Title
How the cognitive mechanisms underlying fast choices influence information spread and response bias amplification in groups

Journal
Proceedings of the Annual Meeting of the Cognitive Science Society, 44(44)

Authors
Novaes Tump, Alan
Pleskac, Tim
Romanczuk, Pawel
et al.

Publication Date
2022

Peer reviewed

How the cognitive mechanisms underlying fast choices influence information spread and response bias amplification in groups.

Alan N. Tump[1,2] **(tump@mpib-berlin.mpg.de), Timothy J. Pleskac**[1,3]**, Pawel Romanczuk**[2,4,5]**, & Ralf H. J. M. Kurvers**[1,2]

[1]Center for Adaptive Rationality, Max Planck Institute for Human Development, 14195 Berlin, Germany

[2]Science of Intelligence, Technische Universität Berlin, 10587 Berlin, Germany

[3]University of Kansas, 66045, Lawrence, United States

[4] Institute for Theoretical Biology, Humboldt Universität zu Berlin, 10115 Berlin, Germany

[5] Bernstein Center for Computational Neuroscience Berlin, 10115 Berlin, Germany

Abstract

Behavioural cascades through social reinforcement are ubiquitous in human and animal groups. Nonetheless, we only have a rudimentary understanding of which choices are more likely to initiate cascades. Here we investigate the role of response time (RT) asymmetries (i.e., one choice alternative being selected faster than the other) in shaping behavioural cascades by combining an empirical and modelling approach. RT asymmetries are found in a wide range of decision-making contexts, including police shooting, risky choice, and memory retrieval. How they shape collective dynamics, is, however, unknown. Applying evidence accumulation models to analyse behaviour in a sequential choice paradigm, we show that RT asymmetries crucially shape behavioural cascades. Using simulations, we show that especially start point biases (and to a less extent varying drift rates) can initiate cascades, as they lead to rapid choices for one choice alternative. Our results highlight the importance of RT asymmetries in shaping collective dynamics.

Keywords: collective dynamics, decision making, information cascades, response bias, diffusion models

Introduction

Across a range of social settings, from pedestrians crossing the street and investors in the stock market, to animals escaping predation, individuals observe the choices of others to inform their own behaviour. In these situations, behavioural cascades can emerge through social reinforcement whereby fast-deciding individuals typically play a crucial role in the evolving collective dynamics and final outcome. To understand the emergent dynamics, it is thus crucial to understand the characteristics of fast choices and their subsequent impact. For example, under many conditions accurate choices are, on average, made faster than inaccurate choices (Ratcliff, Smith, Brown, & McKoon, 2016). Such fast, accurate choices can thereby promote the spread of accurate information to less accurate, slower-deciding individuals (Tump, Pleskac, & Kurvers, 2020; Kurvers, Wolf, Naguib, & Krause, 2015), explaining the emergence of informed leaders and naive followers (Couzin, Krause, Franks, & Levin, 2005; Stroeymeyt, Franks, & Giurfa, 2011; Watts, Nagy, Burt de Perera, & Biro, 2016).

In addition to correct options being selected faster, research on single individuals has shown that across a wide range of decision-making contexts one choice alternative is, on average, selected faster than the other alternative. For example, police officers in a shooter task are faster in deciding to shoot than to not shoot a potentially armed target (Pleskac, Cesario, & Johnson, 2018). In risky choice, the safe option is typically selected faster than the risky option (Zhao, Walasek, & Bhatia, 2020). In memory retrieval, the decision that an item is old (i.e.,"already seen") is made faster than "new" (Bowen, Spaniol, Patel, & Voss, 2016), and in cooperation experiments, larger donations are made faster than smaller ones (Rand, Greene, & Nowak, 2012). Despite the prevalence of such response time (RT) asymmetries, their importance in shaping collective dynamics is currently unknown. This is an important research gap as fast choices are generally expected to be amplified through social interactions. This implies that such RT asymmetries could have large consequences in collective systems by introducing or amplifying choice biases (i.e., increasing the probability of choosing a particular option). We address this gap by investigating the role of RT asymmetries in collective dynamics both empirically and theoretically.

A powerful approach to understanding the latent cognitive mechanisms governing asymmetric RTs are evidence accumulation models. The drift-diffusion model (DDM) is arguably the most widely used for binary decision tasks. It assumes that decision makers gather evidence over time until they reach a threshold and make a decision (Ratcliff et al., 2016). For example, a decision maker having to decide between the options "A" or "B" will start the choice process with an initial state of evidence described by the relative start point. Over time the decision maker gathers further evidence supporting either option "A" or "B". Once the decision maker has gathered enough evidence for one of the options a choice is made accordingly. For individuals in collective systems, the evidence comes from two different sources: either via personal information (e.g., from memory), or via social information (e.g., by observing the choices of others; Germar, Schlemmer, Krug, Voss, & Mojzisch, 2014; Toelch, Panizza, & Heekeren, 2018; Tump et al., 2020; Frydman & Krajbich, 2021). A recent extension of the individual DDM allows modelling the integration of personal and social information dynamically over time, accounting for information flow across individuals (Tump et al., 2020). The observed choices of others enter the accumulation process of undecided individuals by changing their drift rate towards the majority option. It, thereby, captures key features of realistic social dynamics, such as the importance of fast choices on the

In J. Culbertson, A. Perfors, H. Rabagliati & V. Ramenzoni (Eds.), *Proceedings of the 44th Annual Conference of the Cognitive Science Society*.

subsequent choices of group members (Tump et al., 2020). Thus, the model allows us to gain a detailed understanding of the underlying cognitive processes and their consequences for group dynamics. Here, we use the social DDM to delineate which cognitive processes underlie asymmetric response times, and how this, in turn, shapes collective dynamics.

Research on the decision process of single individuals has described four mechanisms how the DDM can generate asymmetric RTs: i) A bias in the relative start point (Fig. 1A). The relative start point influences the amount of additional information that is required for either option. If the start point is biased towards one option, the responses for that option are expected to come faster. Start point biases can be the result of differences in base rates or expected payoffs (Gold & Shadlen, 2007; Leite & Ratcliff, 2011; Mulder, Wagenmakers, Ratcliff, Boekel, & Forstmann, 2012). ii) Varying drift rates (Fig. 1B). The drift rate describes the average amount of evidence accumulated for an option per time unit and can vary over trials, meaning that some trials have a stronger drift towards one option than others. Trials with strong drifts will lead to choices which are fast, and consistent with the drift direction. Trials with lower drifts will contain more random and slower choices. On average, this will lead to faster choices for the more frequently chosen option (White & Poldrack, 2014; Ratcliff et al., 2016). iii) Variance in the start point. This mechanism can explain faster choices for the less frequently chosen option. Choices inconsistent with the drift direction will predominantly appear on trials where the individuals start close the choice threshold opposing the drift direction and, therefore, will be made very fast. Start point variance is typically added to account for fast errors. We do not investigate this further as fast errors are not of focal interest in our study. iv) Collapsing decision threshold. Models with collapsing decision thresholds assume that the decision maker requires less evidence to trigger a decision as time passes. Here, late choices are more random as the choices are based on less evidence. Collapsing bounds and varying drift rates make highly similar predictions and whether or not thresholds collapse over time is hotly debated in the DDM literature (Ratcliff et al., 2016). We, therefore, focus only on the first two potential processes driving asymmetric RTs.

To investigate the role of asymmetric RTs in shaping collective dynamics, we proceed in three steps. First, we use a sequential choice task to study empirically how asymmetric RTs influence human group dynamics. Second, we fit a social DDM to our data to uncover the underlying latent cognitive mechanisms driving these dynamics. Third, we use simulations to investigate how the two key processes driving asymmetric RTs shape choice biases in collectives across a broad range of parameter settings. We show in a binary decision task that if one option is, on average, chosen faster this can bias the information spreading through the group and promote choice biases. Further, we show that the danger of such a bias amplification is especially high in the presence of start point biases but not so much in presence of varying biased drift rates.

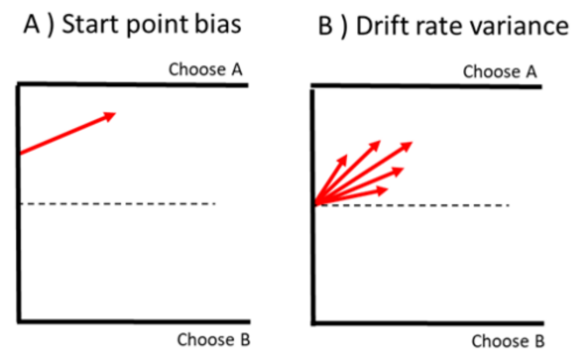

Figure 1: **Possible mechanisms underlying asymmetric RTs.** Both, **(A)** a start point bias towards "A" and **(B)** drift rate variance in combination with a drift towards "A" can explain faster choices for Option "A" compared to "B".

Methods

A total of 120 participants (66 females; 52 males, 2 other, mean age = 27 years, range = 18-39) were recruited from the participant pool of the Max Planck Institute for Human Deveopment. After providing informed consent they were assigned to one of two conditions, either being alone (n=20) or in groups of ten (n=10 groups). Participants within the same group were seated in the same room and all had a separate tablet.

In the experiment, participants were confronted with a visual search task. In each trial, they first briefly (for 2 seconds) were shown an image of a shoal of 72 stylized fish (tuna and sharks aligned in an 8 x 9 grid; see Fig. 2) with either three, four, six, or seven sharks hidden between tuna. After the image was removed the participants had to decide between "escape" and "stay". Participants were instructed to "escape" when there were five or more sharks present and "stay" if there were four or fewer. In such visual search tasks, the responses for finding the target (here sharks) are generally made faster than for not finding it (Palmer, Horowitz, Torralba, & Wolfe, 2011). Hence, we expected faster "escape" choices. Participants could indicate their choice by pressing the respective button on their tablet within 12s. Individuals in the alone condition performed the experiment by themselves. When participants in the group condition made a choice, their choice was immediately displayed on the tablets of all group members, by means of a green bar for the respective option (see Fig. 2). Participants (in both conditions) could only decide once, and not alter their decision. A countdown timer on the screen indicated the remaining time. The separation of each trial into a stimuli phase and a choice phase facilitated participants' visual attention allocation. In the stimuli phase participants could allocate their attention to the image, and in the choice phase to the choices of others. After each trial participants received feedback on whether their choice was correct or not. Participants earned a flat fee of 7€ and could additionally earn a bonus based on their performance (mean

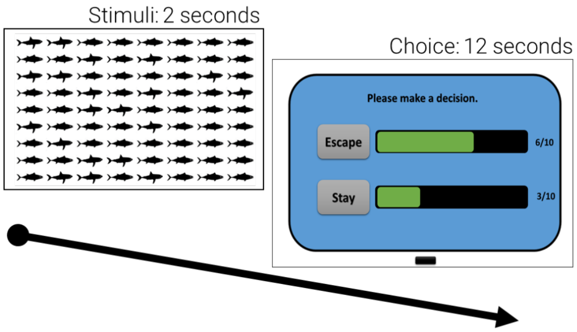

Figure 2: **Illustration of the experimental paradigm.** Participants briefly observe a grid of “sharks” and “tuna”. They then make a decision whether to “stay” or “escape” by pressing the respective button on their tablet. Individuals in groups can observe the choices of others in real-time via counts for the different options.

bonus = 3.57€). Participants started the experiments with a bonus balance of 1€. They earned 0.10€ for each correct decision, and lost that amount for each wrong decision—or when they failed to respond within the time limit. In addition, we introduced a small time cost of 0.001€ per second reflecting naturally-occurring opportunity costs. There were 50 trials in total with each number of sharks (3, 4, 6, or 7) occurring at least 12 times, and with “escape” being the correct option in half of the trials. Prior to the 50 trials, there were two test trials to familiarise the participants with the experiment (not included in the analysis).

To analyse which factors predicted the RTs of individuals, we used Bayesian hierarchical generalized linear models with the “brms” package (Bürkner, 2017), analysing single individuals and groups separately. We used RTs as response variable assuming a shifted lognormal-distribution (Wagenmakers & Brown, 2007). We included the choice (escape/stay) and the choice being correct (correct/wrong) as predictors. Individual identity and for groups also groups identity was included as a random effect. We ran four chains in parallel with 10.000 iterations each, disregarding first half as burn-in.

Social DDM: Model parameter estimation.

To understand how individuals gather evidence and time their decision, we fitted an evidence accumulation model to the data. By accounting for changing drift rates within a trial it allows estimating the influence of social information on the evidence accumulation process. To obtain choice and RT predictions we generated probability density functions by implementing an extended version of a Markov chain approach (Diederich & Busemeyer, 2003). For a detailed description of the implementation see supplementary information `https://osf.io/jn6a7/`.

Note that the social DDM starts modelling the evidence accumulation process at the start of the choice phase, hence after participants observed the stimuli. The evidence state at this point is called the relative start point, and can include already gathered evidence in the form of personal information. Thus, the relative start point β can be decomposed into two components, one related to participants' initial tendencies, and one to participants' discrimination ability. The first, can incorporate potential initial tendencies to escape (or stay) β_{bias} which shifts the relative start point towards (or away from) the escape boundary. Second, individuals may have gathered correct (or incorrect) information β_{disc} during stimuli presentation, which shifts the relative start point towards (or away from) the correct boundary:

$$\beta = \begin{cases} 0.5 + \beta_{bias} + \beta_{disc}, & \text{if escape is correct} \\ 0.5 + \beta_{bias} - \beta_{disc}, & \text{if stay is correct} \end{cases} \tag{1}$$

The personal drift rate δ_p is similarly decomposable into a drift towards the correct option δ_{disc} (i.e., the discrimination ability) and a drift bias δ_{bias} (i.e., a bias in the evidence evaluation process):

$$\delta_p = \begin{cases} \delta_{bias} + \delta_{disc}, & \text{if escape is correct} \\ \delta_{bias} - \delta_{disc}, & \text{if stay is correct} \end{cases} \tag{2}$$

In groups, participants can additionally gather social information by observing the choices of others. This information is integrated as further evidence via the social drift. The strength of the social drift changes over time t whenever another group member makes a choice and is a function of the majority of individuals $M(t)$ who already decided (see also Tump et al., 2020):

$$\delta_s(t) = s \times M(t)^q, \tag{3}$$

with

$$M(t) = N_{escape}(t) - N_{stay}(t). \tag{4}$$

Whereby $N_{escape}(t)$ and $N_{stay}(t)$ are the number of individuals who have decided at time t to escape or stay, respectively. The parameters s and q shape the relationship of majority size and social drift rate whereby s serves as a scaling factor and q influences the shape of the power function. Values of q below one indicate that the impact of an additional individual saturates with increasing majority size $M(t)$. Once the decision threshold θ (or $-\theta$) is reached, a decision to escape (or stay) is made.

For statistical inferences with the social DDM, we used a Differential-Evolution-MCMC algorithm. We ran a Bayesian hierarchical model which allowed us to obtain individual and population-level parameter estimates. We ran 24 chains in parallel, each with a chain length of 10,000 including a burn-in period of 5,000 and a thinning factor of 10 to reduce autocorrelations, fitting the single and group condition separately. For further details of the estimation process see supplementary information. A parameter recovery analysis shows that generating and recovered parameters show strong positive correlations indicating that all parameters are identifiable and interpretable in their magnitude (see supplementary information).

Table 1. Description of the parameters of the social DDM

Model feature	Parameter	Description
Relative start point	$\beta = 0.5 + \beta_{bias} \pm \beta_{disc}$	Incorporates the initial tendency to choose escape (β_{bias}) and already gathered correct evidence (β_{disc}). It is assumed to be drawn from a uniform distribution with a range of s_β (Fig. 4A–C).
Personal drift rate	$\delta_p = \delta_{bias} \pm \delta_{disc}$	The accumulated evidence can consists of evidence for the correct option (δ_{disc}) which can be biased towards escape (δ_{bias}). It is assumed to be normal distributed with a variance of s_δ (Fig. 4D–F).
Social drift rate	$\delta_s = s \times M(t)^q$	Describes the impact of social information, with s scaling the strength of the social drift rate, and q shaping the power function describing the relationship of majority size $M(t)$ and social drift rate (Fig. 4G).
Choice threshold	θ	The amount of evidence an individual has to accumulate to make a decision; θ ($-\theta$) reflects the escape (stay) choice threshold (Fig. 4H).
Nondecision time	*NDT*	Response latency describing any share of the response time which is not captured by the choice process (Fig. 4I).

Social DDM: Agent-based simulations.

To analyse how the cognitive mechanisms underlying evidence accumulation influence the group dynamics we conducted agent-based simulations of the social DDM. We parameterized each agent with the mean of the posterior estimates of all participants in groups of ten. To examine the influence of social interactions on the agents' behaviour we also ran a control simulation with the social drift set to zero (i.e., without social interaction). For each simulation run, we saved the agents' choice and decision order (Fig. 3D). Afterwards, we further examined how the start point bias and the drift variance influence the group dynamics. Because drift variance only predicts faster responses for the more frequently chosen option (i.e., in presence of a drift bias), we systematically varied either the start point bias from -0.2 to 0.2 or the drift bias from -0.3 to 0.5 in combination with a drift variance of zero, one or two (Fig. 5). The code for the analyses and simulations can be accessed at `https://osf.io/jn6a7/`.

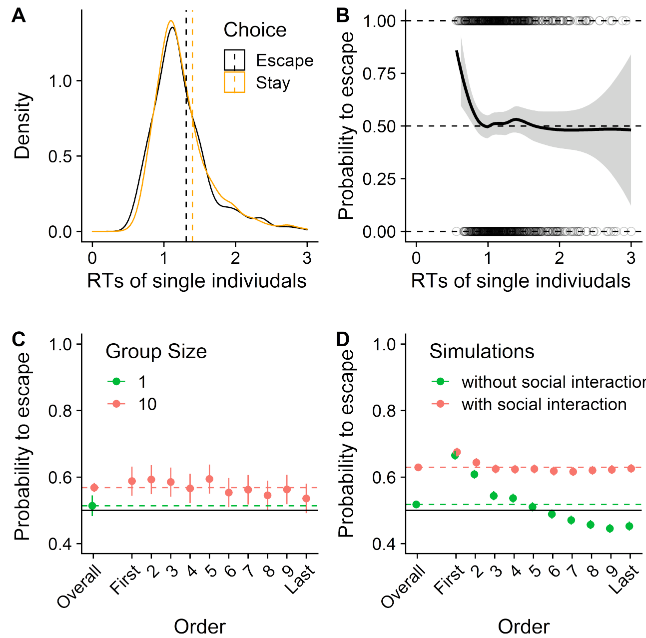

Figure 3: **The relationships between choices, RTs and decision order. (A)** The RT densities for "escape" and "stay" choices of single individuals with a smoothing bandwidth of 0.1 seconds. The vertical dashed lines indicate the mean. **(B)** The RTs of stay (0) and escape (1) choices for single individuals. Each circle represents a single choice, with darker areas containing more choices. The black line indicates the estimated probability to escape at any time point estimated by loess-smoothing with the default smoothing span of 0.75. The uncertainty bands indicate twice the standard error. Note that $\approx 3\%$ of the RTs were above 3 seconds and are not shown. **(C)** The proportion of escapes for singletons (green) and groups (red). For groups, the overall proportion is shown (most left dot), and as a function of the decision order. **(D)** The proportion of escapes for simulated non-interacting (green) and interacting (red) groups. The points and error bars in C–D reflect the mean and twice the standard error, and the horizontal dashed lines indicate average escape probability

Results

Behavioural results.

We begin by examining participants' behaviour alone and in groups. As expected, participants in groups outperformed single individuals (accuracy: 78% versus 71%). We found asymmetric RTs in both conditions. For both individuals alone and in groups the decision to escape was made credibly faster than the stay decision. Single individuals: 1.31s versus 1.40s ($est = -0.09$, CI = [-0.15, -0.03]); groups: 1.97s versus 2.27s ($est = -0.18$, CI = [-0.21, -0.15]). A closer look at the RT distributions of singletons reveals that this difference was most prominent for the leading edge of the distributions (i.e, the fastest choices; Fig. 3A). Figure 3B shows the probability to escape for singletons over time, showing that the earliest choices of singletons were substantially more likely to be escape choices, while later choices were increasingly likely to be stay choices.

These asymmetric RTs might strongly influence the information flow in groups: whereas single individuals only escaped in 51% of the trials (i.e., showed no clear preference for either option), individuals in groups chose to escape in 57% of the trials (Fig. 3C). Comparing the likelihood to escape between singletons and the first deciding individual in a group, we found that the latter was much more likely to escape, despite both making choices in absence of social information. Later-deciding individuals (order ≥ 2) were influenced by these early escaping individuals and also escaped more often as compared to singletons. In summary, on a behavioural level, we found that individuals in groups were more likely to escape, which is most likely due to asymmetric RTs: escape responses were made earlier and swayed others into escaping.

The social dynamic captured by the social DDM.

Next, we used the social DDM to investigate the cognitive mechanisms underlying the escape choice amplification. Figure 4 shows the individual and population-level parameter estimates of singletons (green) and individuals in groups (red). For brevity, we focus our description on individuals in groups. The choice process in groups can, in short, be described by: (i) individuals' relative start point is biased towards escape (β_{bias} = 0.08, CI = [-0.07, 0.09]; Fig. 4A) and closer to the correct decision threshold (β_{disc} = 0.02, CI = [0.01, 0.03]; Fig. 4B), indicating that they gathered, on average, correct evidence while observing the stimuli. (ii) During the choice phase, individuals in groups continued to gather correct (δ_{disc} = 0.58, CI = [0.49, 0.67]; Fig. 4E) and unbiased (δ_{bias} = -0.00, CI = [-0.11, 0.10]; Fig. 4D) evidence. (iii) Furthermore, individuals gathered social information by drifting to the option chosen by the majority of individuals (s = 1.08, CI = [0.95, 1.22]; q = 0.59, CI = [0.51, 0.68]; Fig. 4G). (iv) Finally, once individuals gathered enough evidence they made a choice (θ = 1.97, CI = [1.86, 2.08]; Fig. 4H). Note that individuals in groups required substantially more evidence than single individuals as indicated by a higher choice threshold ($\theta_{groups} - \theta_{singletons}$ = 0.88, CI = [0.70, 1.06]).

Next, we investigated which mechanism(s) of the choice process could explain the asymmetric RTs and the resulting escape choice amplification. Importantly, the start point parameter of individuals in groups (and to a lesser extent of singletons) was biased towards the escape choice, which would predict faster escape choices (Fig. 4A). A variance in drift rate only predicts asymmetric RTs in presence of a drift bias (i.e., faster escapes if individuals drift towards escape). As the personal drift rate of individuals in groups was not biased towards escape, this mechanism cannot explain faster escape choices (Fig. 4D, F). To test whether the social DDM can indeed explain the escape choice amplification through social interactions, we simulated groups of 10 agents which either interacted (via the social drift) or decided independently (i.e., no social coupling). Figure 3D shows that the social coupling is key for recovering our main finding: agents deciding independently did not escape more often than chance and showed a steep drop in likelihood to escape with decision order, which was not observed empirically (Fig. 3C). Interacting agents, on the other hand, showed a bias towards escape, and no (or only a slight) drop of escape probability

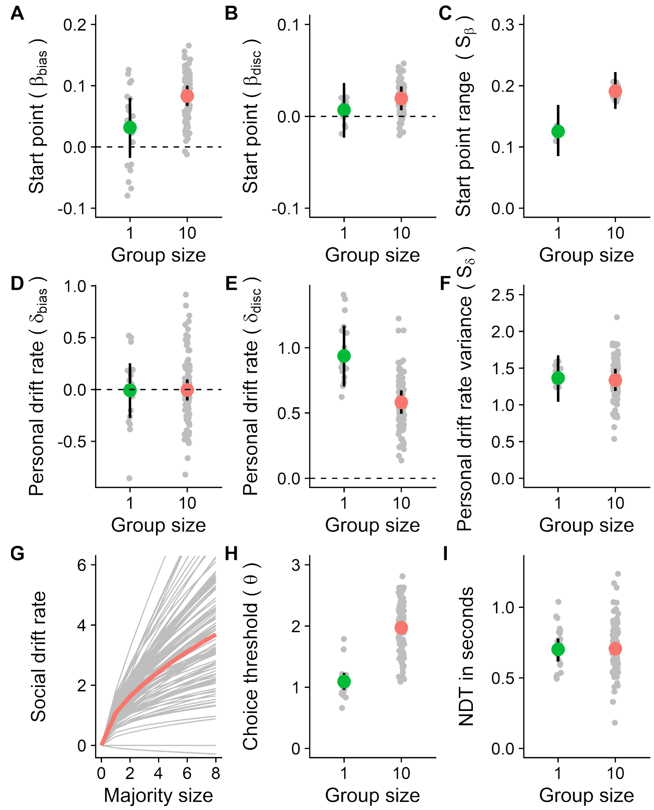

Figure 4: **Parameter estimates of the social DDM.** Shown are the individual (gray) and population-level parameter estimates for single individuals (green) and groups of ten (red). For parameter descriptions see Table 1. Panels **(A–C)** show parameter estimates associated with the relative start point, **(D–F)** with the personal drift rate and **(G)** with the social drift rate. Panels **(H)** and **(I)** show the parameter estimates for the choice threshold and nondecision time. The dots and error bars show the mean and the 95% credible intervals of the posterior distributions.

with decisions order, as empirically observed. Though in both simulations early-deciding agents were more likely to escape, the social coupling was essential for these escape choices to cascade through the group.

The mechanisms driving choice bias amplifications

Finally, we investigated how the two key processes driving asymmetric RTs shape choices biases in collectives across a broader range of parameter settings. First, we investigated the influence of a start point bias, by simulating interacting and non-interacting agents in groups with varying start point biases while the drift bias was set to zero. Figure 5A shows how an increase in the start point bias increases the proportions of escape choices for both group types. However, for interacting agents, the increase is much stronger because of social amplification (see also Fig. 3D). Thus, we expect the influence of start point biases on choice proportions to be strongly amplified in sequentially deciding groups.

Next, we investigated the influence of drift variance while the start point bias was set to zero (Figure 5A & B). As drift variance predicts faster choices of the more frequently chosen option, we further systematically varied the drift bias

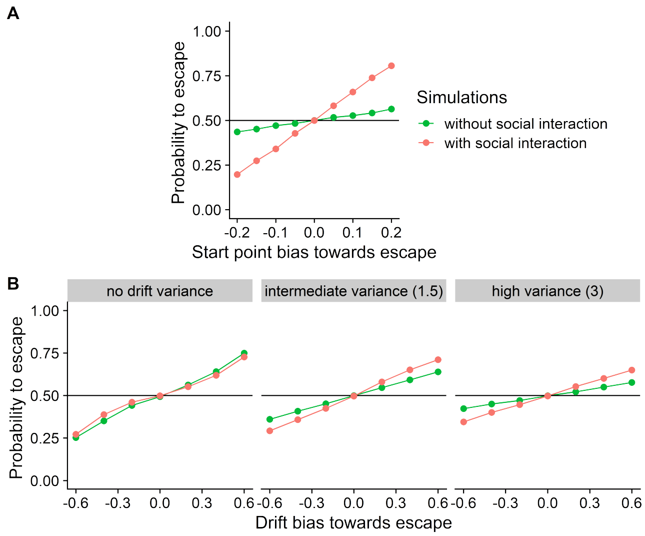

Figure 5: **How start point bias and drift variance can explain choice bias amplification.** The average choice proportions of simulated groups with (red) and without (green) social interaction across varying DDM parameters. **(A)** Increasing the start point bias towards escape slightly increases escape proportions for non-interacting agents. These biases are, however, strongly amplified in interacting agents. **(B)** Interacting and non-interacting agents only show substantial differences in the presence of a strong drift rate bias and drift rate variance. Note that the intermediate variance strength approximates the variance found in this study. The points and error bars reflect the mean and standard error.

whereby a drift bias towards "escape" predicts faster "escape" responses. With little to no intermediate drift variance, even strong biases in the drift rate will not be amplified in groups. Only if both, drift bias and variance are high, interacting agents start escaping substantially more often compared to non-interacting agents. The amplifying effect of the drift rate variance is comparably small to the start point bias because the start point bias deferentially impacts the leading edge of the RT distributions. In other words, the fastest choices are driven by the start point bias. These fast choices are in turn, the most influential ones for social dynamics. Varying drift rates, on the other hand, have only little influence in the leading edge of the RT distribution and impact much more the tail (i.e., late decisions).

Discussion

Despite a long history of research on behavioural cascades, our ability to predict what kind of choice alternatives are prone to cascades is still limited. One reason is that past research tended to investigate collective patterns with simplified assumptions about the underlying cognitive mechanisms (Raafat, Chater, & Frith, 2009; Heyes, 2016; Krause et al., 2021). Here we try a different approach by using the social DDM to gain a detailed understanding of the underlying cognitive processes and their consequences for group dynamics.

We show that if one option is on average chosen faster, this can bias the spread of information through the group. The characteristic of these fast choices is here driven by individuals having a start point bias towards escape. Further, simulations show that a variance in the drift in combination with a strong drift rate bias could also bias the spread of information through groups, however, to a much lesser extent.

In the DDM literature, start point and drift biases have typically been studied in signal-detection tasks (Gold & Shadlen, 2007), whereby individuals predominantly account for differences in potential payoff by adjusting their start point instead of their drift rate. Individuals, in a similar fashion, shift their start point towards the more often correct option in presence of frequency manipulations (Leite & Ratcliff, 2011; Mulder et al., 2012; White & Poldrack, 2014). Thus, start point biases describe an a priori preference for an option, for example, to "shoot" instead of "not-shoot" on a potentially armed target in a shooter task (Pleskac et al., 2018) or to prefer the save versus the risky option in risky choice (Zhao et al., 2020). Especially the fastest decisions are thereby expected to be driven by start point. The more time passes the more are the choices expected to be influenced by new incoming evidence (White & Poldrack, 2014). Drift rate biases, on the other hand, have been manipulated by changing the stimuli evaluation rules (Leite & Ratcliff, 2011; White & Poldrack, 2014). In memory retrieval tasks, for example, where participants had to categorise words as new or old (i.e., already seen on a list) the instruction to only consider items as old if they were associated with strong memories biased the drift rate towards the option "new" (White & Poldrack, 2014). Thus, drift rate biases reflect a biased information evaluation. As this bias introduces tendencies in the evaluation process itself, it persists over time and thereby can explain choice biases even after a long deliberation process (White & Poldrack, 2014). Note that because the start point in this study describes the evidence state after stimuli presentation, we cannot rule out that a drift rate bias during the short stimuli presentation caused a subsequent start point bias. Enabling responses already during the short stimuli presentation would allow to identify potential drift rate biases but also introduce a trade-off between observing the stimuli and choices of others.

Conclusions

In summary, the social interactions in our experiment introduced choice biases—higher probabilities of choosing escape—on a group level which were negligible in single individuals. We identified fast escapes as a driving force which were caused by start point biases. Drift variance has a much weaker bias amplifying effect on group dynamics. These findings have important implications because many choice tasks are characterized by one alternative being, on average, chosen faster. However, whether these choices are expected to be amplified in social contexts depends on the exact underlying choice mechanisms and resulting RT distributions.

Supplementary material. All supplementary information including the empirical data and code for the analyses and simulations can be accessed at `https://osf.io/jn6a7/`.

References

Bowen, H. J., Spaniol, J., Patel, R., & Voss, A. (2016). A diffusion model analysis of decision biases affecting delayed recognition of emotional stimuli. *PLoS One*, *11*(1), e0146769.

Bürkner, P.-C. (2017). brms: An r package for bayesian multilevel models using stan. *Journal of Statistical Software*, *80*(1), 1–28.

Couzin, I. D., Krause, J., Franks, N. R., & Levin, S. A. (2005). Effective leadership and decision-making in animal groups on the move. *Nature*, *433*(7025), 513–516.

Diederich, A., & Busemeyer, J. R. (2003). Simple matrix methods for analyzing diffusion models of choice probability, choice response time, and simple response time. *Journal of Mathematical Psychology*, *47*(3), 304–322.

Frydman, C., & Krajbich, I. (2021). Using response times to infer others' private information: An application to information cascades. *Management Science*.

Germar, M., Schlemmer, A., Krug, K., Voss, A., & Mojzisch, A. (2014). Social influence and perceptual decision making: A diffusion model analysis. *Personality and Social Psychology Bulletin*, *40*(2), 217–231.

Gold, J. I., & Shadlen, M. N. (2007). The neural basis of decision making. *Annual Review of Neuroscience*, *30*, 535–574.

Heyes, C. (2016). Blackboxing: social learning strategies and cultural evolution. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *371*(1693), 20150369.

Krause, J., Romanczuk, P., Cracco, E., Arlidge, W., Nassauer, A., & Brass, M. (2021). Collective rule-breaking. *Trends in Cognitive Sciences*.

Kurvers, R. H. J. M., Wolf, M., Naguib, M., & Krause, J. (2015). Self-organized flexible leadership promotes collective intelligence in human groups. *Royal Society Open Science*, *2*(12), 150222.

Leite, F. P., & Ratcliff, R. (2011). What cognitive processes drive response biases? A diffusion model analysis. *Judgment and Decision Making*, *6*(7), 651–687.

Mulder, M. J., Wagenmakers, E.-J., Ratcliff, R., Boekel, W., & Forstmann, B. U. (2012). Bias in the brain: A diffusion model analysis of prior probability and potential payoff. *Journal of Neuroscience*, *32*(7), 2335–2343.

Palmer, E. M., Horowitz, T. S., Torralba, A., & Wolfe, J. M. (2011). What are the shapes of response time distributions in visual search? *Journal of Experimental Psychology: Human Perception and Performance*, *37*(1), 58.

Pleskac, T. J., Cesario, J., & Johnson, D. J. (2018). How race affects evidence accumulation during the decision to shoot. *Psychonomic Bulletin & Review*, *25*(4), 1301–1330.

Raafat, R. M., Chater, N., & Frith, C. (2009). Herding in humans. *Trends in Cognitive Sciences*, *13*(10), 420–428.

Rand, D. G., Greene, J. D., & Nowak, M. A. (2012). Spontaneous giving and calculated greed. *Nature*, *489*(7416), 427–430.

Ratcliff, R., Smith, P. L., Brown, S. D., & McKoon, G. (2016). Diffusion decision model: Current issues and history. *Trends in Cognitive Sciences*, *20*(4), 260–281.

Stroeymeyt, N., Franks, N. R., & Giurfa, M. (2011). Knowledgeable individuals lead collective decisions in ants. *Journal of Experimental Biology*, *214*(18), 3046–3054.

Toelch, U., Panizza, F., & Heekeren, H. R. (2018). Norm compliance affects perceptual decisions through modulation of a starting point bias. *Royal Society Open Science*, *5*(3), 171268.

Tump, A. N., Pleskac, T. J., & Kurvers, R. H. J. M. (2020). Wise or mad crowds? The cognitive mechanisms underlying information cascades. *Science Advances*, *6*(29), eabb0266.

Wagenmakers, E.-J., & Brown, S. (2007). On the linear relation between the mean and the standard deviation of a response time distribution. *Psychological review*, *114*(3), 830.

Watts, I., Nagy, M., Burt de Perera, T., & Biro, D. (2016). Misinformed leaders lose influence over pigeon flocks. *Biology Letters*, *12*(9), 20160544. (https://doi.org/10.1098/rsbl.2016.0544) doi: https://doi.org/10.1098/rsbl.2016.0544

White, C. N., & Poldrack, R. A. (2014). Decomposing bias in different types of simple decisions. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *40*(2), 385.

Zhao, W. J., Walasek, L., & Bhatia, S. (2020). Psychological mechanisms of loss aversion: A drift-diffusion decomposition. *Cognitive Psychology*, *123*, 101331.