Using dynamic monitoring of choices to predict and understand risk preferences

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Navigating conflict is integral to decision-making, serving a central role both in the subjective experience of choice as well as contemporary theories of how we choose. However, the lack of a sensitive, accessible, and interpretable metric of conflict has led researchers to focus on choice itself rather than how individuals arrive at that choice. Using mouse-tracking—continuously sampling computer mouse location as participants decide—we demonstrate the theoretical and practical uses of dynamic assessments of choice from decision onset through conclusion. Specifically, we use mouse tracking to index conflict, quantified by the relative directness to the chosen option, in a domain for which conflict is integral: decisions involving risk. In deciding whether to accept risk, decision makers must integrate gains, losses, status quos, and outcome probabilities, a process that inevitably involves conflict. Across three preregistered studies, we tracked participants' motor movements while they decided whether to accept or reject gambles. Our results show that 1) mouse-tracking metrics of conflict sensitively detect differences in the subjective value of risky versus certain options; 2) these metrics of conflict strongly predict participants' risk preferences (loss aversion and decreasing marginal utility), even on a single-trial level; 3) these mouse-tracking metrics outperform participants' reaction times in predicting risk preferences; and 4) manipulating risk preferences via a broad versus narrow bracketing manipulation influences conflict as indexed by mouse tracking. Together, these results highlight the importance of measuring conflict during risky choice and demonstrate the usefulness of mouse tracking as a tool to do so.

prospect theory | mouse tracking | dynamic processes | risk | decision-making

"The experience of conflict is the price one pays for the freedom to choose."—Tversky & Shafir, 1992.

Decision-making requires navigating the conflict that arises when choosing between alternatives (1–6). Understanding the processes by which we encounter, experience, and resolve such conflict is therefore a principal goal of decision-making research. Despite this, the focus in decision research is typically on just the end-point of the choice process—the choice itself—rather than the decision process. A major reason for this is the lack of accessible and scalable tools for dynamic measurement, with existing dynamic measures, such as electroencephalography/functional MRI, eye tracking, and reaction time (RT), requiring high resource (and time) investments and/or complex modeling. In the present paper, we propose that measuring computer mouse movements as participants make a choice—i.e., mouse tracking (7–12)—provides a dynamic, accessible, scalable, and sensitive technique for quantifying conflict during choices. In what follows, we first discuss conflict, then propose the advantages of mouse tracking for studying conflict, both in general as well as why it is particularly relevant for the study of decisions involving risk.

Conflict

Choice is a dynamic process: over the time course of a decision, our representations are rapidly evolving and changing (e.g., ref. 13), as are our weighting of options (14) and dimensions (e.g., reward vs. likelihood; refs. 15–17); these combine with inherent stochasticity in the firing rates of neurons that encode this information (18) to produce a (sometimes noisy) signal toward or away from one option. While many factors likely influence the strength, consistency, and overall distribution of these signals (e.g., the clarity and complexity of choices offered), we focus on the mean of the distribution, which depends on the difference in subjective value between the two options. Sometimes, one option will clearly dominate the other, resulting in a series of strong, consistent signals toward the dominant option throughout the time course of the decision. This manifests as a relatively easy choice, and one we define as having relatively lower conflict. Oftentimes, however, no option is clearly dominant, and, as the representations and weightings shift, the signals will be less strong and less consistent (i.e., they may point toward different options). This manifests as a difficult choice, and one we define as having relatively greater conflict. We thus define conflict as the lack of strength and consistency of the signals toward one option over another.

In formulating this definition of conflict, we draw on sequential sampling models (such as the drift diffusion model; refs. 19–21), which provide a modeling framework to quantify the integration of these signals. These models assume that, throughout the time course of a decision, individuals noisily accumulate and compare evidence (i.e., the signals discussed above) in favor

Significance

Choices that consist of risky versus certain options are pervasive and consequential, leading many researchers to investigate when and which individuals select risk over certainty. The present research takes an alternative approach and measures computer mouse movements to assess how people arrive at these decisions. We show that measuring mouse movements while participants are deciding between a risky gamble and a certain payout powerfully detects their conflict about the options, and that this conflict strongly predicts their risk preferences. Further, mouse movements are predictive of risk preferences even when choice outcomes are not. The present research thus demonstrates the unique utility of dynamic measures of choice, as well as the predictive and theoretical importance of conflict in risky decision-making.

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of each option until the evidence favoring an option reaches a predetermined threshold (Fig. 1*A*). Within this framework, conflict can be defined as the inverse of the rate of relative evidence accumulation (drift rate) toward the chosen option.

Past work has used modeling to extract this conflict component from RTs, a necessary step since many factors contribute to RTs beyond solely conflict. Some of these factors occur outside of the comparison process and contribute to what is known as "nondecision time" (22, 23). The two most frequently discussed contributors to nondecision time are initial orienting/encoding (e.g., perceptual representation, reading, retrieval from memory) and motor latency (the time it takes to execute and complete a keypress). Past work has shown that these can account for 30 to 80% of the RT (24, 25). For example, you might encounter an easy decision during a lapse in attention or hesitate before making the button press, leading to a misleadingly long RT. Here, we argue that it may be more fruitful to study conflict by using motor indicators (which may be less influenced by nondecision processes) to assess the strength and consistency of the evidence accumulation process in real time. In particular, we use computer mouse tracking

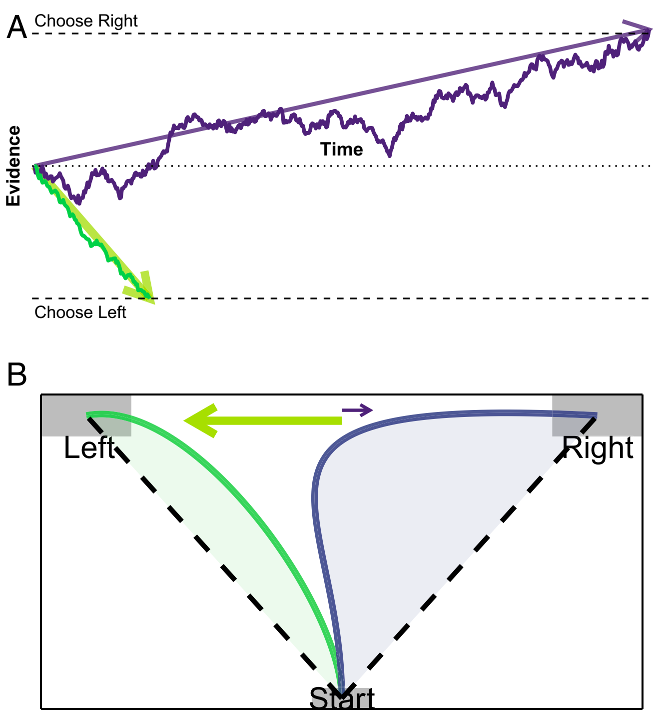

Fig. 1. Schematic of the relationship between a latent drift diffusion model decision process and its physical manifestation in mouse movements. (*A*) The drift diffusion model assumes that, over the course of a decision, the individual accumulates relative evidence in support of one option or another (purple and green lines) until the accumulated evidence reaches a predefined choice threshold (dashed lines at top and bottom), at which point the individual makes that choice. Here, we give two examples, one where the evidence strongly and consistently points toward the leftward option (low conflict, green line) and one where the signal weakly and inconsistently points toward the rightward option (high conflict, purple line), with the drift rate (i.e., the average slope) represented by the arrows of the corresponding color. (*B*) With mouse tracking, the strength and consistency of evidence toward one option over the other should manifest in motor movements that reflect the evidence accumulation process. The arrows at the top represent the relative strength of evidence toward the option (with size and length proportional to the corresponding drift rate in *A*). To quantify conflict, we take the AUC, which compares the area of the actual mouse trajectory (colored lines) to a straight trajectory (dashed black lines), shown here as the shaded region between the trajectories (Fig. 2).

as a reflection of the evidence accumulation process, with less direct, consistent, mouse movements reflecting increased conflict.

Mouse Tracking

Built off cognitive models that propose a dynamic interplay between motor movements and underlying cognition (9, 26), mouse tracking provides a dynamic, millisecond-level window into how a decision unfolds. The data richness of mouse tracking allows for many complementary analysis approaches (11, 27), but one of the most powerful (and most commonly used) approaches is using these trajectories to gauge response conflict between two options by quantifying the directness (or lack thereof) of the mouse from choice onset to choice conclusion. The logic is that, when the chosen option clearly dominates the unchosen option, the mouse trajectory should be attracted toward the chosen option and unattracted toward the unchosen option, manifesting as a relatively straight trajectory. As the unchosen option becomes relatively more attractive, however, the cursor movement should be relatively more attracted to that option, manifesting as a less direct trajectory toward the chosen option.

More precisely, we assume that mouse movements reflect a smoothed version of the relative accumulated evidence (16). Specifically, we believe mouse movements are the result of two forces. First, as participants are instructed to begin moving their mouse as soon as the choices appear on the screen, there is a default vertical force upward. This combines with a horizontal force leftward or rightward proportional to the rate of evidence accumulation. The two forces combine to create either relatively direct or indirect trajectories (Fig. 1*B*). This directness is quantified by taking the area between the actual trajectory and a straight trajectory, and is referred to as the area under the curve* (AUC). An extensive body of research, primarily in the categorization literature, suggests that trajectory directness is reflective of response conflict (reviewed in ref. 7). For instance, there is greater conflict when categorizing atypical (e.g., "whale") compared with typical (e.g., "cat") exemplars as fish versus mammals (28).

As noted above, many dynamic methods exist (e.g., neural measures, eye tracking, and RT), but we believe mouse tracking offers three primary advantages for the study of conflict. First, it provides a face-valid, readily interpretable dynamic assessment of choice. Second, it is easily accessible to researchers and practitioners alike, requiring no expensive equipment or extensive training to use. Third, the approach of measuring cursor movements is scalable beyond the lab, allowing researchers to covertly assess conflict outside of the laboratory (29).

One outstanding question, however, is the relative sensitivity of mouse tracking: whether it can detect subtle contextual differences, as well as how it compares with other measures, most notably RT. In other words, the specific advantages of using mouse tracking over RT to study conflict have not been fully documented. One reason to believe AUC could outperform RT is that AUC may be less influenced by nondecision processes, since initial encoding and motor latencies should have relatively less impact on mouse trajectories compared to RT (for instance, while a delay in clicking the mouse at the end of the trajectory will influence RT, it should not greatly influence AUC). In the present paper, we show both high sensitivity of mouse tracking to details of the choice problems, and that the information gleaned

*Here, our theoretical framework motivates our choice to use AUC rather than other metrics such as the maximum deviation (the furthest point from a straight trajectory) or x-flips (the number of horizontal reversals). Specifically, sequential sampling models posit that evidence accumulation is a noisy, random walk, and so metrics that account for the entire trajectory, such as AUC, should outperform metrics such as maximum deviation (which focuses on only a single point) or x-flips (which only capture changes in direction and not different-sized steps in the same direction). In other words, AUC is better able to integrate and reflect the entirety of the evidence accumulation process.

in this way is more reflective of the underlying cognitive processes than RT.

Decisions Involving Risk

Notably, despite the critical role of conflict in decision-making, mouse tracking has so far been used only sparingly in decision research (11), with most of the research focused on self-control (30–35; but see refs. 36–41). One class of decisions for which conflict is a central component, and for which mouse tracking may be particularly informative, are choices involving risk: choices that pit an outcome that is certain against an outcome that may turn out better or worse. Such choices typically generate conflict because they force individuals to assess whether the possibility of the better outcome is worth the possibility of the worse outcome.

The prevalence and importance of decisions involving risk has led to a comprehensive understanding of when individuals will select risky over certain options (i.e., risk preferences). For instance, this research has demonstrated that individuals are generally (though not always) loss-averse (42–45): losses are disproportionately avoided compared with equivalent gains, which is one of the factors leading to risk aversion in decisions with both positive and negative outcomes (i.e., outcomes that cross the reference point of 0). Furthermore, individuals tend to display decreasing marginal utility (42, 46–49); for example, people value \$10 less than twice as much as they value \$5, making them risk averse for decisions involving positive outcomes (i.e., outcomes that are greater than or equal to the reference point of 0).

Despite much philosophizing about the reasons for risk-averse and loss-averse behavior, relatively less research has focused on how people arrive at those choices [for notable recent exceptions, see refs. (50–52)]. The standard approach reduces a continuous and dynamic decision process into a static and binary choice outcome (important though that outcome may be) and, in doing so, ignores potentially useful information. To illustrate, consider one individual who selects a risky option without much difficulty and another individual who wrestles with the same decision before ultimately selecting the risky option. In this example, the choice outcomes are identical, but the choice process identifies the first individual as being more risk-seeking than the second. Dynamic assessments of conflict may thus provide a much more useful window into the underlying subjective valuations, highlighting the diagnosticity of a given choice process for one's latent risk preferences.

In the present research, we use mouse tracking to quantify conflict in risky choice with four specific goals. First, we aim to show that mouse tracking serves as a highly sensitive metric of conflict, detecting subtle differences in changes to the choice context. Choices under risk are an ideal domain to test the sensitivity of mouse tracking, as changes in the relative values of gains, losses, and certain outcomes have well-understood influences on how individuals subjectively value these gambles. Specifically, we investigate whether choices with more similar subjective values produce greater AUC (even when controlling for RT). Second, we aim to show the utility of tapping into dynamic, continuous metrics of conflict over and above binary choice data to understand how people resolve choices between certain and uncertain options. In particular, we investigate how well mouse tracking predicts risk preferences—prospect-theory parameters of loss aversion and diminishing marginal utility—even when choice is kept constant, as well as predicting choices out of sample. Third, we aim to show the relative strength of mouse tracking over RT. Finally, we investigate whether a typical manipulation of loss aversion (via framing effects) indeed changes mouse-tracking metrics in line with expected shifts in risk preferences.

In summary, we demonstrate the theoretical and practical uses of dynamic assessments of choice from onset of the decision through to the conclusion (i.e., the choice) in decisions for which conflict is integral: decisions involving risk. Specifically, we show that motor indicators of conflict are highly sensitive to differences in subjective value of the choices, are more predictive of risk preferences than RTs, and offer diagnostic information about future choices above and beyond that offered by choice alone.

Results

Across three preregistered studies (n = 148, 105, and 399), we measured participants' mouse movements as they made 215 sequential decisions of whether to accept or reject 50/50 gambles (Fig. 2). Gambles were adapted from Sokol-Hessner and colleagues (53) (*SI Appendix* includes a complete list) and consisted of two types: mixed gambles offered a 50/50 gamble that resulted in either gaining or losing money (e.g., 50% of gaining \$x, 50% chance of losing \$y) versus a certain option that was always equal to \$0. Gain-only gambles offered a certain gain (e.g., \$z) against a 50/50 gamble of either a larger gain (e.g., \$x) or \$0. Each trial started with participants' mouse cursors at the bottom center of the screen, after which the gamble information would appear just above the cursor. Participants then moved their mouse to one of two buttons in the top left and top right corners of the screen that corresponded to rejecting and accepting the gamble. Study 3 further manipulated risk preferences (between participants) via a narrow versus broad bracketing manipulation (53, 54), as described in greater detail below.

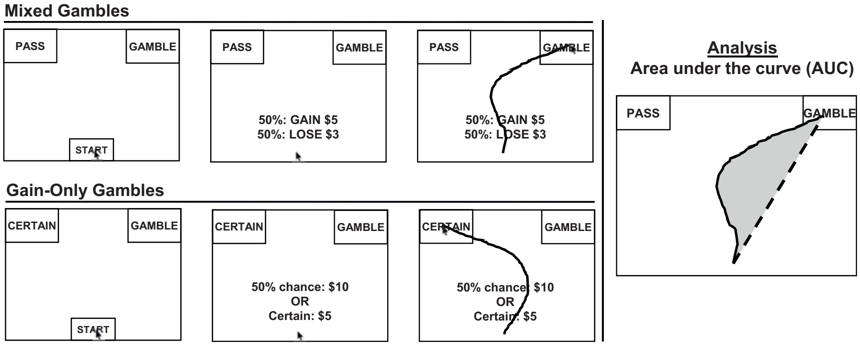

Fig. 2. Schematic of mouse-tracker procedure (*Left*) and analysis (*Right*). (*Left*) Procedure: each trial proceeded as follows. First, participants would click a start button (*Left*), after which the details of the gamble would be displayed (*Center*) and participants would move their mouse to either accept or pass on the gamble (*Right*). Procedure is shown for both mixed gambles (*Top*) and gain-only gambles (*Bottom*). (*Right*) Analysis: to quantify conflict, we take the area between the actual mouse trajectory and a straight trajectory, a metric known as the AUC.

We first calculated participants' prospect theory parameters for loss aversion (λ) and diminishing marginal utility (ρ) via a hierarchical Bayesian framework (55). These parameters serve as stable metrics of participants' risk preferences, with higher λ corresponding to greater risk aversion in mixed gambles and lower ρ corresponding to greater risk aversion in gain-only gambles. It is important to acknowledge that ρ also influences risk preferences in the mixed trials. However, past research with similar paradigms has indicated that λ varies substantially more than ρ, so, for the bulk of our analyses, we focus on λ within the mixed trials and ρ within the gain-only trials.

These parameters also allow us to calculate the subjective value (u) of both the certain and uncertain outcome via the following utility function:

$$u(x) = \begin{cases} x^{\rho}, x>0 \\ -\lambda \cdot (-x)^{\rho}, x \le 0 \end{cases} \quad [1]$$

$$u(gamble) = \left(\frac{1}{2} \cdot u(gain)\right) + \left(\frac{1}{2} \cdot u(loss)\right) \quad [2]$$

Subjective Value and Conflict. We predicted that, the closer the subjective values of the gamble and certain options (i.e., accepting or rejecting the gamble), the greater conflict there would be, as indicated by AUC. To test this, for each trial, we calculated the subjective value of both the gamble and the certain outcome using Eqs. **1** and **2**. We then computed the absolute difference between these subjective values. We then used full mixed-effects models (implemented via the lme4 package in R) to predict trial-by-trial AUC from this difference in subjective value.[†]

Consistent with our hypotheses, in all three studies, we find a significant effect such that larger differences in subjective value corresponded to less conflict, i.e., lower AUC: study 1, $b = -0.03$, SE = 0.008, $t(61.04) = -4.05$, $P < 0.001$; study 2, $b = -0.07$, SE = 0.01, $t(48.69) = -6.57$, $P < 0.001$; study 3 (collapsing across conditions), $b = -0.07$, SE = 0.005, $t(217.61) = -12.82$, $P < 0.001$. Not only is this effect significant, but it appears that mouse tracking is highly sensitive to within-subject variation in subjective value (Fig. 3).

We next sought to investigate whether mouse tracking provides information that is distinct from that of RT. Indeed, the present results hold even when controlling for (raw) RT: study 1, $b = -0.02$, SE = 0.006, $t(57.98) = -3.30$, $P = 0.002$; study 2, $b = -0.04$, SE = 0.006, $t(33.97) = -5.82$, $P < 0.001$; study 3, $b = -0.04$, SE = 0.004, $t(173.44) = -9.34$, $P < 0.001$. This indicates that mouse movements provide information that is nonredundant with RT. This result is unchanged when using log-transformed RT instead: study 1, $b = -0.02$, SE = 0.006, $t(56.84) = -3.65$, $P < 0.001$; study 2, $b = -0.04$, SE = 0.006, $t(33.09) = -6.04$, $P < 0.001$; study 3, $b = -0.03$, SE = 0.003, $t(159.72) = -9.19$, $P < 0.001$.

To further document the ability of mouse tracking to sensitively detect differences in conflict, we sought to demonstrate that mouse movements were responsive to even subtle differences in subjective value. To this end, we divided our data into quintiles based on the subjective value difference of the gambles, such that quintile 1 corresponded to the 20% of trials that had the smallest difference in subjective value. We then tested whether mouse tracking could detect 1) differences in conflict within the quintile and 2) differences in conflict between the quintiles. As the former reduces our sample size by an order of five and the latter converts our continuous predictor to a dichotomous predictor, we pool data from across all studies (for individual analyses of each study, which were highly consistent but not as uniformly significant, are available in *SI Appendix*). Within each quintile, AUC remained significantly negatively related to the difference in subjective value (all Ps < 0.002; detailed statistics are available in *SI Appendix*). AUC could further distinguish between each quintile, with quintiles with smaller differences between subjective values having significantly larger AUC (Ps < 0.001; *SI Appendix*, Fig. S3). The implications of these results are twofold: first, they suggest that conflict is not a dichotomy (i.e., easy versus hard trials), but rather constitutes a continuum. Second, mouse tracking appears to be able to sensitively measure this conflict, with AUC able to detect even subtle differences in the options.

Predictive Strength of Conflict. The preceding analyses suggest that mouse tracking reflects the dynamic choice process, sensitively revealing conflict within choice. Although this suggests that mouse tracking may be a useful tool for measuring conflict, its predictive value remains unclear. In particular, we have argued that mouse tracking provides diagnostic information above and beyond that of choice and RT. Such predictive power is particularly important for applied or field settings, where researchers and practitioners often have access only to a limited choice set or even a single decision. We thus tested whether conflict, as indexed by AUC, would be predictive of participants' risk preferences, even when measured from a single trial where everyone makes the same choice (*SI Appendix* further reports analyses demonstrating that AUC can be used to predict subsequent choices out of sample). This represents a strict test of our hypotheses: individual trials are noisy, but, if they can significantly predict loss aversion or risk aversion, that would suggest that mouse tracking is particularly sensitive to and predictive of risk preferences, even when choice is held constant.

Specifically, if a participant shows little conflict when selecting the risky option, that suggests less risk aversion relative to someone who is highly conflicted when making the same choice. Similarly, someone who is unconflicted when selecting a certain outcome is likely more risk-averse than someone who is conflicted. In the mixed gambles, we therefore hypothesized that conflict when accepting gambles, and a lack of conflict when rejecting gambles, should predict greater loss aversion (higher values of λ). For the gain-only gambles, we hypothesized that conflict when accepting gambles, as well as a lack of conflict when rejecting gambles, should predict decreased marginal sensitivity for rewards (lower values of ρ).

To test the predictive power of mouse tracking, we first selected two mixed gambles and two gain-only gambles from each study in which there was low variance in choice—one gamble overwhelmingly accepted, the other overwhelmingly rejected—but high variance in AUC. We selected the following gambles: mixed, +\$12/−\$4.5 (study 1, 91% accepting), +\$10/−\$20 (study 1, 4% accepting), +\$10/−\$2 (studies 2 and 3, 91% and 94% accepting), +\$8/−\$10 (studies 2 and 3, 4% and 10% accepting); and gain-only, gain \$4, certain \$1 (studies 1 to 3, 78%, 74%, and 83% accepting, respectively), and gain \$3, certain \$2 (studies 1 to 3, 35%, 37%, and 28% accepting, respectively). We then correlated λ (mixed gambles) or ρ (gain-only gambles) with AUC from each trial, excluding the participants who did not select the majority option. Each of these single-trial analyses produced significant correlations such that risk preferences were significantly predicted by conflict. Specifically, for the mixed gambles that were overwhelmingly accepted, greater conflict was associated with greater loss aversion: rs = 0.21 ($P = 0.01$), 0.48 ($P < 0.001$), and 0.30 ($P < 0.001$) for studies 1 to 3, respectively. For the mixed gambles that were rejected, conflict was associated with lower loss aversion: rs = −0.24 ($P = 0.003$), −0.25 ($P = 0.01$),

[†]With one exception, noted later, we use this modeling approach for all trial-by-trial data. Our results hold if we instead use fixed-slope, variable-intercept models.

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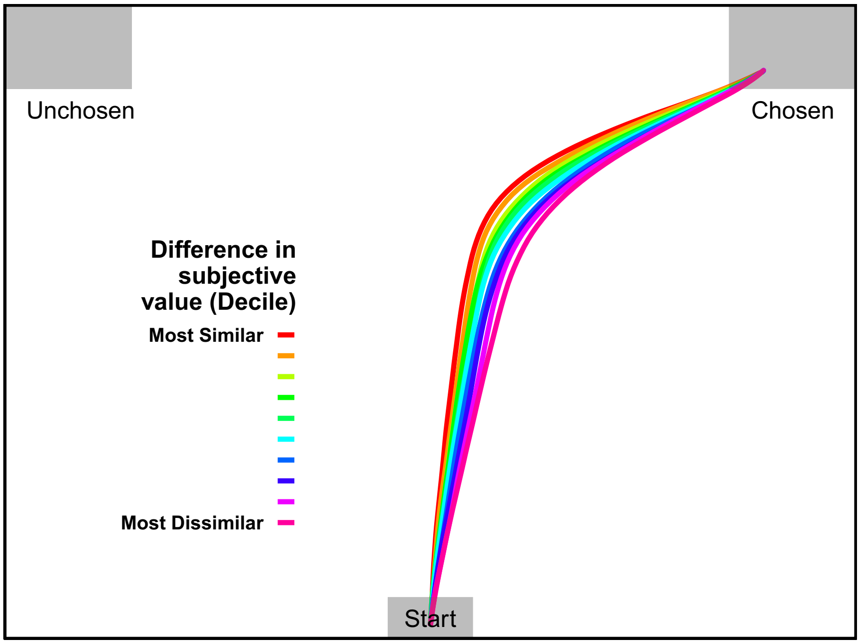

Fig. 3. Average trajectories as a function of the difference in subjective value of the two options. To create this figure, we first calculate, for each participant, the difference in subjective value of each of the 215 gambles. For each participant, we then bin these gambles into 10 deciles corresponding to the difference in subjective value. We then, across participants and across studies, average together the trajectories in a given decile and plot the resultant average trajectories above. For instance, the red line corresponds to the average trajectory of the trials for which the difference in subjective value is in the bottom 10% (i.e., most similar).

and −0.27 ($P < 0.001$). For the gain-only gambles that were accepted, conflict was associated with decreased ρ (i.e., greater decreasing marginal utility): rs = −0.26 (P = 0.006), −0.36 (P = 0.002), and −0.36 ($P < 0.001$). Similarly, for the gain-only gambles that were rejected, conflict was associated with increased ρ (lower decreasing marginal utility): rs = 0.50, 0.42, and 0.41 (all Ps < 0.001).

Performance Across All Trials. As our choices of which individual trials to select were somewhat arbitrary (and not preregistered), we next investigated single-trial performance for every individual trial. For each trial, we first divided participants based on their choice (accept versus reject). Pooling data across our three studies, we then ran separate correlation analyses for those that rejected versus accepted, predicting λ (mixed gambles) or ρ (gain-only gambles) from AUC on that specific trial. Each analysis was only run if there were at least 30 participants making that selection; of 652 different trials, we had an adequate sample for 540 (83%). Of these 540 trials, 407 (75%) produced significant differentiation in λ or ρ (Fig. 4 and *SI Appendix*, Tables S7 and S8). Specifically, in the mixed gambles, conflict significantly correlated with λ in 307 of 440 trials (70% of analyses run), and, in the gain-only gambles, conflict significantly predicted ρ in every trial (Ps < 0.006).

These results provide strong support that conflict indexed by AUC can be highly informative of the underlying decision processes contributing to choice, and contains highly diagnostic information even when choice itself is kept constant. These results are particularly notable given that single-trial prediction on any indirect measure is challenging due to noise in behavior, which speaks further to the usefulness of mouse tracking.

Comparing Mouse Tracking with RT. The above analyses afford an opportunity to address a remaining question: the relative strength of mouse tracking compared with RT as a measure of conflict. To this end, we conduct two related analyses: first, we predicted risk preferences from single-trial AUC and RT, controlling for one another. Second, we compared the predictive power (i.e., correlation strength) of single-trial AUC to that of single-trial RT.

When predicting risk preferences simultaneously from AUC and RT, of the 407 trials for which AUC significantly predicted λ or ρ, only 32 trials became nonsignificant when controlling for RT (69% of all analyses were significant; 100 of 100 gain-only trials and 275 of 440 mixed trials). Reaction time, however, dropped from 338 trials (63%) significantly correlating with λ or ρ to 218 trials (40%, 81 of 100 gain-only trials and 137 of 440 mixed trials) when controlling for AUC.

Second, when comparing the strength of correlation, AUC outperforms RT by an average of 0.08 [AUC mean absolute r = 0.25, RT mean absolute r = 0.17, $t(539) = -18.27$, $P < 0.001$], indicating that AUC provides greater predictive power than RT. This advantage appears to be strongest for predicting λ [AUC mean absolute r = 0.23, RT mean absolute r = 0.14, $t(439) = 17.07$, $P < 0.001$], even though it still was prominent for predicting ρ [AUC mean absolute r = 0.33, RT mean absolute r = 0.28, $t(99) = 7.61$, $P < 0.001$]. Together, these results indicate that mouse tracking is more reflective of risk preferences than RT in our experiments.

Bootstrap Analysis. The preceding analyses suggest that, on a single-trial basis, AUC outperforms RT. We next investigated how AUC compares with RT when applied to larger datasets—in other words, do the benefits of mouse tracking persist when adding additional trials? To test this, we conducted a bootstrap analysis in which we compared the predictive accuracy of AUC vs. RT for λ and ρ when averaging across the measures in N randomly sampled trials.

For each trial,[‡] we ordered participants according to their choice and AUC. Specifically, we first selected participants who

[‡]For the mixed gambles, studies 2 and 3 contained different gambles than study 1. As such, we report here analyses of the mixed gambles separately for 1) study 1 and 2) studies 2 and 3 (pooled). As all gain-only gambles were identical, we present the data for gain-only gambles pooled across all three studies.

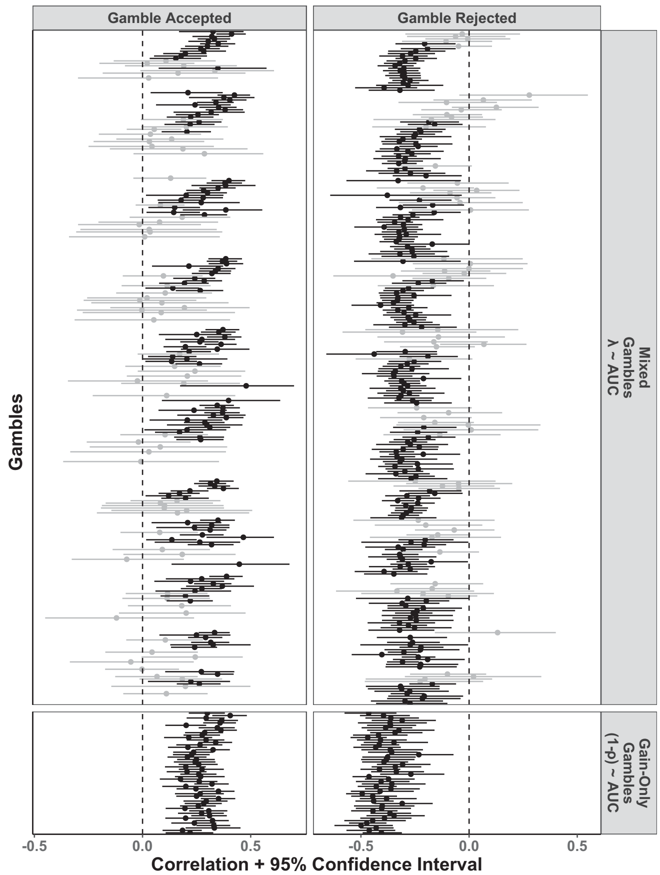

Fig. 4. Predicting loss aversion (mixed gambles, top) and risk aversion (gain-only gambles, bottom) from conflict (indexed via AUC) on individual trials, pooled across studies. Each point plus error bars corresponds to the correlation plus 95% CI between λ and conflict, or risk aversion ($1 - \rho$) and conflict on a single trial, with significant analyses colored black and nonsignificant analyses colored gray. Analyses were run separately for those that accepted the gamble (*Left*) and those that rejected the gamble (*Right*). Values significantly greater than 0 correspond to a positive relationship between conflict and loss/risk aversion, whereas values significantly less than 0 correspond to a negative relationship between conflict and loss/risk aversion. Analyses that did not have at least $n = 30$ are omitted. Specific breakdowns are given in the *SI Appendix*.

chose to reject the gamble, then ordered them based on (increasing) AUC scores, such that the person with the lowest rank was the individual who rejected the gamble with the most direct trajectory (i.e., lowest AUC score) and the person with the highest rank was the individual who rejected the gamble with the least direct trajectory (i.e., highest AUC score). We then appended to this ranking the participants who accepted the gamble, sorted based on descending AUC scores, such that the lowest-ranked individual accepted the gamble with the least direct trajectory and the highest-ranked individual accepted the gamble with the most direct trajectory. This provides a ranking of participants for each trial, with those who chose without conflict at the ends of the spectrum and those with the most conflict in the middle. Finally, we divided these rankings by the number of participants in each trial to make comparisons across trials (which varied slightly in the number of participants due to outlier screening). We then replicated this process with RT rather than AUC, ordering from fastest to slowest for rejected gambles and then slowest to fastest for accepted gambles (we note that this ordering, from rejecting to accepting, is arbitrary).

We then selected N trials at random (with replacement), averaged participants' normalized rankings (separately for RT and AUC) across these N trials, and then correlated these average rankings with participants' rank-order λ and ρ. These correlations were negative for λ and positive for ρ (because higher λ will make people more hesitant to accept, but higher ρ will make them less hesitant to accept), but, to ease interpretation and comparisons of AUC and RT across λ and ρ, we multiplied all λ correlations by -1, yielding positive correlations. For each value of N, we repeated this process 10,000 times and used the resulting distribution to provide point estimates and 95% CIs (Fig. 5 and *SI Appendix*, Fig. S8).

First, we replicate the above single-trial analysis, showing that AUC outperforms RT on a single trial ($n = 1$), though, as before, this effect was more dramatic for predicting λ than ρ (a pattern which was consistent for all bootstrap analyses). Second, when predicting λ, the point estimates for AUC consistently outperform those for RT, with AUC above RT for over 50 trials. Third, AUC appears to approach its asymptotes quicker than RT (when predicting λ), meaning that, for smaller datasets, each additional trial provides greater predictive power for AUC compared to RT. Finally, AUC provides a significantly narrower CI than RT across trials: paired-samples t tests, study 1, λ, $t(164) = 36.56$, $P < 0.001$; studies 2 and 3, λ, $t(164) = 19.91$, $P < 0.001$; and studies 1 and 3, ρ, $t(49) = 7.06$, $P < 0.001$. For predicting λ, this effect was particularly notable, with the CIs for AUC roughly half the size of those for RT (study 1, average AUC CI spread = 0.07, average RT CI spread = 0.15; studies 2 and 3, average AUC CI spread = 0.05, average RT CI spread = 0.09).

To provide context for these analyses, we can investigate the relative performance for AUC and RT at different numbers of trials, as well as how many trials it takes to reach some threshold. If we select $n = 3$ trials at random, we recover an average cross-subject correlation between AUC and λ of $r = 0.60$, 95% CI = 0.44 to 0.74 for study 1 and $r = 0.68$, 95% CI = 0.55 to 0.79 for studies 2 and 3, providing both a stronger correlation and a narrower CI compared to the correlation between RT and λ: $r = 0.49$, 95% CI = 0.25 to 0.70 for study 1 and $r = 0.60$, 95% CI = 0.40 to 0.76 for studies 2 and 3. At $n = 10$ trials, we recover an average cross-subject correlation between AUC and λ of $r = 0.74$, 95% CI = 0.65 to 0.81 for study 1 and $r = 0.81$, 95% CI = 0.74 to 0.86 for studies 2 and 3, again outperforming the correlation between RT and λ: $r = 0.67$, 95% CI = 0.48 to 0.79 for study 1 and $r = 0.77$, 95% CI = 0.63 to 0.84 for studies 2 and 3. We can further interrogate how many trials is required to get a correlation with λ of at least 0.75 (i.e., the lower bound of the CI exceeds 0.75). For AUC, it takes 33 trials (study 1) and 11 trials (studies 2 and 3), compared to RT, which takes 126 trials (study 1) and 25 trials (studies 2 and 3).[§] Together, these analyses demonstrate both the robustness of AUC estimates of risk preferences, as well as their relative performance to RTs.

Manipulating Preferences. Our previous analyses relied on correlational evidence: measured valuation corresponded to AUC. In our final study, we set out to show that AUC is responsive to manipulations of preferences (rather than solely measured preferences). This constitutes an important, stricter test of our hypotheses, allowing us to causally demonstrate the effect of valuation on conflict. To this end, in study 3, participants were instructed to use broad ("think like a trader") versus narrow ("consider only this single choice") bracketing. In the narrow bracketing condition, participants were asked to consider each gamble independently, "in complete isolation from all other decisions," which past work has found enhances the relatively

[§]We suspect the discrepancies between study 1 and studies 2 and 3 are likely due to differences in sample size; whereas study 1 had $n = 148$, studies 2 and 3 had $n = 504$.

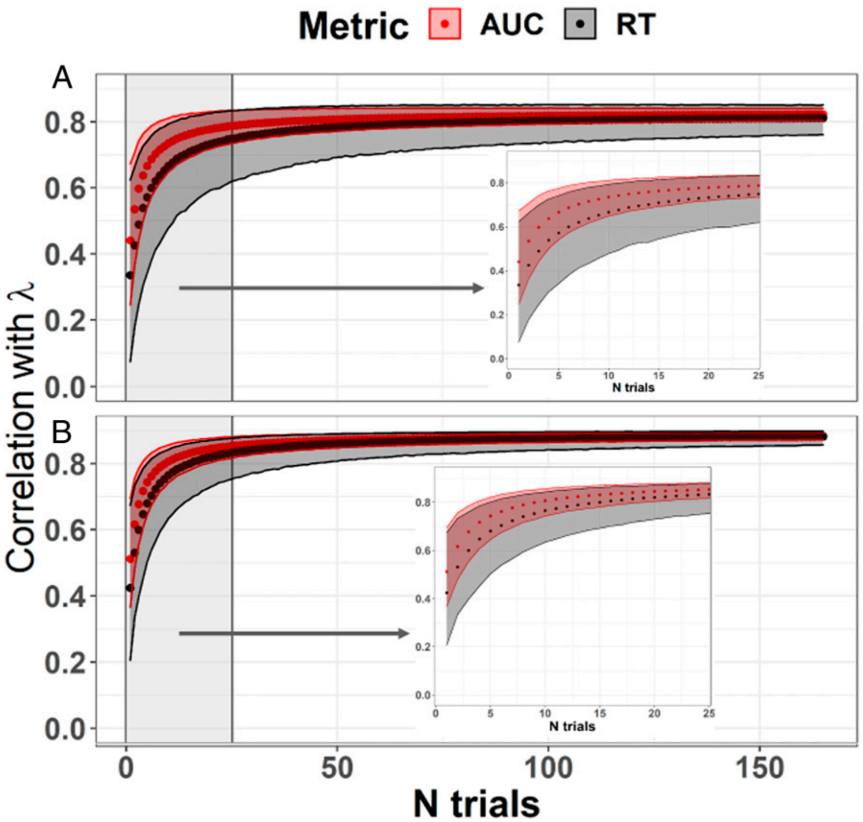

Fig. 5. Bootstrap results showing the correlation between λ and average AUC rank (red) or average RT rank (black) in study 1 (*A*) and studies 2 and 3 (*B*) as a function of the number of trials included to generate the ranking. Red and black ribbons represent the 95% CIs for AUC and RT, respectively. (*Insets*) Enlarged views of the first 25 trials. AUC consistently outperforms RT (red points are higher than black points, particularly for smaller *N*) and provided a narrower CI (red ribbon is approximately half the size as the black ribbon), indicating AUC provides a more accurate and precise measure of loss aversion.

acute negative emotions evoked by the prospect of a loss and thus leads to greater loss aversion (53). The broad-bracketing condition asks participants to consider each gamble as one of a series of similar decisions and to "imagine yourself as a trader," which past work has similarly found to reduce emotions associated with losses, leading to reduced loss aversion (53). If broad bracketing causes subjects to be willing to take on more risk, we should observe less conflict when accepting a gamble and more conflict when rejecting a gamble.

We first replicated the analyses reported in Sokol-Hessner and colleagues (53): broad (vs. narrow) bracketing led to lower loss aversion, $b = -0.092$, SE = 0.045, $t(397) = -2.05$, $P = 0.04$ (this effect was somewhat weaker than in their study, likely due in part to the between-subjects nature of our manipulation). Consistent with our predictions, we found a significant interaction[¶] between our manipulation (broad vs. narrow) and participants' choices (accept vs. reject) on conflict (estimated at the trial level using a fixed-slope variable intercept model): $b = -0.10$, SE = 0.02, $t(8321) = -6.16$, $P < 0.001$, such that broad (compared with narrow) bracketing led to greater conflict when participants elected to pass on the gamble, but less conflict when participants accepted the gamble (Fig. 6).

¶This analysis did not converge when using variable slope models, and as such we report here the results of the fixed-slope variable intercept model. To address possible concerns of inflated degrees of freedom in this test, we also conducted this model instead using clustered SEs which produced a consistent (though marginally significant) interaction, $b = -0.14$, SE = 0.08, $t(8321) = -6.16$, $P < 0.001$, $t = -1.81$, $P = 0.07$.

General Discussion

Conflict is integral to both the subjective experience of choice and contemporary theoretical understanding of decision-making. In deciding whether to accept risk, decision makers must integrate gains, losses, reference points, and outcome probabilities in order to reach a decision, a process for which conflict is often inevitable. However, the lack of compelling, accessible, and interpretable metrics has limited research on conflict, with researchers largely focusing on choice outcomes rather than how

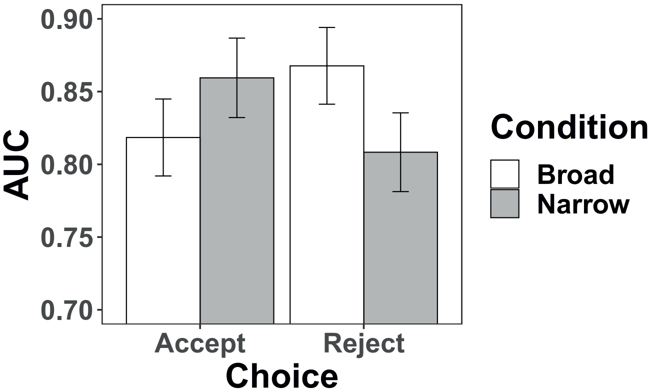

Fig. 6. AUC as a function of choice (reject vs. accept) and condition (broad vs. narrow). Higher numbers correspond to greater conflict. Under broad bracketing, there was more conflict when rejecting gambles and less conflict when accepting gambles. Error bars correspond to SEs.

participants arrived at those choices. Across three studies, we have shown that mouse tracking can precisely quantify conflict, and we have demonstrated the central importance and subsequent predictive power, above and beyond RT, of mouse-tracking data within risky choices.

We first demonstrated that mouse tracking is a highly sensitive metric for choice conflict in decisions under risk, showing that motor movements are extremely responsive to the choice options. That is, the more similar the subjective values of accepting versus rejecting a gamble, the less direct participants' trajectories were to the chosen option, even when controlling for RT. Mouse tracking was further able to detect differences in gradations, with AUC able to differentiate conflict both within and between quintiles of the difference in subjective value. These results also are consistent with our theoretical framework, which argues that conflict is a continuous phenomenon. Rather than being bimodal (with difficult and easy choices), conflict appears to exist across a spectrum, with a corresponding spectrum of mouse trajectories.

We next demonstrated that conflict, as measured by mouse tracking, is highly predictive of participants' risk preferences out of sample, with conflict predicting loss aversion and diminishing marginal utility, at the single-trial level. Conflict was also predictive of subsequent choices (reported in the *SI Appendix*). Notably, conflict was still highly informative even when choice outcomes did not differ among participants. We additionally showed the predictive strength of mouse tracking over and above RT: for both single-trial and multitrial contexts, mouse tracking provided stronger and more precise estimates of participants' risk preferences. Finally, we showed that manipulations of risk preferences shifted the amount of conflict when making choices: individuals adopting broad bracketing were less conflicted when selecting gambles and more conflicted when rejecting gambles compared with individuals adopting a narrow bracketing. This builds on prior work showing differences in arousal as a function of bracketing (53) and suggests that bracketing changes participants' subjective experiences of these choices. Taken together, our findings highlight the importance and utility of using dynamic assessments of choice, rather than choice outcomes alone, to understand preferences.

Implications and Future Directions. Although conflict is often either implicitly or explicitly a central component of our theoretical understanding (not to mention our subjective experience) of decision-making (6), conflict itself is often overlooked in empirical investigations, mostly due to a lack of effective measurement tools (for some notable exceptions, see refs. 56–61). Our work significantly advances an emerging body of research suggesting that mouse tracking is a sensitive metric to capture the onset, magnitude, and evolution of conflict within decision-making (reviewed in ref. 11). Our work further demonstrates the relative advantages of mouse tracking over the most prominent measure of conflict, RT. Specifically, mouse tracking is both nonredundant with RT (as they are only moderately correlated, $r = 0.32$ across studies, and our results hold when controlling for RT) and more predictive of underlying risk preferences. Together, these results suggest mouse tracking may be better suited for studying conflict than RT. Mouse tracking's advantage may be due to nonconflict factors such as nondecision time and response caution (that are known to affect RT) having relatively less impact on mouse trajectories. Future research should investigate this possibility. Future research should also address whether the advantages of mouse tracking over RT generalize beyond economic decision-making. Overall, by harnessing motor conflict during choice, mouse tracking offers a window into the dynamic push and pull between competing alternatives.

Our results also highlight an interesting discrepancy: mouse tracking particularly outperforms RT for predicting loss aversion compared to diminishing marginal utility. One possible explanation is that loss aversion (captured by the mixed gambles) constitutes a stronger, more variable force on participants' choices than diminishing marginal utility. Indeed, past work using similar tasks has largely focused on loss aversion rather than diminishing marginal utility (53, 59).

By drawing on sequential sampling models to define and understand conflict, our work adds clarity to what conflict is in terms of how and when it emerges, changes, and resolves. In this framework, the amount of conflict is inversely related to the rate of evidence accumulation toward the better option, which itself is a function of the difference in subjective value between the two options. Mouse tracking seems to provide a direct glimpse at this process. Although a detailed discussion and analysis of the relation between mouse-tracking metrics and sequential sampling model parameters is beyond the scope of this paper, we believe this to be a highly fruitful avenue for future research (16). Additionally, future research should investigate the connection between drift diffusion model parameters and other metrics of mouse tracking, such as incorporation times (16).

The present work also deepens our understanding of the nature of conflict. In particular, researchers and practitioners alike sometimes discuss conflict as if it were either present or absent (i.e., a binary variable). Our work demonstrates that conflict exists on a continuum, with the degree of conflict being highly sensitive to the decision setting. The present work thus suggests that the current understanding of conflict may be too simplistic, and that the ability to more precisely quantify conflict via mouse tracking will allow for developing and testing more comprehensive models of conflict. As an example, recent research has suggested conflict can occur nonconsciously (58, 61, 62), but it remains unclear how much conflict must be present for individuals to subjectively experience the choice as difficult. Additionally, conflict is a central component of most models of cognitive control (e.g., refs. 63, 64), and the ability to precisely quantify conflict empowers researchers to test more nuanced theoretical models of control. We invite future research using mouse tracking to develop more comprehensive understanding of conflict, as well the cognitive operations for which conflict is crucial.

Our work further indicates that conflict can provide unique insights into preferences, even when choice is held constant. This suggests that those interested in predicting behavior should look not solely to choice outcomes, but also to measures of conflict such as mouse tracking. Future work integrating metrics of conflict into parameter estimates of risk preferences may provide more stable, predictive estimates compared to those solely based on choices. Similarly, those looking to nudge individuals toward a certain type of choice would likely find their efforts more effective for those who are conflicted compared with those who are not (65). Researchers and practitioners alike could use metrics of mouse movements to gauge conflict, for example, in online settings, to better understand individuals' preferences and to more effectively target interventions. The metric of conflict need not be restricted to mouse movements; those interested in predicting or persuading behavior could explore other conflict measures (e.g., scrolling, times visiting and departing a product page before purchase).

Finally, it is important to recognize some limitations of mouse tracking. First, although the present study has demonstrated the sensitivity and predictive utility of mouse tracking in a highly controlled experimental setup (i.e., mouse cursors always starting at the same location, with response options appearing simultaneously in the corners of the screen), real-world digital interactions do not always offer this same degree of control. It remains to be seen whether mouse tracking retains its edge over RT in the more noisy, real-world applications of online decision-making. Further, with the rise of mobile devices as the primary way many people access the internet, future research should investigate motor indicators of conflict that do not require a mouse (e.g., scrolling up and down a page). Additionally, oftentimes individuals are choosing between several options, not just two. Although mouse tracking can be extended to decisions with more than two choices (66–68), interpretation of such setups are less straightforward. We invite future research demonstrating the robustness (or lack thereof) of mouse tracking to real-world decision-making.

Conclusions

Choice is not a discrete event, but rather the output of a dynamic cognitive process, which is reflected in motor movement. The act of making a decision requires integrating across different decision dimensions—often dimensions that are not directly alignable (69)—before ultimately making a selection. In the case of choices involving risk, this requires navigating the conflict between outcome desirability and likelihood, a case in which there are no objectively correct answers. By using dynamic assessments of the evolution and resolution of conflict, we can better understand and predict how people choose under risk.

Methods

All protocols were approved by the Ohio State University (studies 1 and 2) or Yale University (study 3) institutional review boards, and all participants provided informed consent. All materials, data, scripts, and preregistrations are available online via the Open Science Framework at https://osf.io/c7e4x/. As our analysis strategy has evolved since the beginning of the project, our ultimate analyses differ somewhat from our preregistrations, and we detail these discrepancies in the *SI Appendix*.

Participants. Undergraduate students at a large midwestern university (study 1, $n = 148$, and study 2, $n = 105$) participated for partial completion of course requirements. Study 3 consisted of 407 participants who completed the experiment in exchange for $10 at the behavioral research lab of a northeastern university (two participants did not finish and are excluded from analyses). Across all studies, we excluded participants who elected to gamble on every trial or pass on every trial. In studies 1 and 2, no participants displayed this behavior, and, in study 3, this excluded four participants who passed on every gamble and two participants who accepted every gamble.

Gambles: Study 1. Participants completed 215 gambles adapted from Sokol-Hessner and colleagues (53). All gambles pitted a 50/50 gamble (risky) against some certain outcome. There were two different types of gambles: mixed gambles and gain-only gambles (*SI Appendix*, Tables S1–S3, provide a full list of gambles). For the mixed gambles (165 total), the safe option was always $0. The risky option always had a 50% chance of gaining some money for the participant and a 50% chance of losing some money for the participant. The gain amounts consisted of 11 possible values ($2, $4, $5, $6, $8, $9, $10, $12, $14, $15, and $16), and the loss amounts were determined by multiplying the gain amounts by multipliers from −1/4 to −2 in 1/8 increments, yielding 15 different loss amounts per gain amount (e.g., gain $8 vs. lose $4). For the gain-only gambles (50 total), the safe option always offered the participant a certain gain (e.g., $5) pitted against a gamble in which, 50% of the time, the participant would gain more money (e.g., $10), and, 50% of the time, they would receive nothing ($0).

Gambles: Studies 2 and 3. Study 2 was identical to study 1 except the method of calculating the amounts in the mixed gambles changed slightly. Specifically, to keep the expected value (EV) of the gamble uniformly distributed, we calculated the loss amounts to achieve a specific EV of the gamble. For each gain amount, we calculated loss amounts for which taking the gamble would yield an EV of −5 to +5 in 0.5 increments. We further removed any gambles in which the loss amount was greater than 0 (e.g., an EV of +5 with a gain amount of +2 would require a "loss" amount of +8), as well as the corresponding gambles with negative EV (e.g., the −5 EV was removed if the +5 EV was not valid), thus keeping EV uniformly distributed across the trials. The gain-only trials remained unchanged. Study 3 used identical gambles to study 2. Further, study 2 used a modified lottery paradigm, such that participants were (truthfully) told that some participants would be chosen at random to have one gamble chosen at random to be played out with real money.

Mouse Tracking Setup and Procedure. Fig. 2 shows the flow of a single trial for both the mixed and gain-only gambles. Each trial started with a screen with a button labeled "START" at the bottom center and two response buttons labeled "GAMBLE" and either "PASS" (mixed gambles) or "CERTAIN" (gain-only gambles) in the upper left and right sides of the screen. Response button locations were constant for each participant, but were counterbalanced across participants. Once participants pressed the start button, the "gamble" and "certain" information appeared on the screen just above where the start button was located. For the mixed gambles, this included the amount they would gain from the gamble if it were successful and the amount that they would lose if it were unsuccessful (participants were informed that passing would result in $0 for certain). For the gain-only gambles, this included the amount they would gain if the gamble were successful and the amount they could receive for certain (participants were informed that unsuccessful gambles would result in $0). Participants then moved their mouse to the upper-left or upper-right corner of the screen to make their selection. Upon selection, the gamble information would disappear and the start button would reappear.

Participants were instructed to begin moving their mouse as soon as the options appeared on the screen, and, if they did not start moving their mouse within 450 ms on a given trial, they were given a reminder dialogue box at the end of the trial. Participants first completed all 165 mixed gambles before completing the 50 gain-only gambles. Each set of gambles started with 3 practice trials. All studies were implemented using mouse tracker (70).

Manipulation of Risk Preferences. As we were also interested in how conflict would respond to manipulations of risk preferences, in study 3, we used a bracketing manipulation taken from Sokol-Hessner and colleagues (53) to make participants either more loss-averse (narrow bracketing, i.e., considering every trial in a vacuum) or less loss-averse (broad bracketing, i.e., considering every trial as one of many). Full manipulation text is provided in the *SI Appendix*. We note that our replication is not direct: Sokol-Hessner and colleagues (53) used a within-subjects manipulation, whereas we use a between-subjects manipulation.

Data Preparation and Cleaning. Following established procedures for cleaning mouse trajectories (8), we first time-normalize the trajectories, yielding 101 x–y coordinates per trajectory, which were then rescaled to always terminate in the right-hand response location. Following this, we removed trajectories that were greater than 3 SDs from the mean on AUC, RT, and time to initial mouse movement. This excluded 4%, 4%, and 3% of total trials in studies 1 to 3, respectively. For each trajectory, we then computed the AUC, calculated by quantifying the area between the actual trajectory and a straight trajectory (Figs. 1 and 2).

Prospect Theory Parameters. For each participant, we computed prospect theory parameters for loss aversion (λ) and diminishing marginal utility (ρ) using each of participants' 215 decisions via a Bayesian hierarchical framework, implemented in the hBayesDM package (55). Further details on parameter estimation and summaries are given in *SI Appendix*, Table S4 and Figs. S1 and S2.

Data Availability. Participant mouse movements and choices data have been deposited to the Open Science Framework (https://osf.io/c7e4x/).

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