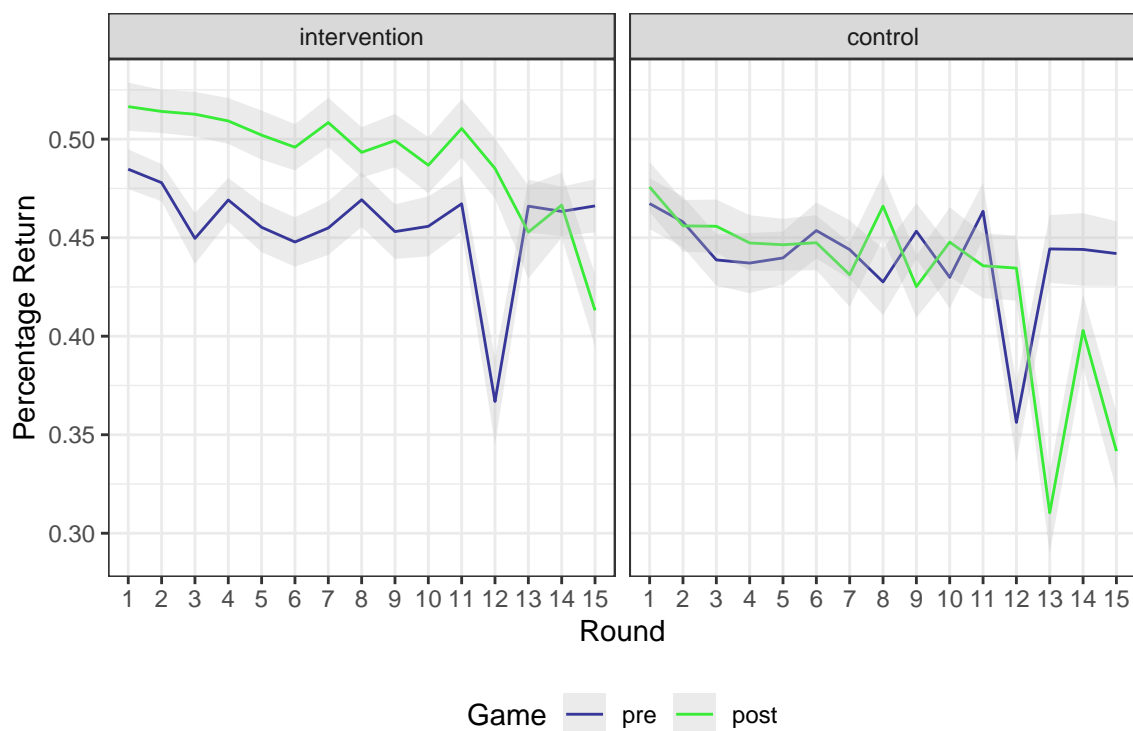
Figure 3: Average and standard errors of the trustee's return as a percentage of the multiplied investment received for each round and for both conditions. The red line shows the returns pre-manipulation and the blue line post-manipulation.We note a different reaction to the pre-programmed one-off low investment between the two conditions: Whilst there is a dip in returns pre-manipulation for both conditions, post manipulation we see higher returns in the intervention condition compared to the dip in returns seen in the control condition in the right panel

the control condition changed their returns in pre-transgression trials between the first and second RTG, $\Delta M = 0.00$, 95% CI $[-0.01, 0.02]$, $t(318.64) = 0.21$, $p = .833$. Full results are provided in the supplement.

Applying the same model to the returns after the transgression (see the supplement for full results), we again find a significant interaction between Condition and Game. Participants in the control condition decreased their post-transgression returns from the first to the second RTG, $\Delta M = 0.07$, 95% CI $[0.04, 0.10]$, $t(325.03) = 5.17$, $p < .001$. There was no significant change for participants in the intervention condition, $\Delta M = -0.01$, 95% CI $[-0.04, 0.02]$, $t(313.90) = -0.83$, $p = .407$. When questionnaire scores for borderline traits, mentalising and emotion regulation abilities were added as explanatory variables, we found no interaction effect of these questionnaire scores with the Condition variable, nor a main effect of the questionnaire scores on participants returns in the RTG.

Taken together, we find that participants in the control condition sent lower percentage returns in the second game, despite the HMM investor sending on average higher investments in the second game. Those in the intervention group returned higher percentage returns in the second game, with the investor also sending higher investments. These higher returns in the intervention compared to the control condition were not purely driven by reciprocity towards higher investments, since we found a Condition by Game interaction whilst controlling for investment in the model, and a reduced effect of investment in the intervention condition. Whilst the intervention increased participants returns overall, it did not appear to increase participants' returns after the transgression by the other player. However, it may have countered the tendency to lower returns after the transgression in the second game compared to the first game, which was shown by participants in the control condition.

3.1   Emotion self-reports

Participants in the intervention condition rated their emotion on valence (negative to positive) and arousal (low to high) after each investment. To assess the impact of the intervention on these emotional reactions, we used linear mixed-effects models (one for valence, and one for arousal) with fixed effects for Game (pre vs post intervention) and Investment, as well as interaction between Investment and Game, with participant-wide random intercepts and random slopes for Game. This showed that higher investments were associated with more positive emotions, $F(1, 3, 448.17) = 2, 108.08$, $p < .001$, and higher arousal, $F(1, 3, 453.24) = 1, 505.03$, $p < .001$. In addition, the positiveness of emotion declined between the two games, $F(1, 117.20) = 17.99$, $p < .001$, as did arousal, $F(1, 117.19) = 5.52$, $p = .021$. There was no indication that the effect of the investment on either aspect of emotion was affected by the intervention, as there was no interaction between Investment and Game on valence, $F(1, 3, 419.70) = 1.49$, $p = .222$, or arousal, $F(1, 3, 409.69) = 0.12$, $p = .726$. This indicates that participants in the intervention condition returned higher amounts post-intervention, despite their emotional reaction to investments remaining largely the same.

3.2   Evaluation of the investor

Participants rated the HMM investor in the second game as less cooperative ($\Delta M = 0.42$, 95% CI $[0.15, 0.69]$, $t(317) = 3.10$, $p = .002$), less trustworthy ($\Delta M = 0.43$, 95% CI $[0.16, 0.70]$, $t(317) = 3.19$, $p = .002$), less friendly ($\Delta M = 0.40$, 95% CI $[0.17, 0.64]$, $t(317) = 3.36$, $p = .001$) and more selfish ($\Delta M = -0.36$, 95% CI $[-0.61, -0.10]$, $t(317) = -2.76$, $p = .006$), than the HMM investor in the first game. Participants in the intervention condition rated players higher than those in the control condition on cooperativeness ($\Delta M = 0.40$, 95% CI $[0.00, 0.80]$, $t(317) = 1.95$, $p = .052$) and lower on selfishness ($\Delta M = -0.41$, 95% CI $[-0.80, -0.02]$, $t(317) = -2.04$, $p = .042$). There was no evidence for an interaction effect between Condition and Game on any of the attributes.

When asked during debrief whether they thought the investors they faced were Human or not, 40% of participants thought they were either facing a human or were not sure of the nature of the opponent. Many answers reflected participants projecting human traits such as "spitefulness" or "greed" onto the artificial opponent's behaviour.

3.3   Transfer to the repeated Prisoner's Dilemma game

We next asked whether the intervention had any discernible effect on participants' behaviour in a different, repeated Prisoner's Dilemma game. Predicting the probability of a cooperative action with a logistic mixed-effects regression model, with Condition and Phase (before or after defection trial) as fixed effects and a random intercept for participants, showed a decline in cooperation after defection by the other player, $\chi^2(1) = 237.67$, $p < .001$, but no evidence for a different cooperation rate in the intervention condition compared to the control condition, $\chi^2(1) = 0.10$,
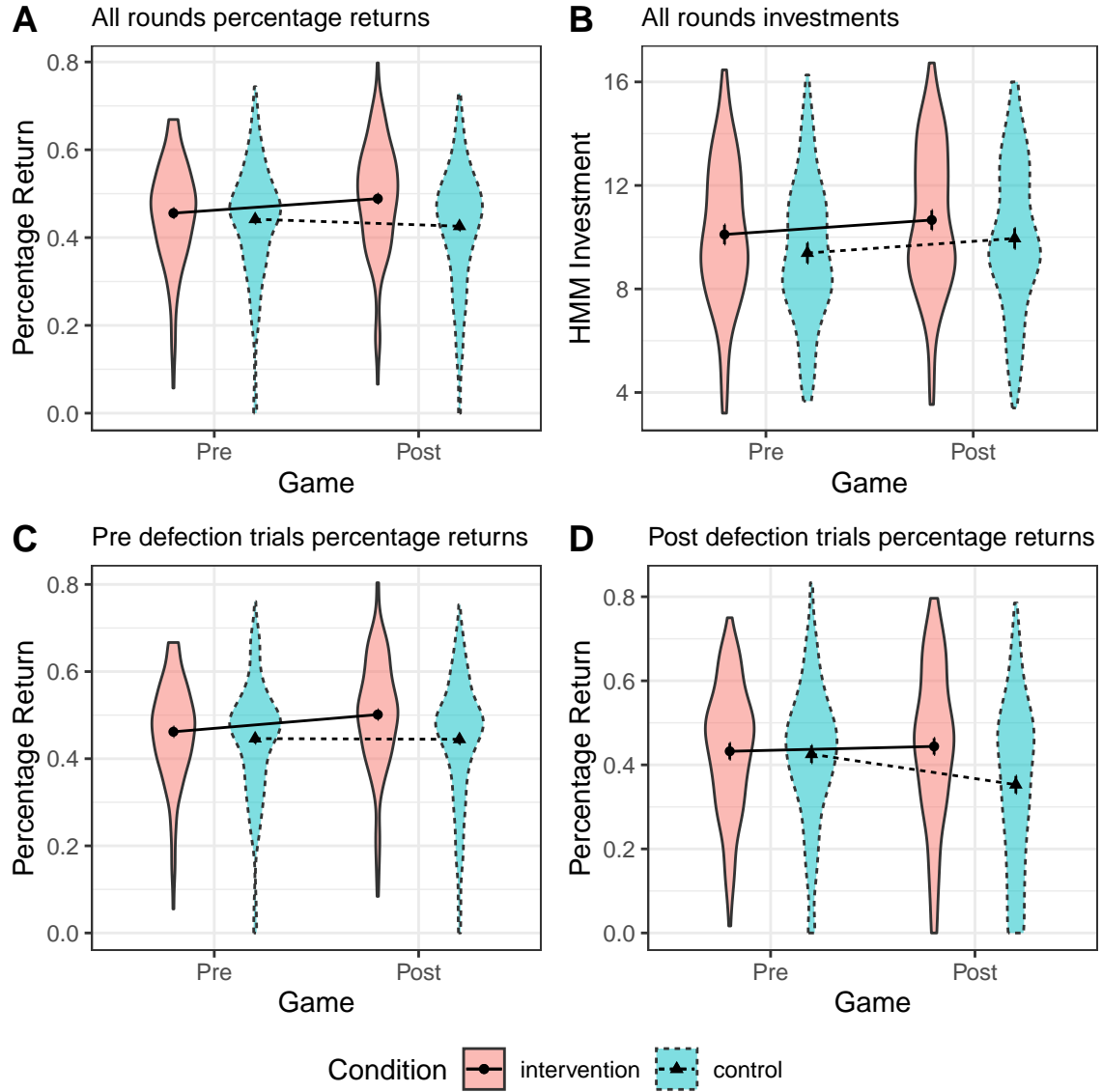
Figure 4: A: Marginal means and distributions of percentage trustee returns over all rounds, shown across participants by Game number and Condition. B: Marginal means and distributions of investments over all rounds for HMM investors, by Game number and Condition. C: Marginal means and distributions of percentage trustee returns across all participants for pre-defection trials only, by Game number and Condition. D: Marginal means and distributions of percentage trustee returns across all participants for post-defection trials only, by Game number and Condition.
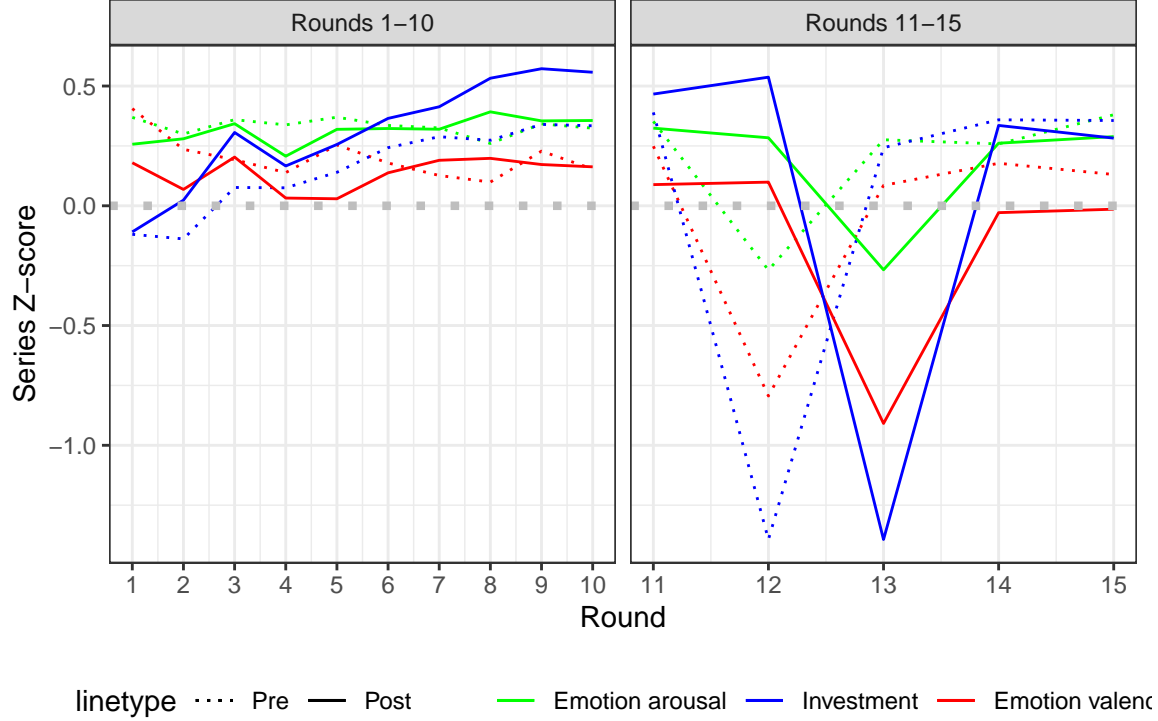
Figure 5: Self-reported emotion valence and arousal as well as investment z-scores for each round of the repeated Trust Game averaged across participants in the intervention condition only.

$p = .754$, or a different response to defection between the conditions, $\chi^2(1) = 0.23$, $p = .635$. As such, there is no evidence that the intervention affected behaviour in this game.

4 HMM analysis of participant returns

We used hidden Markov models (HMMs) to further assess differences between the intervention and control condition in participants' reactions to the investor. As in the models for the investor, these HMMs assume behaviour is governed by latent states, with participants' switches between states now dependent on the investments made. We also allowed for differences between games and conditions in how investments govern state transitions. More in particular, we fitted five main models which all regressed state transition probabilities onto investments, as well as on additional contrast-coded predictors for condition and/or game number. In the most complex model (HMM-full), the transition probabilities were allowed to differ between all four combinations of game number and condition. The HMM-coax model allowed differences between post-intervention and the other three conditions (pre-intervention, pre-control, post-control) assuming these latter were the same. Similarly, the HMM-ctrl model allowed differences between post-control and the other three conditions. The HMM-prepost model allowed differences between the first and second RGT. Finally, the HMM-inv model did not allow transition probabilities to differ between conditions or game numbers, modelling them only as a function of investment. As the number of hidden states was unknown, for each model we estimated versions with 2 to 7 states, and used the BIC to select the best fitting model. Generally, best fitting models had between 5 to 7 hidden states.

Focussing on models with 5 latent states (which is the optimal number for the HMM-full model), likelihood ratio tests showed that the HMM-full model fits significantly better than HMM-ctrl ($\chi^2(40) = 138.82$, $p < .001$), HMM-coax ($\chi^2(40) = 265.73$, $p < .001$) and HMM-prepost ($\chi^2(40) = 125.67$, $p < .001$). This is consistent with state transitions differing both due to game number and condition as can be seen in Figure 6.

Taking the best-fitting 5-state HMM-full model, we used a local decoding procedure to assign observations (participants' returns on trials) to latent states. The states are ordered by expected return, with state 1 having the lowest mean return and state 5 the highest. Figure 7 shows that participants were more likely to be in a lower return
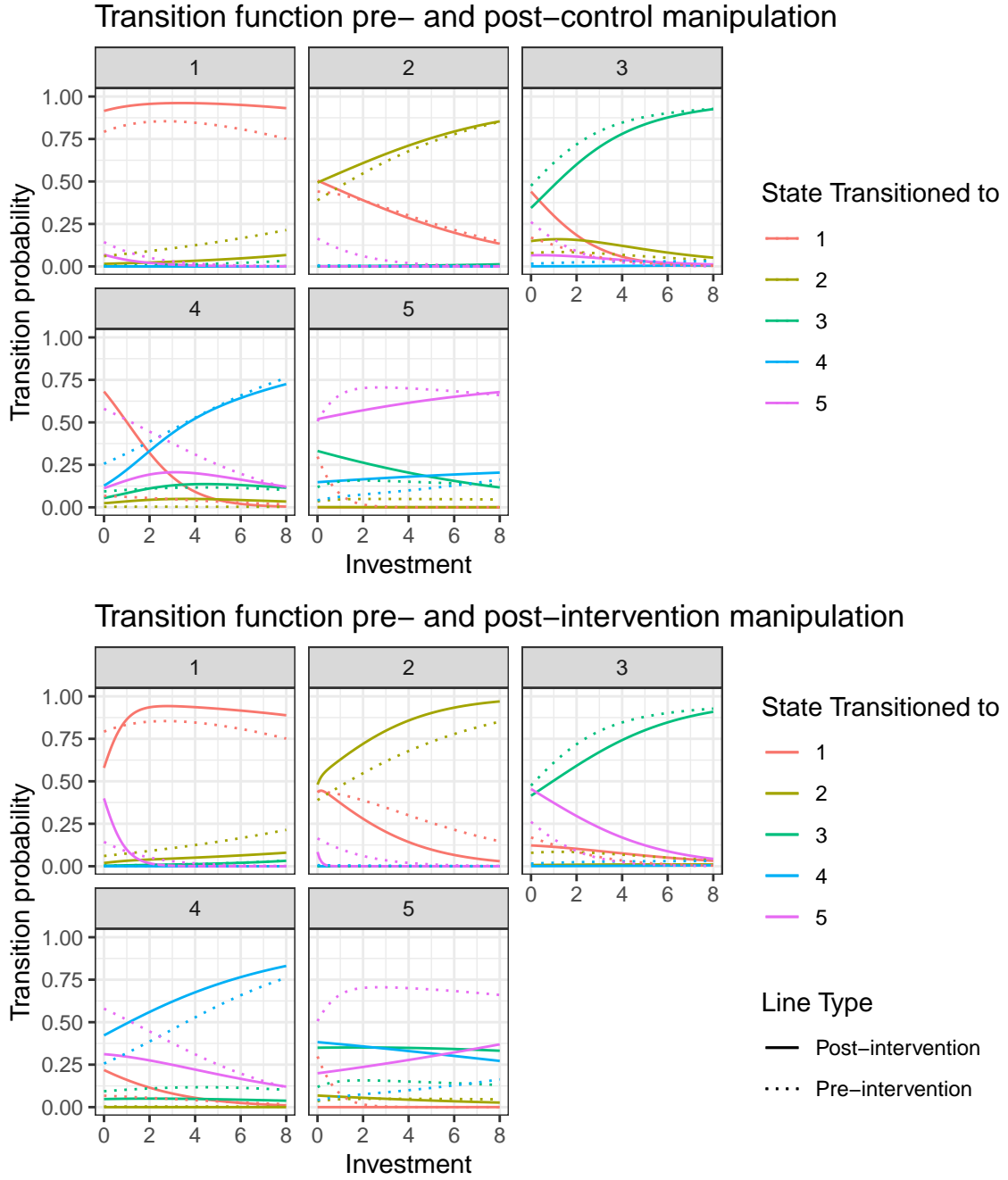
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Figure 6: Transition function for the HMM-full trustee model. Each panel represents the state transitioned from, and each color the state transitioned to. Solid lines show estimated transition probabillities post-manipulation. Dotted lines show the same probabilities prior to the manipulation
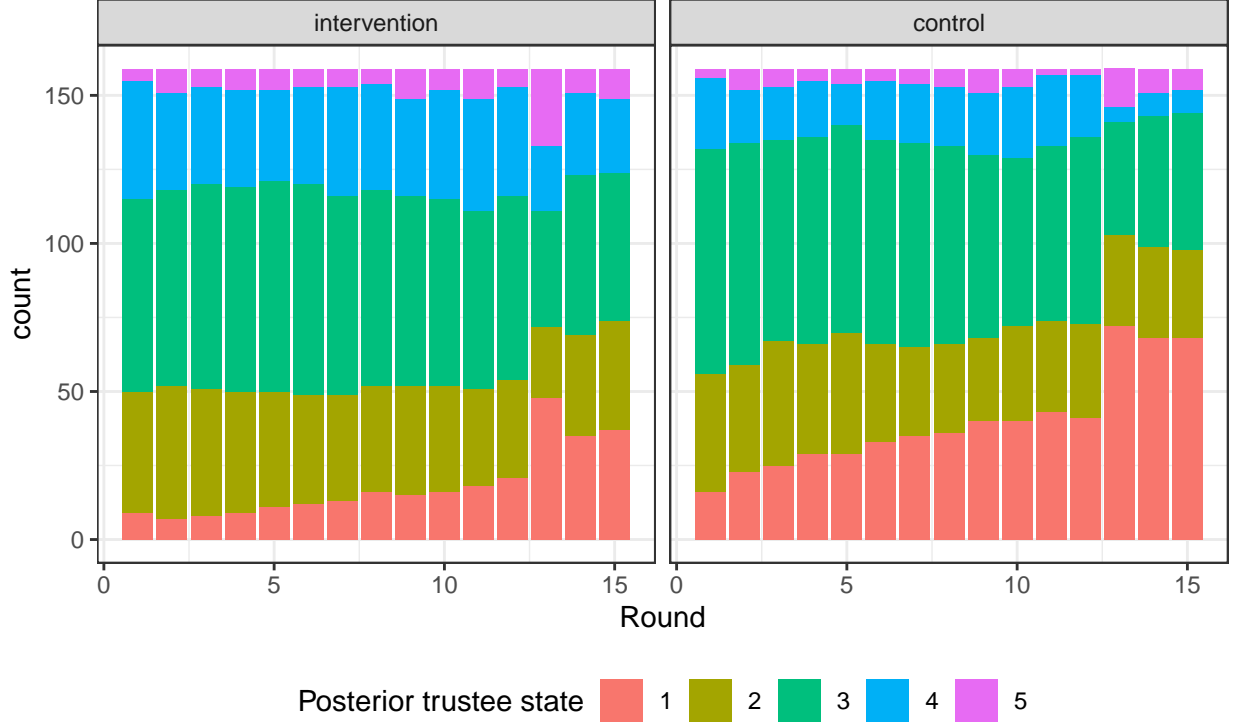
Figure 7: Distribution of posterior trustee states post manipulation by condition for all rounds, as estimated by the most likely posterior state in the best fitting HMM model (HMM-full) using a local decoding procedure.

state in the control condition compared to the intervention condition both pre and post defection. For instance, in round 5, state 1 was the most likely posterior state for only 7% of participants in the intervention condition compared to 24% in the control condition ($\chi^2(1) = 8.26, p < 0.01$). For the post-defection trial after the intervention (round 14), state 1 was the most likely state for only 22% of participants in the intervention condition compared to 43% in the control condition ($\chi^2(1) = 14.70, p < 0.001$). Whilst the posterior states indicate that the intervention was effective, a non-negligible proportion of participants in the intervention condition did not exhibit the coaxing behaviour promoted by the intervention. Directly following the low investment in round 13, 30.2% of participants in the intervention condition were assigned to state 1 with the lowest average returns. There is thus clear heterogeneity in the effectiveness of the intervention.

5   Discussion

In this experiment, human participants took the role of the trustee in a repeated trust game (RTG) where they faced artificial computer agents who's behaviour was partly determined by participants' returns. The behaviour of the artificial investors was determined by a 3-state hidden Markov model (HMM), which was estimated from the behaviour of humans in the RTG in prior research. Overall, investments and returns by the artificial and human agents replicated that of human dyads in prior research using the RTG (Charness, Cobo-Reyes, and Jiménez 2008; Fiedler, Haruvy, and Li 2011). This, together with participants' reported uncertainty about whether they faced a human or artificial investor, shows the potential of using HMM-based artificial agents to mimic human behaviour in economic games, whilst offering a higher degree of experimental control.

The aim of the cognitive intervention was to articulate the potential unwanted effects of acting on impulse after a transgressive action from the investor in the form of a one-off low investment. After the intervention, participants sent back higher returns compared to before the intervention, and did not decrease their returns after a transgressive action like participants in the control condition did. The overall higher returns after the intervention occurred despite participants' emotional reactions to the investments remaining largely the same as before the intervention. This indicates the intervention achieved its goal of encouraging participants to respond in a non-impulsive and considered manner, overriding an emotional urge to retaliate.

That participants generally send higher returns to the investor after the intervention is unlikely due to a general learning effect unrelated to the intervention, as participants in the control condition did not increase their returns. Also, as participants in the intervention and control condition faced the same HMM investor, the higher post-intervention returns are not solely due to a difference in investor behaviour. As the investor reacts to participants' returns, those who return more will generally see higher investments. But this is driven by the magnitude of their returns, not by a change in the strategy of the investor. Finally, as there were no differences between conditions in how participants rated the first and second HMM agent on attributes such as cooperativeness and trust, the increased returns are unlikely to be the result of a more favourable evaluation of the investor. Rather, we find it most likely that the increased returns are due to participants inferring from the intervention that pro-social and trustworthy behaviour may generally motivate the investor to send high investments, which can provide more beneficial outcomes to them in the long run.

The effect of the intervention was not transferred to the Repeated Prisoner's Dilemma (RPD) game. There was no difference between the intervention and control condition in the rate of cooperation, whether before or after a preprogrammed defection by the artificial agent. As the prisoner's dilemma is a popular economic game, it is possible that participants had a strong prior commitment towards the strategy they would adopt, which was not overridden by the intervention. The RPD also involves much coarser actions (cooperate vs defect) than the finer-grained returns in the RTG. This would make it more difficult to observe more subtle effects of the intervention. As such, the RPD might not be the best choice for any knowledge transfer. In any case, we can not rule out that the effects of the brief cognitive intervention, which explicitly focused on the RTG, are confined to the RTG. Future research will need to assess whether transfer to other games is possible.

Analysing participants' behaviour with hidden Markov models, we found clear individual differences in how returns changed between the pre- and post-intervention RTG, which can be seen as a proxy for the effectiveness of the intervention. Some participants may not have been convinced that coaxing via high returns was a good way to establish cooperation and decided to reduce their returns in the second trust game. Their impulse to "punish" the other player for a transgression may have been too strong to be overridden by the intervention. This was also evident from the participants' replies to a question about whether they would change their behaviour, just after receiving the intervention. Other participants responded to the intervention and increased their returns. Heterogeneity in response to treatment is common in psychiatry and related fields. Such heterogeneity may reflect the complex nature of mental health problems, which may be best viewed as complex systems involving interactions between neuro-computational processes and socio-environmental contexts evolving over time (Fried and Cramer 2017). This view was used to justify computational psychiatry's difficulty in establishing differential and reliable predictors of likely treatment response (Hitchcock, Fried, and Frank 2022). Here, we found heterogeneity in reaction to a relatively explicit intervention by a sample of participants from the general population. This suggests that the issue of variable treatment responses may result from the interaction of two sources of variability: the phenotyping of the disorder as well as the phenomenological aspects of the intervention itself. As such, a rigorous exploration of the determinants of inter-individual differences to an intervention in the general patient population is required. Overall, we are encouraged that our brief cognitive intervention, consisting of reading a short text detailing a non-impulsive reaction to low investments, can lead to clearly differentiated behaviour. In future studies, we aim to explore the effects of improved cognitive interventions to enhance cooperative behaviour. We may enhance engagement by making the intervention more interactive and visually appealing, rather than the "dry" textual format used in the experiment. It would also be of interest to test such interventions with who suffer from an inability or unwillingness to repair relationships after an accidental breakdown of trust, such as people with Borderline Personality Disorder. The relative ease by which online interventions can be assigned, and the opportunity for people to test the effect of their behaviour with artificial, but human-like agents, may pave the way for efficient, low-cost, effective treatment programmes which may help a wide-variety of people overcome detrimental actions in social situations.

6   Conclusion

We explored the effect of a brief cognitive intervention on the behaviour of human trustees facing adaptive artificial investors designed to replicate the behaviour of human investors in the repeated trust game. Each state defines different levels of a cooperative response with the agent able to transition between these states based on the behavior of the human opponent. Feedback from participants indicated that these agents were sometimes perceived as humans. Their strategy led to emergent cooperative behaviour when playing the repeated trust game with human players. The intervention, promoting a less impulsive reaction to transgressive actions, led to coaxing behavior and less negative reciprocity when the investor sent a very low investment. It also led to more trustworthy behavior prior to the pre-programmed defection trial and to coaxing behavior after defection. Whilst this intervention effect varied between

participants and generally was not transferred to a new game, an HMM analysis of participant's play post intervention showed differentiated patterns of transitions between latent states, indicating a change in the effect of the opponent action on the probability of transitioning between latent mental states.

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