Avoiding costly mistakes in groups: The evolution of error management in collective decision making

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Abstract

Balancing the costs of alternative decisions is a fundamental challenge for decision makers. This is especially critical in social situations, where the choices individuals face are often associated with highly asymmetric error costs—such as pedestrian groups crossing the street, police squads holding a suspect at gunpoint, or animal groups evading predation. While a broad literature has explored how individuals acting alone adapt to asymmetric error costs, little is known about how individuals in groups cope with these costs. Here we investigate adaptive decision strategies of individuals in groups facing asymmetric error costs, modeling scenarios where individuals aim to maximize group-level payoff (“cooperative groups”) or individual-level payoff (“competitive groups”). We extended the drift–diffusion model to the social domain in which individuals first gather personal information independently; they can then either wait for additional social information or decide early, thereby potentially influencing others. We combined this social drift–diffusion model with an evolutionary algorithm to derive adaptive behavior. Under asymmetric costs, small cooperative groups evolved response biases to avoid the costly error. Large cooperative groups, however, did not evolve response biases, since the danger of response biases triggering false information cascades...
increases with group size. We show that individuals in competitive groups face a social dilemma: They evolve higher response biases and wait for more information, thereby undermining group performance. Our results have broad implications for understanding social dynamics in situations with asymmetric costs, such as crowd panics and predator detection.

**Significance Statement:** Decision makers must continuously balance the error costs of alternative decisions. Do I cross a busy street now or wait? Acting independently, individuals can develop response biases to avoid more costly errors (e.g., when in doubt, wait). In groups, early decisions can spread via social influence and promote safe or risky behavior. Here, we model how groups can make accurate decisions in such situations. We find that large groups should avoid response biases because such biases rapidly amplify in groups. Selfish individuals undermine the group’s performance for own benefits by developing high response biases and wait for more information. Our results help shed light on social dynamics in critical situations such as groups crossing a busy street or crowd panics.

**Keywords:** social dilemma, collective dynamics, decision making, information cascades, heuristics and biases, error management

Decision makers must continuously balance the error costs of alternative decisions. Should I stay home or meet up with a friend during a pandemic? Should I buy a house or keep renting? Should I invest in risky stocks or safe bonds? A fundamental characteristic of most decision-making environments is that the costs of different errors are not symmetrical (Conradt and Roper, 2003; Haselton et al., 2015; Johnson et al., 2013; Marshall et al., 2019; Mulder et al., 2012). For example, mistakenly identifying a stick as a snake is largely harmless, whereas believing a snake is a stick can be a lethal mistake. It is therefore crucial to incorporate such error cost asymmetries into accounts of adaptive decision making. A large body of literature (e.g., signal detection theory and error management theory) has investigated how individuals adjust their decision-making strategies to differences in error cost (or base rate) asymmetries, showing that individuals facing asymmetric costs develop a response bias—an increase in the probability of choosing a particular option—to avoid the more costly error (Green and Swets, 1966; Maddox, 2002; Mulder et al., 2012; Ratcliff and McKoon, 2008; Swets et al., 2000). However, the question of how groups of decision makers deal with asymmetric error costs has received far less attention, even though individual decision makers in collective systems often face highly asymmetric costs—for instance, pedestrian groups crossing a busy street (Faria et al., 2010), crowds panicking (Moussaïd et al., 2016), investors creating economic bubbles (Welch, 2000), police officers holding a suspect at gunpoint (Pleskac et al., 2018), or animal groups evading predation (Lima, 1995). In collective systems, individual choices can spread via social
influence through the group and steer others towards or away from making the more costly error; the consequences can be devastating for both individuals and the group (or society) as a whole. Understanding the dynamics of these cascades, in particular when and why they go wrong (e.g., deadly crowd panics or police officers shooting unarmed suspects), is important for a wide range of social systems.

Some studies have investigated collective decision making under asymmetric error costs, but using strongly idealized decision-making processes. Wolf et al. (2013) studied how to optimally pool information in a collective decision-making scenario where individuals simultaneously indicated their personal decision (i.e., independent voting) in a binary classification task. In binary classification, individuals categorise the world into one of two possible states: signal (e.g., a predator, disease, or other threat) or no signal. In doing so, they trade-off between two possible types of error: misses (incorrectly deciding a signal is absent) and false alarms (incorrectly deciding a signal is present; Beauchamp and Ruxton, 2007; Green and Swets, 1966; Macmillan and Creelman, 2004; Swets et al., 2000). Wolf et al. (2013) showed that in the presence of a response bias, optimal decisions arise when individuals do not simply follow the majority but instead set a quorum threshold between the true and false positive rate of their group members. Building on this, Marshall et al. (2019) showed that such quorum thresholds are extremely powerful for optimizing decision making across a broad range of environmental conditions (see also Ben-Yashar and Nitzan, 1997).

The studies listed above assumed that all group members announce their personal decision independently, and that individuals can use the group’s average opinion as social information for revising their initial independent choice. Both assumptions are unrealistic for decision-making processes in almost all biological systems (e.g., see Sankey et al., 2021), where individuals decide sequentially, with more knowledgeable (or confident) individuals making faster decisions (Couzin et al., 2005; Kurvers et al., 2015; Stroeymeyt et al., 2011; Tump et al., 2020; Watts et al., 2016). Early decisions can influence later-deciding individuals, and, in extreme cases, early-deciding individuals can trigger information cascades in which all individuals imitate these early decisions (Anderson and Holt, 1997; Banerjee, 1992; Bikhchandani et al., 1998; Gallup et al., 2012).

**Model and Results**

To study adaptive decision making under asymmetric error costs, we developed a dynamic agent-based model embodying a realistic decision-making scenario of sequential decision making (Fig. 1). We modeled the decision process using a social drift–diffusion model (social DDM) in which a group of individuals faces a binary decision task (signal present or absent), with four possible decision outcomes: Individuals can correctly decide that a signal is present, correctly decide that a signal is absent, incorrectly decide that a signal is present, or incorrectly decide that a signal is absent. In
Figure 1: Illustration of the social drift–diffusion model. Each individual, represented by a jagged line, must decide whether a signal is present (left panel) or absent (right panel). If the signal is present, the individual can decide correctly (hit) or wrongly (miss). If the signal is absent, the individual can decide correctly (correct rejection; CR) or wrongly (false alarm; FA). An individual’s start point depends on the information it gathered prior to the social phase ($\delta p$) and its start point bias ($z_p$). Here the start point bias is towards the decision boundary of the signal, implying that an individual is more likely to make a correct (wrong) decision when the signal is present (absent). At the start of the drift, no individual reached either decision boundary, implying that social information was absent. As individuals diffuse they hit a decision boundary and make a decision. Undecided individuals, in turn, start drifting towards the choice of the individual(s) that already decided, reflecting the process of social information use.

the model, individuals first independently accumulate personal information about the state of the world. In a second phase, they can gather social information (i.e., they can incorporate the choices of others).

The first phase, in which individuals accumulate personal evidence, is formalized by a diffusion process [Gold and Shadlen, 2007; Pleskac and Busemeyer, 2010], whereby individuals start with a start point bias $z_p$, which describes an initial preference for the signal or no signal option. Over time, they gather on average correct evidence described by a drift rate $\delta_p$ towards the correct option. The total amount of evidence $L(t_p)$ at time point $t_p$ is described by a normal distribution with a mean of

$$E[L(t_p)] = \begin{cases} z_p + \delta_p \times t_p, & \text{if signal is present} \\ z_p - \delta_p \times t_p, & \text{if signal is absent} \end{cases}$$

(1)

and a variance of

$$\text{Var}[L(t_p)] = \sigma^2_p \times t_p,$$

(2)

with $\sigma_p$ being the diffusion rate ($\sigma_p$ and $t_p$ are set to 1 for simplicity). The parameters $z_p$ and $\delta_p$ change the evidence state in distinct ways: A positive (negative) $z_p$ shifts the mean towards the decision boundary of the signal (no signal) option; a positive (negative) $\delta_p$ shifts the mean towards the decision boundary of the correct (wrong) decision (Fig. 1).

Next, individuals enter a social phase—also formalized as a drift–diffusion process. In this
phase, individuals no longer sample information from the environment; instead, they can update their evidence based on the decisions of others. The evidence $L(t)$ is gathered over time $t$ until a decision is made (i.e., the evidence level exceeds the decision boundary). This process is described by a random-walk process with discrete time steps $\Delta t$:

$$L(t + \Delta t) = L(t) + \delta_s \times \Delta t + \sqrt{\Delta t} \times \epsilon(t),$$

(3)

with $\delta_s$ representing the social drift rate and $\epsilon(t)$ representing Gaussian white noise with a mean of 0 and a variance of 1 (changing the variance rescales the other parameters and does not change the model prediction; see Ratcliff and McKoon 2008). The social drift rate $\delta_s(t)$ describes the change in an individual’s drift rate depending on the decisions of others (i.e., the impact of social information) and is modeled proportionally to the majority size $M(t)$ of individuals that had already decided at time point $t$ (e.g., see Bikhchandani et al. 1998; Tump et al. 2020):

$$M(t) = N^+(t) - N^-(t),$$

(4)

$$\delta_s(t) = s \times M(t),$$

(5)

where $N^+(t)$ and $N^-(t)$ are the number of individuals that decided the signal was present or absent, respectively, at time point $t$, and $s$ is scaling the strength of the social drift. The amount of evidence an individual accumulates before making a decision is determined by the boundary separation $\theta$ with the decision boundaries set at $\pm \theta$. Our model directly links individuals’ established cognitive processes to the unfolding collective dynamics. It ensures that individuals with strong personal information will, on average, start closer to one of the decision boundaries and thus make faster decisions, as observed in groups across many biological systems (Couzin et al. 2005; Kurvers et al. 2015; Reeves 2000; Stroeymeyt et al. 2011). These fast decisions can, in turn, influence the drift rate of undecided individuals, thus capturing the natural dynamic of information flow from highly informed to lowly informed individuals (Tump et al. 2020).

While some model parameters are not fully under an individual’s control (e.g., amount of personal information available), other behavioral parameters can be strategically adjusted, including start point bias, social information use, and the amount of evidence needed to make a decision. To retrieve the adaptive behavioral parameters we embedded the social DDM into an evolutionary algorithm. Evolutionary algorithms allow fitness-maximizing parameter settings to evolve by exposing them to selection pressure and mutation (Hamblin 2013), making them highly suitable for game-theoretic problems, where the optimal behavior of individuals depends on the behavior of others. We systematically varied group size and the asymmetry in error costs in order to study
their combined effect on the evolution of the three key decision-making traits: start point bias, social information use, and the amount of evidence needed to make a decision. Individuals were rewarded (penalized) for correct (wrong) choices using three types of error costs: symmetric costs, moderate cost asymmetry (i.e., a miss more costly than a false alarm; see Materials and Methods), and strong cost asymmetry. We added a small time cost, reflecting common real-life opportunity costs (e.g., time spent making a decision cannot be spent on other activities). We started with groups of individuals whose interests were completely aligned, with individuals equally sharing a group payoff (“cooperative groups”). We then investigated whether the collective interest was at odds with individuals’ self-interest (i.e., a social dilemma; Van Lange et al., 2013), by examining how introducing individual-level competition (i.e., a payoff solely based on own performance) shaped evolved behaviors and corresponding payoffs across group sizes and error cost asymmetries.

**Asymmetry in error costs.** Figure 2 shows the evolved parameters for different group sizes and error costs in cooperative groups. When errors costs were symmetrical, no start point bias developed in cooperative groups of any size (Fig. 2A). With increasing cost asymmetry, individuals acting alone and in small cooperative groups evolved a bias towards the signal decision boundary avoiding the costly error. Large cooperative groups, however, did not evolve a bias even under high asymmetric error costs. An explanation for the lack of bias in large cooperative groups can be found in Figure 3, which shows the hit and correct rejection rates, as well as the payoffs, for different group sizes and biases (while fixing the boundary separation and social drift rate at the evolved level of the specific group size; see Fig. 2). Across all group sizes, increasing the start point bias increased the hit rate but decreased the correct rejection rate. Under symmetrical costs, the highest payoffs were obtained at a bias level of 0, which maximizes the combined sum of the hit and correct rejection rate. However, when misses became more costly than false alarms, single individuals and small groups maximized their payoff at a relatively high bias to avoid costly misses. In large groups,

![Figure 2: Outcomes of the evolutionary algorithms per group size and error cost in cooperative groups.](image)
Figure 3: Hit and correct rejection rates (black lines, left axis) and payoff (colored lines, right axis) as a function of start point bias for different group sizes and error costs for cooperative groups. Across all group sizes, increasing the start point bias towards the decision boundary of the signal leads to an increase in the hit rate, but simultaneously to a decrease of the correct rejection rate. Under symmetrical error costs, individuals across all group sizes maximize their payoff by maximizing the hit and correct rejection rate alike; this occurs at a bias close to 0. Under asymmetric costs, individuals need to ensure a high hit rate in order to avoid costly misses. Small groups achieve this by developing a bias. Large groups achieve a high hit (and correct rejection) rate without a start point bias, and therefore maximize the payoff at a much lower bias. Boundary separation and social drift were fixed at the endpoints of the evolutionary algorithms for each combination of group size and error cost.

by contrast, a bias close to 0 was optimal. Large groups achieved high hit and correct rejection rates without a start point bias, and were very sensitive to small biases. Increasing their start point bias did increase their hit rate, but this did not outweigh the associated costs of the steep drop in the correct rejection rate. The steepness of this drop increased with group size. In other words, a strong bias in large groups would lead to many false alarms; this can be avoided by reducing the bias.

This is further illustrated in Figure 4A, which directly compares the performance of different-sized groups across different bias levels at the highest level of error cost asymmetry. Large groups were sensitive to biases: They outperformed small groups in the absence of a starting point bias, but were outperformed by small groups under high levels of start point bias.

Boundary separation. Figure 2B shows that individuals in larger groups evolved a larger boundary separation, implying that they required more evidence to trigger a decision. This effect was independent of asymmetry in error costs. Figure 3B directly compares the payoffs of different-sized groups for different levels of boundary separation at the highest level of error cost asymmetry, further confirming the benefits of evolving higher boundary separations for larger groups. Individuals need more information in larger groups because the potential benefits of social information are higher in larger groups; the relative benefits of waiting longer for social information should therefore also be higher.
Figure 4: Payoff analysis with varying start point bias, boundary separation or social drift. (A–C) The mean payoff of individuals in different-sized, cooperative groups across the three key parameters under high asymmetric error costs (cost asymmetry: 4). In these simulations, one evolved parameter was varied (x-axis), while the other two were fixed at their evolved level of cooperative groups. Larger groups maximized their payoffs (indicated by dots) at (A) a lower start point bias and (B) higher boundary separation compared to small groups. (C) All group sizes maximized their payoff at the highest level of social drift. Dashed horizontal lines show the mean payoff of the first responder. With increasing social drift rate, the mean payoff of all group members approximated the payoff of the first responder. (D–F) The benefits of individuals in competitive groups having above-average values in the three key parameters under high asymmetric error costs. Positive (negative) y-values indicate that individuals with above-average (below-average) values in the respective parameter achieved a higher payoff. Competitive groups evolved parameter values at which their members did not profit from having a higher (or lower) parameter value (i.e., where colored lines meet the solid horizontal line at zero), which approximates the outcomes of the evolutionary algorithm. These values partly differed from optimal outcomes in cooperative groups (dots), indicating a social dilemma. At these evolved endpoints of the cooperative groups individuals in competitive groups benefited from having a higher (D) start point bias and (E) boundary separation. (F) Cooperative and competitive groups did not differ in their evolved value of social drift.
**Social drift.** Across all group sizes and error costs, the social drift evolved to the maximum allowed level (Fig. 2C). The evolution of these extreme parameters indicates the effectiveness of a simple “copy-the-first” heuristic, whereby individuals immediately imitate the decision of the first responder via a strong social drift. This simple heuristic performs so well because of the way personal information is gathered. Individuals with more accurate personal information start, on average, closer to a decision boundary than do individuals with less accurate information. This gives rise to a process of self-organization, with more accurate individuals making faster decisions (Tump et al. 2020). The first responder therefore generally achieves a higher payoff compared to later-deciding individuals, independent of social drift rate or group size (indicated by dashed lines being higher than solid lines in Fig. 2C). For later-deciding individuals, the best strategy is thus to increase the social drift rate in order to imitate the first decision, thereby saving costly time.

**Competitive versus cooperative groups.** Across all group sizes, competitive groups developed a stronger start point bias towards the signal boundary than did cooperative groups (Fig. 5A). To investigate this result, we introduced interindividual heterogeneity in the bias level within competitive groups and compared the payoffs of these different bias levels. At the start point bias level that maximized the mean group payoff (dots in Fig. 4A, D), competitive individuals with a higher start point bias gained higher individual payoffs, and this advantage only disappeared when the group had a substantially higher mean bias (Fig. 4D). This could be due to the tension between providing good information to group members and maximizing one’s own payoff. Reducing their start point bias enables individuals to provide more accurate social information, while increasing their start point bias helps them avoid the high personal costs of a miss—but this comes at the expense of accuracy and therefore results in more misleading social information.

For all group sizes, competitive groups evolved higher boundary separations than did cooperative groups (Fig. 5B). Figure 4E shows that, at the maximum payoff level of cooperative groups (dots), competitive individuals benefited from having a slightly higher boundary separation. Only at substantially higher levels of mean group boundary separation did this benefit disappear, thus driving the boundary separation in competitive groups to higher values.

Both cooperative and competitive groups evolved to the maximum level of social drift (Fig. 5C). In line with this, individuals with a lower social drift rate never outperformed individuals with a higher social drift rate (indicated by the strictly positive values in Fig. 4F). This suggests strong benefits of using social information, or even copying the first responder, independent of group size or cooperative setting.

Finally, we found that with increasing group size, individuals in cooperative groups achieved a higher payoff than did individuals in competitive groups (Fig. 5D). The payoff of cooperative
Figure 5: Evolutionary outcomes of cooperative and competitive groups at an error cost ratio of 4. Across all group sizes, competitive groups evolved (A) a larger start point bias and (B) larger boundary separation, indicating a conflict between individual- and group-level interests. (C) Both cooperative and competitive groups evolved maximum social drift rates. (D) At large, but not small, group sizes, cooperative groups outperformed competitive groups. Dots and error bars represent the mean and variance of the endpoints of the evolutionary simulations, respectively.

groups increased more with larger group size compared to the payoff of competitive groups. This is because the larger start point bias and boundary separation that evolved in competitive groups partly undermined the benefits of collective decision making.

Discussion

We investigated the evolution of individuals’ adaptive decision rules across different group sizes, cost asymmetries, and competitiveness. When the cost of a miss was higher than the cost of a false alarm, individuals in small groups evolved a start point bias to avoid the costly misses. This corroborates earlier findings showing that individuals faced with asymmetric error costs shift their decision criterion (in a signal detection theory analysis; Maddox, 2002) or their start point bias (in a DDM framework; Mulder et al., 2012; Leite and Ratcliff, 2011) to avoid the more costly error. Strong start point biases are adaptive in small groups, but in large groups they amplify quickly, typically leading groups to decide for signal. This results in a high hit rate, but also a high false alarm rate; larger collectives may therefore suffer when individuals do not adjust their biases accordingly.

Individual response biases can have dramatic consequences for collective systems. For instance, after terrorist attacks like 9/11 in 2001 or the Paris attacks in 2015, some individuals may have adjusted their response bias towards an alarm response. This type of adjustment might be wise in a small group, but can quickly escalate in large crowds, which are more vulnerable to false alarms. In post-9/11 Chicago, for example, several club visitors mistook pepper spray for a poison gas attack; the resulting panic left 21 dead (CNN, 2003). The risk of amplification is further worsened in competitive groups, which evolve a higher bias than cooperative groups do. When individuals aim to maximize their own payoff, they are willing to accept a higher level of false alarms at the expense of the collective well-being. Indeed, in our model large competitive groups performed substantially worse than large cooperative groups did, partly due to a higher evolved start point bias. In high-stress situations (e.g., a perceived terrorist attack) people’s behavior often shifts from cooperative to
competitive (Mintz, 1951; Moussaid and Trauernicht, 2016). Taken together, our results highlight a social dilemma and the potential danger posed to groups by individuals with a high response bias. Future research should aim to provide a more detailed understanding of how information spreads in such situations.

Groups are particularly vulnerable to information cascades due to their high reliance on social information. We found that social drift rate evolves to a maximum across group size, cost asymmetry, and competitiveness, indicating a reliance on a copy-the-first strategy. This finding confirms previous studies on strategic delay, which describe a Nash equilibrium in which everyone initially delays their choice (Gal and Lundholm, 1995; Zhang, 1997). As time passes, the individual with the best information can assume that, since no-one else has made a decision, their information is better than that of other group members. Because the individual with the best information is expected to decide first, others then simply imitate this decision. Adopting a copy-the-first strategy allows individuals to rely on the social source with the strongest evidence; it also saves time, since individuals do not need to wait for others to decide.

Crucially, these studies—and ours—assume that individuals have the same speed–accuracy trade-off (e.g., the same boundary separation; Chittka et al., 2009). If individuals differ in their speed–accuracy trade-off (Ducatez et al., 2015), the positive association between first responder and information quality will attenuate. In this scenario the first responder is more likely to emphasize speed, at the expense of accuracy. When individuals differ in their speed–accuracy trade-off, favoring the decisions of individuals who respond quickly might undermine the benefits of a copy-the-first strategy. Individual differences in speed–accuracy trade-offs could explain why few, if any, empirical studies have found that individuals simply copy the first decision maker (e.g., Kurvers et al., 2015). Future research could investigate how individual heterogeneity in speed–accuracy trade-offs affects decision making in collective systems. Another interesting extension of our framework is the evolution of more complex strategies when integrating social information. In our modeling framework, we assumed a linear relationship between majority size and drift rate. Yet nonlinear responses to social information, such as quorum thresholds, have also been described in the literature (Kurvers et al., 2014; Marshall et al., 2019; Sumpter, 2006; Sumpter and Pratt, 2009). Nonlinear response strategies, which initially down-weight small minorities, then ramp up social information use once the majority reaches a certain threshold, could be explored further within our framework.

The willingness to wait for social information—described by boundary separation—also influences collective dynamics. We found that boundary separation increased with group size, meaning that individuals in larger groups required more evidence to make a decision. This effect was particularly prominent in competitive groups, where individuals profited from requiring more evidence than others at the expense of group performance. These results resemble a well-known finding in social psychology first demonstrated by Darley and Latané (1968): the bystander effect. According to the
bystander effect, people are less likely to offer help the more other people are present. We show that waiting longer to see whether others respond can be an adaptive strategy, as individuals in larger groups should only make a choice (e.g., whether to offer help) with strong evidence. Matching this prediction, a study using CCTV footage found that increased bystander presence reduced individuals’ likelihood of intervening (e.g., via increased boundary separations) while simultaneously increasing the likelihood of someone intervening [Philpot et al., 2020]. The bystander effect could be explained as a rational adaptation to maximize informational gain in varying group sizes. However, future work should investigate this explanation in situations less fraught with moral connotations.

Conclusion. To conclude, in the presence of asymmetric error costs, individuals should adjust their response bias to the group size in order to maximize their payoff. In particular, individuals in large groups should avoid strong start point biases, which would frequently trigger false information cascades. Further, individuals face a social dilemma: The indifference of competitive individuals to the negative consequences of their response bias and their tendency to wait for more social information leads groups—especially large groups—to fail to reap the collective benefits of making collective decisions. In the real world, asymmetric costs are the rule rather than the exception; our results therefore have important implications for understanding a wide range of social dynamics, including police officers’ decisions to shoot, crowd panics, and escape responses under predation risk.

Materials and Methods

The evolutionary algorithm. We combined the social DDM into an evolutionary algorithm to derive the adaptive behavior. Each individual had three evolving traits: start point bias $z_p$, boundary separation $\theta$, and strength of the social drift $s$ (Table 1). The parameters covered a wide range, ensuring the best solutions were included (range for start point bias: -0.5–2; boundary separation: 0.01–12; social drift: 0–2). To ensure that the endpoints of the simulations were independent of their starting conditions, we sampled the initial parameters from a beta distribution with the minimum and maximum scaled to the respective evaluated parameter range, whereby the mean of the beta distribution was sampled from a uniform distribution. In each generation, individuals were randomly and repeatedly (on average 10 times) sampled from the population. They performed the social DDM simulation as described above in the presence of other individuals (in different-sized groups; see below). Population size was fixed at 1,000 individuals across all conditions. After these simulations, individuals produced offspring based on their sum payoff, implemented via tournament selection: Three individuals were randomly sampled from the population and the individual with the highest payoff passed its traits to the next generation (results do not change when sampling more than three individuals). This procedure was repeated 1,000 times. Finally, the traits of the new generation were
Table 1. Description of the Model Parameters. Underlined parameters evolve in the evolutionary algorithm.

<table>
<thead>
<tr>
<th>Model feature</th>
<th>Parameter</th>
<th>Description</th>
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<tr>
<td>Start point in social phase</td>
<td>$L(t_p) \sim N(\bar{z}_p \pm \delta_p, \sigma_p)$</td>
<td>Parameters influencing the evidence gathered during the personal phase $L(t_p)$, which then served as the start point in the social phase. $\delta_p, \bar{z}_p$ determine the mean and $\sigma_p$ the variance of a normal distribution. A positive (negative) $\delta_p$ shifts the mean towards the correct (wrong) option, reflecting the amount of correct evidence gathered. A positive (negative) $\bar{z}_p$ shifts the mean towards the signal (no signal) response.</td>
</tr>
<tr>
<td>Boundary separation</td>
<td>$\theta$</td>
<td>The boundary separation determines how much evidence an individual accumulates before making a decision. Increasing the boundary separation increases the potential for social information use.</td>
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<tr>
<td>Social drift rate</td>
<td>$\delta_s(t) = s \times M(t)$</td>
<td>$\delta_s(t)$ describes the incorporation of social information with $s$ regulating the influence of the majority size (of the individuals who already decided for a particular option $M(t)$) on the social drift rate.</td>
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Exposed to mutation and crossover to ensure variation. Crossover was implemented by swapping two traits between a focal and a randomly drawn individual with a probability of 0.05. For the mutation process, we added Gaussian noise to a trait with a mutation probability of 0.02 and a standard deviation of 5% of the evaluated parameter ranges. These procedures were repeated for 1,000 generations, ensuring that populations converged to stable endpoints. We measured the evolved parameters by averaging the parameter values of the last 10 generations across eight populations.

We systematically varied three features—group size, error cost asymmetry, and payoff—to study their impact on the evolved parameter traits. First, we varied the group size (1, 5, 10, 20, and 50) in which individuals made decisions. Second, we varied error cost asymmetry. Under symmetric costs, an individual received one unit of payoff for a correct decision (hit or correct rejection) and lost one unit for a wrong decision (miss or false alarm). We modeled asymmetries in error costs by increasing the cost ratio of a miss compared to that of a false alarm, reflecting that missing a signal (e.g., a predator or disease) is generally more costly than a false alarm. Across the three cost scenarios the average error cost was kept constant at 1 unit but we varied the miss/false alarm cost ratio (1, 2, and 4). The costs of a miss was set at either 1, $\frac{4}{3}$, or $\frac{8}{5}$, and the cost of a false alarm at 1, $\frac{2}{3}$, or $\frac{2}{5}$. Individuals further experienced time costs of 0.05 units per second (see Fig. S3 for sensitivity analysis). This time cost reflects the commonplace benefit of making fast choices (Chittka et al., 2009); it also means that a certain point in time, the benefit of a correct choice no longer outweighs the time costs. Third, we varied payoff: Individuals received a payoff based on either the mean group payoff (cooperative scenario) or their own payoff (competitive scenario).
After running the evolutionary algorithm we inspected the population trajectories. In all scenarios, populations converged to a single equilibrium, independent of the starting conditions. This indicates that the algorithm found a single robust solution for each combination of group size, error cost asymmetry, and competitiveness. Thus, we did not find stable co-existences of different strategies. Figure S1 shows the trajectories of the three evolving parameters for randomly sampled exemplary scenarios. As a sensitivity analysis we repeated the simulations with varying time costs and distribution characteristics of personal information. The main findings were replicated (see Supplementary Figures S2–S5).

**Performance evaluation.** To gain a deeper understanding of individuals’ behavior at the evolutionary endpoints, we performed additional social DDM analyses with fixed parameter settings (i.e., no evolution of parameters). To investigate the effect of the start point bias $z_p$, boundary separation $\theta$, and social drift $s$, on individuals’ performance (i.e., their payoff and their hit and correct rejection rates), we varied the parameter of interest—for different group sizes and error costs—while fixing the other two parameters at their evolved level of cooperative groups, and measured individuals’ performance over 1,000,000 repetitions (see Figs. 3 and 4A–C).

**Evaluating the influence of competition.** Because the endpoints of cooperative and competitive groups differed (see Results), we studied how competition drives populations away from the optimal behavior of cooperative groups. We again varied the start point bias $z_p$, boundary separation $\theta$, or social drift $s$ while fixing the remaining two parameters at their evolved level of cooperative groups. We also introduced interindividual heterogeneity by assigning half of the individuals of each group a higher parameter value, and the other half a lower value, splitting groups of five randomly (difference for start point bias: 0.2; boundary separation: 0.4; social drift: 0.1). This allowed us to measure the benefits of having a higher (or lower) parameter value than the other group members and, thereby, the effect of competition. We measured payoffs over 1,000,000 repetitions for each parameter combination (see Fig. 4D–F). Competitive groups are expected to evolve parameters such that individuals do not gain a personal advantage by having higher or lower parameters. Note that this analysis only approximates the evolutionary endpoints of competitive groups because of a different implementation (see Fig. 5A–C). Here in this analysis, the group consists of two distinct behavioral types with two fixed parameters; in the evolutionary algorithm groups are heterogeneous across all parameters and the parameters can freely evolve in concert.

**Data and code availability:** The code for the analyses can be accessed at [https://osf.io/a9xkc/](https://osf.io/a9xkc/).

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**References**


Figure S1: Example trajectories of the evolutionary algorithm. Shown are the evolutionary trajectories of bias (left), boundary separation (center), and social drift rate (right), for six additional scenarios. These scenarios were randomly drawn from all 30 analysed scenarios. The corresponding parameter settings are shown in the right panels. Colored lines represent the average parameter value within each of the eight evolving populations; black lines indicate the average across all eight populations.
Figure S2: Sensitivity analysis showing the outcomes of the evolutionary algorithm for different time costs and group sizes in competitive and cooperative groups at an error cost ratio of 4. Central panels show the time cost (indicated in gray) used in the main analysis. Upper (lower) panels show very small (large) time costs. Under very small and large time costs almost all main results were reproduced: (A) Small (but not large) groups evolved a start point bias, with competitive groups evolving a higher bias; (B) larger groups evolved a higher boundary separation, with competitive groups evolving a higher boundary separation; (C) groups evolved a high social drift rate, reflecting a copy-the-first heuristic; and (D) larger groups performed better, with cooperative groups outperforming competitive groups. Two scenarios deviated slightly from the main results. First, at very low time costs (0.01), large (50) cooperative groups did not evolve a social drift rate close to 2, but instead fluctuated around a value above 1. In large groups such social drift values already result in a high likelihood to copy first responders. Given the extremely low time costs, further increasing the drift does not improve the performance. Second, in large groups (50) facing high time costs (0.25), not all competitive populations converged to the same solution, as evidenced by the broad error bars. This is further investigated in Fig. S3. Dots and error bars represent the mean and standard deviation, respectively, across the eight populations.

Figure S3: In large (50) competitive groups under high time costs (0.25), populations converged to one of two equilibria. One equilibrium (blue, turquoise, green and light green lines) followed the pattern of our main result, namely (A) low start point bias, (B) medium boundary separation, (C) maximum social drift, and (D) high performance. In the other equilibrium (purple, pink, orange and brown lines), populations converged to a nonsocial behavior with individuals (A) being highly biased, (B) barely waiting, and (C) not incorporating social information, resulting in (D) low performance. This solution is stable, since a less biased individual with larger boundaries is likely to suffer from higher time cost by waiting for and ultimately following other individuals (who almost always choose ‘signal’). Each line represents the average parameter value of one of the eight evolving populations.
Figure S4: Sensitivity analysis showing the outcomes of the evolutionary algorithm for different distributions of personal information in competitive and cooperative groups at an error cost ratio of 4. Central panels show the personal information distribution used in the main analysis. Left (right) panels show very low (high) mean start points $\delta_p$; upper (lower) panels show very small (large) variance $\sigma_p^2$ (both indicated in gray). The results approximate the main results for a wide range of characteristics of the personal information distribution. For a few conditions populations did not evolve to a single equilibrium, as evidenced by the broad error bars. This is investigated in Fig. S5. Dots and error bars represent the mean and standard deviation, respectively, across the eight populations.

Figure S5: Examples of evolutionary algorithm simulations of scenarios shown in Fig. S4 where populations did not converge to a single equilibrium. (A–D) In competitive groups (group size = 20) with low $\delta_p$ and intermediate $\sigma_p^2$ populations either converged to be highly biased, making rapid choices (i.e., low boundary separation; e.g., pink and purple lines) or to be less biased with larger boundary separation (green and light red lines). (E–H) Similarly, in competitive groups (group size = 20) with high $\sigma_p^2$ and intermediate $\delta_p$, populations converged either to highly biased groups with low boundary separation (e.g., brown and blue lines) or less biased groups with higher boundary separation (green and purple lines). For both examples of nonconvergence, reducing the start point bias (or increasing the boundary separation) in a highly biased population is likely to be disadvantageous. Such a strategy would likely result in similar choices, since the group members are likely to pull the individual towards the signal response, but at higher time costs because the response would be slightly delayed. Each line represents the average parameter value of one of the eight evolving populations.