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Review

How Mouse-tracking Can Advance Social Cognitive Theory

Paul E. Stillman,[1,*] Xi Shen,[2] and Melissa J. Ferguson[2]

Mouse-tracking – measuring computer-mouse movements made by participants while they choose between response options – is an emerging tool that offers an accessible, data-rich, and real-time window into how people categorize and make decisions. In the present article we review recent research in social cognition that uses mouse-tracking to test models and advance theory. In particular, mouse-tracking allows examination of nuanced predictions about both the nature of conflict (e.g., its antecedents and consequences) as well as how this conflict is resolved (e.g., how decisions evolve). We demonstrate how mouse-tracking can further our theoretical understanding by highlighting research in two domains – social categorization and self-control. We conclude with future directions and a discussion of the limitations of mouse-tracking as a method.

Highlights

Computer-mouse movements reflect underlying cognitive processes, and, by continuously measuring mouse movements while participants make a judgment or decision (i.e., mouse-tracking), researchers can get a real-time window into how such choices evolve.

Mouse-tracking has the potential to offer a sensitive measure of the conflict present between two response options, allowing researchers to test theoretical predictions about the antecedents and consequences of decisional conflict.

The rich temporal data offered by mouse-tracking allows testing of nuanced theories regarding how decisions evolve, and allow researchers to make specific predictions about the time-course of the evolution of a decision.

Recent research in social cognition – most notably in social categorization and self-control literatures – has begun to use mouse-tracking to predict and understand judgments and decisions that are complex and consequential.

The Emergence and Resolution of Conflict

Navigating the world requires us to make representations, categorizations, and decisions given limited or ambiguous information. These judgments and decisions are often complex, requiring us to integrate across many different, and sometimes competing, sources of information and value [1]. Central to such judgments and decisions therefore is the resolution of **decision conflict** (see Glossary) between multiple possible alternatives. This essential act of resolving (or failing to resolve) conflict, whether in categorization, evaluation, or choice, is at the heart of many literatures across social and cognitive psychology. For example, how do we identify the person across the room as a woman or a man? – or decide whether to have a salad rather than a burger at lunch? – or decide to help someone who does not look like us? Resolution of conflict between different possible alternatives is a common theme across these ostensibly very different domains – namely social categorization, self-control, and prejudice (respectively). Within each of these domains, how people resolve conflict is the subject of numerous theories that seek to understand the mechanisms of how we reach a judgment or decision.

An emerging real-time technique to more directly tap into the processes underlying conflict is **mouse-tracking** – measuring the computer-mouse movements made by participants while they make a decision [2–7]. This approach offers an accessible, data-rich, real-time window into decision-making processes, and offers two major advances for probing theoretical predictions. First, mouse-tracking has the potential to gauge more precisely the relative amount (i.e., magnitude) of conflict present during a given decision, allowing researchers to test predictions related to the antecedents and consequences of conflict. Second, mouse-tracking provides a real-time window into the temporal unfolding of how this conflict is resolved, allowing researchers to test theories about how judgments and decisions unfold. In the present article we provide an overview of mouse-tracking, and review recent research using mouse-tracking to advance theoretical models in social cognition and cognitive psychology.

[1]Department of Psychology, Ohio State University, Columbus, OH 43210, USA
[2]Department of Psychology, Cornell University, Ithaca, NY 14853, USA

*Correspondence: stillman.10@osu.edu (P.E. Stillman).

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Assessing Conflict: Traditional Approaches and Challenges

Theoretical investigations into conflict generally focus on two related questions. First, when does conflict arise – in other words, what are the contextual or individual factors that predict the magnitude of conflict for a given judgment or decision? The entire area of self-control, for instance, is predicated on the idea that some choices are especially difficult owing to the conflict between immediate versus delayed gratification (i.e., they present a considerable conflict [8,9]), and many theories predict that the strength of this conflict should predict long-term success in reaching one's goals [10–13].

Second, how is this conflict resolved so as to arrive at a representation or decision? This question is the explicit or implicit focus of many theories in psychology and cognitive science (e.g., [14,15]). As one example, some **dual-system theories** [16,17] (which have been applied to many topics across social and cognitive psychology [18–22]) posit a temporal sequence for the unfolding of decisions such that more automatic processes (e.g., emotion) are influential early, whereas more controlled processes (e.g., reason) are influential later on in the decision stream. Some dual-system models also posit differential interaction between the two systems at different stages of processing (e.g., [23]). Models such as these are thus equipped to make nuanced predictions about the temporal unfolding of conflict.

Although these questions about conflict – its magnitude and its resolution – are focal to many domains of research, an enduring challenge to testing theories related to conflict is that most contemporary methods of evaluating conflict are static and blunt, and are thus not optimal for testing fine-grained temporal predictions. For instance, magnitude of conflict is often measured via either self-report [24] – which can be problematic given social desirability concerns as well as participants lacking introspective access [25] – or via reaction time – which, although containing information on conflict, additionally carry many related components of decision processes (e.g., perceptual delay, accuracy motives, etc. [26]), and thus often require complex modeling to isolate conflict components (e.g., [27,28]). These considerations have led researchers (e.g., in self-control [11,29,30]) to infer conflict from attitudes or behavior, rather than measure it directly. Similarly, most behavioral approaches lack the millisecond-level resolution ideal for understanding how judgments and decisions evolve in real time. Although researchers can use online methods such as eye-tracking, electroencephalography (EEG), and reaction times, these methods can be opaque (not to mention expensive and time-consuming), complicating attempts to directly interpret how a given decision unfolds [3].

Overview of Mouse-Tracking

Although cognitive models of choice and categorization have historically assumed a sequential unfolding whereby motor output is initiated once a decision is reached, recent research suggests that these processes unfold in a largely overlapping manner [31]. This work has shown that motor movements are updated continuously to reflect underlying cognitive processing ([2,7,32–36], recently reviewed in [3]). This suggests that mouse trajectories can be used as a proxy to study the underlying categorization and decision processes in real time.

Multiple stand-alone programs with user-friendly interfaces (e.g., MouseTracker [5], and Mousetrap [37]), as well as functionality in most modern experiment building tools (e.g., PsychoPy [38]), make mouse-tracking a relatively accessible method, with the difficulty level on a par with programming a standard reaction-time task. Mouse-tracking experiments generally involve a repeated binary choice selection task in which the mouse cursor of the participant starts at the bottom center of the computer screen, and the two response options appear in the upper left and upper right corners. Participants then make a response while the

Glossary

Area under the curve (AUC): the amount of area between the actual trajectory and a straight trajectory.
Dual-system theories: a class of models in which two systems are posited to interact to give rise to judgments and decisions – a quick, irrational, automatic system (system I) influences judgments and decisions early on, following which a slow, rational, controlled system (system II) can come online (given motivation and ability) and inhibit the response of system I if need be.
Dynamical frameworks: a class of models that make no clear distinctions between the roles of automatic and controlled processes (e.g., automatic processes can both support and hinder self-control), and instead emphasize the dynamic evolution of choices based on the nonlinear integration of multiple sources of information over time.
Decision conflict: the relative amount of conflict when deciding between two possible choices. For instance, self-control decisions are difficult owing to the decisional conflict between short-term and long-term gratification.
Integration times: the time at which choice attributes begin to influence mouse movements (i.e., when those attributes are integrated into a decision).
Maximum deviation (MD): the maximum distance between the actual trajectory and a straight trajectory.
Mouse-tracking: a method for studying judgment and decision-making in which mouse-movements made by participants are continuously measured while they make a decision (Figure 1).
Response conflict: the relative amount of conflict present when deciding between two possible responses – be they perceptual, categorical, or decisional. In mouse-tracking, this is represented by deviations from a straight path towards the chosen option.
X-flips: the number of times the mouse cursor reverses direction in the *x* plane.
X-location: the location of the cursor on the screen along the *x* dimension.

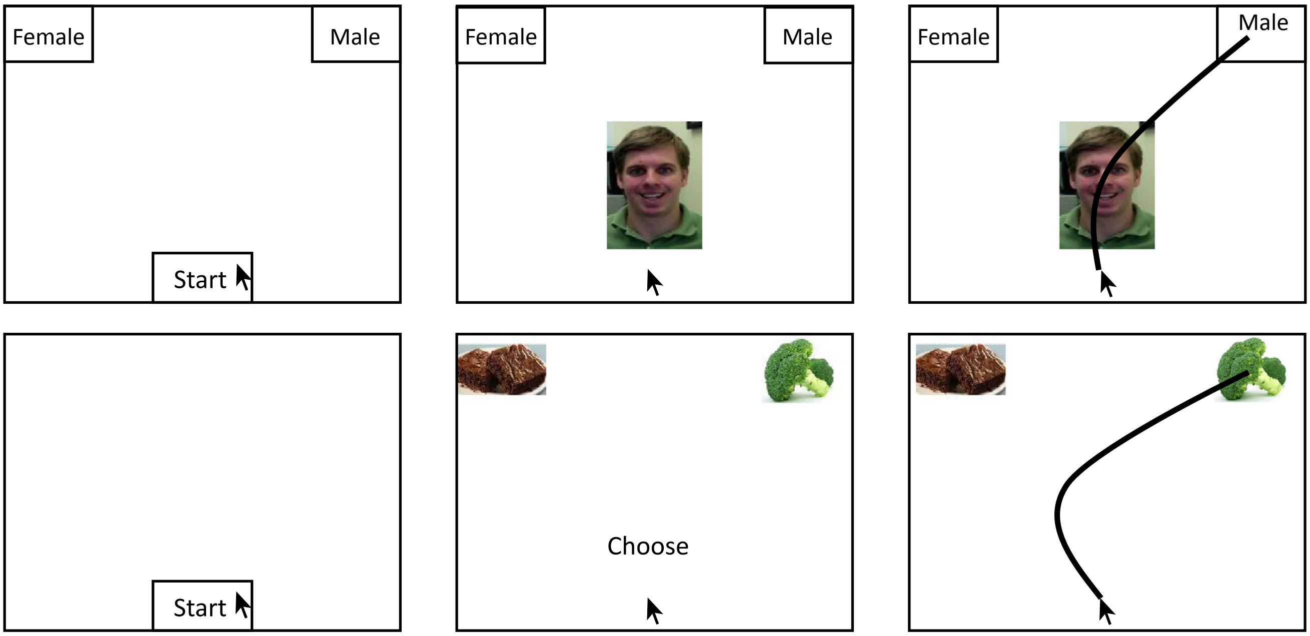


Figure 1. An Example of a Single Trial for Categorization (Top) and Decision (Bottom) Tasks. Participants first click the start button (left), following which their cursor is centered, and the target stimulus (for categorization tasks) or response options (for decision tasks) appear on the screen (middle). Once the target or response options appear on the screen, participants use their mouse to select a single response option (right).

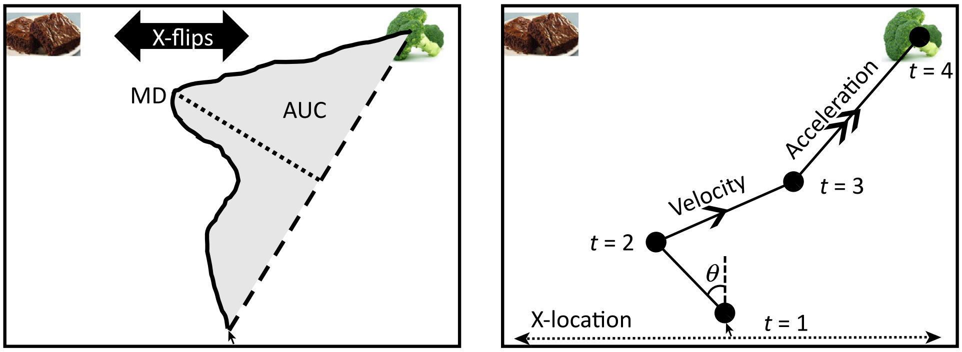
computer samples their cursor location hundreds of times per second (Figure 1). The response options vary depending on the task, but two of the most common setups involve either categorizing a given stimulus into one of two possible response categories (e.g., categorizing a face as Black or White), or having participants choose which of two options they prefer (e.g., broccoli versus brownie).

This is repeated for many (e.g., 25–200) trials, varying the stimuli or response options (or both) on each trial. Overall it yields, for each trial, a rich temporal profile of where the mouse cursors were located on the screen – in other words, the mouse trajectories from the beginning of the trial to when the participant selected a response option.

The richness of these trajectories allows many complementary approaches to data analysis. These metrics can be divided roughly into two classes that reflect the different questions that can be answered by mouse-tracking – those that quantify the magnitude of conflict present, and those that quantify the emergence and resolution of this conflict. Throughout the literature these metrics are used either as dependent variables (e.g., to test theories about relative presence or absence of conflict according to situational or individual differences [32]) or as independent variables to test whether and when individual differences in conflict predict behavior [39,40]. We briefly detail below the most common metrics computed from these trajectories (Figure 2); a more thorough discussion of different metrics is given in Box 1, and a discussion of how mouse-tracking differs from other methods is given in Box 2.

Quantifying Conflict

The most commonly used metrics in mouse-tracking research quantify the magnitude of **response conflict** between the choice outcomes by gauging the relative directness with



Trends in Cognitive Sciences

Figure 2. Depiction of Common ways of Quantifying Mouse-Tracking Data. (Left) Typical ways of inferring conflict or uncertainty for a given trajectory (solid black line). X-flips refer to the number of times the trajectory changes direction in the x plane (three times in the given example). For the other two metrics, the actual trajectory is compared to a straight trajectory (dashed line), with the area under the curve (AUC) representing the area between these two trajectories (grey shaded area), whereas the maximum deviation (MD) represents the maximum distance between the straight and actual trajectories (dotted line). We note that AUC and MD, while not identical, are highly correlated (r = 0.8 to 0.9 in most studies). (Right) Typical ways of analyzing the temporal information given by mouse-tracking. These measures quantify the nature of movements at different timepoints (or the relationship between timepoints) – for illustration, the figure shows four timepoints, but the actual number is typically at least 101. **X-location** refers to where on the x dimension the cursor is located, whereas velocity and acceleration correspond to how fast the cursor was moving or accelerating between time points. Finally, angle (θ) refers to how direct towards one option the movement was between time t and $t + 1$. These approaches can be modeled to find out when in the time-stream participant mouse movements (e.g., their angles or their X-locations) are influenced by different attributes of the options – which we term 'integration times' [40,55,110] (Box 1).

which participants make their response. This is done by comparing the actual trajectory to a straight trajectory from start to response termination, and trajectories that are more similar to the straight trajectory are interpreted as reflecting less conflict between the two options [5]. For instance, the **area under the curve** (AUC) quantifies response conflict by calculating the area between the actual and the idealized straight trajectory, and the **maximum deviation** (MD) calculates how far the furthest point on the actual trajectory is from the idealized straight trajectory (Figure 2).

The Evolution of Choice

Other metrics take advantage of the rich temporal nature of mouse trajectories and use it to answer questions about how a given decision evolves. These approaches are less standardized across studies, but include metrics quantifying acceleration and velocity [36], entropy analyses [41], the time at which different attributes are integrated into mouse movements (**integration times** [40]), and the nature by which the trajectory unfolds – in other words, whether trajectories appear to evolve sequentially or dynamically (Box 1) [42,43].

Review of Recent Work

We next turn to recent advances using mouse-tracking to probe underlying mechanisms supporting categorization and decision-making – specifically, using mouse-tracking to more sensitively gauge conflict, or using mouse-tracking to understand the temporal unfolding and resolution of this conflict. Within these two approaches, we primarily focus on studies in two domains in which a growing body of research using both approaches to inform theories of the real-time processes supporting such decisions: social categorization research (with an emphasis in stereotyping and prejudice) and self-control research. These domains are particularly relevant because they both involve an often conflicting and complex evolution of representations in which many factors interact (potentially at different times within the process) to ultimately influence, often in highly consequential ways, how we behave.

Directly Tapping into Conflict

Stereotyping and Prejudice

One domain in which conflict is centrally important is social categorization – most notably, categorization judgments of others that are influenced by stereotypes and prejudices. These judgments are often conflicting due to information in the world being ambiguous, as well as to stereotype knowledge biasing categorizations. Mouse-tracking has emerged as an important

Box 1. Overview of Mouse-Tracking Analysis

Conflict

The most common approaches to analyzing mouse trajectories involve quantifying the relative conflict present on a given trial. These approaches compare the actual trajectory with a straight trajectory (Figure 2), with the logic that the greater the deviation from a straight path towards the chosen option, the greater the conflict between the two responses [5]. Across many domains, these metrics have been shown to be a sensitive indicator of response conflict ([3] for review). Further, in emerging work linking neural activity to mouse trajectories, it appears that these trajectories are consistently linked to anterior cingulate cortex activity [53,55,75,76] – a region thought to be central in conflict detection and resolution.

Entropy and Uncertainty

Other metrics investigate the relative uncertainty or unpredictability that a given trajectory displays, for instance by counting the number of times the cursor reverses direction in the *x* axis (‘X-flips’), and calculating the sample entropy of the trajectory (i.e., how predictable the trajectory is [6]). Researchers have begun to develop entropy decomposition models to describe more powerfully how mouse movements are related to judgments and decisions [41].

Nature of Trajectory Evolution

To test whether the evolution of a trajectory follows a sequential (e.g., dual-system) or dynamic evolution, researchers can assess whether the distribution of AUC scores is bimodal [43]. If decisions evolve via an initial response (driven by system I) that is then overridden or confirmed (by system II), then trials should either have relatively small (when system I is confirmed) or large (when system I is overridden) amounts of conflict, resulting in a bimodal distribution of AUC scores. However, if responses evolve dynamically, AUC scores should range continuously from small to large, and therefore should be distributed unimodally (Figure I). To test this, researchers can use the Hartigan dip statistic [111], which tests whether distributions are bimodal or unimodal. Another approach focuses on whether the trajectory displays a large midflight correction (as would be expected for trials in which system II overrides system I). Past work [39,42] has shown that trajectories with MD greater than 0.9 reliably show this large midflight correction, correctly classifying up to 90% of trials.

X-Location, Velocity, and Acceleration Profiles

Researchers can also investigate how X-location, velocity, and acceleration profiles unfold. Specifically, drawing on research in dynamical systems, researchers can use these profiles to adjudicate between predictions of sequential versus dynamical systems, as well as to investigate the relative presence or absence of conflict [36]. Other researchers have recently begun to apply principal components analyses to these data to interrogate early, middle, and later influences on cursor location [6].

Integration Times

Another approach to investigate the temporal dynamics involves predicting when in the trajectory the angle of movement (e.g., from one time-point to the next) is significantly influenced by attributes of the stimuli. For instance, Sullivan and colleagues [40] found that on average taste information significantly influenced participants relatively faster than did health information. Thus, these approaches can provide important information regarding the relative timing of when attributes are integrated into a decision.

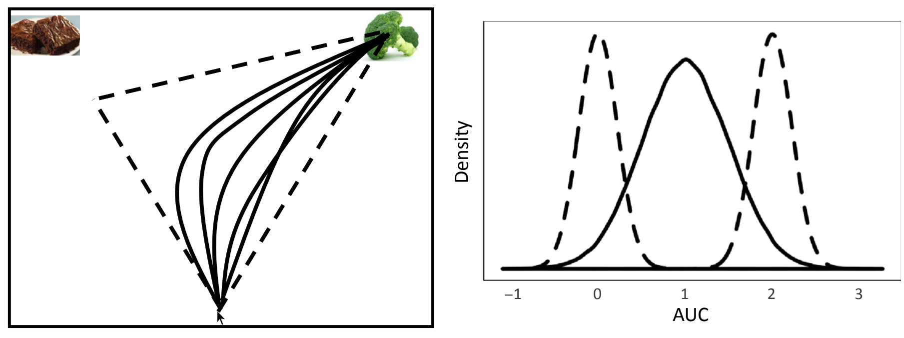


Figure I. Differential Predictions of Classical Dual Systems (Dashed Lines) Versus Dynamical Systems (Solid Lines). Predictions are represented as hypothesized trajectories (left) or density plots of AUC scores (right). Models that posit automatic system influence, followed by controlled system influence (e.g., classical dual-system models), predict trajectories that either are relatively straight (when the two systems agree) or have large midflight corrections (when the systems disagree), yielding either small or large AUC scores. Dynamical systems, on the other hand, predict dynamic competition of both options, yielding variable graded trajectories for which AUC scores are unimodally distributed.

tool to investigate the antecedents and consequences of both of these sources of conflict. Early mouse-tracking research documented that dynamic category conflict can be revealed via mouse-tracking. For instance, individuals show greater conflict when categorizing faces (whether categorizing according to race, gender, or displayed emotion) when those faces are ambiguous (e.g., lighter-skinned black faces, men with long hair, surprised faces [4,32,44,45]). Other work has shown that this conflict is influenced by other contextual and perceptual features, such as the attire [46] and voice [47] of the target, with more stereotype-consistent features leading to less conflict while making categorization judgments. Together, this work suggests that both top-down and bottom-up features drive category competition when making judgments about faces [48]. Researchers have similarly used mouse-tracking to test more nuanced models of the structure of stereotypes, as well as how facial category competition manifests in the brain [49,50]. For instance, when categorizing faces as male or female, participant mouse trajectories were more direct in response to Black men (relative to Asian men) and Asian women (relative to Black women), suggesting that these racial and gender categories are interrelated rather than independent [51], which was corroborated by detected neural patterns [49].

More recent research focuses on more completely understanding conflict while making categorization judgments. This work has revealed several antecedents and consequences of categorizational conflict. For instance, this work has shown ingroup favoritism for judging happy (relative to fearful) expressions [44], greater negativity bias when disambiguating ambiguous emotions while under stress [52], and that more prejudiced individuals show more conflict when presented with non-prototypic Black faces [53]. In addition, this conflict appears to be predictive of subsequent behavior. For instance, individuals who had reported low interracial exposure demonstrated greater conflict (as indexed by **X-flips**) when categorizing mixed-race targets [54]. Crucially, this conflict was predictive of trust bias against mixed-race targets. Similarly, conflict while categorizing politicians as male or female predicted voting behavior, such that greater conflict (i.e., for women who were less stereotypically female) was associated with fewer votes [55].

Box 2. Relation to Other Real-Time Metrics

A natural question in mouse-tracking research concerns how (or if) mouse-tracking is distinct from existing measures that attempt to understand how choices unfold – most notably reaction times, eye-tracking, EEG, and fMRI. Each of these real-time methods carries their own advantages and disadvantages, and it is not our intention to imply that mouse-tracking is strictly better than these alternative techniques (indeed, an emerging trend in research is to combine multiple modalities of real-time assessment to obtain an even richer sense of how judgments and decisions play out in real time [49,50,53,55,68,83]). Instead, we view the strengths of mouse-tracking as twofold. First, these other techniques are often opaque and require inferences based on complex models and/or past research to understand how their measurements correspond to the evolution of a decision (e.g., event-related potentials for EEG, saccades and fixations for eye-tracking). Mouse-tracking, by contrast, offers readily interpretable millisecond-by-millisecond information on how a decision evolves. Second, mouse-tracking offers greater accessibility – with the startup investment (both in equipment cost and knowledge required) being considerably lower than eye-tracking, EEG, or fMRI. This accessibility makes mouse-tracking ideal for researchers who want a real-time understanding of choice evolution but do not wish to devote a major component of their research program to mastering the required methods and analysis tools.

To illustrate the differences between mouse-tracking and other metrics, it is useful to compare mouse-tracking with reaction times. Reaction times have been, and continue to be, highly informative for a range of research questions, including those related to conflict and its resolution (e.g., [112]). One of the drawbacks of reaction times, however, is that they are somewhat of a black box [80] – many factors contribute to how long a response will take, and only some of those elements relate to conflict itself. Although reaction times can be modeled (e.g., via drift diffusion modeling [113]), to more precisely isolate the different components that contribute to reaction time (e.g., response conflict, time to comprehend options, response biases, etc.), the complexity of these approaches makes interpretation less straightforward. One strength of mouse-tracking may therefore be the ability to unpack relatively opaque reaction times [80] by adding information of the relative movements of the mouse leading up to a response. In addition, although some approaches (e.g., stimulus onset asynchrony [114]) can make reaction times useful for understanding how conflict evolves, mouse-tracking may build on this by offering more precise (and more face-valid) millisecond-by-millisecond information on how conflict unfolds without the need for complex experimental setups.

Empirical results seem to support the notion that mouse-tracking and reaction times may offer complementary information ([3] for a more extensive discussion). For instance, reaction time and metrics such as AUC are only moderately correlated (in one set of studies, approximately $r = 0.4$ across studies [39]). Further, controlling for reaction time often does not eliminate findings related to mouse-tracking conflict, and using reaction time as a dependent variable sometimes yields differing results compared to mouse-tracking metrics ([36,39,66], a more in-depth consideration is given in [80]). Together, this suggests that, although related, mouse-tracking and reaction times yield distinct pictures of how judgments and decisions play out in real time, although future research is still necessary to precisely understand the similarities and differences between these related metrics.

Beyond detecting the conflict present when identifying the category to which a given individual belongs, researchers have used mouse-tracking to investigate the evaluation of others, and how underlying biases can influence the evaluation process. For example, researchers asked US participants to report their attitudes (i.e., ‘like’ versus ‘dislike’) towards ‘White people’ and ‘Black people’ [36]. They found that, although participants almost unanimously reported liking both targets, their trajectories when indicating that they liked Black (vs White) targets veered significantly closer to the ‘dislike’ response, suggesting that negativity towards Black people led to significantly greater conflict (see also [56]).

Self-Control

Another domain in which conflict is integral is that of self-control. Although theoretical models of self-control typically recognize (and make predictions about) the importance of conflict [57–61], these predictions are rarely tested using real-time measures of conflict, and often instead rely on choice or attitudinal measures to infer conflict [62–64]. Recent work in mouse-tracking suggests that trajectory directness may be a window into the conflict present for a given decision. Indeed, several investigations have found that mouse-tracking conflict metrics (e.g., AUC, MD) are strongly related to the contextual features of a given decision [39,65–70]. For instance, past work has shown that evaluating ambivalent (vs univalent) attitude objects evokes greater MD [69,70]. In addition, past work on intertemporal choice shows that conflict, as measured by mouse-tracking, corresponds to the difference in subjective values of a given choice, such that the closer the two subjective values (i.e., the immediate and delayed outcomes are similarly valued), the greater the AUC and MD [65,66,71]. Other work has shown this in domains beyond intertemporal choice, such as food choices [39,72].

Beyond simply documenting greater conflict in response to more difficult decisions, self-control researchers have recently begun to use these metrics to advance theory on the predictive power of conflict. In particular, the relative presence or absence of conflict when electing long-term goals over short-term temptations has been hypothesized to be diagnostic of underlying self-control ability. Recent mouse-tracking papers suggest that this is indeed the case, with conflict during mouse-tracking decisions predicting (in some cases, strongly predicting) subsequent behavior [39,66,72,73]. For example, researchers recently showed that conflict when electing between healthy and unhealthy foods subsequently predicted whether participants chose an apple over a candy bar [39].

Finally, self-control researchers have begun to use mouse-tracking to predict who experiences conflict, and when. Although past theorizing on self-control has suggested that those with good self-control may simply be those who are less conflicted when presented with temptation, this has typically been assessed only via attitudes and choice behavior. Consistent with these predictions, recent work has found that those with better self-control (measured via self-report, manipulated, or inferred through outcome variables such as body mass index or grade point average) were less conflicted when choosing long-term goals over short-term temptations [39,72]. Related work has found that good self-control may further shift when conflict peaks while evaluating food items [69].

Cognitive psychologists have similarly leveraged mouse-tracking (as well as conceptually similar 'reach tracking' in which participants select options on a touch screen rather than with a mouse [7,74]) in the context of Stroop and flanker tasks to gain a more precise understanding of how we exert inhibitory control. For instance, motor movements in the context of the Stroop and flanker tasks have helped to identify dissociable processes involved in inhibitory control. Researchers [75,76] found that, whereas trajectory directness reflected competitive inhibition on a given trial (i.e., whether trials were congruent or incongruent), trajectory initiation time reflected global inhibition – variable motor initiation thresholds that are updated after each trial, and are that are thought to reflect the balancing of speed and accuracy tradeoffs by delaying or speeding motor initiation [14,77]. These results thus support models that emphasize multiple dissociable components of impulse inhibition in a way that had been difficult to distinguish using existing techniques such as reaction times ([75,76], also [78]).

Overall, social categorization and self-control research has greatly benefited from using mouse-tracking to better understand the antecedents and consequences of conflict during categorization, evaluation, and choice. Beyond these, mouse-tracking has begun to be adopted in other domains in which conflict is central. For instance, attitude researchers have long emphasized the importance of attitudinal ambivalence (i.e., how conflicted an individual is about his/her attitude) in predicting how likely attitudes are to predict behavior [79]. Researchers have recently begun to use mouse-tracking to measure ambivalence, and to compare it to explicit ratings of ambivalence and certainty [69,80]. Moreover, conflict is an integral component of many decisions beyond self-control dilemmas, and researchers have thus begun to investigate conflict in the domains of moral reasoning [81], emotional judgments [44,82], and risky decision-making [83]. Researchers in cognitive psychology have similarly begun to use mouse-tracking to adjudicate between different types of models for processes such as perceptual decision-making [84,85], memory [86,87], language processing [88–91], and attention [92].

Temporal Dynamics of Conflict Resolution

In addition to tapping directly into conflict, mouse-tracking is particularly powerful because it allows testing of how conflict is resolved – in other words, the temporal evolution and unfolding of a categorization or decision. This makes mouse-tracking uniquely positioned to test frameworks that make nuanced predictions of how categorization and decision processes unfold in real-time [6].

Dual Versus Dynamical Systems

One class of models that make predictions about the temporal sequence of judgments and decisions are dual-system frameworks. These frameworks suggest that judgments and decisions unfold via a two-system sequence whereby initially a quick, emotional system drives representation and choice (i.e., system I), and, following a delay, a slower, rational system can effortfully exert top-down control to reverse (or affirm) this initial response ([16,17,20,22,23]; models that stipulate dual processes rather than dual systems are given in [26,93]). For instance, in the context of stereotyping, some dual-system approaches suggest that we have automatic tendencies to stereotype, which (given proper motivation and ability [94]) can be effortfully overridden by controlled processes [21,95–97]. In the context of self-control, dual-system frameworks emphasize impulse inhibition, whereby there is an initial impulse towards the temptation, followed by an effortful correction to the goal [16,22,98]. Most dual-system frameworks do not expect the two systems to always be in conflict, but suggest instead that system II either affirms or corrects the initial response of system I. In the context of mouse-tracking, such systems might predict either (i) trajectories that are direct towards one option, and then perform a sizable mid-flight correction (system II corrects), or (ii) relatively direct trajectories towards the chosen option (system II affirms).

There are, however, other classes of models, which we refer to collectively as **dynamical frameworks**, that do not pose two competing processes or systems, but instead emphasize that a range of conscious and nonconscious processes simultaneously compete when making a judgment or decision [31,48,99–101]. For instance, in social categorization, these models emphasize simultaneous activation of multiple categories, which then dynamically compete [48]. Similarly, in self-control, these models emphasize the numerous unintentional or sometimes non-conscious processes that support electing goals over temptations [29,62,102–106]. These models predict mouse trajectories that are curved (reflecting dynamic competition between the two options) rather than abrupt or straight.

Across domains, the mouse-tracking paradigm has produced relatively more support for dynamical, rather than dual-system, approaches. For instance, in the stereotyping and prejudice domains, trajectories typically appear to be graded rather than discrete, suggesting that categories dynamically, rather than sequentially, compete [32,42,43,45]. Similarly, in the context of self-control, impulse inhibition trajectories (i.e., straight towards the temptation followed by correction to the goal) occurred in only $\sim$25% of choices [39]. In addition, the remaining trials were graded (and were influenced by the desirability of the unchosen option) rather than directly towards the chosen option. Together, this suggests that the dynamical account may be more reflective of how decisions actually unfold.

In research examining explicit evaluation and prejudice, when White and Asian participants responded that they liked (versus disliked) Black people (as they overwhelmingly did), their trajectories nevertheless showed more conflict as well as disorder (in X-flips) compared with when they indicated that they liked White people [36]. Moreover, the changes in the velocity of their trajectories were predicted by models assuming nonlinear competitive dynamics over time [107]. These findings on the velocity and disorder of the trajectories are in line with a process that assumes parallel distributed processing with partially active representations that compete continuously so as to drive the eventual response. This additional examination showcases some of the benefits of using mouse-tracking. Whereas the finding that participants veered closer to the 'dislike' versus the 'like' option might be easily interpreted in terms of dual processes or systems (early bias that is then corrected), the examination of disorder and velocity – analyses that would not be possible by examining only reaction time – add precision and show that the data are strongly predicted by a dynamical (or, self-organizing) framework instead (see also [108]).

It is important to note that many dual-system frameworks are not as rigid as those outlined above, and allow for parallel influence between the two systems from the onset of a decision [20,22,23], or allow inhibition processes to be more gradually applied (both would result in more graded trajectories). Our aim is not to say that one class of models is correct or incorrect, but rather to showcase how mouse-tracking can be used to develop more nuanced understandings of the temporal unfolding of judgments and decisions. For instance, in the context of self-control, impulse inhibition does appear to take place (based on assumptions about what mouse-tracking reveals) in some decisions, suggesting that models of self-control must be able to account for both early (relatively 'automatic') and late (relatively effortful) influences of goals on choice. It is also important to note that there do seem to be contexts in which sequential processing is more likely to occur [6,80,109]. For instance, when evaluating sentences as true or false, those responses that involved negation were more likely to show sequential (i.e., trajectories that were either abrupt or straight), rather than graded, processing compared to sentences that did not involve negation [109].

Other Temporal Predictions

In the domain of self-control, By using integration time, recent work has investigated when in the time-course particular factors begin to influence mouse movements. For instance, researchers found that, in general, individuals processed the tastiness of foods faster than the healthiness of those foods [40]. Notably, however, this difference was reduced among those with better self-control. Extending this, other work has demonstrated that the time at which people incorporate health information is malleable, showing that presenting calorie information alongside food choices significantly increased the speed with which health information influenced the mouse trajectories of the participants [110].

Summary and Limitations

Mouse-tracking offers a highly sensitive, real-time look into how conflict emerges and is resolved in judgments and decisions. The information contained in mouse-tracking offers an accessible, powerful, and unique way to test and advance theory about conflict in domains across cognitive and social psychology. These advances correspond to the two major methods of analyzing mouse trajectories. First, mouse-tracking can sensitively detect response conflict between two options in a given decision. Across many domains, researchers have used this to probe the antecedents and consequences of decisional conflict. In the same way as reaction time offers a more direct means to study cognitive accessibility, the relative pull of an unchosen option during mouse-tracking allows a potentially more direct measure of the conflict between two choices.

Second, the real-time nature of mouse trajectories allows researchers to investigate how a given judgment or decision evolves. This in turn allows the testing and development of nuanced models of how the underlying cognitive architecture ultimately settles on a representation or choice. Together, these tools allow researchers to move beyond static choices to exploit the dynamic nature of judgment and choice.

Although we have argued for the strength of mouse-tracking, it is important to note that the structure of mouse-tracking experiments make them unsuitable for particular domains. For example, mouse movements on a single trial can be noisy, requiring a multitrial approach that in some cases is infeasible. Similarly, mouse-tracking is best suited for domains in which the targets and/or response options are easy to perceive quickly. Any domains in which participants must read or comprehend highly complex information will be confounded by reading time, and the direct relationship between underlying choice processes and mouse movement will be weakened, at least for the early parts of the trajectory. In addition, the nature of mouse-tracking requires choices to be made explicitly, which can be problematic for behaviors that are normally measured via indirect means. Similarly, mouse-tracking generally restricts responses to two opposing options, which may not reflect how participants might spontaneously categorize or decide in response to a given stimulus (e.g., there are subtle differences between 'like/dislike' and 'good/bad' when evaluating objects). As such, care must be taken when electing the response options during a categorization or evaluation task. Finally, it is important to recognize that some participants can occasionally adopt strategies that invalidate the assumptions of mouse-tracking (e.g., moving the mouse a small amount, then not moving it until a decision has been reached), although in our experience this is relatively uncommon, and tendencies to do so can be examined in the data (e.g., with velocity profiles). Overall, we believe that many research questions can circumvent these limitations, and we believe that multiple fields are ripe for investigation via mouse-tracking. We invite future work in this area (see Outstanding Questions).

Concluding Remarks

Theoretical development in social cognition has outpaced the methods for probing the cognitive architecture underlying judgments and decisions. Using real-time methods such as mouse-tracking, researchers are now equipped to pursue a fine-grained understanding of how the mind processes and responds to complex information. Future work will continue to challenge and refine our conception of how the brain categorizes and makes decisions, with mouse-tracking as an essential tool for exploration.

Outstanding Questions

Can models account for both dynamical and sequential unfolding of processing? Although research to date suggests that judgments and decisions predominantly unfold dynamically (rather than sequentially), research has also demonstrated that sequential unfolding can occur. Going forward, researchers should attempt to refine and develop models (whether primarily dynamic or dual-system) that allow for both dynamical competition and sequential processing. Ideally, these models should further be able to specify (and therefore predict) when these will occur – predictions that can be tested via mouse-tracking.

What are the similarities and differences between mouse-tracking, self-report, and other real-time metrics as measures of conflict? Similarly, are there differences in what these different measures predict in terms of behavior and outcomes? By investigating the interrelation amongst these measures, future research may be able to reach a better understanding of each specific approach. Furthermore, by better understanding the differential predictive validity of these approaches, researchers can learn when each technique is maximally useful.

Can researchers develop generative computational models that are able to accurately simulate mouse trajectories?

To what degree are mouse-movements implicit (unintentional)? One notable aspect of the paradigm is that, although the mouse movements themselves are measured in an unintentional way, they are part of an intentional response. That is, people are intentionally moving their mouse towards one of the responses, but they may be unaware of how exactly they are moving it. This raises questions about how this mix of explicit and implicit dimensions of the paradigm interact.

What are the precise components of conflict? While we have referred to conflict as a unitary construct, there are many elements that contribute to it. Mouse-tracking may serve as a tool to better understand the true nature of conflict.

References

1. Berkman, E.T. *et al.* (2017) Self-control as value-based choice. *Curr. Dir. Psychol. Sci.* 26, 422–428
2. Dale, R. *et al.* (2007) Graded motor responses in the time course of categorizing atypical exemplars. *Mem. Cognit.* 35, 15–28
3. Freeman, J.B. Doing psychological science by hand. *Curr. Dir. Psychol. Sci.* (in press)
4. Freeman, J.B. and Ambady, N. (2009) Motions of the hand expose the partial and parallel activation of stereotypes. *Psychol. Sci.* 20, 1183–1188
5. Freeman, J.B. and Ambady, N. (2010) MouseTracker: software for studying real-time mental processing using a computer mouse-tracking method. *Behav. Res. Methods* 42, 226–241
6. Hehman, E. *et al.* (2015) Advanced mouse-tracking analytic techniques for enhancing psychological science. *Group Process. Intergroup Relat.* 18, 384–401
7. Song, J.-H. and Nakayama, K. (2006) Role of focal attention on latencies and trajectories of visually guided manual pointing. *J. Vis.* 6, 11
8. Mischel, W. (2014) *The Marshmallow Test: Mastering Self-Control,* Little, Brown and Company
9. Mischel, W. *et al.* (1989) Delay of gratification in children. *Science* 244, 933–938
10. Duckworth, A.L. *et al.* (2013) Is it really self-control? Examining the predictive power of the delay of gratification task. *Pers. Soc. Psychol. Bull.* 39, 843–855
11. Fishbach, A. *et al.* (2010) Counteractive evaluation: asymmetric shifts in the implicit value of conflicting motivations. *J. Exp. Soc. Psychol.* 46, 29–38
12. Moffitt, T.E. *et al.* (2011) A gradient of childhood self-control predicts health, wealth, and public safety. *Proc. Natl. Acad. Sci.* 108, 2693–2698
13. Tangney, J.P. *et al.* (2004) High self-control predicts good adjustment, less pathology, better grades, and interpersonal success. *J. Pers.* 72, 271–324
14. Shenhav, A. *et al.* (2013) The expected value of control: an integrative theory of anterior cingulate cortex function. *Neuron* 79, 217–240
15. Myrseth, K.O.R. and Fishbach, A. (2009) Self-control: a function of knowing when and how to exercise restraint. *Curr. Dir. Psychol. Sci.* 18, 247–252

16. Kahneman, D. (2011) *Thinking, Fast and Slow,* Macmillan
17. Shiv, B. and Fedorikhin, A. (1999) Heart and mind in conflict: the interplay of affect and cognition in consumer decision making. *J. Consum. Res.* 26, 278–292
18. Metcalfe, J. and Mischel, W. (1999) A hot/cool-system analysis of delay of gratification: dynamics of willpower. *Psychol. Rev.* 106, 3–19
19. Wilson, T.D. *et al.* (2000) A model of dual attitudes. *Psychol. Rev.* 107, 101–126
20. Dhar, R. and Gorlin, M. (2013) A dual-system framework to understand preference construction processes in choice. *J. Consum. Psychol.* 23, 528–542
21. Devine, P.G. (1989) Stereotypes and prejudice: their automatic and controlled components. *J. Pers. Soc. Psychol.* 56, 5–18
22. Hofmann, W. *et al.* (2009) Impulse and self-control from a dual-systems perspective. *Perspect. Psychol. Sci.* 4, 162–176
23. Strack, F. and Deutsch, R. (2004) Reflective and impulsive determinants of social behavior. *Personal. Soc. Psychol. Rev.* 8, 220–247
24. Emmons, R.A. (1986) Personal strivings: an approach to personality and subjective well-being. *J. Pers. Soc. Psychol.* 51, 1058–1068
25. Kleiman, T. and Hassin, R.R. (2011) Non-conscious goal conflicts. *J. Exp. Soc. Psychol.* 47, 521–532
26. Gawronski, B. *et al.* (2007) What do implicit measures tell us? Scrutinizing the validity of three common assumptions. *Perspect. Psychol. Sci.* 2, 181–193
27. Krajbich, I. *et al.* (2012) The attentional drift-diffusion model extends to simple purchasing decisions. *Front. Psychol.* 3, 193
28. Krajbich, I. *et al.* (2015) A common mechanism underlying food choice and social decisions. *PLoS Comput. Biol.* 11, e1004371
29. Fujita, K. and Han, H.A. (2009) Moving beyond deliberative control of impulses the effect of construal levels on evaluative associations in self-control conflicts. *Psychol. Sci.* 20, 799–804
30. Fujita, K. and Carnevale, J.J. (2012) Transcending temptation through abstraction the role of construal level in self-control. *Curr. Dir. Psychol. Sci.* 21, 248–252
31. Spivey, M. (2008) *The Continuity of Mind,* Oxford University Press
32. Freeman, J.B. *et al.* (2008) Will a category cue attract you? Motor output reveals dynamic competition across person construal. *J. Exp. Psychol. Gen.* 137, 673–690
33. Freeman, J.B. *et al.* (2011) Hand in motion reveals mind in motion. *Cognition* 2, 59
34. McKinstry, C. *et al.* (2008) Action dynamics reveal parallel competition in decision making. *Psychol. Sci.* 19, 22–24
35. Spivey, M.J. *et al.* (2005) Continuous attraction toward phonological competitors. *Proc. Natl. Acad. Sci.* 102, 10393–10398
36. Wojnowicz, M.T. *et al.* (2009) The self-organization of explicit attitudes. *Psychol. Sci.* 20, 1428–1435
37. Kieslich, P.J. and Henninger, F. (2017) Mousetrap: an integrated, open-source mouse-tracking package. *Behav. Res. Methods* 49, 1652–1667
38. Peirce, J.W. (2007) PsychoPy – psychophysics software in Python. *J. Neurosci. Methods* 162, 8–13
39. Stillman, P.E. *et al.* (2017) Resisting temptation: tracking how self-control conflicts are successfully resolved in real time. *Psychol. Sci.* 28, 1240–1258
40. Sullivan, N. *et al.* (2015) Dietary self-control is related to the speed with which attributes of healthfulness and tastiness are processed. *Psychol. Sci.* 26, 122–134
41. Calcagnì, A. *et al.* (2017) Analyzing spatial data from mouse tracker methodology: An entropic approach. *Behav. Res. Methods* 49, 2012–2030
42. Freeman, J.B. (2014) Abrupt category shifts during real-time person perception. *Psychon. Bull. Rev.* 21, 85–92
43. Freeman, J.B. and Dale, R. (2012) Assessing bimodality to detect the presence of a dual cognitive process. *Behav. Res. Methods* 45, 83–97
44. Lazerus, T. *et al.* (2016) Positivity bias in judging ingroup members' emotional expressions. *Emot. Wash. DC* 16, 1117–1125
45. Freeman, J.B. *et al.* (2010) Continuous dynamics in the real-time perception of race. *J. Exp. Soc. Psychol.* 46, 179–185
46. Freeman, J.B. *et al.* (2011) Looking the part: social status cues shape race perception. *PLoS One* 6, e25107
47. Freeman, J.B. and Ambady, N. (2011) When two become one: temporally dynamic integration of the face and voice. *J. Exp. Soc. Psychol.* 47, 259–263
48. Freeman, J.B. and Ambady, N. (2011) A dynamic interactive theory of person construal. *Psychol. Rev.* 118, 247–279
49. Stolier, R.M. and Freeman, J.B. (2016) Neural pattern similarity reveals the inherent intersection of social categories. *Nat. Neurosci.* 19, 795–797
50. Stolier, R.M. and Freeman, J.B. (2017) A neural mechanism of social categorization. *J. Neurosci.* 37, 5711–5721
51. Johnson, K.L. *et al.* (2012) Race is gendered: how covarying phenotypes and stereotypes bias sex categorization. *J. Pers. Soc. Psychol.* 102, 116–131
52. Brown, C.C. *et al.* (2017) Cortisol responses enhance negative valence perception for ambiguous facial expressions. *Sci. Rep.* 7, 15107
53. Cassidy, B.S. *et al.* (2017) Looking the part (to me): effects of racial prototypicality on race perception vary by prejudice. *Soc. Cogn. Affect. Neurosci.* 12, 685–694
54. Freeman, J.B. *et al.* (2016) A perceptual pathway to bias: interracial exposure reduces abrupt shifts in real-time race perception that predict mixed-race bias. *Psychol. Sci.* 27, 502–517
55. Hehman, E. *et al.* (2014) Early processing of gendered facial cues predicts the electoral success of female politicians. *Soc. Psychol. Personal Sci.* 5, 815–824
56. Smeding, A. *et al.* (2016) Tracking and simulating dynamics of implicit stereotypes: a situated social cognition perspective. *J. Pers. Soc. Psychol.* 111, 817–834
57. Fujita, K. (2011) On conceptualizing self-control as more than the effortful inhibition of impulses. *Personal. Soc. Psychol. Rev.* 15, 352–366
58. Kotabe, H.P. and Hofmann, W. (2015) On integrating the components of self-control. *Perspect. Psychol. Sci.* 10, 618–638
59. Inzlicht, M. *et al.* (2014) Why self-control seems (but may not be) limited. *Trends Cogn. Sci.* 18, 127–133
60. Muraven, M. and Baumeister, R.F. (2000) Self-regulation and depletion of limited resources: Does self-control resemble a muscle? *Psychol. Bull.* 126, 247–259
61. Stroebe, W. *et al.* (2008) Why dieters fail: testing the goal conflict model of eating. *J. Exp. Soc. Psychol.* 44, 26–36
62. Fishbach, A. and Shah, J.Y. (2006) Self-control in action: implicit dispositions toward goals and away from temptations. *J. Pers. Soc. Psychol.* 90, 820–832
63. Ferguson, M.J. (2007) On the automatic evaluation of end-states. *J. Pers. Soc. Psychol.* 92, 596–611
64. Gollwitzer, P.M. and Brandstätter, V. (1997) Implementation intentions and effective goal pursuit. *J. Pers. Soc. Psychol.* 73, 186–199
65. Dshemuchadse, M. *et al.* (2013) How decisions emerge: action dynamics in intertemporal decision making. *J. Exp. Psychol. Gen.* 142, 93–100
66. O'Hora, D. *et al.* (2016) Decisions in motion: decision dynamics during intertemporal choice reflect subjective evaluation of delayed rewards. *Sci. Rep.* 6, 20740
67. Calluso, C. *et al.* (2015) Interindividual variability in functional connectivity as long-term correlate of temporal discounting. *PLoS One* 10, e0119710
68. Calluso, C. *et al.* (2015) Analysis of hand kinematics reveals inter-individual differences in intertemporal decision dynamics. *Exp. Brain Res.* 233, 3597–3611
69. Gillebaart, M. *et al.* (2016) Effects of trait self-control on response conflict about healthy and unhealthy food. *J. Pers.* 84, 789–798

70. Schneider, I.K. *et al.* (2015) The path of ambivalence: tracing the pull of opposing evaluations using mouse trajectories. *Front. Psychol.* 6
71. Scherbaum, S. *et al.* (2016) Process dynamics in delay discounting decisions: an attractor dynamics approach. *Judgm. Decis. Mak.* 11, 472–495
72. Ha, O.-R. *et al.* (2016) Healthy eating decisions require efficient dietary self-control in children: a mouse-tracking food decision study. *Appetite* 105, 575–581
73. Stillman, P.E. and Ferguson, M.J. Decisional conflict predicts impatience. *J. Assoc. Consum. Res.* (in press)
74. Moher, J. and Song, J.-H. (2013) Context-dependent sequential effects of target selection for action. *J. Vis.* 13, 10–10
75. Erb, C.D. *et al.* (2016) Reach tracking reveals dissociable processes underlying cognitive control. *Cognition* 152, 114–126
76. Erb, C.D. *et al.* (2018) Reach tracking reveals dissociable processes underlying inhibitory control in 5- to 10-year-olds and adults. *Dev. Sci.* 21, e12523
77. Munakata, Y. *et al.* (2011) A unified framework for inhibitory control. *Trends Cogn. Sci.* 15, 453–459
78. Yamamoto, N. *et al.* (2016) A reverse Stroop task with mouse-tracking. *Front. Psychol.* 7
79. Petty, R.E. and Krosnick, J.A. (1995) *Attitude Strength: Antecedents and Consequences,* Psychology Press
80. Schneider, I.K. and Schwarz, N. (2017) Mixed feelings: the case of ambivalence. *Curr. Opin. Behav. Sci.* 15, 39–45
81. Koop, G.J. (2013) An assessment of the temporal dynamics of moral decisions. *Judgm. Decis. Mak.* 8, 527–539
82. Yamauchi, T. and Xiao, K. (2017) Reading emotion from mouse cursor motions: affective computing approach. *Cogn. Sci.* Published online November 13, 2017. http://dx.doi.org/10.1111/cogs.12557
83. Koop, G.J. and Johnson, J.G. (2011) Response dynamics: a new window on the decision process. *Judgm. Decis. Mak.* 6, 750–758
84. Lepora, N.F. and Pezzulo, G. (2015) Embodied choice: how action influences perceptual decision making. *PLoS Comput. Biol.* 11, e1004110
85. Quétard, B. *et al.* (2016) Differential effects of visual uncertainty and contextual guidance on perceptual decisions: Evidence from eye and mouse tracking in visual search. *J. Vis.* 16, 28–28
86. Abney, D.H. *et al.* (2015) Response dynamics in prospective memory. *Psychon. Bull. Rev.* 22, 1020–1028
87. Papesh, M.H. and Goldinger, S.D. (2012) Memory in motion: movement dynamics reveal memory strength. *Psychon. Bull. Rev.* 19, 906–913
88. Barca, L. *et al.* (2016) The effects of phonological similarity on the semantic categorisation of pictorial and lexical stimuli: evidence from continuous behavioural measures. *J. Cogn. Psychol.* 28, 159–170
89. Crossley, S. *et al.* (2018) The action dynamics of native and non-native speakers of English in processing active and passive sentences. *Linguist. Approaches Biling.* 8,Published online February 22, 2018. http://dx.doi.org/10.1075/lab.17028.cro
90. Sulpizio, S. *et al.* (2015) The sound of voice: voice-based categorization of speakers' sexual orientation within and across languages. *PLoS One* 10, e0128882
91. Incera, S. and McLennan, C.T. (2016) Mouse tracking reveals that bilinguals behave like experts. *Biling. Lang. Cogn.* 19, 610–620
92. Xiao, K. and Yamauchi, T. (2017) The role of attention in subliminal semantic processing: A mouse tracking study. *PLoS One* 12, e0178740
93. Gawronski, B. and Bodenhausen, G.V. (2011) The associative–propositional evaluation model: theory, evidence, and open questions. In *Advances in Experimental Social Psychology* (Vol. 44) (Olson, J.M. and Zanna, M.P., eds), pp. 59–127, Academic Press
94. Fazio, R.H. (1990) Multiple processes by which attitudes guide behavior: the mode model as an integrative framework. In *Advances in Experimental Social Psychology* (Vol. 23) (Zanna, M.P., ed), pp. 75–109, Academic Press
95. Greenwald, A.G. and Banaji, M.R. (1995) Implicit social cognition: attitudes, self-esteem, and stereotypes. *Psychol. Rev.* 102, 4–27
96. Fazio, R.H. *et al.* (1995) Variability in automatic activation as an unobtrusive measure of racial attitudes: a bona fide pipeline? *J. Pers. Soc. Psychol.* 69, 1013–1027
97. Bargh, J.A. (1999) The cognitive monster: the case against the controllability of automatic stereotype effects. In *Dual-Process Theories in Social Psychology* (Chaiken, S. and Trope, Y., eds), pp. 361–382, Guilford Press
98. Fudenberg, D. and Levine, D.K. (2006) A dual-self model of impulse control. *Am. Econ. Rev.* 96, 1449–1476
99. Cunningham, W.A. *et al.* (2013) Emotional states from affective dynamics. *Emot. Rev.* 5, 344–355
100. Ferguson, M.J. *et al.* (2014) Rethinking duality: criticisms and ways forward. In *Dual-Process Theories of the Social Mind* (Sherman, J.W., ed.), pp. 578–594, New York, Guilford Press
101. Melnikoff, D.E. and Bargh, J.A. (2018) The mythical number two. *Trends Cogn. Sci.* 22, 280–293
102. Carnevale, J.J. *et al.* (2015) Immersion versus transcendence: how pictures and words impact evaluative associations assessed by the implicit association test. *Soc. Psychol. Personal. Sci.* 6, 92–100
103. Fishbach, A. and Trope, Y. (2005) The substitutability of external control and self-control. *J. Exp. Soc. Psychol.* 41, 256–270
104. Trope, Y. and Fishbach, A. (2000) Counteractive self-control in overcoming temptation. *J. Pers. Soc. Psychol.* 79, 493–506
105. Fishbach, A. *et al.* (2003) Leading us not into temptation: momentary allurements elicit overriding goal activation. *J. Pers. Soc. Psychol.* 84, 296–309
106. Critcher, C.R. and Ferguson, M.J. (2016) 'Whether I like it or not, it's important': implicit importance of means predicts self-regulatory persistence and success. *J. Pers. Soc. Psychol.* 110, 818–839
107. Usher, M. and McClelland, J.L. (2001) The time course of perceptual choice: the leaky, competing accumulator model. *Psychol. Rev.* 108, 550–592
108. Ferguson, M.J. and Wojnowicz, M.T. (2011) The when and how of evaluative readiness: a social cognitive neuroscience perspective. *Soc. Personal. Psychol. Compass* 5, 1018–1038
109. Dale, R. and Duran, N.D. (2011) The cognitive dynamics of negated sentence verification. *Cogn. Sci.* 35, 983–996
110. Lim, S.-L. *et al.* (2018) Calorie labeling promotes dietary self-control by shifting the temporal dynamics of health- and taste-attribute integration in overweight individuals. *Psychol. Sci.* 29, 447–462
111. Hartigan, J.A. and Hartigan, P.M. (1985) The dip test of unimodality. *Ann. Stat.* 13, 70–84
112. Houwer, J.D. (2003) On the role of stimulus–response and stimulus–stimulus compatibility in the Stroop effect. *Mem. Cognit.* 31, 353–359
113. Krajbich, I. and Rangel, A. (2011) Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proc. Natl. Acad. Sci.* 108, 13852–13857
114. Spruyt, A. *et al.* (2007) On the nature of the affective priming effect: effects of stimulus onset asynchrony and congruency proportion in naming and evaluative categorization. *Mem. Cognit.* 35, 95–106