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Intra-Choice Dynamics Shape Social Decisions

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Abstract

Do people have well-defined social preferences waiting to be applied when making decisions? Or do they have to construct social decisions on the spot? If the latter, how are those decisions influenced by the way in which information is acquired and evaluated? These temporal dynamics are fundamental to understanding how people trade off selfishness and pro-sociality. Here, we investigate how the temporal dynamics of the choice process shape social decisions in three studies using response times and mouse tracking. In the first study, participants made binary decisions in mini-dictator games with and without time constraints. Using mouse-trajectories and a starting-time drift-diffusion model (stDDM), we find that, regardless of time constraints, selfish participants were delayed in processing others' payoffs, while the opposite was true for pro-social participants. The independent mouse-trajectory and computational modeling analyses identified consistent measures of the delay between considering one's own and others' payoffs (self-onset delay, SOD). The SOD correlated with individual differences in pro-sociality and predicted heterogeneous effects of time constraints on preferences. We confirmed these results in two additional studies, one a purely behavioral study in which participants made decisions by pressing computer keys, and the other a replication of the mouse-tracking study. Together these results indicate that people preferentially process either self or others' payoffs early in the choice process. The intra-choice dynamics are crucial in shaping social preferences and might be manipulated via nudge policies (e.g., manipulating the display order or saliency of self and others' outcomes) for behavior in managerial or other contexts.

Key words: social preferences; information processing; drift-diffusion model; mouse-tracking

1. Introduction

Social decisions involving tradeoffs between selfishness and pro-sociality are ubiquitous in managerial settings, organizations, and societies. For instance, many decisions in teams or organizations concern the distribution of money or other scarce resources between individuals. Managers that prioritize fairness of relationships between themselves and employees, as well as relationships between team members, may have positive effects on organizational performance (Breugem et al. 2022, Cappelen et al. 2007, Moon 2017, Pfeffer 2007). Thus, it is important to understand how people construct social preferences to make decisions, as well as how/why social decision making may change in different circumstances. Do people have well-defined social preferences waiting to be applied when making decisions? Or do they have to construct social decisions on the spot? If the latter, how are those decisions influenced by the way in which information is acquired and evaluated?

Traditionally, researchers have assumed that social decisions are determined by the given values of the selfish and pro-social attributes together with subjective weights assigned to those attributes (Bolton and Ockenfels 2000, Charness and Rabin 2002, Fehr and Schmidt 1999, Liebrand and McClintock 1988). In recent years, research has increasingly turned to the dynamics underlying decisions and proposed dynamical models of the decision process. These models have the advantage of accounting for and being informed/constrained by more than just choice data; they can explain or incorporate response times (RTs, Baldassi et al. 2020, Clithero 2018b, Frydman and Nave 2017, Guo et al. 2017, Mischkowski et al. 2018, Pleskac and Busemeyer 2010, Roe et al. 2001, Spiliopoulos and Ortmann 2018, Trueblood et al. 2014, Webb 2019), eye-movements (Fiedler et al. 2013, Fisher 2021, Krajbich et al. 2010), and brain activity (Basten et al. 2010, Edelson et al. 2018, Gluth et al. 2012, Pisauro et al. 2017, Turner et al. 2013). They allow us to decompose the decision process and ask to what extent it is driven by categorical predispositions (Desai and Krajbich 2022, Kvam and Busemeyer 2020, White and Poldrack 2014, Zhao et al. 2020), attentional priorities (Amasino et al. 2019, Sheng et al. 2020, Teoh et al. 2020), attribute latencies (Amasino et al. 2019, Maier et al. 2020, Sullivan et al. 2015, Sullivan and Huettel 2021), and the relative weights on the attributes. This is, in turn, improves out-of-sample predictions for distinct contexts, for example allowing us to predict how behavior would change under time constraints (Chen and Krajbich 2018, Clithero 2018a, Guo et al. 2017, Milosavljevic et al. 2010, Spiliopoulos and Ortmann 2018, Trueblood et al. 2014).

Controversial results on the effects of time pressure and delay in social decision-making (Rand et al. 2012, Tinghög et al. 2013, Verkoeijen and Bouwmeester 2014) have brought further attention to the mechanisms of the choice process. Some researchers have argued for a dual-process account in which there is a fast and intuitive pro-social process and a slower, deliberative selfish process (Artavia-Mora et al. 2017, Cappelen et al. 2016, Mischkowski et al. 2018, Rand et al. 2012), although others have found that faster-responding subjects were more selfish (Piovesan and Wengström 2009). Studies based on sequential sampling models have shown that both fast and slow decisions can be explained by a single comparison process (Chen and Krajbich 2018, Hutcherson et al. 2015, Krajbich et al. 2015a, Krajbich et al. 2015b, Teoh et al. 2020). The sequential sampling approach is analogous to the standard utility-function modeling approach, but yields both choice outcomes and RTs. In these models, the specified payoffs and subjective weights on those payoffs determine the rate at which support (or evidence) is gathered in favor of the pro-social or selfish options and determine both the choice outcome and RT.

In addition to their subjective weights on self and others' payoffs, people may have general predispositions that favor pro-social or selfish choices regardless of the details of a particular choice problem (Chen and Krajbich 2018). Within the sequential sampling framework, such a predisposition can be quantified by the so-called starting point (analogous to a prior in a Bayesian framework), which measures the relative amount of evidence required to take one type of action versus another (e.g., pro-social vs. selfish). Note that, despite the label "starting point", this term does not necessarily indicate different levels of relative evidence at the start of a trial, instead it indicates that the amount of newly sampled, trial-specific relative evidence required to select one type of choice is higher or lower than the other. Sequential sampling models predict that time pressure (delay) should exacerbate (diminish) the influence of predispositions on social choices (Chen and Krajbich 2018). Additionally, time pressure may change attentional priorities to self versus others' payoffs leading to choices in favor of the payoff attended to first or most (Teoh et al. 2020).

Here, we investigate the temporal dynamics underlying social decisions and how intra-choice dynamics shape social preferences using two mouse-tracking and one behavioral studies. In the first mouse-tracking study, participants made a series of decisions about two options that typically involved conflict between selfishness and pro-sociality while we tracked their mouse trajectories. The mouse-trajectory offers an accessible, data-rich, and real-time window into how people categorize and form preferences and decisions (Freeman and Ambady 2010, Konovalov and Krajbich 2020, Stillman et al. 2020, Stillman et al. 2018). We use those mouse trajectories to identify the relative onset time of self and others' payoffs considerations (self-onset delay, SOD). Independently of the mouse trajectories, we model the choice and RT distributions using a starting-time drift-diffusion model (stDDM), which quantifies both the weights given to the attributes and their onset times (Amasino et al. 2019, Maier et al. 2020, Sullivan and Huettel 2021). Based on these analyses, we evaluate how the SOD along with the predispositions and the weights explain individual differences in social preferences and preference changes across time pressure and delay conditions.

Our results reveal that people are heterogeneous in the order of processing self and others' payoffs over the course of a decision. Selfish participants process self payoffs (*self* attribute) earlier than others' payoffs (*other* attribute), while the opposite is true for pro-social participants. The participants' pro-sociality in the time-free condition correlates with mouse-trajectory-derived self-onset delay (MTSOD) in the time-free, time-pressure, and time-delay conditions. The SOD estimated with the starting-time drift-diffusion model (stDDM), i.e., response-time-derived self-onset delay (RTSOD), is highly correlated with the mouse-trajectory-derived self-onset delay (MTSOD) across participants, lending credence to both methods of estimating this aspect of the decision process. We find that time pressure amplifies participants' general preferences, making them more pro-social or selfish, while time delay attenuates these general preferences, making them less extreme. These effects of time pressure and delay are explained by the magnitude of the SOD in conjunction with the subjective weights on self and others' payoffs.

In the second purely behavioral study, participants made decisions by pressing keys rather than moving the mouse. In the third replication mouse-tracking study, we randomized the games across time conditions for each participant. Using these data, we checked and confirmed the robustness of the main results above: differences in processing delays explain individual differences in social preferences and predict social preference changes under time pressure versus delay.

These results reveal the intra-choice dynamics underlying social decisions and how people construct social preferences through a sequential sampling process. Using two independent analyses, the mouse-trajectory analysis and the computational modeling analysis, we identify that people are heterogenous in the onset times of considering self and others' payoffs when deciding whether to be pro-social or selfish. We find that the attributes of the choice problem are, to some degree, evaluated sequentially. In other words, the attributes do not all affect the choice process to the same degree over the whole course of the decision. This is consistent with work on Decision Field Theory (Roe et al. 2001) and multi-attribute attentional DDM (Fisher 2021, Yang and Krajbich 2022), which argue that attention can shift between both options and attributes over the course of the decision.

In contrast to Rand et al.'s (2012) theory that people are intuitively pro-social and then become more selfish with deliberation, we show that the effects of time constraints depend on individual-specific processing dynamics. Our results show that, more than predispositions, the

SOD (the relative onset time of self and others' payoffs considerations) is a key predictor in explaining people's social preferences and predicting how their preferences change under time pressure versus delay. This finding not only supports models of sequential (rather than parallel) information processing, but also highlight the important possibility that features of the choice problem itself (i.e., choice architecture manipulations) could be used to promote pro-social decision making within managerial or other contexts. For instance, time delay/pressure will not be an effective manipulation to promote pro-sociality, on average, because time constraints do not alter social preferences in the same way for everyone. Instead, one could provide information about others' outcomes before one's own outcomes (Johnson et al. 2007, Teoh et al. 2020, Weber et al. 2007), in order to promote more pro-social behavior.

2. Study 1: Mouse-Tracking Experiment

2.1. Materials and Methods

2.1.1. Experimental Task

In the experiment, participants made binary decisions in 300 mini-dictator games, where they allocated money between themselves (dictator) and another participant (receiver) (Fig. 1). 240 out of the 300 games involved a conflict between selfishness and advantageous inequality aversion (Fehr and Schmidt 1999). In other words, each of these decisions offered participants the opportunity to reduce inequality by increasing the other's payoffs and decreasing their own. In the other 60 games, there was no conflict between selfishness and advantageous inequality aversion. In all games, the self and others' payoffs were integers from 10 to 99. The differences between self payoffs were from 1 to 10, and the differences between others' payoffs were from 1 to 62. When generating these games, we first fixed the parameters for a subgroup of 50 games (Games ID 1-50). We then decreased or increased all the payoffs by 1 (to get 2 subgroups, 100 games), 2 (to get 2 subgroups, 100 games) or 3 (to get 1 subgroup, 50 games). Thus, the differences between self payoffs and the differences between others' payoffs were identical across the six subgroups, though the payoffs were slightly different.[1]

We divided the 300 trials into four blocks in the experiment. The first and the last were time-free blocks (100 trials, 2 subgroups in each) in which participants had unlimited time to make each of their decisions. The other two in between were time-pressure and time-delay blocks (50 trials, 1 subgroup in each). This ensured that the mini-dictator games in different time conditions had the same properties, i.e., identical differences between self payoffs and identical difference between others' payoffs. In the time-pressure block, participants had to make each decision within 2 seconds. In the time-delay block, participants had to make each decision after the game had been displayed for 10 seconds. The order of the time-pressure and time-delay blocks was counterbalanced across participants, as were the positions of the self and others' payoffs (top or bottom). The locations (left or right) of the selfish and pro-social options were randomized across trials.

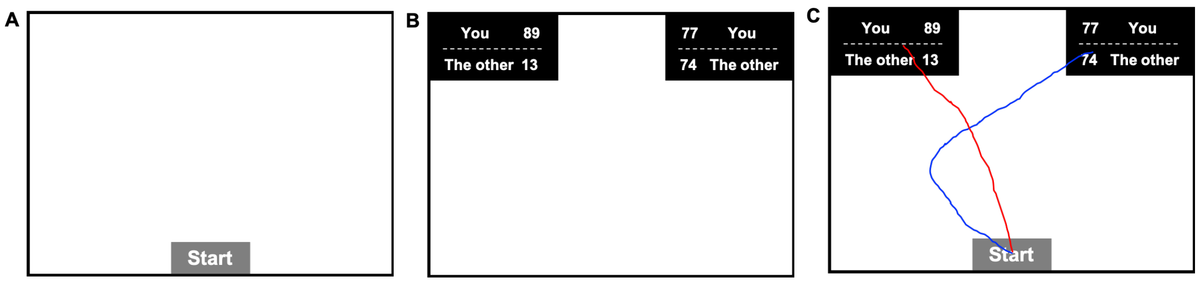

Fig. 1. Timeline of the time-free condition. (A) Participants clicked the "Start" button at the bottom center of the screen to proceed to the decision stage. (B) The decision stage consisted of two options, one in each top corner of the screen. In this example, the top left corner contains the selfish option, which has a higher payoff for self (89 vs. 77) and the top right corner contains the pro-social option, which has a higher payoff for other (74 vs. 13). (C) The blue and red curves illustrate possible mouse trajectories for choosing the pro-social and selfish options, respectively. Participants made their choice by clicking the mouse button once the cursor was on an option. Note: the text is translated from Mandarin and enlarged for display purposes.

[1] In the experiment, the self payoff of 91 in a game was mistakenly input as 11. All participants in Study 1 made decisions for the trial with mistaken parameter. Thus, this error had no systematic effects on our results.

2.1.2. Procedure

We provided participants with instructions before each block. They could only start the experiment when they correctly answered the comprehension questions at the end of the instructions. Each participant was paired with another participant and played both the role of dictator and receiver. Both participants made decisions in the role of dictator and thus the pairing was purely for calculating payoffs at the end. Specifically, participants made decisions by moving the mouse cursor toward an option in the upper left or right corners of the screen and clicking that option. In addition to the choice and the associated RT, we tracked the mouse cursor's (x, y) position using MouseTracker (Freeman and Ambady 2010) with a temporal resolution of 70 Hz. Participants were instructed to start moving their mouse as soon as the two options appeared on the screen in the time-free and pressure conditions, and as soon as the 10-second delay was over in the time-delay condition. If they did not begin moving their mouse within 1 s in a given trial, a reminder dialogue box would appear on the screen after that trial. At the end of the experiment, one of the trials was randomly selected and paid out according to the participant's decision. That is, each participant's total payoff included the dictator's payoff in the selected trial, the receiver's payoff in their partner's selected trial, and the show-up fee.

2.1.3. Participants

A total of 117 university students (61 females, $mean = 21.4$ years, $sd = 2.0$ years) participated in Study 1 from April 20 to May 24, 2019. All participants were right-handed. On average, participants earned 6.6 US Dollars (including the show-up fee). The Internal Review Board of Zhejiang University approved the experiment, and all participants provided written informed consent.

2.1.4. Within-participant out-of-sample analysis

In the experiment, we used the 50 games with GameID 1-50 for the time-pressure condition, the 50 games with GameID 51-100 for the time-delay condition, and the 200 games with GameID 101-300 for the time-free condition. The order of the games was randomly displayed within each time condition for each participant. In the analysis below, we estimated participants' preferences in the time-free condition (β_f) using the 100 games with GameID 201-300. The mouse-trajectory analysis and computational modeling in the time-free condition was based on the 100 games with GameID 101-200.

2.2. Results

2.2.1. Behavioral Results

Participants chose the pro-social option more frequently than the selfish option in the experiment. The payoff differences in this study were designed to elicit a relatively high number of pro-social responses even though the average person places more importance on self, relative to other, payoffs. In the time-free condition, the mean fraction of pro-social choices at the participant level was 62.3% (*sd* = 24.3%). In the time-pressure and time-delay conditions, the mean fractions of pro-social decisions were 51.2% (*sd* = 25.6%) and 66.2% (*sd* = 24.1%), respectively. The mean RTs were 2.462 (*sd* = 1.697), 1.226 (*sd* = 0.277), 1.203 (after the enforced delay of 10 seconds, *sd* = 0.781) seconds in the time-free, time-pressure and time-delay conditions respectively. Thus, in contrast to the predictions of an intuitive pro-social process, participants became more selfish under time pressure (two-sided Wilcoxon signed-rank test, $V = 5775.5$, $p = 10^{-11}$) and more pro-social under time delay ($V = 1554$, $p = 10^{-5}$), on average. However, there was substantial heterogeneity in pro-social behavior and substantial heterogeneity in the size and direction of the time manipulation effects across individuals. We sought to explain this interindividual variability with the mouse-tracking data and computational modeling.

2.2.2. Effects of Self and Others' Payoffs on Mouse Trajectories

We first analyze, on average, how the subjective utility difference between the two options affects the mouse trajectories. To calculate the subjective utility difference between the two options, we estimated participants' pro-sociality. More specifically, we employed the inequality aversion model proposed by Fehr and Schmidt (1999) to estimate participants' social preferences (advantageous inequality aversion, β) using maximum likelihood estimation (MLE). A participant's utility for each option in the mini-dictator game is given by

$$U(P_{self}, P_{other}) = P_{self} - \beta(P_{self} - P_{other}) \tag{1}$$

where P_{self} and P_{other} are the self and others' payoffs, respectively. The parameter β indicates the participant's social preference, with higher β indicating stronger pro-sociality. Using each participant's estimated β in each time condition, we calculated the absolute subjective utility difference between the two options for each trial. The most common approach to analyzing mouse trajectories is to quantify the relative conflict present on a given trial (Stillman et al. 2018). Here, we compare the actual trajectory with a straight trajectory, with the logic that the greater the deviation from a straight path towards the chosen option, the greater the conflict between the two responses. Thus, the conflict is quantified by taking the area between the actual trajectory and a straight trajectory and is referred to as the area under the curve (AUC). Consistent with Stillman et al. (2020), in the time-free condition, the larger subjective utility difference corresponded to less conflict, i.e., lower AUC (model 1 in Table A1 of SI Note A, $coef = -0.044$, $p = 10^{-16}$). And it appeared that the mouse trajectory was sensitive to within-subject variation in subjective utility difference (Fig. A1 in SI Note A). In the time-pressure condition, the subjective utility difference had no significant effects on AUC (model 3, $coef = -0.000$, $p = 0.493$), and in the time-delay condition, the subjective utility difference had weaker effects on AUC (model 7, $coef = 0.037$, $p = 10^{-16}$) than the time-free condition (model 5, $coef = -0.004$, $p = 0.028$; see SI Note A for more details).

Next, we investigated how the attributes of self and other's payoff affected the mouse trajectories. To do so, we normalized the coordinates of the center of the "Start" button to (0,0), the top left to $(-1,1)$, and the top right to $(1,1)$ (Lim et al. 2018, Sullivan et al. 2015). We divided the RT of each decision into 100 equal time-intervals.[2] The start position of each mouse trajectory was at time point 1, and the time an option was clicked was at time point 101. For

[2] The response time (RT) in the time-delay condition was from the time when participants could move their mouse to the time when they clicked the mouse.

each of the 101 time points, we calculated a trajectory angle from the position at that time to (0, 0). The trajectory angle was $-45°$ along the line directly to the left option, $+45°$ along the line directly to the right option, and $0°$ along the line directly upwards (see Fig. A2 in SI Note A for illustrations of the trajectory angle).

We estimated linear regressions of how the trajectory angle at each time point was affected by the relative payoffs for self (DiffSelf = $\text{SelfPayoff}_{\text{right}} - \text{SelfPayoff}_{\text{left}}$) and for other (DiffOther = $\text{OtherPayoff}_{\text{right}} - \text{OtherPayoff}_{\text{left}}$) for the three time conditions separately. The regression for participant i at time point t in each time condition was:

$$\text{Angle}_{itj} = \gamma_{itc} + \gamma_{its} \times DiffSelf_j + \gamma_{ito} \times DiffOther_j \tag{2}$$

where γ_{itc} is the constant, γ_{its} is the coefficient for the difference in self payoffs, γ_{ito} is the coefficient for the difference in the other's payoffs, and j is the index of trials (observations).

At the participant level, the average coefficient on the self payoff (free: $mean = 0.355$, $sd = 0.201$; pressure: $mean = 0.619$, $sd = 0.669$; delay: $mean = 1.831$, $sd = 0.972$) was greater than the average coefficient on the other's payoff (free: $mean = 0.074$, $sd = 0.187$; pressure: $mean = 0.060$, $sd = 0.158$; delay: $mean = 0.442$, $sd = 0.316$) (two-sided Wilcoxon signed-rank tests, free: $V = 5951$, $p = 10^{-11}$; pressure: $V = 5887$, $p = 10^{-11}$; delay: $V = 6712$, $p = 10^{-16}$). That is, the self payoff had a stronger influence than the other's payoff on the mouse position over the course of the decision in the time-free, time-pressure and time-delay conditions (Fig. B1 in SI Note B).

To examine whether self and other's payoffs had different effects for participants with different degrees of pro-sociality, we grouped participants into four bins of equal size based on the quartiles (Q_1, Q_2, Q_3) of their preferences in the time-free condition (β_f) (extremely selfish group: $\beta_f \leq Q_1$; selfish group: $Q_1 < \beta_f \leq Q_2$; pro-social group: $Q_2 < \beta_f \leq Q_3$; extremely pro-social group: $\beta_f > Q_3$). Fig. 2 plots the coefficient difference between self and other's payoffs for each group, and shows that self and other's payoffs had different effects on the mouse-trajectories at different times for these four sub-groups. For participants in the extremely selfish, selfish and pro-social groups, self payoffs had stronger effects on the mouse trajectory than others' payoffs across all three conditions. In the extremely pro-social group, i.e., the most pro-social participants, the effects of others' payoffs, relative to self payoffs, were stronger in the time-free condition, equally strong in the time-pressure condition, and weaker in the time-delay condition. Moreover, the coefficient difference between self and others' payoffs decreased from the extremely selfish group to the extremely pro-social group in all three conditions (Fig. 2, see SI Note B for more details).

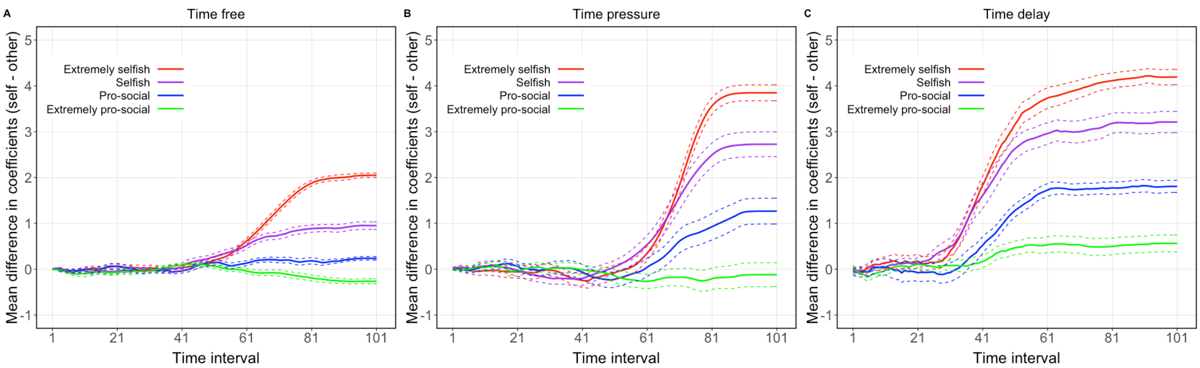

Fig. 2. The mean difference between the effects (coefficients) of the self and others' payoffs on the mouse trajectories. (A) Time-free condition; (B) Time-pressure condition; (C) Time-delay condition. Error bands denote standard errors.

2.2.3. Mouse-Trajectory-Derived Onset Time for Self and Others' Payoffs

Next, we estimated the onset time for each attribute using the mouse-trajectory data, namely the time that each attribute began (and continued) to significantly affect the mouse trajectory. We define the mouse-trajectory-derived self-onset delay (MTSOD) as the time that the self payoffs began to affect the mouse trajectory minus the time that the others' payoffs began to affect it. Thus, the MTSOD was negative if self payoffs affected the mouse trajectory earlier than the others' payoffs, and positive if the others' payoffs affected the mouse trajectory earlier than the self payoffs.

In the mouse-trajectory analysis above, we normalized each of the mouse trajectories into 100 intervals. This might distort onset times because a unit of MTSOD in trials with longer durations is longer in absolute time than a unit of MTSOD in trials with shorter durations. Therefore, here we extended the mouse trajectory at the last time point of each trial out to the maximum RT across all trials in each time condition.[3] Before doing this, we excluded trials with extremely long or short RTs using the IQR method. At the aggregate level, we eliminated trials with RTs above the 0.75 quartile by more than 1.5 times the interquartile range, or below the 0.25 quantile by more than 1.5 times the interquartile range in each time condition. In this case, 6.4%, 0.9% and 7.4% of the trials were excluded in the time-free, time-pressure, and time-delay conditions, respectively. Then we divided each of the extended trajectories into 100 equal intervals. In this case, all the mouse-trajectories in each time condition have the same duration, i.e., the maximum RT of that time condition.

We used the linear regression (2) above to identify the onset time of self and others' payoffs in the time-free, time-pressure, and time-delay conditions separately. This was done by carrying out a two-tailed test of the hypothesis that the estimated regression coefficient of interest would be significant at the level of 0.001, for each individual and time interval. We were interested in when they became significantly positive. The earliest time point at which the test was satisfied was then labeled as the onset time of that attribute for that participant. If an attribute never became significant, we set the onset time as 102. In the time-free condition, the mean MTSOD at the participant level was 7.957 (median = 21.000, *sd* = 62.560). The mean MTSODs were -7.632 (median = 0.000, *sd* = 42.590) and 6.709 (median = 4.000, *sd* = 48.216) in the time-pressure and delay conditions, respectively.

Fig. 3A plots the MTSOD across time-free and pressure conditions for each participant.[4] When analyzing the MTSOD data across all participants, we found that their magnitude

[3] We can get similar mouse-trajectory-derived self-onset delay (MTSOD) if we extend the trajectory at the last time point of each trial out to the maximum RT at the participant level or if we normalize each of the mouse trajectories into 100 intervals, the same as Sullivan et al. (2015) and Lim et al. (2018) (see SI Note F for more details).

[4] It is tricky to compare the MTSOD in the time-delay condition with other time conditions, since we cannot clearly identify the decision time frame, i.e., we do not know how much participants processed information during the 10-seconds enforced delay.

decreased under time pressure. Compared to the time-free condition, time pressure decreased the MTSOD for the 69 participants with positive MTSOD in the time-free condition (two-sided Wilcoxon signed-rank test, $V = 2202$, $p = 10^{-10}$), and increased (i.e., pushed closer to zero) the MTSOD for the 45 participants with negative MTSOD in the time-free condition ($V = 203.5$, $p = 10^{-4}$). This indicates that time pressure reduced the initial processing time advantage for the earlier-considered attribute. Note that the MTSODs were often reduced to zero in the time-pressure condition and there were 27 participants for whom neither payoff was deemed significant before the end of the decision. This is due to the fact that we used stringent significance thresholds ($p = 0.001$) when identifying the onset times; however the correlation between MTSOD and preferences is robust to the choice of significance threshold (Table C2 in SI Note C).

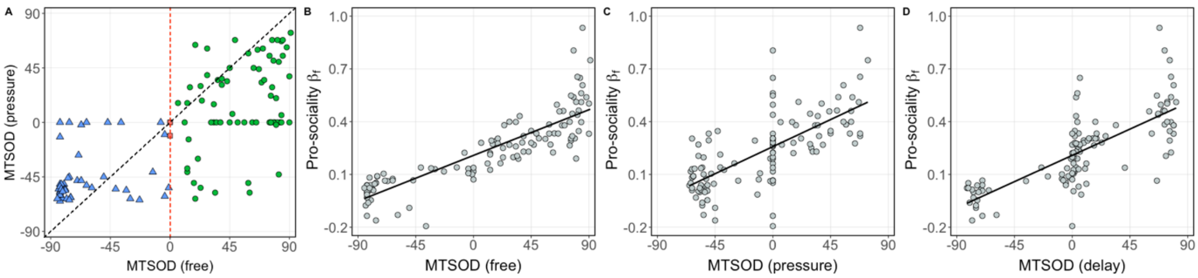

Fig. 3. Mouse-trajectory-derived self-onset delay (MTSOD) across time-free and pressure conditions (A) and correlations between pro-sociality and MTSOD (B-D). In (A), participants that consider self or others' payoffs first in the time-free condition are shown in green or blue, respectively. The black dotted line indicates the 45-degree line where all dots would fall if the MTSOD was equal in both conditions. (B) Pro-social preference parameter (β_f) in the time-free condition vs. MTSOD in the time-free condition; (C) β_f vs. MTSOD in the time-pressure condition; (D) β_f vs. MTSOD in the time-delay condition. The solid lines are the fitted regression lines. Each dot represents one participant.

In order to directly quantify the relationship between MTSOD and pro-social preferences, we computed their correlation (Fig. 3). In the time-free condition, the MTSOD computed from one half of the trials was correlated with the advantageous inequality aversion parameter, β_f, estimated from the other half of the time-free trials (Fig. 3B, two-sided Pearson correlation test,

$r(117) = 0.851$, $p = 10^{-16}$). That is, the earlier the participant started to process the other's payoff relative to the self payoff, the more pro-social the participant was. Moreover, the MTSODs for both time-pressure (Fig. 3C) and delay (Fig. 3D) conditions were correlated with β_f (pressure: $r(117)$ =0.690, p =10^{-16}; delay: $r(117)$ =0.761, p =10^{-16}). The results are similar if we exclude cases where an attribute did not become significant before the response was made (SI Note C). The separate mouse-trajectory-derived onset times of the self and others' payoffs were each significantly correlated with β_f as well (see SI Note D). [5] These results show that the mouse-trajectory data provide information about participants' social preferences, even under time constraints. Moreover, the MTSOD can explain additional variability in individual choices beyond the utility parameters (partial F-tests, free: F-value=84.459, $p = 10^{-14}$, pressure: F-value=182.320, $p = 10^{-16}$; delay: F-value=38.306, $p = 10^{-8}$, SI Note E and G). These findings alleviate the potential concern that the relationship between MTSOD and social preferences might be an artifact of the fact that relatively larger influences of self or other's payoffs could make it easier to detect the onset of one attribute earlier in the mouse trajectory (Sullivan et al. 2015).

2.2.4. Computational Modeling of Choice Outcomes and Response Times

To model the decision process, we employed a time-varying DDM. This DDM allows for different onset times for each attribute to affect the drift rate, and thus we refer to it as the starting-time drift-diffusion model or stDDM (Amasino et al. 2019, Maier et al. 2020) (Fig. 4). The drift rate captures the rate of evidence accumulation in favor of one option over the other. Here, we model the drift rate as a linear function of the difference in self payoffs (*SelfDiff*), the other's payoffs (*OtherDiff*), and a constant (to account for any fixed bias towards the selfish or pro-social option during the evidence accumulation process). Additionally, we allow for a delay

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[5] If we exclude participants whose onset time of the self or the other attribute was greater than 101, β_f was correlated with the onset times of the self and others' payoffs in the time-free and time-pressure conditions. And β_f was correlated with the onset times of the self payoffs but not significantly correlated with the onset times of the others' payoffs in the time-delay condition (SI Note D).

before one of the payoff differences affects the drift rate. If the self payoff enters into the process first, the update equation for the relative evidence (R) is:

$$R_{t+1} = R_t + \left(\omega_c + \omega_s * SelfDiff + \left(t > |\frac{SOD}{\mathrm{dt}}|\right) * \omega_o * OtherDiff\right) * \mathrm{dt} + \varepsilon \tag{3}$$

If the other's payoff enters the process first, the update equation for the relative evidence is:

$$R_{t+1} = R_t + \left(\omega_c + \left(t > |\frac{SOD}{\mathrm{dt}}|\right) * \omega_s * SelfDiff + \omega_o * OtherDiff\right) * \mathrm{dt} + \varepsilon \tag{4}$$

where *SOD* (self-onset delay) is the time that the self payoff begins to affect the decision process minus the time that the other's payoff begins to affect it, and ε represents zero-mean Gaussian noise. In addition to these drift-rate parameters, the stDDM includes three additional parameters for: (1) threshold (a); (2) non-decision time (t_0); (3) starting point (z). The starting point captures the participant's predisposition towards selfish or pro-social options.

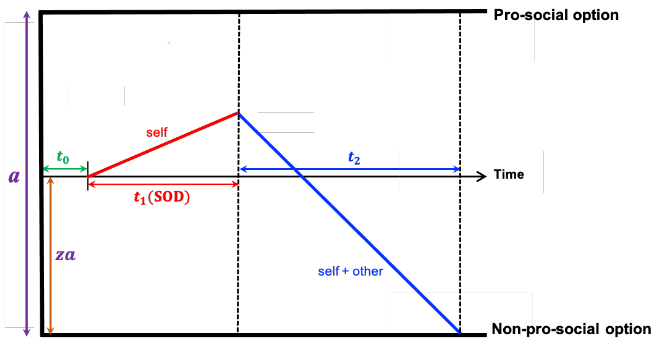

Fig. 4. A graphical illustration of the starting-time drift diffusion model (stDDM). a denotes the boundary, t_0 denotes the non-decision time, and z is the starting point parameter which indicates the prior bias towards the pro-social option ($z > 0.5$) or the non-pro-social (selfish) option ($z < 0.5$). The red and blue trajectory displays an example of the evolution of the relative evidence. In the example, the self payoff enters the evidence accumulation process first at t_0 and the other's payoff (other) enters into the process later at time t_0+t_1. We refer to the duration of t_1 as the self-onset delay (SOD). For illustrative purposes, here we have omitted the diffusion noise in the process and only shown the average drift rates.

It is worth noting an important aspect of the two drift weighting parameters in our stDDM. It is common to interpret the two parameters ω_s and ω_o as the subjective weights on self and other attributes (Amasino et al. 2019, Chen and Krajbich 2018, Hutcherson et al. 2015, Maier et al. 2020). However, DDMs that are specified with parameters for both attributes are mathematically equivalent to models in which there is a single parameter that determines the relative weight on self vs. other (or any other pair of attributes) and a second drift scaling/inverse-temperature parameter that determines how consistently people choose in line with those relative weights (Krajbich 2021). The two ways of specifying the model are equivalent, and therefore neither is more or less correct than the other. However, we should be cautious in how we interpret the two weighting parameters on each attribute, bearing in mind that the relative magnitude of the two parameters is what should capture the underlying level of pro-sociality.

We fit the stDDM to the choice and RT data in the time-free condition using a hierarchical Bayesian toolbox (Lombardi and Hare 2021) that provides estimates of the parameters both at the group (SI Note H) and participant levels. We coded the decision as pro-social if the participant chose the option with the higher payoff for the other participant, and coded the decision as non-pro-social (selfish) if the participant chose the option with the lower payoff for the other participant. Thus, a starting point greater than 0.5 represents a prior bias towards the pro-social option, and a starting point less than 0.5 represents a prior bias towards the selfish option. Without loss of generality, we fixed the noise parameter (ε) to 1 in the estimation.

Parameter recovery analyses demonstrated that choice and RT patterns simulated using estimates of the stDDM could be recovered in each case. In other words, our estimation procedures for the stDDM yielded accurate estimates for known parameter values (SI Note I). Critically, this stDDM formulation can accurately distinguish between the effects of a starting-point bias (i.e., predisposition), preferential consideration of one attribute earlier in the decision process (i.e., SOD), and the subjective weights of each attribute.

The parameter *SOD* from the stDDM (response-time-derived self-onset delay, RTSOD) was correlated with the MTSOD (Fig. 5A, two-sided Pearson correlation test, $r(117) = 0.762$, $p = 10^{-16}$; see SI Note J for the correlation between RTSOD and RTs). In both cases, the SOD is computed as self minus other payoff consideration onset time, so positive values indicate that consideration of the self payoff is delayed relative to the other's payoff. In RTSOD, the units are seconds, while in MTSOD the units are the percent of maximum RT across all trials in the time-free condition. Furthermore, 66 out of 86 participants whose RTSOD was positive also had a positive MTSOD (two-sided Binomial test, $p = 10^{-6}$), and 26 out of 31 participants whose RTSOD was negative had a negative MTSOD ($p = 10^{-4}$). This indicates a strong correspondence between the SOD derived from the mouse-tracking data and that from the choice + RT data. The correspondence between MTSOD and RTSOD together with the robustness checks and parameter recovery tests for these analyses give us confidence in the SOD measures. Moreover, the within-subject out-of-sample prediction exercises show that the stDDM has better predictive performance than the standard DDM in predicting participants' choices (higher Cramer's λ, Chen and Krajbich 2018, Clithero 2018a, Cramer 1999) and RTs (lower squared error, SI Note K).[6] This indicates that the starting point in the standard DDM (predisposition) cannot adequately capture a delayed start in processing some attributes relative to others. The difference between the SOD and predisposition is that the predisposition is the prior bias before processing any information from the current choice problem, i.e., it does not depend on trial-level variables. The attribute latency (SOD), also captures a general tendency to consider self or other first, but its effects on choice outcomes depend on the trial-specific self and other payoffs as well.

2.2.5. Explaining Individual Differences in Social Preferences and Preference Changes across Time Conditions

To evaluate which components in the stDDM predicted pro-sociality in the time-free condition, we ran an OLS regression explaining β_f derived from one half of the time-free trials, with all the stDDM parameters fit to the other half of the time-free trials. We found that the

[6] We note that the standard DDM had better predictive performance than the stDDM for some participants, especially for participants whose self-onset delay (SOD) is around 0 or whose relative weight between other's and self payoffs in the standard DDM is very small (near 0) or negative. Thus, the stDDM was more predictive of choices than the standard DDM for more pro-social participants and on choices with selfish outcomes (see SI Note K for more details).

starting point (z), drift-rate constant (ω_c), response-time-derived self-onset delay (RTSOD), and subjective weights on self and others' payoffs (ω_s and ω_o) were all significant predictors of β_f (model 1 in Table 1; see also SI Note L). As noted above in the description of the stDDM, the drift weight parameters on self and other payoffs (ω_s and ω_o) represent a combination of the overall drift scaling and the relative contribution each payoff makes in determining utility. By including the ratios ω_c/ω_s and ω_o/ω_s in the linear regression model, we make ω_s the drift scaling parameter and ω_o the effective trade-off between self and other payoffs in determining choice outcomes.

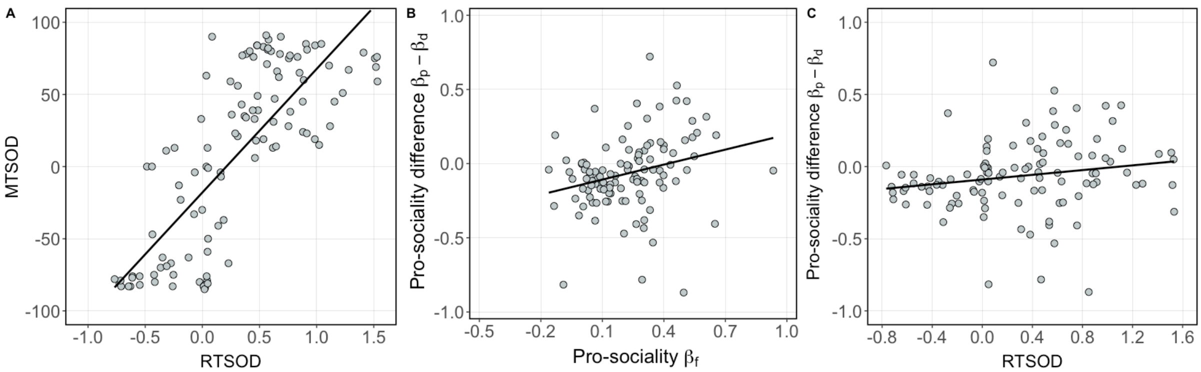

Fig. 5. (A) Correlation between the response-time-derived self-onset delay (RTSOD) and the mouse-trajectory-derived self-onset delay (MTSOD); (B) Correlation between time-free preferences ($\boldsymbol{\beta_f}$) and the preference change across time-pressure and delay conditions ($\boldsymbol{\beta_p - \beta_d}$); (C) Correlation between RTSOD and $\boldsymbol{\beta_p - \beta_d}$. The solid line is the fitted regression line. Each dot represents one participant. Six participants whose $\beta_p - \beta_d$ values are beyond $[-1,1]$ are not shown in (B) and (C), but were included in the correlation analysis.

Our results reveal that participants' preferences changed across time conditions. Time pressure amplified the degree to which participants preferred selfish relative to pro-social outcomes, or vice versa. In contrast, time delay reduced the strength of their preference for the category they preferred in the time-free condition. As shown in Fig. 5B, the time-free preference (β_f) was correlated with the preference change across time-pressure and time-delay conditions ($\beta_p - \beta_d$) (two-sided Spearman correlation tests, $\rho = 0.313$, $p < 0.001$, see also SI Note M). Moreover, the RTSOD from the stDDM was correlated with the preference change across time-pressure and delay conditions ($\beta_p - \beta_d$) (Fig. 5C, two-sided Spearman correlation tests, $\rho = 0.310$, $p < 0.001$).

Table 1. OLS regressions of pro-social preference (β_f) and preference change ($\beta_p - \beta_d$) across time conditions on stDDM parameters from Study 1.

	β_f	$\beta_p - \beta_d$
	(1)	(2)
Constant	-0.094	-0.474
	(0.091)	(0.294)
z	0.868***	1.221**
	(0.185)	(0.596)
ω_c	0.383***	0.137
	(0.034)	(0.110)
$RTSOD$	0.082**	-0.067
	(0.023)	(0.074)
ω_s	-0.992***	-0.412
	(0.236)	(0.760)
ω_o	4.299***	2.013
	(0.426)	(1.372)
t_0	-0.082**	-0.120
	(0.035)	(0.112)
a	-0.013	-0.020
	(0.012)	(0.038)
ω_c/ω_s	0.000	-0.001
	(0.000)	(0.001)
ω_o/ω_s	-0.005	-0.005
	(0.005)	(0.016)
$RTSOD \times \omega_s$	-0.078	-0.697
	(0.344)	(1.107)
$RTSOD \times \omega_o$	1.770	11.355**
	(1.717)	(5.529)
R^2	0.868	0.140
Adj. R^2	0.853	0.045
Num. obs.	111	111

Notes: In model (1), the dependent variable is the advantageous inequality preference parameter, β_f, in the time-free condition. We estimated the stDDM using half of the trials and estimated β_f using the other half of the trials in the time-free condition. In models (2), the dependent variable is the difference in the pro-social preference parameters, $\beta_p - \beta_d$. Participants whose β_f was out of [-1, 2] and $\beta_p - \beta_d$ was out of [-1, 1] were not included in the OLS regressions.

Abbreviations: z is the starting point, ω_c is the drift constant, ω_s and ω_o are stDDM parameters quantifying the relative contributions of the differences in self and other payoffs, respectively, to the drift rate, t_0 is the non-decision time, a is the magnitude of the boundary separation.

***p < 0.01, **p < 0.05.

We ran an OLS regression of $(\beta_p - \beta_d)$ on all the stDDM parameters fit to the time-free trials to test if any of them could explain individual differences in the effects of the time pressure or delay treatments (Model 2 in Table 1). There was a significant main effect for starting point indicating that participants' predispositions revealed during time-free choices were indicative of how they would behave under time-pressure versus delay. In addition to the main effect of predispositions, there was a significant interaction between the $RTSOD$ and ω_o parameters (see also SI Note N for a direct replication of Chen and Krajbich (2018) using a standard DDM). Note that the $RTSOD$ parameter interacts with the weighting parameters within the stDDM as depicted in Fig. 4, and thus this interaction is not surprising. The $RTSOD$ parameter is computed as self minus others' payoff consideration onset time. Therefore, larger values of ω_o and $RTSOD$ combine to yield more pro-social choices, whereas small values of those two parameters lead to more selfish choices.

3. Study 2: Response-Time Experiment from Chen and Krajbich (2018)

Study 1 was a mouse-tracking experiment where RTs are potentially distorted due to the hand movements. To verify the stDDM results with a more standard response method, we analyzed a second dataset where participants made decisions using keyboards. We sought to confirm whether the self-onset delay (SOD) explains individual differences in pro-sociality and how it changes across time-pressure and delay conditions, along with other parameters in the stDDM. Specifically, we used the data from Chen and Krajbich (2018). Chen and Krajbich (2018) show that the starting point (predisposition) in the standard DDM (referred to there as biased DDM) explains participants' preferences and the heterogeneous effects of time constraints on preferences. That is, the predisposition to behave pro-socially or selfishly can be captured by the starting point of the standard DDM. As people consider the payoffs and accumulate evidence over time, they may overcome their initial predispositions. Reanalyzing these decisions with the stDDM revealed important nuances in the results that were not evident from the standard DDM results. Specifically, some of the individual variability in pro-social preferences within the time-free condition originally linked to the starting point in the standard DDM instead turns out to be driven by differences in intra-choice dynamics (i.e., SOD). Moreover, we can explain more of the effects of time pressure or delay on social preferences by using a decision model that quantifies both predispositions and self-onset delays.

3.1. Materials and Methods

Similar to Study 1, participants in Chen and Krajbich (2018) made binary decisions in 200 mini-dictator games. Each decision involved a conflict between selfishness and advantageous inequality aversion. The 200 games were divided into four blocks of 50 games each. Two of them were time-free blocks and the other two were time-pressure and time-delay blocks. The main difference between the experiments in Chen and Krajbich (2018) and Study 1 was that participants made their decisions either by pressing key “F” to choose the left option or pressing key “J” to choose the right option. In total 102 participants (56 females) participated in the experiment.

3.2. Computational Modeling of Choice Outcomes and Response Times

We fit the stDDM to the choice and RT data in half of the time-free trials both at the group (SI Note O) and participant levels. Consistent with Study 1, we coded the decision as pro-social if the participant chose the option with higher payoff for the receiver, and coded the decision as selfish if the participant chose the option with the lower payoff for the receiver. Thus, a starting point greater than 0.5 represents a predisposition towards the pro-social option, and a starting point less than 0.5 represents a predisposition towards the selfish option. Note that the starting point in Chen and Krajbich (2018) was defined in the opposite way (i.e., greater than 0.5 favored selfish).

Reassuringly, the results from the stDDM fits to Study 2 were very similar to Study 1. The average starting point was slightly less than 0.5 (Study 1: 0.473, Study 2: 0.446), the RTSOD was significantly positive (Study 1: 0.303, Study 2: 0.524), the drift-rate constant was positive (Study

1: 0.243, Study 2: 0.137), and the ratio of the weights on the self-payoff and other-payoff was substantially larger than one (Study 1: 6.57, Study 2: 4.94).

The RTSOD from stDDM was correlated with pro-sociality across participants (Fig. 6A, two-sided Spearman correlation test, $\rho = 0.763$, $p = 10^{-16}$). Moreover, the RTSOD from stDDM was correlated with the preference change across time-pressure and delay conditions (Fig. 6B, $\rho = 0.347$, $p < 0.001$).

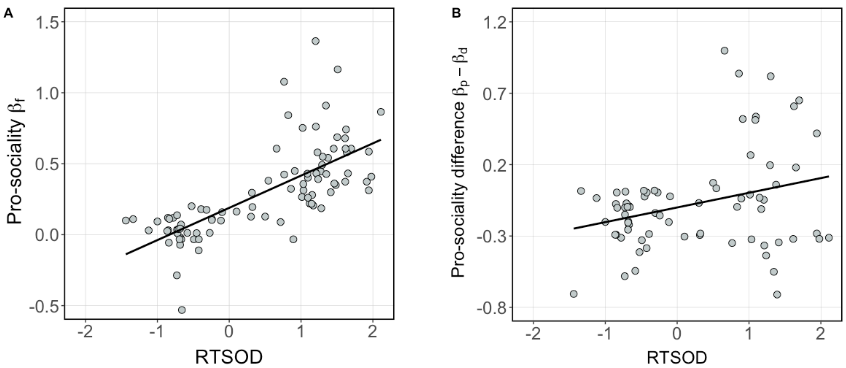

Fig. 6. Study 2: (A) Correlation between RTSOD from stDDM and pro-sociality in the time-free condition; (B) Correlation between RTSOD from stDDM and preference change across time-pressure and delay conditions. For each participant, pro-sociality (β_f) was estimated using half of the time-free trials, and the stDDM was estimated using the other half of the time-free trials. 12 participants whose β_f were out of [-1, 2] are not included in (A) and 30 participants whose $\beta_p - \beta_d$ were out of [-1,1] are not included in (B), but all participants were included in the correlation analysis. The solid line is the fitted regression line. Each dot represents one participant.

Here, we go beyond Chen and Krajbich (2018), which focused solely on the starting point in the standard DDM, to explain individual differences in social preferences and how preferences change across time-pressure and delay conditions. We investigate whether including a self-onset delay (SOD) in the DDM allows us to better explain behavior. The OLS regression in Table P1 (Model 1) of SI Note P shows that when both starting point and RTSODs are estimated in the stDDM, the RTSOD parameter is significant in explaining pro-sociality in the time-free condition (p =10^{-6}), while the starting point is not significant (p =0.239). Model 2 in Table P1 shows that there was a significant main effect of RTSOD (p =0.004) and a marginally significant interaction between the RTSOD and ω_o parameters (p =0.068) in predicting the change in behavior across time-constrained conditions. The starting point was not significant (p =0.112), unlike in Chen and Krajbich (2018).

Thus, advancing beyond the prior work we show that people are heterogenous in the consideration onset times of self and others' payoffs. Our results indicate that individual attributes do not affect the choice process to the same degree over the whole course of the decision. Even after accounting for predispositions, the intra-choice dynamics quantified by the SOD explain significantly more of the participants' preferences and how their preferences change across time-pressure and delay conditions.

4. Study 3: Mouse-Tracking Replication of Chen and Krajbich (2018)

In Studies 1 and 2, the differences between self payoffs and others' payoffs were identical across time conditions. However, the payoffs themselves were slightly different. Thus, the differences in MTSOD and RTSOD between time conditions could have been due to the differences in payoffs rather than time constraints. To address this concern and check the robustness of the earlier studies, we conducted a replication experiment of Chen and Krajbich (2018) adding additional decision trials, using mouse-tracking instead of button-press responses, and randomizing the assignment of the choice problems to the three time conditions.

4.1. Materials and Methods

Chen and Krajbich (2018) consisted of 200 mini-dictator games. To make it comparable with Study 1 (300 games), in this mouse-tracking study we generated another 100 games (two subgroups) using the rules in Chen and Krajbich (2018). That is, we decreased the payoffs in half of the games in Subgroup 1 (with Game ID of 1-50) by 2 or 3 and increased the payoffs in the other half of the games by 2 or 3. This ensured that the differences in self payoffs and other's payoffs were identical across the six subgroups.

In the experiment, we randomly assigned the six subgroups of games into time-free (4 subgroups, 200 games), time-pressure (1 subgroup, 50 games), and time-delay (1 subgroup, 50 games) conditions at the participant level. Thus, the games were not systematically different across the three conditions at the aggregate level. Other than creating and randomizing the games across conditions in this manner, we used the same procedures in this experiment as in Study 1. In total 103 university students (56 females, $mean = 20.0$ years, $sd = 2.0$ years) participated in this experiment from November 20 to December 24, 2021. All participants were right-handed. On average, participants earned 6.4 US Dollars (including the show-up fee). The Internal Review Board of Zhejiang university approved the experiment, and all participants provided written informed consent.

4.2. Mouse-Trajectory Analysis

We used the same econometric analysis as in Study 1 to identify the MTSOD in the time-free, time-pressure, and time-delay conditions. Fig. 7A plots the MTSOD across time-free and pressure conditions across participants. Compared to the time-free condition, time pressure decreased the MTSOD for the 47 participants with positive MTSOD in the time-free condition (two-sided Wilcoxon signed-rank test, $V = 1092.5$, $p = 10^{-8}$), and increased the MTSOD for the 51 participants with negative MTSOD in the time-free condition ($V = 457$, $p = 0.054$). That is, time pressure reduced the initial processing time advantage for the earlier-considered attribute relative to the unconstrained choices. Moreover, the MTSOD estimated for the time-free, time-pressure, and time-delay conditions were correlated with pro-sociality (β_f) in the time-free condition (Fig. Q2, two-sided Pearson correlation tests, free: $r(103) = 0.668$, $p = 10^{-14}$; pressure: $r(103) = 0.566$, $p = 10^{-9}$; delay: $r(103) = 0.613$, $p = 10^{-11}$). This indicates that the earlier the participant started to process others' payoffs relative to self payoffs, the more pro-social the participant was.

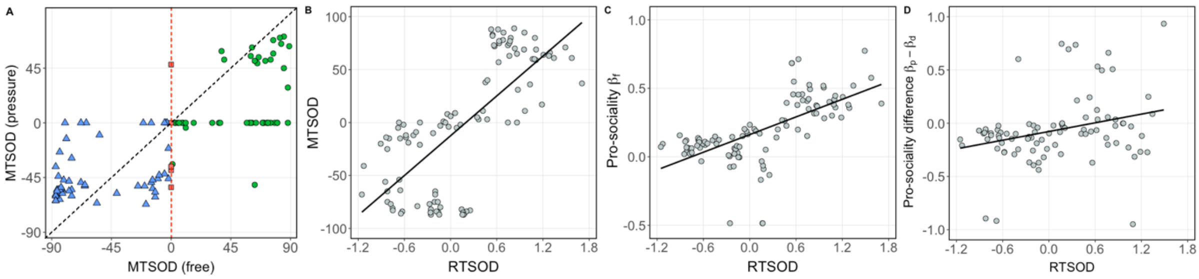

Fig. 7. **Study 3: (A) Mouse-trajectory-derived self-onset delay (MTSOD) across time-free and pressure conditions; (B) Correlation between the response-time-derived self-onset delay (RTSOD) from the stDDM and the MTSOD in the time-free condition; (C) Correlation between RTSOD and pro-sociality in the time-free condition; (D) Correlation between RTSOD and preferences change across time pressure and delay conditions.** In (A), participants that consider self or others' payoffs first in the time-free condition are shown in green or blue, respectively. The dotted black line indicates the 45-degree line where all dots would fall if the MTSOD was equal in both conditions. Pro-sociality (β_f) was estimated using half of the time-free trials, and the stDDM was estimated using the other half of the time-free trials. Three participants whose β_f were out of [-1, 1] are not included in (C) and fifteen participants whose $\beta_p - \beta_d$ were out of [-1,1] are not included in (D), but all participants were included in the correlation analysis. The solid line is the fitted regression line. Each dot represents one participant.

4.3. Computational Modeling Analysis

We fit the stDDM to the choice and RT data in half of the time-free trials. The RTSOD in the stDDM was correlated with the MTSOD (Fig. 7B, two-sided Pearson correlation test, $r(103) = 0.718$, $p = 10^{-16}$). Furthermore, 45 out of 57 participants whose RTSOD was positive had a positive MTSOD (two-sided Binomial test, $p = 10^{-5}$), and 41 out of 46 participants whose RTSOD was negative had a negative MTSOD ($p = 10^{-8}$). The RTSOD in stDDM was correlated with pro-sociality across participants in the time-free condition (Fig. 7C, two-sided Spearman correlation test, $\rho = 0.713$, $p = 10^{-16}$), and the RTSOD in stDDM was also correlated with preference changes across time-pressure and delay conditions (Fig. 7D, $\rho = 0.440$, $p = 10^{-6}$).

The OLS regression in Table Q1 (Model 1) of SI Note Q shows that there was a significant interaction between the RTSOD and ω_s parameters ($p = 10^{-6}$) in explaining pro-sociality in the time-free condition, while the starting point was not significant (p =0.101). Model 2 in Table Q1 shows that there was a significant main effect of RTSOD (p =0.035) in explaining preference changes across time-pressure and delay conditions, while the starting point was not significant (p =0.604). Therefore, this study confirmed the key result in the two studies above, namely that intra-choice dynamics quantified by the SOD are important factors in determining social preferences and how those preferences may change under different time conditions.

5. Between-subjects Predictions of Preference Changes

Lastly, we used a machine learning approach known as random forests (Breiman 2001) to make between-participant, cross-validated predictions of social preferences in the time-free condition and the change in those preferences across the time-pressure and delay conditions. We chose the random forests algorithm because it uses a different subset of the available variables (e.g., 3 out of 7 parameters) to train on in each iteration. Comparing the mean squared error (MSE) of classifiers that omit versus include a specific parameter provides a measure of the importance of each parameter that is less arbitrary than comparisons of p-values for regression coefficients (Azen and Budescu 2003, Budescu 1993). This is particularly important when some of the prediction variables are correlated with one another, which is the case in the regressions summarized in Tables 1, P1, and Q1.

5.1. Machine Learning Materials and Methods

In this analysis, we combined the data from all three studies and used the standard DDM or stDDM parameters as variables to train a machine learning algorithm to predict social preferences. We applied the same exclusion criteria used for the linear regressions in Tables 1, P1, and Q1, leaving 265 participants in this analysis. We used the randomForest package (Liaw and Wiener 2002) in R (Team 2022), which implements Breiman's random forest algorithm (Breiman 2001). First, to avoid over-fitting during training, we tuned the algorithm to find the optimal number of variables to include in each decision tree. The standard DDM and stDDM have a total of 6 and 7 parameters, respectively. The optimal number of variables was 3 for both models when predicting social preferences in the time-free condition (β_f) and 2 for both models when predicting preference changes between time-pressure and delay conditions ($\beta_p - \beta_d$). Next, we trained 5000 decision trees on different randomly selected subsets of approximately two-thirds of the participants and recorded the MSE of the out-of-sample predictions for the remaining third of the participants. The out-of-sample prediction for each participant's social preference in the time-free condition or change in preference across the time-pressure and delay conditions was the average predicted value across all decision trees in which the participant was part of the out-of-sample test set. The overall performance of the algorithm was quantified using the R^2 (R-squared) between the predicted and empirically observed preferences. We also computed the probability that the stDDM predictions were better than those from the standard DDM on each of the 5000 decision trees using the parameters from those models. The importance of each parameter in predicting preferences was calculated as the mean increase in MSE for all decision trees that omitted the parameter compared to those that included it.

5.2. Machine Learning Results

Our random forests machine learning analysis indicated that intra-choice dynamics are important for predicting social preferences across individuals. Random forests based on stDDM parameters compared to standard DDM parameters were better at predicting participants' social preferences (β_f) within the time-free condition (R^2 = 0.653 versus 0.600, probability of lower error from stDDM = 0.9998) and their preference changes ($\beta_p - \beta_d$) across the time-pressure and delay conditions (R^2 = 0.088 versus 0.024, probability of lower error from stDDM = 0.995) at the group level (see also Appendix Fig. R1 and Appendix Table R1). The relative importance of each stDDM and standard DDM parameter in predicting preference changes is shown in Fig. 8 (see also Appendix Table R2). The stDDM parameters that contributed most to predicting preference changes were the RTSOD, drift rate constant, and relative drift weight on other and self payoffs. These parameters determine the evidence accumulation rate and how it changes over time within a given choice, i.e., the intra-choice dynamics.

Note that the drift constant parameter quantifies the tendency to move toward selecting the pro-social or selfish option irrespective of the payoff amounts in a given trial. In other words, the drift rate constant influences the process of evidence accumulation directly, which makes it different from the starting point. The starting-point parameter quantifies the relative amount of evidence required to select the pro-social versus the selfish option but does not affect the accumulation process itself (Urai et al. 2019). Thus, the results of the random forest analysis show that parameters quantifying the dynamics of the evidence accumulation process are important for predicting social preferences across individuals.

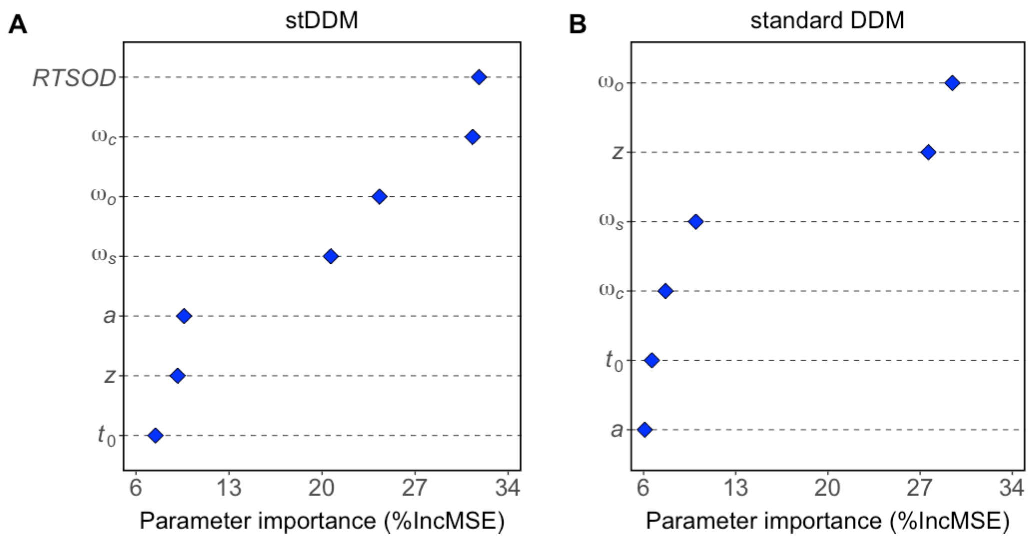

Fig. 8. The importance of each parameter in the stDDM (A) and standard DDM (B) in predicting preference changes across time-pressure and delay conditions. The x-axis shows the percent increase in mean squared error (MSE) for classifiers that omit the parameter listed in each row. The larger the increase in MSE, the more important the parameter is for predicting an individual's change in social preferences under time pressure relative to time delay. $RTSOD$ is the response-time-derived self-onset delay in the stDDM, ω_c is the drift constant, ω_o and ω_s are DDM parameters quantifying the relative drift weight on other and self payoffs respectively, a is the magnitude of the boundary separation, z is the starting point, and t_0 is the non-decision time.

6. Discussion and Conclusion

Our results reveal how people process information to make social decisions and help to identify important sources of individual variability in this process. In particular, we find that self and other's outcomes enter the decision process at different times, and that these onset times are important for predicting the effects of time pressure or delay.

We draw our conclusions from a combination of process data, time manipulations, and computational modelling. In Study 1, using mouse-tracking techniques, we find that in the absence of time constraints, participants who are more selfish process their own payoffs earlier than others' payoffs while more pro-social participants process others' payoffs earlier than their own payoffs. A separate analysis of the choice and RT data using the stDDM confirmed these mouse-tracking results. In Studies 2 and 3, we replicated these results using experiments in which participants made decisions with and without mouse tracking.

The attribute onset times determine when a given payoff enters the decision process. The payoffs are then multiplied by their subjective weights to determine the drift rate. Thus, the full impact of the difference in onset times (SOD) depends on the relative weights on the self and others' payoffs. While on average the relative weight on self payoffs is higher, the others' payoffs tend to affect the mouse trajectories first, although we have shown there is substantial individual variability in both weights and consideration onset times (e.g., Fig. 2A vs Fig. 3B). When striving to understand social decisions at the mechanistic level, researchers need to quantify and evaluate all of these factors. Combining all these mechanisms can better explain individual differences in pro-sociality.

Our results provide an insight into human pro-sociality: Selfish people tend to first consider information about themselves over information about others, while pro-social people do the opposite. This is consistent with other eye-tracking work on social preferences (Fiedler et al. 2013, Smith and Krajbich 2018, Teoh et al. 2020) and suggests that the relative influence of different attributes changes over the course of a decision. These findings raise questions about why some people first consider themselves while others do the opposite. Does it reflect top-down, goal-directed information search based on their preferences, or does it also/instead reflect bottom-up saliency of self-relevant information (Ghaffari and Fiedler 2018)? While our results cannot definitively resolve these questions, the fact that initial processing advantages for one attribute over another decrease under time pressure suggests that information search and processing is context-dependent and not fully determined by bottom-up saliency. Our findings also raise questions about the distinction between sequential processing and parallel processing either across the whole decision or within certain phases of the process (Townsend, 1990, Townsend and Nozawa, 1995), which is an interesting direction for future study.

While we found that the self-onset delay (SOD) predicted participants' preference changes across time-pressure and delay conditions in the three studies, we found that the starting point (predisposition) in the stDDM only predicted changes in preferences in Study 1, but not in Studies 2 and 3. This is in contrast to the standard DDM, in which the starting point does predict preference changes across all three studies. So, while the starting point is a useful parameter for understanding social preferences and how they change under time constraints, part of its power seems to come from its ability to partially account for variance that is better captured by the SOD – which is fixed at zero in the standard DDM (see Fig. I3 and Fig. N2).

Our work highlights the usefulness of process-tracing methods (especially mouse tracking) in decision science and management. Mouse-tracking is an emerging tool that offers an accessible, data-rich, and real-time window into how people categorize and make decisions (Chen and Fischbacher 2016, Cheng and González-Vallejo 2018, Falandays et al. 2021, Freeman et al. 2008, Konovalov and Krajbich 2020, Koop 2013, Koop and Johnson 2011, Kvam and Busemeyer 2020, Lepora and Pezzulo 2015, Spivey et al. 2005, Stillman et al. 2018, Sullivan et al. 2015). As we continue to develop and refine dynamical models of the choice process, such choice-process measures become increasingly important. Mouse-tracking is especially useful when experimental manipulations obscure the true timing of the decision process. For example, here, and in previous work (Chen & Krajbich, 2018), we only fit the DDM to the time-free condition. This is because it is not clear how exactly people adapt their choice boundaries to deal with a short time limit (Hawkins et al. 2015, Palestro et al. 2018), and because we cannot observe the true RT in the time-delay condition. This makes it problematic to fit any DDM to the time-delay data. Fortunately, the high correlation between SODs based on the mouse-tracking and choice + RT data indicate that one measure can substitute for the other if either accurate RT data or mouse-tracking data are not available.

Another advantage of mouse-tracking data is that it can yield trial-level measures (Stillman et al. 2020) while computational models of choice and RT data (e.g. with the stDDM) must be fit to many trials simultaneously. For instance, Stillman et al. (2020) have shown that the mouse-tracking metrics of conflict predict participants' risk preferences at the single-trial level, and that mouse-tracking metrics outperform RT in predicting risk preferences. This suggests that mouse-trajectory data are useful in revealing people's preferences and worth collecting in experiments and in practice (e.g., for predicting consumers' preferences based on their trajectory data while browsing) (Fisher forthcoming).

Our results also contribute to the research on decisions under time constraints. Time constraints are common in social decisions. For example, managers often need to quickly make distribution decisions about how to allocate work between their team members. Another example is that bargainers must often reach agreements before deadlines (Karagözoğlu and Kocher 2019, Roth et al. 1988). Our results show that the effects of time constraints depend on individual-specific processing dynamics, and thus we need to take this into account when designing policies and institutions. Time constraints have often been used or studied in other, less explicitly social decisions as well, e.g., risk decisions (Olschewski and Rieskamp 2021, Saqib and Chan 2015), intertemporal choices (Dai and Fishbach 2013, Imas et al. forthcoming) and others (Baldassi et al. 2020). Within the value-based DDM framework, previous studies have used the starting point (Chen and Krajbich 2018, Desai and Krajbich 2022, Zhao et al. 2020) and threshold (Milosavljevic et al. 2010) parameters to quantify and explain the effects of time constraints on people's preferences. Our results show that dynamic intra-choice changes in the evidence accumulation process is another, potentially even more important factor to account for.

It is important for managers and policy makers to understand and predict the range and probability of changes in social decision making that may occur in response to interventions or policy changes before they are implemented. This means that we need to understand not just the mean or median response, but also individual variability. Greater knowledge of the dynamic cognitive and neural mechanisms that drive choices is an important step towards this understanding. Our findings demonstrate that the time when a specific attribute begins to influence the decision process – a factor that has so far been relatively neglected – is an important determinant of social behavior. This highlights the possibility that features of how the choice problem is presented (i.e., choice architecture manipulations) could be used to promote pro-social decision making within managerial or other contexts. The previous results from Chen and Krajbich (2018) suggested that choice independent predispositions were a primary driver of social preferences changes under time pressure or delay. To influence such a predisposition an intervention or nudge would have to take effect prior to the decision. However, our current results indicate that intra-choice dynamics also play a role in social preferences and their changes under time pressure/delay, which opens up a wider set of possibilities for promoting pro-social decisions. For instance, manipulating the order in which people consider different attributes (Johnson et al. 2007, Teoh et al. 2020, Weber et al. 2007) might be a more effective strategy for altering real-world behavior.

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