COMPROMISE AND BLAME DURING RISKY DYADIC FORAGING

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Significance Statement

From hunting to financial decisions, humans must coordinate with others who have different risk preferences, yet how people navigate these conflicts remains poorly understood. We developed a dyadic foraging task where pairs jointly managed risk-reward tradeoffs and found that people often compromise by flexibly incorporating partner's preferences into their own decisions while learning under risk. Despite frequent compromise, people showed egocentric biases when judging responsibility: they took more credit for successes and deflected blame for failures, and this bias predicted reduced willingness to compromise. Notably, although compromise could come at a cost of immediate rewards, it had a social value: people who compromised more were rated as more desirable partners and received less blame. By uncovering the computational and psychological mechanisms underlying compromise, our findings illuminate how people balance self-interest with social goals during collective decision-making under risk.

Abstract

Foraging requires balancing risks and rewards while learning from outcomes. Social foraging poses additional challenges: evaluating others' actions and deciding when to compromise in the face of differing risk preferences. Yet when and why people compromise, how they evaluate each other's responsibilities during foraging together for rewards, and the computational and psychological underpinnings of these processes remain poorly understood. Here we introduce a novel dyadic foraging paradigm that captures naturalistic variation in risk preference by having two participants jointly choose between locations that yield rewards but carry risks and evaluate each other's responsibility for shared outcomes. Across two studies (exploratory N = 250, preregistered confirmatory N = 514), people tended to compromise rather than counteract their partner, especially under diverging risk preferences and when compromise was reciprocated. Compromise behavior was explained by a reinforcement learning model showing that individuals integrate their own and their partner's preferences. Responsibility attributions exhibited egocentric biases—participants claiming more credit for wins than blame for losses—and these biases predicted individual differences in compromise behavior. The interplay between individual differences in risk and responsibility attribution further shaped coordination patterns. Finally, we show that compromising improved performance for risk-averse individuals, increased desirability as a social partner and led to more favorable responsibility attributions, suggesting multiple benefits of compromising. By linking decisions about risk-reward trade-offs to metacognitive judgments about responsibility, our study reveals the social and cognitive processes underlying compromise in risky foraging and, more broadly, in collaborative contexts with conflicting preferences.

Keywords: risk preferences, social foraging, responsibility attribution, coordination dynamics, collective decision-making, metacognition

Introduction

Our ability to collaborate during foraging plays a fundamental role in human evolution and success [1–3]. A key feature of successful collaborations is the ability to reach a consensus [4–6] in deciding the best outcome for the group, which requires individuals to compromise between their own interests and those of others. Compromising becomes particularly important when individuals hold misaligned goals, varying preferences, and differing perceptions of their own and others' contributions. While prior work has highlighted the benefits of collective action, such as increased diversity of ideas, enhanced problem-solving, and opportunities for knowledge pooling and social learning [1,7–10], less is known about how people navigate conflicting preferences in joint decision-making, particularly how they compromise with each other and share responsibility when risk preferences diverge.

Despite coming at the cost of self-interest, compromising with others can facilitate learning by exposing individuals to unexplored options, reduce uncertainty about others' behavior [11,12], and be socially rewarding[1]. Importantly, compromise is often necessary for successful coordination, especially when individuals differ in their preferences and goals. For example, in a stag-hunt game, risk preferences shape foraging decisions: risky people prefer to hunt for stags, yet risk-averse people prefer hares. Hunting for stags potentially yields more benefits, but it also increases risk. When partners must jointly decide what to hunt, those with divergent preferences need to compromise on a shared strategy. Previous research has shown that people often align their decisions with others, even when doing so leads to suboptimal outcomes [15,16]. Computationally, such alignment is supported by mentalizing others' preferences and integrating them with one's own[17,18]. When conflicts arise, people can reach a compromise through different strategies – either by converging on an option that maximizes joint interests or by developing reciprocal norms across repeated decisions, whereby they take turns to maximize their own interests[19,20]. However, much of this research relies on experimental designs that reduce social decision-making to a binary choice between compromising (or coming to a consensus) and maximizing self-interest [21], which limits the opportunity for individuals to modulate their degree of compromise by steering the group towards one's own preferences or actively counteracting others' actions. This leaves open the question of how shared decisions unfold in continuous choice spaces—ranging from compromise to counteracting—and what motivates individuals to adopt one strategy over another.

Beyond conflicts over shared decisions, differences in risk preferences between group members can lead to conflicts over responsibility attribution in collaborative tasks: who deserves more credit or blame when each individual's actions jointly determine the outcome? In these contexts of shared responsibility, people have been shown to base judgements of credit and blame on collaborators' effort [22,23], their contributions [24]and on social norms and values such as fairness and equality[25–28]. Multiple lines of evidence on second-person responsibility attribution have also shown that people are often biased and tend to give themselves more credit for positive outcomes, while rarely blaming themselves for negative ones [29–31]. On one hand, these metacognitive evaluations can serve functions beyond retrospective judgements about self and other. They can help individuals interpret the outcome and evaluate their relative contributions to motivate changes in future actions[32] in ways that facilitate learning and coordination with others [33,34]. For example, people who judge themselves to be more responsible for risky outcomes tend to regulate their risk-taking more than those who did not [35–37]. On the other hand, anticipation of moral evaluations from others can motivate individuals to cooperate and behave more prosocially [38,39]. Together, these findings imply that responsibility judgments are often biased yet play a causal role in shaping social decision-making, raising a central question for collaborative risk-taking: how are responsibility judgement formed when risky outcomes depend on joint actions, and how do such metacognitive judgements and biases influence decisions to compromise or counteract?

To study these conflicts under risk in a more ecologically inspired framework [9,40], we developed a dyadic risky foraging task, where two individuals needed to jointly select between options that varied in risk and reward [40–44], and attribute responsibility for shared outcomes. Previous work on social foraging paradigms have shown that foraging with others can reduce the perception of risk [45], give opportunities to socially learn from each other [10], and improve decision quality and buffer against environmental uncertainty [8,46–48]. At the same time, coordinating with others can be challenging under risky environments where individuals can differ in how they trade-off risk and rewards[4,49–51]. Such differences may reflect stable individual traits, such as intolerance of uncertainty or anxiety[52], or may arise from biased learning from past experiences[53]. Risky environments can obscure individual contributions to collective outcomes, increasing the importance of evaluating others' contributions for effective coordinating and resources sharing [54]. However, little is known about how individuals navigate continuous compromise-counteraction dynamics when risk preferences diverge, and how differences in risk-taking shape responsibility judgements for joint outcomes and their impact on coordination strategies.

In our dyadic foraging task, participants navigated a 1D grid of nine spatially correlated foraging locations such that both risk and reward increased as locations approached a predator on the right (Fig. 1A). To induce naturalistic uncertainty, we scaled risk and reward based on proximity to the predator (See Supp. Fig. 3C). Participants first completed an individual foraging phase where they repeatedly chose where to forage and learnt about the environment and predator attack patterns. Then, they were randomly paired into dyads to complete a joint foraging phase, where their joint foraging location was calculated as the mean of their independent choices at each trial. In the dyad phase, we additionally asked participants to privately attribute responsibility for every trial's outcome to self and their partner (on a Likert scale with five options). We predicted that (a) individuals would take their partner's preferences into account and compromise more often than they would counteract, (b) participants would assign credit and blame based on both trial outcomes and differences between their own and their partner's choices, with a bias toward self-crediting, and (c) self-attribution bias would be negatively correlated with the tendency to compromise, such that individuals with stronger self-crediting biases would be less likely to compromise, and that this interplay will shape whether dyads converge or diverge. To test the validity of our task measures, we further predicted that individual traits of intolerance to uncertainty and social value orientation are linked to risk-preferences in foraging and responsibility judgements, respectively.

Results

People compromise with their partner in risk-based decisions.

First, we asked if individuals adjust their risk preferences based on the social context (i.e., partner's foraging choices). We compared each participant's mean location during the solo phase to their mean location in the group phase, separated by their level of riskiness within the dyad (Fig. 1C). We found that risk-averse (exploratory sample, $t_{rel} = 3.36, p < 0.001$; confirmatory sample, $t_{rel} = 6.23, p < 0.001$) and risk-prone individuals (exploratory sample, $t_{rel} = -7.05, p <$

0.001; confirmatory sample, $t_{rel} = -9.05, p < 0.001$) shifted their choices during the dyadic phase: risk-averse individuals made riskier (i.e., more forward) choices and risk-prone individuals made less risky (i.e., more backward) choices compared to their individual foraging phase. This shift suggests that, overall, people were more likely to compromise with their partner (i.e. move towards the partner) than counteract (i.e., move away from the partner in the direction of one's own initial preference). These differences in riskiness within a dyad also corresponded with stable individual trait differences in uncertainty aversion (Supp. Fig. 1C), suggesting that they reflect broader dispositional tendencies.

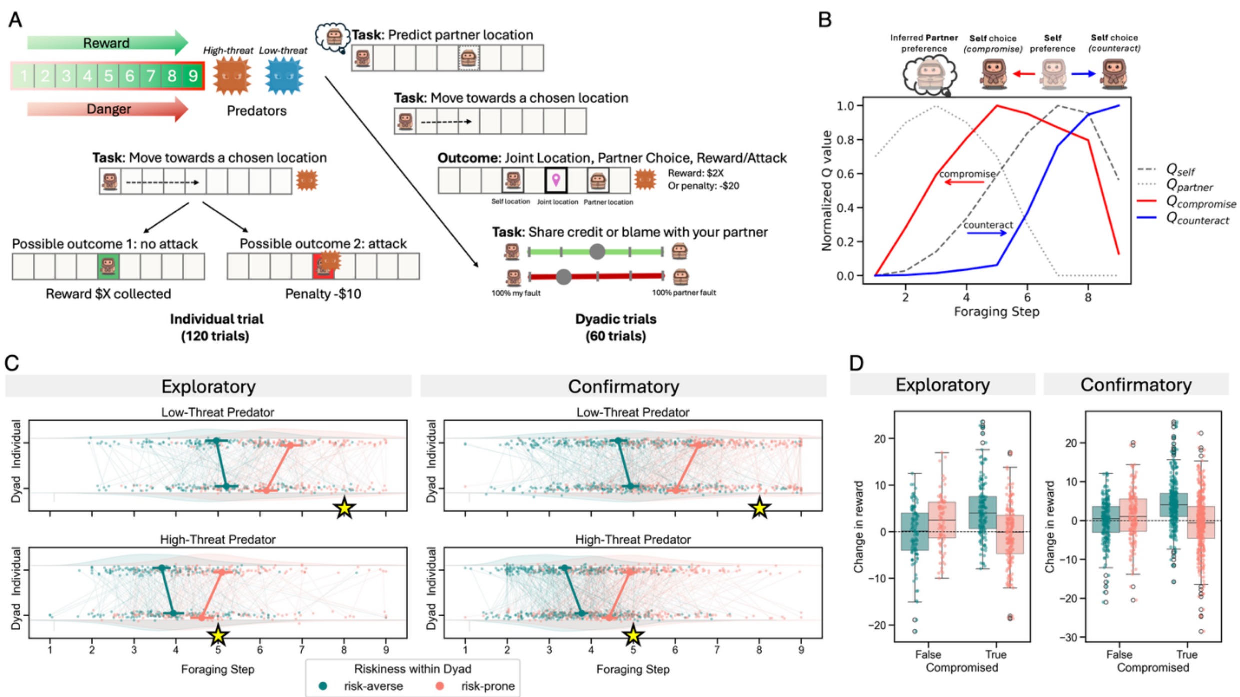

Fig. 1. Overview of the task, computational model and behavioral results. (A) Task paradigm. Squares 1–9 represent the nine foraging steps players can choose from, with squares closer to the predator carrying higher risk than the squares away. Participants first completed 120 rounds of individual foraging (left) and were then paired with another participant for an additional 60 rounds of dyadic foraging (right). In the dyad phase, the joint choice was the average of the two players' independent choices and after every trial, they were asked to share credit or blame with their partner. **(B)** Illustrative example of the Other-regarding Preference Model. This model assumes that players adjust their choices based on their own preferences and their predictions of their partner's preferences. Specifically, the value for each location is given by $\mathrm{Q} = \mathrm{wQ}_{\mathrm{partner}} + (1-\mathrm{w})\mathrm{Q}_{\mathrm{self}}$ with $w > 0$ indicating compromise and $w < 0$ indicating counteract. The model is illustrated $w = 0.4$ for $Q_{compromise}$ and $w = -1$ for $Q_{compensate}$. **(C)** Foraging choice separated by predator (panels), phase (x-axis), and player's riskiness within the dyad (color). Participants chose a more backward (i.e., less risky) location when encountering the high-threat predator, and they chose a more forward (i.e., more risky) location when encountering the low-threat predator (exploratory sample $Step_{low-threat} = 4.37 \pm 0.09$, $Step_{high-threat} = 5.77 \pm 0.10$; confirmatory sample $Step_{low-threat} = 4.15 \pm 0.06$ $Step_{high-threat} = 5.59 \pm 0.08$). At the group level, the mean location choice of dyads resembled that of the solo phase for both predators

(exploratory sample, $Step_{low-threat} = 5.67 \pm 0.10$, $Step_{high-threat} = 4.27 \pm 0.09$; confirmatory sample $Step_{low-threat} = 5.46 \pm 0.07$, $Step_{high-threat} = 4.12 \pm 0.06$). Riskiness within the dyad is defined by the average foraging choice of the last 60 rounds of individual foraging. Stars indicate the optimal foraging locations that maximize the expected reward (see Supp. Fig. 3D for calculation). While participants' decisions under the high-threat predator were closely aligned with expected optimal values, their choices under the low-threat predators were significantly more risk-averse than optimal. **(D)** Reward change from individual to dyadic phase by compromise (x-axis) and player's riskiness within the dyad (color). We binarized compromise (split at 0) and riskiness for illustrative purposes. Boxplots show the median and the interquartile range (25th–75th percentiles).

Compromise facilitated learning and increased rewards for risk-averse individuals

Next, we tested whether compromising was an optimal strategy in terms of the rewards obtained by the participants. On average, participants increased reward in the dyad phase compared to the individual phase (exploratory $t_{rel} = 5.11$, $p < 0.001$; confirmatory $t_{rel} = 5.94$, $p < 0.001$), suggesting an overall benefit of foraging in groups. To rule out the possibility that this increase resulted from reduced threat sensitivity with repeated predator exposure, we examined whether reward increased over trials in the individual phase (after 60 trials) and found no evidence of systematic improvement (Supp. Fig. 4A).

We further investigated whether reward gains differed by compromise level and risk strategy. We operationalized compromise as the degree to which participants adjusted their foraging location toward their partner's baseline risk preference. We regressed the increase in reward (average reward in dyadic phase minus average reward in individual phase) on the degree of compromise and self-partner baseline risk difference (Supp. table 3, Fig. 1D). We found a positive main effect of compromise (exploratory, $\beta_{compromise} = 1.00, p < 0.001$; confirmatory, $\beta_{compromise} = 0.51, p < 0.001$), a negative main effect of self-partner risk difference (exploratory, $\beta_{risk\_diff} = -0.36, p = 0.022$; confirmatory, $\beta_{risk\_diff} = -0.63, p = 0.001$), and a negative interaction effect (exploratory, $\beta_{interaction} = -0.50, p < 0.001$; confirmatory, $\beta_{interaction} = -0.33, p < 0.001$). These effects indicate that compromise was beneficial for more risk-averse individuals, and that its benefits decreased for more risk-prone individuals. For risk-averse individuals, shifting toward a riskier partner may have facilitated exploration of less frequently visited states and thereby increased their rewards. We found that risk-averse partners increased their foraging location in post-dyad solo trials compared to pre-dyad solo phase, suggesting that they socially learned from their partners (see supp. Fig. 5). By contrast, for risk-prone individuals who already tended to choose options closer to the optimal, compromising conferred no additional foraging benefits, and they reverted to riskier locations in the post-dyad solo trials (Supp. Fig. 5).

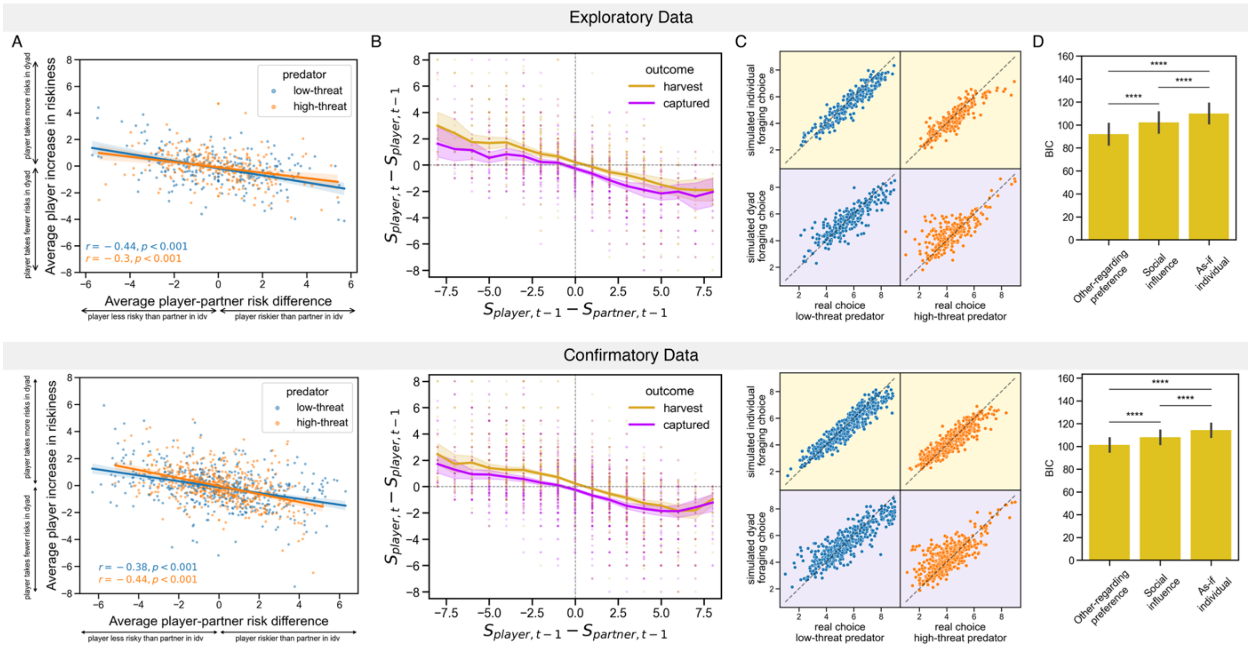

Fig. 2**. Trial-by-trial Changes in Foraging Choices and Computational Modeling of Compromise. (A)** Regression plot showing a negative correlation between the change in player riskiness (average step from the individual to dyadic phase) and the baseline risk differences between player and partner (player's individual-phase average step minus partner's individual-phase average step), for both predators. An ANOVA on absolute step change confirmed that this tendency to compromise did not differ significantly across predator types (exploratory sample, $F = 2.88, p = 0.09$; confirmatory sample, $F = 0.91, p = 0.34$). **(B)** Plot of trial-by-trial changes in player riskiness during the dyadic phase as a function of player-partner choice differences and outcome in the previous round. Error bars indicate 95% credible interval across participants. **(C)** Predictions of each participant's average step based on the best-fitting computational models against their true average, separated by phase and predator. **(D)** Model comparison based on the BIC values of the three models. Error bars indicate standard errors across participants.

The degree of compromise is based on risk differences and the partner's tendency to compromise

Next, we investigated whether decisions to compromise were driven by their partner's risk preference, partner's compromise, and trial outcomes. We found a negative relationship between an individual's risk change and their partner's risk preference. People who were paired with a riskier partner became riskier, and people who were paired with a less risky partner became less risky in the group phase (Fig. 2A), indicating that the magnitude of compromise scaled with the difference in risk preferences between partners.

To test whether compromise was reciprocal and depended on the outcome of a trial, we investigated changes in player location on a trial-by-trial level (Fig. 2B). Specifically, we asked if participants moved closer to their partner's location based on the distance between them, the outcome of the previous trial (reward or attack), and their partner's decision to compromise in the previous trial (Supp. table 1).

We regressed each participant's step change ($S_{player,t+1} - S_{player,t}$) on self-partner distance ($S_{player,t} - S_{partner,t}$), partner's previous step change ($S_{partner,t} - S_{partner,t-1}$), and trial outcome (harvest or captured). We found that the update in participant's location is negatively correlated with self-partner distance (exploratory sample, $\beta_{self-partner\ distance} = -0.38 \pm 0.02$, $p < 0.001$; confirmatory sample, $\beta_{self-partner\ distance} = -0.36 \pm 0.03$, $p < 0.001$), and with partner's previous step change (exploratory sample, $\beta_{partner\ changed} = -0.16 \pm 0.01$, $p < 0.001$; confirmatory sample, $\beta_{partner\ changed} = -0.14 \pm 0.03$, $p < 0.001$) (Fig. 2B). These effects imply that participants were more likely to move forward (or backward) when they were farther behind from their partner (or farther ahead), and when their partner had previously moved backward (or forward), suggesting a reciprocal compromise.

Additionally, participants showed win-stay-lose-shift behavior, moving forward after rewards (exploratory sample, $\beta_{harvest} = 0.20 \pm 0.03$, $p < 0.001$; confirmatory sample, $\beta_{harvest} = 0.16 \pm 0.01$, $p < 0.001$) and backward after attacks (exploratory sample, $\beta_{captured} = -0.42 \pm 0.05$, $p < 0.001$; confirmatory sample, $\beta_{captured} = -0.35 \pm 0.02$, $p < 0.001$). We did not find any interaction effect between trial outcome and self-partner distance on step changes.

Furthermore, to test whether participants consider their partner's choices on a trial-by-trial basis, we examined how response times varied with the discrepancy between self- and predicted partner choices. We regressed log-transformed response times (RT) on the choice discrepancy ($S_{player} - S_{prediction}$), while controlling for player step choice which affected the time taken to make a given move (higher location value required more presses). While the RT analyses were not preregistered, we report them here given their relevance and note that the findings replicated across both samples. We found a positive effect of discrepancy between the players' choices on response times (exploratory sample, $\beta_{discrepancy} = 0.028 \pm 0.005$, $p < 0.001$; confirmatory sample, $\beta_{discrepancy} = 0.022 \pm 0.004$, $p < 0.001$; full regression result see Supp. table 4). This effect suggests that larger differences in risk preference between players require more strategic deliberation.

Taken together, these results suggest that people were more likely to compromise than counteract, and that the level of compromise was based on trial-by-trial risk differences and reciprocity.

Computational models show people integrate partner's preferences in their choices

We developed computational models to identify the mechanisms underlying convergence in risk preferences. Although participants shifted toward their partners' risk attitudes, multiple processes could produce this pattern: (1) being pulled into previously unvisited states could facilitate better learning of the environment, indirectly producing convergence without social influence; (2) the social context could shift general risk preferences (e.g., through risk dilution or increased uncertainty); or (3) participants could actively incorporate their partner's revealed preferences on a trial-by-trial basis. To distinguish between these possibilities, we developed a reinforcement learning model with risk sensitivity and generalization to capture baseline individual foraging behavior (see Methods), and we compared three extensions of this model (Fig. 1B), each corresponding to a distinct hypothesized process during the dyadic phase. The *as-if individual* model captures convergence driven solely by improved learning or exploration, without incorporating social information. The *social-influence* model implements a global shift in risk preference by updating an individual's risk preference toward their partner's preference over time. Finally, the *other-regarding preferences* model captures contingent social integration, in which individuals integrate their own and their partner's risk preferences on a trial-by-trial basis when deciding whether to compromise (Fig. 1B).

Model comparison results show that the *other-regarding preference* model fits the data best (Fig. 2D). To validate the model, we simulated data using fitted parameters and found that the model successfully reproduces key features of participants' choices (Fig. 2C). We also correlated the model fits with participants' behavior to demonstrate that the parameters of *other-regarding preference* model capture different aspects of observed behavior (Supp. Fig. 2). Our results show that the parameter, w, which modulates how much people incorporate others' preferences, correlates with the self-partner distance (Supp. Fig. 2A).

Response time results (see previous result section and Supp. table 4) further corroborated the validity of the *other-regarding preference* model: response times increased when self-preferred choices deviated more from the partner's predicted choice. Neither the *social-influence* model, which assumes a general shift in risk attitude, nor the *as-if individual* model, which assumes no consideration of partners' choices, can account for response time sensitivity to trial-by-trial choice differences between self and partner. In contrast, the *other-regarding preference* model explains this result by suggesting that participants integrated their partner's trial-by-trial preferences into their own decisions, with greater preference divergence increasing computational load. This implies that compromise in dyads is not simply the outcome of a global shift in preferences but instead emerges from individuals weighing their own and their partner's intentions on each trial.

Finally, we examined whether compromise behavior was strategic or universal by testing whether the compromise parameter (w) varied with individual characteristics. If compromise were strategic, we would expect individuals to modulate their compromise based on whether it benefits them: risk-averse individuals should compromise more, while risk-prone individuals should compromise less. However, we found no significant difference in w between riskier and more risk-averse partners (exploratory sample, t_{ind} = -1.78, $p = 0.08$; confirmatory sample $t_{ind} = -0.05$, $p = 0.96$), even if compromising is beneficial for risk-averse individuals and disadvantageous for risk-prone individuals. Additionally, we found no correlation between level of compromising (w) and rewards in the solo phase (exploratory sample, $r = -0.04$, $p = 0.38$; confirmatory sample, $r = -0.03$, p = 0.20), suggesting that compromise was not driven by performance-based learning.

People attribute credit or blame based on relative positions and trial outcome, but with an egocentric bias

Following each trial in the dyadic phase, once the outcome was revealed, we asked participants to share credit or blame with their partner. The responses were not shown to the other partner, and instead, they served as a measure of self-evaluation, as participants had to decide whether they personally deserved more credit or blame for the result, independent of how the other person might perceive the situation.

We examined how people divide responsibility based on choice differences with their partner and whether they share blame or credit differently across outcomes (i.e., harvest or captured). Using a linear mixed-effect regression, we found a significant effect of self-partner distance, trial outcome, and their interaction on blame (Fig. 3A). People who were more forward tended to take more responsibility (exploratory sample, $\beta_{self-partner\ distance} = 0.04, p < 0.001$; confirmatory sample, $\beta_{self-partner\ distance} = 0.04, p < 0.001$). However, their judgments were biased by the outcome.

Participants took more credit for harvesting rewards than blame for being captured (exploratory sample, $\beta_{captured} = -0.08$, p<0.001; confirmatory sample $\beta_{captured} = -0.06$, p<0.001). This egocentric bias is modulated by relative position: participants at safer locations showed stronger egocentric bias, splitting credit equally with their partner for rewards but accepting less blame for attacks (exploratory sample, $\beta_{interaction} = 0.02$, $p < 0.001$; confirmatory sample $\beta_{interaction} = 0.02$, $p < 0.001$). We also found greater disagreement between partners after attacks versus rewards (exploratory sample, $t_{ind} = 3.58$, $p < 0.001$; confirmatory sample $t_{ind} = 8.27$, $p < 0.001$), suggesting that negative outcomes exacerbate attributional asymmetries.

We also examined if such attribution bias is trait-dependent by correlating participants' self-blame/credit with their social value orientation (SVO) score [55]. We found that higher SVO score (i.e., more prosocial) was correlated with more equal credit after harvesting rewards (exploratory sample $r = -0.19$, $p = 0.005$; confirmatory sample $r = -0.14$, $p = 0.002$), but there was no correlation between SVO and blame after being captured (Supp. Fig. 1a).

Less ego-centric bias in responsibility attribution correlates with willingness to compromise

To assess how evaluation of relative responsibility for an outcome interacts with decisions to compromise, we first asked whether responsibility attribution predicted subsequent changes in foraging choices. We found that, after getting attacked, participants were more likely to move towards their partner if they blamed themselves more for the loss (Fig. 3B). This asymmetry is likely due to the higher sensitivity to self-partner distance in responsibility attribution after losses than after wins.

We next examined whether ego-centric bias predicted willingness to compromise. We split participants into high- and low-compromise groups based on the median weight (*w,* from the model) they placed on their partner's preferences and quantified each participant's ego-centric bias as the difference in responsibility taken for harvests versus captures. Low-compromise participants exhibited greater ego-centric bias (Fig. 3D, exploratory sample, $t_{ind} = -2.86$, $\mathrm{p} = 0.004$; confirmatory sample $t_{ind} = -5.16, p < 0.001$), suggesting that stronger self-centered attribution is associated with a reduced willingness to compromise. However, this finding is confounded by our earlier result showing that shorter self-partner distances correspond to more equal responsibility sharing. Since the high-compromise group tends to be closer to their partners than the low-compromise group, their lower self-attribution bias may simply reflect their smaller choice distances.

To rule out this confound, we ran a regression predicting responsibility attribution controlling for self–partner choice difference and trial outcome. We observed a positive main effect of compromise (exploratory sample, $\beta_{low-compromise} = 0.027, p = 0.04$; confirmatory sample, $\beta_{low-compromise} = 0.035$, $p < 0.001$), and a negative interaction effect between compromise and outcome (exploratory sample, $\beta_{outcome*\,compromise} = -0.05$, $p = 0.02$; confirmatory sample, $\beta_{outcome*\,compromise} = -0.06, p < 0.001$), indicating lower-compromise participants attributed themselves more credit for harvesting reward and less blame for being captured (Fig. 3C). Overall, our results show that the more participants credited themselves, the less willing they were to adjust their choice to align with their partner, suggesting that egocentric biases may hinder compromise.

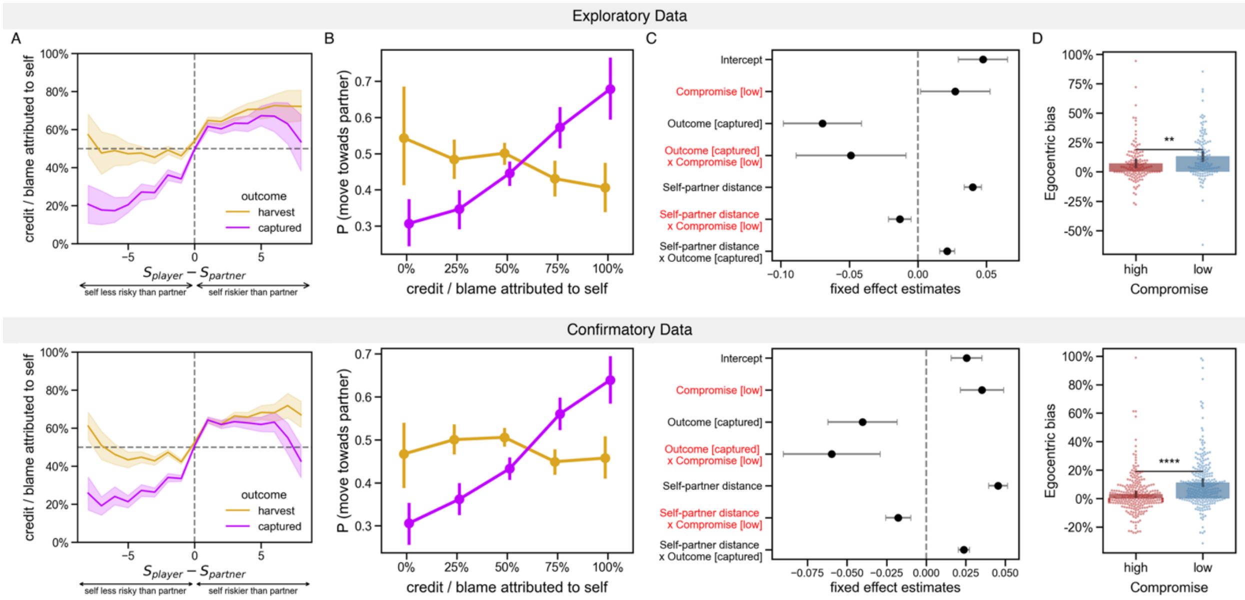

Fig. 3. Judgements of Credit/Blame and their relationship to Compromise. (A) Percentage of credit/blame player attributed to themselves, as a function of player-partner step difference (x-axis) and trial outcome (color). Error bars indicate 95% credible interval across participants. **(B)** Trial-by-trial level degree of compromise as a function of credit/blame attributed to oneself in the previous trial and the previous trial's outcome. The y-axis is calculated as whether the player moved towards the partner (1 or 0) from trial t-1 to trial t. Error bars indicate 95% credible interval across participants. **(C)** Fixed effects with a 95% credible interval from the hierarchical regression. The reference level is the combination of *reward* outcome and *high* compromise. **(D)** Relationship between compromise and bias. We calculated the difference between average self-credit after harvesting rewards and average self-blame after being captured as a measure of egocentric bias (y-axis). To divide the participants into high or low compromise, we performed a median split on the model-derived parameter, *w*. A higher weight on others' preferences was correlated with lower egocentric bias.

Risk preferences and bias predict joint risk-adjustment patterns

Next, we tested whether dyads coordinated with each other in different ways by mutually adjusting their risk-taking, and what influenced these patterns in our task. To classify these patterns, we defined a two-dimensional space capturing changes in risk preferences from individual to dyad phase for the risk-averse and risk-prone partner in each dyad, separately for each predator (Supp. Fig. 4). Splitting each axis at zero yielded four categories: risk-increase (i.e., both moved forward; exploratory N=43; confirmatory N=91), risk-decrease (i.e., both moved backward; exploratory N=74; confirmatory N=149), risk-converge (i.e., both moved toward each other; exploratory N=100; confirmatory N=214), and risk-diverge (i.e., both moved away from each other; exploratory N=17; confirmatory N=51) (Fig. 4A). In line with our results so far that show that people tend to compromise, we found that many dyads fall under the *risk-converge* category. Even in *risk-increase* and *risk-decrease* categories, partners showed asymmetric adjustments: in the *risk-increase* group, risk-averse partners exhibited a larger increase in risk-taking relative to their risk-prone partners; conversely, in the *risk-decrease* category, risk-prone partners showed a larger decrease in risk-taking.

We found that inter-individual differences in baseline risk predicted how the dyads jointly adjusted their risk. First, dyads with higher average risk preferences tend to reduce their risk-taking during the dyadic phase, while those with lower average risk preferences tend to increase it (Fig. 4B). Second, dyads with smaller initial differences tended to shift in the same direction (*risk-increase* or *risk-decrease*), whereas dyads with larger differences either converged or diverged (Fig. 4C). Critically, egocentric bias determined whether partners with large differences converged or diverged, with divergent dyads exhibiting greater bias (Fig. 4D). To explore how risk differences and egocentric biases mechanistically shape these patterns, we designed an agent-based model where agents updated their risk preferences using a win-stay, lose-shift rule modulated by bias (see Methods and Supp. Fig. 7). The model replicated our empirical patterns: partners with similar risk preferences moved in the same direction; but when partners differed greatly, bias determined whether they converged or diverged—low-bias agents converged by updating their positions in a complementary way, whereas high-bias agents resisted updating when outcomes were misaligned with their preferences, leading to divergence. These results imply that egocentric bias can regulate how shared outcomes are translated into learning signals, thereby shaping emergent coordination dynamics.

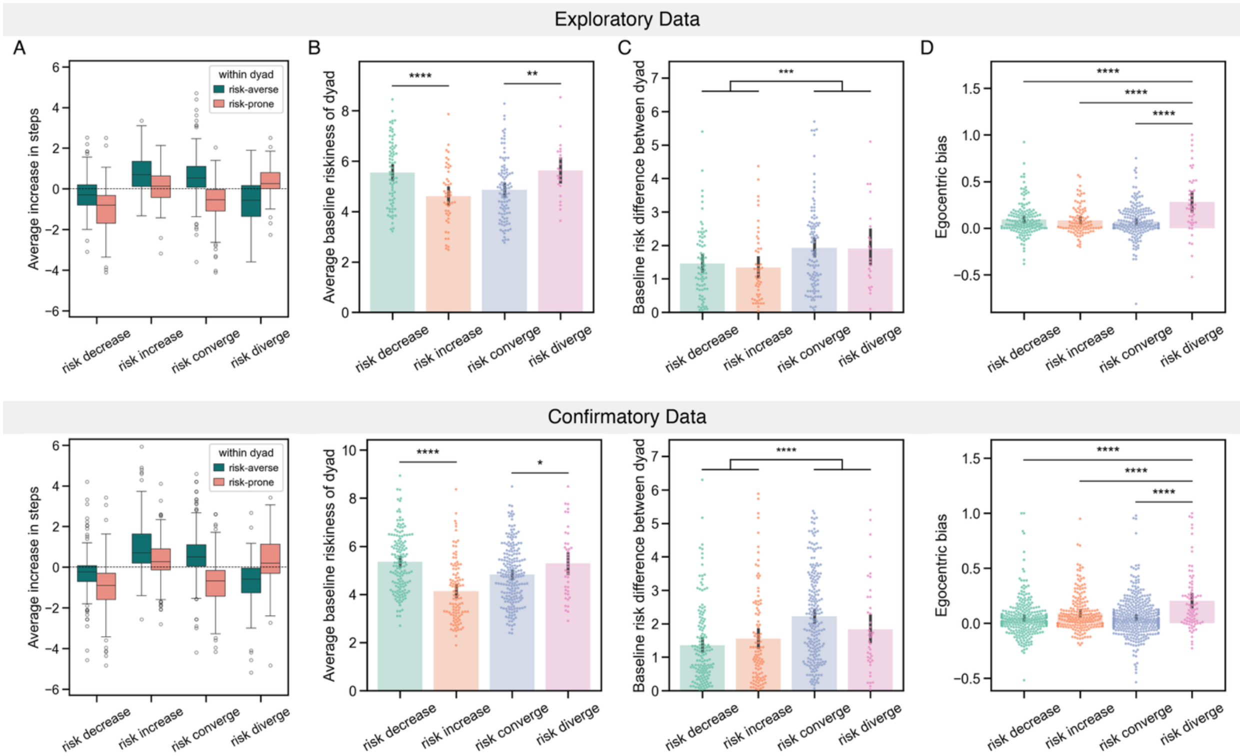

Fig. 4. Dyadic Risk-Adjustment Patterns. (A) Distribution of participants' change in riskiness from solo to dyad phase, separated by cluster and relative risk level within the dyad. Except in the *risk-diverge* case, dyads mostly adjust their behavior in opposite directions, narrowing the initial gap in risk preferences. **(B)** We calculated the average of the two players' solo choices to quantify the dyad's baseline risk preference. We then plotted this average by cluster. Dyads with lower baseline risk increased in risk whereas dyads with higher baseline risk decreased in risk in the dyadic phase (t_{ind}=3.75, p<0.001; t_{ind}=7.85, p<0.001). In addition, dyads that converged in risk (compromised) had lower baseline risk yet dyads that diverged (counteracted) had higher baseline risk (t_{ind}=-2.51, p=0.01; t_{ind}=-2.87, p=0.004). **(C)** We computed the mean solo choice difference between the two players in a dyad as a measure of baseline risk difference. We then plotted this difference by cluster. Dyads with higher differences in baseline risk were more likely to converge (compromise) or diverge (counteract), while dyads with lower differences in risk were more likely to move in the same direction (exploratory sample, t_{ind}=3.40, p<0.001; confirmatory sample, t_{ind}=-6.17, p<0.001). **(D)** Average egocentric bias (difference between self-blame for losses and self-credit for wins) by cluster. Dyads in the risk-diverge cluster showed higher ego-centric bias than dyads in all other clusters. Each dot indicates average egocentric bias per participant per predator.

People rate partners who compromise as more preferable and blame them less

Finally, we asked why people compromise so often, even when it is suboptimal to do so. We hypothesized that compromising might hold an implicit social value that could motivate decisions to compromise. In exploratory analyses, we tested whether there is a social benefit to compromising such that people prefer partners who compromise. We found a negative correlation (exploratory sample, $r = -0.38, p < 0.01$; confirmatory sample, $r = -0.19, p < 0.01$; Supp. Fig. 1D) between participants' post-task partner preference rating and self-partner foraging distance in the dyad phase. This effect still exists after controlling for joint reward, suggesting that people enjoyed playing with others whose choices aligned with theirs, independent of their actual earnings. Furthermore, we calculated the average responsibility that the partner assigned to the player (flipped for captured trials) and correlated that with the player's compromise parameter, w. We found a positive correlation (exploratory sample, $r = 0.18, p < 0.001$; confirmatory sample, $r = 0.14, p = 0.001$; Supp. Fig. 4C), indicating that players who compromised more tended to be assigned more credits and less blame by their partners. These results indicate that compromise carries a social value and may explain why risk-prone individuals compromise even when doing so does not increase their foraging reward.

Discussion

When people make risky decisions together, they must navigate not only uncertainty about outcomes but also the need to compromise with others' risk preferences. These inter-individual differences can create tension between personal motives and collective goals. To understand collaboration under preference divergence, we investigated two key facets: compromise (i.e., how people adjust decisions toward their partner's preferences) and responsibility attribution (i.e., how they evaluate each other's contributions to shared outcomes). To study these processes, we developed a dyadic foraging task in a risky environment where partners adapt their decisions to one another while assigning credit or blame for joint outcomes. We found that people often compromise to reconcile these differences, and differing preferences drive credit/blame evaluations, which in turn influence whether individuals choose to compromise or to counteract. We further showed that individual risk preferences and responsibility attribution biases can predict how dyads coordinated (i.e., risk-adjustment patterns). Our findings highlight how individual differences in risk preferences, willingness to compromise, and attributional biases interact to shape joint decision-making under risk.

We found that differences in risk-preferences did not elicit strategic counteraction; instead, our results revealed a tendency to compromise, with individuals adjusting their choices toward their partner's risk level even in the absence of immediate reward benefits. Critically, compromise was not indiscriminate; rather, it systematically depended on the partner's tendency to compromise (i.e., reciprocity), their risk differences and trial outcomes. Computational modeling revealed that this pattern emerged from trial-by-trial integration of partner preferences rather than global shifts in risk attitude or improved environmental learning. These results align with previous work showing that humans are biased toward conformity and consensus [18,56–58] and guided by norms of reciprocity and fairness [19,28,59]. Moreover, our results contextualize these processes beyond binary choice frameworks to a continuous choice space, identifying compromise as a social and cognitive mechanism through which social preferences are flexibly weighted during shared decision-making under uncertainty.

Our results also show how people share responsibility during shared decision-making and its relationship with compromise. We found that people showed systematic biases in how they attributed responsibility for shared outcomes: they claimed more credit after success than blame after failure. Larger individual differences in foraging choices amplified these asymmetries, particularly after unsuccessful outcomes. Moreover, prosocial individuals (measured via Social Value Orientation[55,60]) shared credit more equally after success, though this did not extend to blame-sharing after failure. While past studies have documented ego-centric biases [61], these studies typically rely on binary judgments ("high credit" vs. "low credit") and are detached from actual actions or outcomes [23,24]. In contrast, our design required participants to make trial-by-trial, graded attributions based on real outcomes during active task performance, allowing us to dynamically link responsibility judgments to participants' and their partner's actions. Our findings highlight that attributional bias persists even when contributions are transparent, is asymmetrically shaped by outcomes and modulated by individual differences, with consequences for subsequent compromise.

Previous research suggests that attributional biases influence learning [62], but their role in coordination and collective behavior has been less studied. Our results show that coordination depends on how individuals evaluate their own and their partner's contributions; when these judgments are biased, they can hinder individuals' willingness to compromise. Empirical results, supported by agent-based simulations, demonstrate that patterns of risk convergence and divergence can emerge from individuals adjusting their foraging choices based on outcomes, individual differences, and biased credit assignment. However, because our study did not include experimental manipulations to isolate causality, it remains possible that attributional bias reflects, rather than drives, an individual's tendency to compromise: individuals may assign responsibility post-hoc to justify their behavior rather than to motivate it. Nonetheless, prior work suggests that causal attributions may serve an important function for future planning and behavioral adjustment [63]. Future research should directly test this directionality and examine how metacognitive evaluations shape coordination under uncertainty.

In our study, participants had no explicit monetary incentive to compromise—the joint outcome (i.e., the mean of participants' locations) was identical regardless of whether their choices converged or diverged. Nevertheless, people routinely chose to compromise. We identify three potential factors that could have led to such frequent compromising. First, participants attributed more blame to partners who compromised less, whereas individuals who compromised were rated as more desirable partners, indicating a clear social value to compromising. This aligns with prior work showing that compromise helps individuals diffuse responsibility within groups [26,29]. Second, for suboptimal (e.g., risk-averse) individuals, compromising with more optimal (e.g., risk-prone) individuals conferred learning benefits, which led to an increase in their foraging rewards. Third, our results on reaction times suggest a cognitive benefit of compromising. Larger differences in location preferences required more deliberation, whereas compromising may serve as a low-effort heuristic that reduces the cost of continuous strategizing [64]. Experiments that manipulate various costs and benefits of compromise can further shed light on the underlying mechanisms that drive decisions to compromise in joint action [5].

These findings were enabled by several distinctive features of our task. Most dyadic decision-making research applies binary choice paradigms in static environments [20,65,66]. While informative, such tasks simplify real-world dynamics, where choices are often continuous rather than discrete that allow for incremental changes in behavior which can be especially important in social contexts [9,67–69]. To capture these dynamics, our task offered multiple choices that were arranged as a continuous and spatially correlated grid. This design not only helped reveal differences in risk preferences but also allowed dynamic adjustments in the social phase. The combination of solo and social phases in our task further allowed us to study compromise as a dynamic process shaped by both stable individual differences in risk preference and ongoing social coordination. As evidence of our task's ecological-validity, we found that relative risk-averseness and risk-proneness in the dyadic phase corresponded with stable traits of uncertainty aversion measured independently (Supp. Fig. 1C), suggesting that our task captures meaningful individual differences that generalize beyond the specific foraging context. Varying the degree of environmental uncertainty or the transparency of partner information could further disentangle how learning about the environment versus learning about the partner shapes coordination dynamics.

In conclusion, our study makes several important contributions to research on joint decision-making, social foraging, coordination, and social interaction. We extend existing foraging paradigms by introducing a more continuous choice environment and by enabling large-scale online dyadic interactions. By integrating foraging decisions with responsibility attribution, we show how attributional biases emerge from both choices and outcomes, while opening new avenues for understanding the cognitive and motivational bases of compromise in collective dynamics. Future work can explore how these effects scale beyond a dyad, examining how group size, composition, or organization (e.g., leader-follower) affects decisions to compromise[70,71] and share responsibility. Extending this paradigm also offers a path toward a more integrative understanding of risk-taking[72,73], social valuation, and norms, and how these processes vary across development[74,75] and cultural contexts. Ultimately, examining how people navigate collaboration amid conflicting preferences is key to understanding why some collaborations endure while others fracture—dynamics central to team performance, organizational dynamics, and collective action on shared challenges.

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Methods

This study was preregistered at https://osf.io/mjcx5. Code and data are available at https://github.com/gracewndeng99/dyadForaging.

Experimental Paradigm

Solo Phase: Participants were asked to operate an avatar to forage in a virtual environment with predators. The goal of the task was to maximize rewards while avoiding being attacked. In order to incentivize the goal, they were given bonus money based on the collected rewards. Participants first did the task on their own for 120 trials with two different predators (60 trials each). Both predators were more likely to attack when the participant got closer, but each predator differed in their attack probability (Supp. Fig. 3C). Rewards increased exponentially as participants got closer to the predator. At each trial, the participant could choose one of the 9 squares to forage at, and each square was associated with a known reward and unknown probability of being attacked by the predator. Participant's avatar was spawned at square 1 at the beginning of each trial and they could move their avatar by pressing either the left or right arrow key. After the participant had submitted their choice by hitting the space bar, whether the predator attacks would be revealed. If the predator did not attack, the participant would earn the reward associated with the chosen location. If the predator attacked, the participant would lose a fixed 10 points. Participants needed to learn the attack probability of the two predators and make choices to maximize their reward. The two predators were indicated by two different colors and appeared in a random and inter-mixed order. Predator-color mappings were counterbalanced across participants. Participants were told that their choices in the last 60 trials of the individual foraging phase would be counted in their bonus payment.

Dyadic Phase: After the participant has finished the solo phase, they would be randomly paired with another online participant and enter a group foraging phase. They would forage in the same environment and encounter the same two predators. They would encounter one predator first and then another predator. With each predator, they would play 30 trials. At each trial, each participant was first asked to make a prediction about where their partner would choose. Then, they would move their avatar to their desired location. After both participants had made their choice, their chosen locations would be revealed to each other, and their avatars would move to the middle of their chosen locations (rounded up if the middle is not an integer). Then, the predator would attack or not based on the probability of attack at the middle location. The reward structure remained the same as the solo phase, except both the reward and the loss were doubled for the group. Then, each participant was asked to assign the responsibility of the outcome between themselves and their partner. In the case of an attack, participants were asked to attribute blame between self and partner on a scale of 5 choices ranging from "completely self" to "completely partner". If they harvested a reward, participants were asked to attribute credit between self and partner on a scale of 5 choices ranging from "completely self" to "completely partner". They were told the choice was private and would not affect their or their partner's bonus. Both the participant and their partner would be paid a bonus based on their accumulated rewards. After both participants in the pair had finished every question, they would start the next trial at the same time.

Data Collection

For the exploratory data, we collected data from 250 participants (125 groups). For the confirmatory data, we collected one batch from 304 participants (152 groups) and another batch from 210 participants (105 groups). Participants were recruited through the online platform Prolific, and each participant conducted a 45-minute task plus a 5-minute questionnaire at the end. Each participant was paid $10 for completing the task and a bonus depending on their performance in the task. Participants were excluded if they did not respond in more than a third of the trials in the dyadic phase.

We collected each participant's foraging location choice and response time in both the individual and group phases. In the group phase, we additionally collected 1) participant's prediction about their partner's choice, and 2) the participant's responsibility attribution of the outcome (see Supp. Fig. 3A for the distribution of these variables). After the task, we also collected some questionnaire measurements including IUS, STAI-T, SVO, and partner preference rating ("How much did you enjoy playing with your partner?").

In the solo phase, we analyzed data after the first 60 trials to account for a sufficient learning period. We define each participant's baseline riskiness as the average foraging choice of the last 60 trials of individual foraging. In the dyadic phase, participants were classified into risk-averse or risk-prone within the dyad based on their baseline riskiness.

In batch 2 of the confirmatory dataset, we included an additional 30 rounds of individual foraging after the dyad phase, with results reported in the Supplementary Materials. Participants were not informed of this extension. Because the individual and dyadic task phases were identical across the two confirmatory batches, we combined them for the main analyses.

Computational Models

We developed a series of computational models to capture: 1) how people learn and generalize the attack patterns of predators, and 2) how people coordinate with another individual. In these models, participants first learn the attack probability of the chosen state based on the outcome, then update the attack probability of the others state, and finally make a choice balancing risk and reward.

To capture generalization, we assumed that participants update the safety values of not only the visited locations but all other locations after every outcome. We also assumed that an individual generates a prediction error at the chosen location based on the observed outcome and propagates this error to unvisited locations. They then update the values of the unvisited locations proportionally to the prediction error.

$$\Pi_{safety}(s, t+1) = \Pi_{safety}(s,t) + \alpha_t \left(O_t - \Pi_{safety}(s,t) \right)$$

$$\Pi_{safety}(s', t+1) = \Pi_{safety}(s',t) + \alpha_t \left(\left(O_t - \Pi_{safety}(s,t) \right) \gamma^{|s'-s|} \right) \ \forall s' \neq s$$

We assumed that participants started with a linearly decreasing safety value across locations such that squares closest to the predator had a safety value of 0.1 and the squares farthest away from the predator had a safety value of 1. Additionally, we modeled the learning rate as decreasing linearly with the number of encounters with each predator.

To capture internal risk preferences, we fit a reward sensitivity parameter that quantifies how much individuals value rewards [76]. The model predicted the participant's choice on each trial as the state with the highest Q-value (Supp. Fig. 3D, 3E).

$$Q(s,t) = \Pi_{safety}(s,t) rewards^{\theta} - \left(1 - \Pi_{safety}(s,t)\right) |loss|^{\theta}$$

For the group phase, we compared three classes of models. *The as-if-individual model* assumes that individuals do not consider their partner's actions and choose locations to maximize their own utility. *The social influence model a*ssumes that an individual's internal risk preference is influenced by their partner's risk preference. In this model, δ captures the additional change in riskiness in the group setting. A $\delta > 0$ indicates an increase in riskiness in the group phase, and vice versa.

$$Q(s,t) = \Pi_{safety}(s,t) rewards^{(\theta+\delta)} - \left(1 - \Pi_{safety}(s,t)\right) |loss|^{(\theta+\delta)}$$

The other-regarding preference model assumes that an individual values both their own risk preferences and those of their partner. In this model, the group utility is a weighted combination of the individual's preferences and those of their partner. We used participants' predictions of their partner's choice to construct a $Q_{partner}$ value function, assigning a value of 1 to the predicted location, with values decreasing as locations became farther from the predicted choice. A weight $w = -1$ indicates that the individual only values their own preferences and counteracts their partner's choice. A weight $w = 0$ suggests that the individual is insensitive to their partner's choice. A weight $w = 1$ means that the individual fully aligns with their partner's choice.

$$Q(s,t) = \begin{cases} (1-w)Q_{self}(s,t) + w\mathrm{Q}_{\mathrm{partner}}(s_{partner}, t) \; if \; w > 0 \\ (1-w)Q_{self}(s,t) + w\mathrm{Q}_{\mathrm{partner}}(2 * argmax_s Q_{self}(s,t) - s_{partner}, t) \; if \; w < 0 \end{cases}$$

To find the best-fitting parameters for each subject, we minimized the mean-squared error (MSE) between model predicted choice and the subject's choice on each trial. We applied a grid generational search procedure with three successive generations. In the first generation, parameters were sampled from a coarse grid over the full search space $(w, \alpha, \gamma, \theta)$, where $w, \alpha, \gamma \in [0, 1]$ and $\theta \in [0, 1.5]$. At each generation, the grid resolution was reduced by a factor of five, and the search was centered on the parameter region that minimized MSE in the preceding generation. This iterative refinement allowed us to efficiently locate the parameter set yielding the lowest MSE while avoiding exhaustive evaluation of the entire space. For model parameter recovery, we first simulated each subject's choices based on their best-fitting parameters. We then re-fitted the same model on the simulated data and compared the recovered best-fitting parameters against the parameters that generated the data (supp. Fig. 3d). Model comparison was conducted using the Bayesian Information Criterion (BIC). Additionally, we conducted posterior prediction checks by comparing each participants' simulated choices with their actual choices.

Agent-based Modelling

The model simulated the 1-D grid of the task and applied the same functions to generate outcomes of win or loss (i.e. reward or attack) based on agents' joint location (or mean location). Each agent had a risk preference as an initial strategy which defined the location they tend to choose. We ran the simulation for all combinations of risk preferences of two agents.

At each time step, each agent picked a location based on their preference. Their joint location was the mean of their individual choices, and the trial outcome was based on the joint location and the predator attack probability. Then, each agent updated their preference using an update rule in a win-stay, lose-shift manner, modulated by their relative position, trial outcome and egocentric bias. Specifically, each agent has a bias ranging from 0 to 1. If the agent was ahead of their partner, they moved ahead after a win with probability 0.1 (1) and moved backwards after a loss with probability 1 – bias (2); if the agent was behind the partner, they moved backwards after a loss with probability 0.9 (3) and moved ahead after a win with probability 1- bias (4). Magnitude of the movement, whether forward or backward was dependent on the difference between agents' location and scaled by the length of the grid:

$\Delta x_i \sim Bernoulli(0.1) \times ||\Delta d||, if\ outcome = \text{win}\ and\ \Delta d > 0$ (1)

$\Delta x_i \sim Bernoulli(1 - bias) \times ||\Delta d||, if\ outcome = win\ and\ \Delta d < 0$ (2)

$\Delta x_i \sim -Bernoulli(0.9) \times ||\Delta d||, if\ outcome = \text{lose}\ and\ \Delta d < 0$ (3)

$\Delta x_i \sim -Bernoulli(1-bias) \times ||\Delta d||, ifoutcome=lose\ and\ \Delta d > 0$ (4)

$\Delta x_i = 0, otherwise$ (5)

Hierarchical Regressions

All the linear regressions were performed using hierarchical models implemented with the statsmodels package in Python. Random coefficients were included for all parameters and regressions were estimated at the group level. The regression formulas and complete results are provided in the Supplementary Materials.

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