

How Consumers Resolve Conflict over Branded Products: Evidence from Mouse Cursor Trajectories

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Abstract

Consumers differ in the extent to which brands drive their choices. The current research investigates the psychology underlying such decisions by using a cursor-tracking paradigm that captures consumers' decision-making processes in real time. Results indicate that while consumers typically process brand attributes relatively later than product attributes, the timing of this processing varies across individuals and affects choice. Specifically, when consumers trade off brand and product desirability (i.e., when deciding between a more [less] preferred product from a less [more] preferred brand), the earlier that brand attributes are considered, the more likely consumers are to choose the option from the preferred brand. Increasing the prominence of brand (vs. product) attributes leads to earlier brand attribute processing and a higher likelihood of choosing the preferred brand. These findings hold across a limited number of choice trials and for decisions involving three attributes (brand, product, and price). This research highlights the applicability of cursor tracking in revealing the psychological drivers of consumer choices in real time.

Keywords

information processing, cursor tracking, decision making, choice attributes, branding, product–brand conflicts, cognitive processes

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Consumers routinely make decisions among branded products on offer. Consider an individual deciding whether to buy a T-shirt from New Balance or shorts from Nike. Although the consumer prefers the aesthetics of the T-shirt to the shorts (i.e., perceives the T-shirt to be more desirable than the shorts), this consumer generally prefers the Nike brand to New Balance (i.e., considers the shorts' brand to be more desirable than the T-shirt's brand). To purchase an item, this person needs to consider how desirable they find each product and brand and integrate their assessment to select the preferred product–brand combination.

To understand how consumers make such decisions, researchers have traditionally relied on retrospective or indirect methods, such as self-reports (e.g., Hofmann et al. 2012; Lopez et al. 2014) or inferences drawn from choices (e.g., Samuelson 1938). Yet such approaches can miss valuable information about the underlying choice process that is relevant to marketers as consumers make decisions in real time (Stillman and Ferguson 2019).

To provide a more complete picture of the consumer decision process, the current article utilizes cursor tracking—an emerging technique that covertly tracks the location of a computer cursor at a high temporal resolution as individuals move their cursor to select an alternative (Dotan et al. 2019;

Freeman 2018; Stillman, Medvedev, and Ferguson 2017, 2018). By capturing the trajectory of a cursor's locations, we can estimate brand consideration time—the initial time at which consumers start to consider a brand's desirability—and product consideration time—the initial time at which consumers start to consider a product's desirability. We propose that such attribute consideration times differ, and that these relative differences in consideration time influence consumers' choice of branded products. We predict that the earlier a brand is considered in the decision process, the more likely a consumer is to resolve choice conflicts in favor of the preferred brand (in the previous example, choosing the Nike shorts over the New Balance T-shirt). Moreover, we propose that relative differences in attribute consideration time are influenced by basic marketing actions, such as making the brand name more visible by giving it a more prominent location on the screen or through promotional campaigns emphasizing a brand's value.

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Methodologically, our investigation into the relationship between attribute consideration time and choice makes several advancements that highlight the utility of cursor tracking for consumer researchers. First, we demonstrate the robustness of attribute consideration time across multiple estimation strategies, highlighting that this psychological construct can be accurately captured as consumers make natural, real-time choices. This showcases the viability of this technique for other contexts (e.g., digital analysis of e-commerce platforms, research on different stages of decision-making processes). Second, we demonstrate the practical significance of attribute consideration time by revealing that differences in when attributes are first considered strongly predict decisions, both in- and out-of-sample. Further, we find that attribute consideration time offers marketers a tool beyond traditional marketing metrics, as it provides information independent of conjoint weights and improves on common sequential sampling models. Third, differences in attribute consideration time can serve as an additional metric to understand how consumers deploy attention, offering a more convenient method for measuring attentional deployment, which has typically been assessed via eye movements (e.g., Orquin and Mueller Loose 2013). Lastly, we advance research that focuses on detailing computations in two-attribute choice (Lim et al. 2018; Philastides and Ratcliff 2013; Sullivan et al. 2015) by examining decisions over three attributes. These advancements highlight the value of utilizing cursor tracking—and in particular, attribute consideration time—as a methodological tool to understand the dynamic and hidden motivations that influence consumer choice (Hui, Fader, and Bradlow 2009).

Next, we review literature supporting the prediction that attribute consideration time is associated with and influences choice, drawing on memory-based models. We then unpack the literature on cursor tracking, detailing how such reaching paradigms are an underutilized tool that provide insight into decision mechanisms. We unite these two literature streams on model-based foundations and cursor tracking and offer an illustrative example mapping our theory directly onto the cursor-tracking paradigm (Figure 1). We then detail our predictions for why both individual and context-specific factors influence attribute consideration time, which we test in four studies (Studies 1–3 and a supplemental study reported in Web Appendix A).

Conceptual Framework

Model-Based Foundations for Attribute Consideration Time

When consumers make choices between pairs of branded products, they need to process information related to the perceived desirability of the product, brand, and any other relevant attribute. Why should the initial time at which consumers begin to consider such attributes influence choice? For one, sequential sampling models suggest that people accumulate evidence for a particular option over time by integrating evidence into a

relative signal of decision value (e.g., Busemeyer and Diederich 2002; Busemeyer and Townsend 1993; Ratcliff 1978; Ratcliff et al. 2016). These models suggest that consumers make a choice when they accumulate enough evidence in favor of one option, such that the decision value crosses a threshold.

While many traditional sequential sampling models, such as the standard drift-diffusion model (DDM; Ratcliff et al. 2016), do not allow different attributes of the decision process to influence the relative decision value signal at distinct times, recent research has found that differences in the *time* at which an attribute enters the relative decision value signal can influence choice (Maier et al. 2020; Sullivan and Huettel 2021).¹ For example, this work has fit DDMs and found that model fits are improved when attributes are allowed to impact the evolution of the relative decision value signal at different times.

Recall the example of a shopper who faced a choice between a product they preferred more (T-shirt over shorts) and a brand they preferred more (Nike over New Balance). Each option consists of both a product and brand, which, according to prior research on sequential sampling models, produce an overall valuation when integrated together.

Models that permit attributes to influence evidence accumulation at distinct time points suggest that a consumer who processes desirability of the brand relatively earlier than desirability of the product is more likely to resolve product–brand conflict in favor of the preferred brand (i.e., make more brand-based choices). This is because the earlier the brand is considered, relative to the product, the more total time in the decision process the consumer has spent integrating information about the brand. By the same logic, if a consumer processes desirability of the product before desirability of the brand (i.e., earlier consideration time of the product compared with the brand), they are more likely to resolve the product–brand conflict in favor of the preferred product. An earlier consideration time for the product, relative to the brand, means that more total time in the decision process has been spent integrating information about the product, rather than the brand. Critically, this provides a natural linkage between relative consideration time (i.e., the difference in when two attributes are first considered) and an attribute's weight: the relatively earlier an attribute is processed, the larger its weight will be in determining choice.

This prediction about the relationship between attribute consideration time and choice is consistent with memory-based models.

¹ Other related work has found that the relative decision value can fluctuate depending on the currently attended (i.e., fixated) item, such that unattended features are discounted (Fisher 2017; Krajbich, Armel, and Rangel 2010; Krajbich and Rangel 2011). Thus, these models have proposed a link between consideration and eye fixations. However, such models have not previously considered whether attributes of the choice set influence the relative decision value at different points in the decision process. Similar to these models that use empirical fixations to identify when choice options are considered, we use the empirical relationship between cursor trajectories and attribute values to identify when an attribute is initially considered, as detailed subsequently.

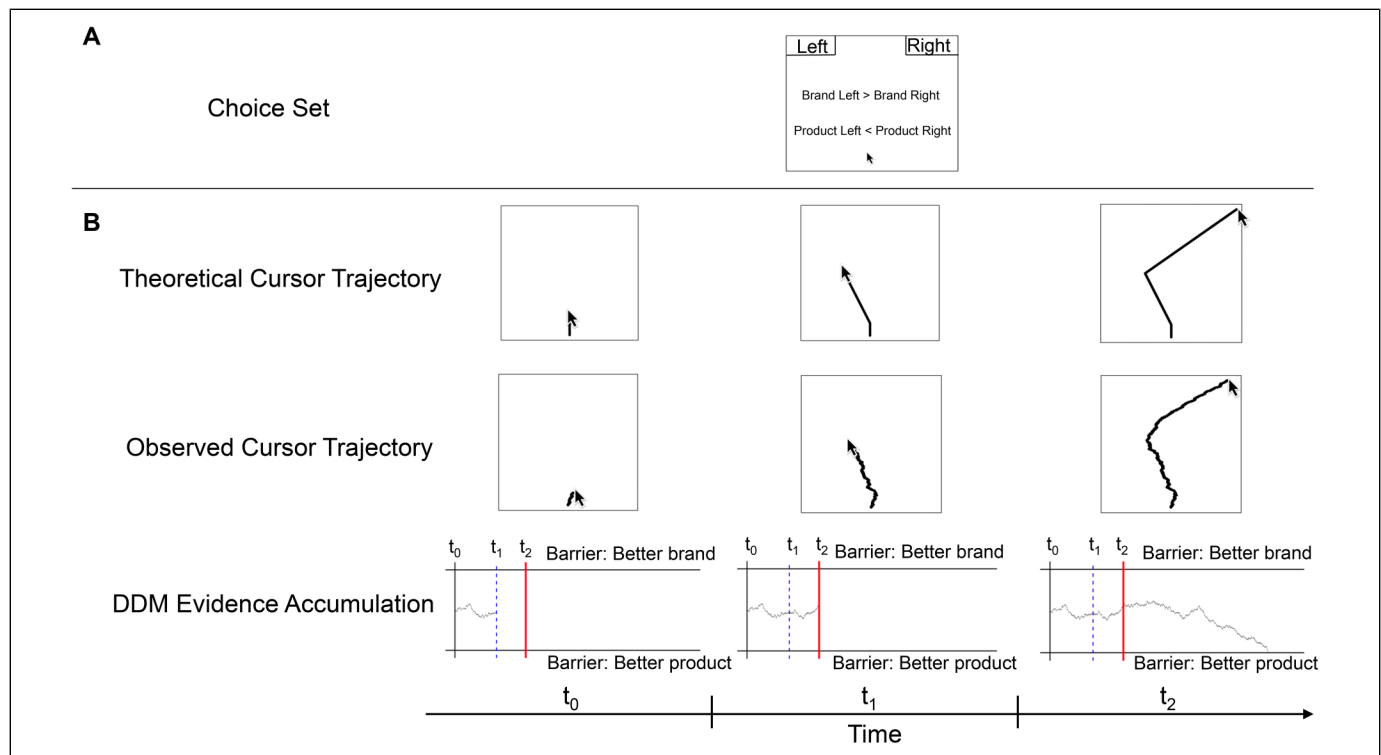


Figure 1. Illustrative Example of a Choice Process for One Consumer.

Notes: In Panel A, a consumer faces a decision between a less preferred product from a more preferred brand (left-hand option) and a more preferred product from a less preferred brand (right-hand option). Assume that for this decision, the difference in the consumer's valuation between the two products is larger than the difference in the consumer's valuation between the two brands. That is, the consumer strongly prefers the right product, but weakly prefers the left brand. Panel B shows the relationship between the theoretical cursor trajectory, the observed cursor trajectory, and a latent DDM evidence accumulation process over time.

At time t_0 : The consumer has not yet attended to an attribute. Theoretically, the cursor drifts directly upward without favoring an option (see "Theoretical Cursor Trajectory"). Empirically, we observe cursor trajectories that mimic this pattern with additional noise in the process (see "Observed Cursor Trajectory"). This cursor trajectory is correlated with the slope of the evidence accumulation process such that at this early time point, evidence accumulation is driven only by noise (see "DDM Evidence Accumulation").

At time t_1 : Assume that the consumer attends to the brand attribute. Thus, cursor trajectories are directed toward the left-hand option with the preferred brand (see "Theoretical Cursor Trajectory" and "Observed Cursor Trajectory"), and evidence accumulation drifts toward the option with the preferred brand (see "DDM Evidence Accumulation").

At time t_2 : Assume that the consumer attends to the product attribute. Cursor trajectories are directed toward the right-hand option with the preferred product (see "Theoretical Cursor Trajectory" and "Observed Cursor Trajectory"), and evidence accumulation drifts toward the option with the preferred brand (see "DDM Evidence Accumulation"). At this point, the consumer has reached the "right" box to enter a decision with the mouse cursor (see "Choice Set" in Panel A) and has gained enough evidence in favor of the right-hand option to end the choice process.

For example, query theory (Johnson, Häubl, and Keinan 2007; Weber et al. 2007) proposes that the value of an alternative is constructed serially through posing queries about the alternative. Value is ascribed by querying memory for past experiences; consumers leverage their memory to provide evidence that they apply prospectively to the decision at hand. The order in which memory is probed (i.e., the order in which queries are generated) affects choice by influencing valuations, with earlier queries more heavily affecting value. That is, query theory also finds that the order in which attributes are considered can impact choice, and it provides a plausible mechanism through which consideration time can enter into a dynamic sampling model.

A related process is at play in multistage choice, wherein the order in which attribute level choices are made affects memory and mental representation of the chosen option, with earlier

attribute choices playing a larger role in the mental representation of the chosen option (Schrift et al. 2018). Based on this research, if queries about products are posed earlier than queries about brands, the consumer would be more likely to resolve conflicts in favor of the preferred product.

Beyond query theory, research on sequential sampling models suggests that evidence accumulates based on memories or thoughts that stimuli evoke (Bakkour et al. 2019; Pärnamets et al. 2015; Shadlen and Shohamy 2016; Stewart, Chater, and Brown 2006). For example, when making a choice between two branded products, people might recall their past experience with each respective brand and each respective product. Hence, how memory is consulted can influence the evolution of the relative decision value that underlies a given choice. Sequential sampling models thus support the idea that considering an attribute earlier in the process leads that attribute to have a greater

influence on choice because processing of attributes from memory likely occurs sequentially (Shadlen and Shohamy 2016; Stewart, Chater, and Brown 2006).

Whereas this prior research supports the prediction that the relatively earlier an attribute enters the decision process, the more likely it is to affect the decision, some theories predict the opposite. For example, recency effects suggest that the last processed or attended feature has the largest effect on memory and choice (Häubl, Dellaert, and Donkers 2010; Li and Epley 2009; Wedel and Pieters 2000). These results differ from ours because they rely on the memory of option information (e.g., comparing the effect of an advertisement presented earlier or later); in this context, information presented most recently tends to be remembered better (Hendrick and Costantini 1970). However, memory decay is less relevant in paradigms such as ours, which examine decision processes for choices between visible options presented simultaneously.²

Estimating Attribute Consideration Time

If the relative time that attributes are considered influences choice, how can this metric be estimated? The solution comes from a growing literature in psychology, wherein continuously tracking the movement of a finger or computer cursor to a choice option reveals information about the timing and order of distinct cognitive processing stages of the decision (for a review, see Dotan et al. [2019]). Whereas traditional models assumed a serial process between the selection of an alternative and the execution involved in reaching toward it (e.g., Miller, Galanter, and Pribram 1960), more recent evidence has challenged this assumption. These studies find that movements are not launched once cognitive processing has finished; instead, movements continuously update in real time, occurring parallel to ongoing cognitive processes such that motor movements reflect partial information acquisition (Chapman et al. 2010; Dotan et al. 2019; Friedman, Brown, and Finkbeiner 2013; Resulaj et al. 2009). This finding that movements reveal underlying cognitive processes is especially valid when movements are continuous (Dotan and Dehaene 2013; McKinsty, Dale, and Spivey 2008; Spivey and Grosjean 2005) and initiated before choice options are revealed (Dotan and Dehaene 2016; Scherbaum et al. 2010; Scherbaum and Kieslich 2018).

To illustrate the link between physical tracking movements and covert processing mechanisms, consider the simple arithmetic task from Pinheiro-Chagas et al. (2017). Participants solved single-digit addition or subtraction prompts (e.g., $9 - 1$) and then pointed to the solution on a 0–10 number line. To select the solution, participants moved the mouse cursor from the bottom of the screen to the appropriate answer at the top of the screen. Movements were initially influenced by the first operand and, 150 ms after the initial influence, were affected

by the second operand. This supports the idea that trajectories reflect *ongoing* processing components, rather than showing that actions are made after all processing has finished. If the latter were true, one would expect to see both operands influence movements simultaneously.

Relatedly, Dotan, Meyniel, and Dehaene (2018) conducted a study that revealed, one by one, a series of one, three, or five arrows pointing either left or right. Participants dragged their finger toward the left or right response button to indicate the direction that the majority of the arrows pointed. If people process each arrow individually and use this accumulated information to update their finger trajectory, their finger trajectory should deviate toward a different side of the screen when the arrows change direction, even before the end of the trial. This is the pattern that emerged, as the “left, right, left” arrow sequences had trajectories that fluctuated more than the “left, left, left” arrow sequences. Additional trajectory analysis, similar to the type we employ, identified the initial time at which each arrow was processed and found that arrows displayed earlier in the sequence altered trajectories before arrows displayed later in the sequence.

These two prior examples support the idea that consumers update their cursor movements in real time and that these movements are connected to how consumers accumulate evidence for choice alternatives over time. Note that the tracking paradigms detailed here, similar to what we utilize, differ from prior marketing research that used a cursor’s location to reveal certain features of choice sets (e.g., Johnson, Schulte-Mecklenbeck, and Willemsen 2008). For example, in Mouselab, consumers move their cursor over boxes with hidden information to reveal that information. This allows researchers to examine what features consumers sought, in what order, and for how long (Payne, Bettman, and Johnson 1988; Sen and Johnson 1997), similar to eye-tracking data. Advances in Mouselab techniques eventually led to examining the velocity, acceleration, and orientation of cursors in this setting. (For a review of different process-tracing tools, see Schulte-Mecklenbeck et al. [2017].) The cursor-tracking technique we employ differs in that it assesses the trajectory cursors take to different choice options, allowing us to uncover how consumers integrate attribute desirability into their choices of branded products and, more broadly, examine the psychological drivers of consumer choice as they unfold in real time.

Illustrative Example of How Cursor Trajectories Capture Evidence Accumulation

We unite literature on the use of cursor tracking to study decision processing with research on DDM, a common sequential sampling model of evidence accumulation (Ratcliff et al. 2016). Figure 1 depicts our proposed theory.³ Figure 1, Panel A, illustrates the introductory example wherein an individual

² For this reason, our findings are also unlikely to be explained by fluency—that is, the notion that greater exposure duration increases liking (Janiszewski and Meyvis 2001; Reber, Winkielman, and Schwarz 1998).

³ Although this section explores evidence accumulation in the context of a DDM, the results are generalizable to other evidence accumulation models.

faces a decision between a less-preferred product from a more-preferred brand (Nike shorts) and a more-preferred product from a less-preferred brand (New Balance T-shirt). In this example, assume that the valuation difference between the two products is larger than the difference between the two brands, such that the consumer strongly prefers T-shirts over shorts but only weakly prefers Nike over New Balance. As is standard across this cursor-tracking paradigm, the consumer makes a choice by moving the cursor from the bottom of the screen to one of the top boxes that denotes a choice option. We use the trajectory that the cursor takes as consumers make a decision to reveal insights about the decision process.

As shown in Figure 1, Panel B, we decompose this choice into several distinct segments, moving from left to right, that reflect the initial time and order in which relevant attributes are considered and integrated into the decision-making process. Initially, when the consumer first views the choice set, there is a brief period in which the attributes are not yet processed. Theoretically, the cursor should move directly upward from its starting point, as cursor movements reflect evidence accumulation, and, at this point, no evidence has been accumulated in favor of an option. Likewise, in the DDM, evidence accumulation before attributes are processed represents noise (i.e., nondecision time). Thus, both cursor trajectories and latent evidence accumulated from the DDM reflect only noise before any attributes have been attended.

Next, we propose that the consumer initially considers one attribute. For illustrative purposes, assume that the consumer initially considers desirability of the brand attribute. At this time point, cursor trajectories move toward the option with the preferred brand (i.e., toward the left-hand option). Likewise, latent evidence accumulation from the DDM also moves toward the option that is preferred in terms of the initially considered attribute.

Eventually, the consumer considers the second attribute (in this example, the product). At this point, information about both attributes is available and used in the decision process. In our example, since the valuations are such that the consumer has a stronger preference over product differences than brand differences, trajectories and evidence accumulation move toward the alternative with the strongly preferred product until that option is selected.

There are several details about the relationship between cursor trajectories, evidence accumulation, and attribute consideration time that are worth emphasizing. First, in the Figure 1 example, the brand has an earlier consideration time than the product, but we hypothesize that this relationship can differ across people and contexts, as detailed in the following section.

Second, a primary contribution of this article is estimating attribute consideration times from cursor trajectory data. While cursor trajectories represent underlying evidence accumulation, they can also be noisy. We utilize two methods to detect the signal from noise: measuring many decisions from the same individuals (Studies 1 and 3) and measuring a few decisions across many individuals (Study 2). Both approaches

provide sufficient data to accurately compute attribute consideration time.⁴

Finally, most research has operationalized attention as eye fixations, the idea being that eye fixations indicate the feature that one is currently considering (Just and Carpenter 1980), although covert attention can also influence decisions (Egley, Driver, and Rafal 1994; Posner, Nissen, and Ogden 1977). Unlike eye fixations, which are a form of external attention, cursor trajectories serve as a measure of *internal* attention to reveal the order and the time at which features begin to influence the decision process. Why is this distinction important? External attention from eye fixations can be drawn to visually salient, but irrelevant, stimuli, which is not the case when assessing attention via cursor trajectories. If attention is only measured via eye fixations, researchers may incorrectly conclude that irrelevant stimuli are more important than they actually are. In addition, if attributes are considered at different times as we propose, the assumption that many models of attention and choice rely on—that attention is both randomly distributed and independent of a choice feature's value (e.g., Krajovich, Armel, and Rangel 2010)—may not hold. Instead, if individuals consistently process certain attributes before others, as our estimates of consideration time suggest, this requires a rethinking of how to model the relationship between eye fixations and choice.

Individual and Context-Specific Factors Affect Attribute Consideration Time

If attribute consideration time can influence choice, what factors influence consideration time? Furthermore, why might there be variance across consumers in the time at which attributes are first considered? We propose that an attribute's consideration time is determined through both (1) a stable and individual-specific component and (2) a context-dependent component.

The first component reflects consumers' individual preferences formed over time, in part through early life experiences (Bronnenberg, Dubé, and Gentzkow 2012). Consumers vary in the extent to which they rely on brands or other attributes when making decisions, with some relying much more on brands as signals of quality than others (Gardner and Levy 1955; Rao and Monroe 1989). Indeed, some consumers pay more for branded products than private label products (Steenkamp, Van Heerde, and Geyskens 2010). Consumers who process brand attributes relatively earlier may have learned over time to process brand desirability before product

⁴ Note that while trajectories carry some noise, they are less noisy than alternative metrics for estimating attribute consideration time. For example, we also estimate attribute consideration time from an underlying cognitive model that utilizes response times (see Web Appendix B2.3). However, unlike cursor trajectories, which are derived from a rich data set that uses the entire cursor path, response times between decision onset and final choice represent only a single data point. Thus, estimates of consideration time from trajectory data are less noisy and have stronger predictive power, further emphasizing the value of cursor trajectory data.

Table 1. Summary of Key Findings.

Finding	Study
1. On average, consumers process desirability of product attributes relatively earlier than brand attributes. In Study 1, this corresponds to processing product 160 ms earlier than brand.	Studies 1–3 and supplemental study
2. Consumers who process brand attributes relatively earlier are also more likely to resolve product–brand conflict in favor of the preferred brand.	Studies 1–3 and supplemental study
3. The relationship between a relatively earlier brand consideration time and greater brand-based choice is mediated by the difference in weights assigned to each attribute.	Studies 1–3 and supplemental study
4. When brand (product) information is made prominent via a spatial manipulation, consumers weight brand (product) desirability relatively more in choices. This relationship is mediated by consumers processing brand attributes relatively earlier than product attributes, causally linking attribute consideration time and choice.	Studies 1 and 2
5. In choices involving three attributes (brand, product, and price), consumers process product desirability earlier than price desirability. Consumers processed price and brand desirability at a similar time.	Study 3
6. Advertisements emphasizing brand (vs. product) value change decisions, in part, by causing an earlier consideration of brand (vs. product) attributes. This leads to greater relative weighting of brand desirability over product desirability in choices, causally linking attribute consideration time and choice.	Supplemental study

Notes: Findings 1–3 and 5 treat attribute consideration time as a participant-specific constant.

desirability to choose products that they believe have strong reputational advantages. Overall, this first component reflects a baseline tendency for how consumers systematically consult their memory and prioritize certain attributes (e.g., brand or product desirability) relevant to the decision.

The second component reflects the sensitivity of attribute consideration time to various contextual factors, including marketing actions. For example, altering the visual prominence of brand information might lead to a relatively earlier consideration time by exogenously shifting the order in which memories are consulted. By this logic, marketing promotions highlighting the value of a strong brand, for example, can also alter consideration time and influence consumer decisions. Shifting attribute consideration time provides a common mechanism through which various marketing actions might influence consumer choice. Note that even if contextual changes do not systematically adjust which attribute consumers process first, they may still alter the difference in relative consideration time given to certain attributes; according to the models that inspire our hypotheses, this would also shift consumers' choices.

Empirical Overview

To estimate differences in the consideration time of attributes relevant to brand-based decisions, we utilize a cursor-tracking paradigm that covertly records the location of a computer's cursor at high temporal frequency. We predict a positive relationship between a relatively earlier brand consideration time and brand-based choice, that is, choice of a preferred brand over a preferred product. This is because the relatively earlier that brands are considered, the more time one spends integrating brand desirability into the choice process. In addition, we predict that manipulations, such as subtle marketing strategies that cause consumers to consider brand desirability relatively earlier, will lead to more brand-based decisions.

We examine attribute consideration time across four studies (Studies 1–3 and a supplemental study reported in Web

Appendix A). Study 1 examines the relationship between product and brand consideration time and choice when consumers make decisions about branded food products and branded clothing products; it also introduces a spatial manipulation of food product and brand information to provide a causal test that attribute consideration time influences choices. Study 2 generalizes Study 1 to fewer choice trials; it also provides an a priori test of whether the spatial location of product and brand attributes affects attribute consideration time. Study 3 advances our model by examining choice over three attributes (brands, products, and price). The supplemental study in Web Appendix A examines how a marketing strategy (i.e., promoting brand vs. product desirability) shifts choice. Table 1 summarizes key findings.

Study 1: Consequential Choice of Branded Food and Clothing Products

Study 1 examined how the consideration time of product and brand desirability relates to consumer decisions and reliance on brands for two common categories of decisions: choices between branded food products and choices between branded clothing items. These choices were incentive compatible; participants received the outcome of one of their choices for each decision category (Ding, Grewal, and Liechty 2005; Toubia et al. 2012; Yang, Toubia, and De Jong 2018).

First, regarding the individual-specific component we propose, we tested whether brand-based decisions (i.e., resolving choices involving product–brand conflict by choosing the preferred brand over the preferred product) are predicted by the time at which consumers start to consider brand desirability relative to product desirability. We expected a positive relationship, such that consumers who consider brand desirability relatively earlier make more brand-based decisions.

Second, regarding the context-specific component, we counterbalanced the spatial location of product and brand attributes within the food-choice task to explore whether choice is

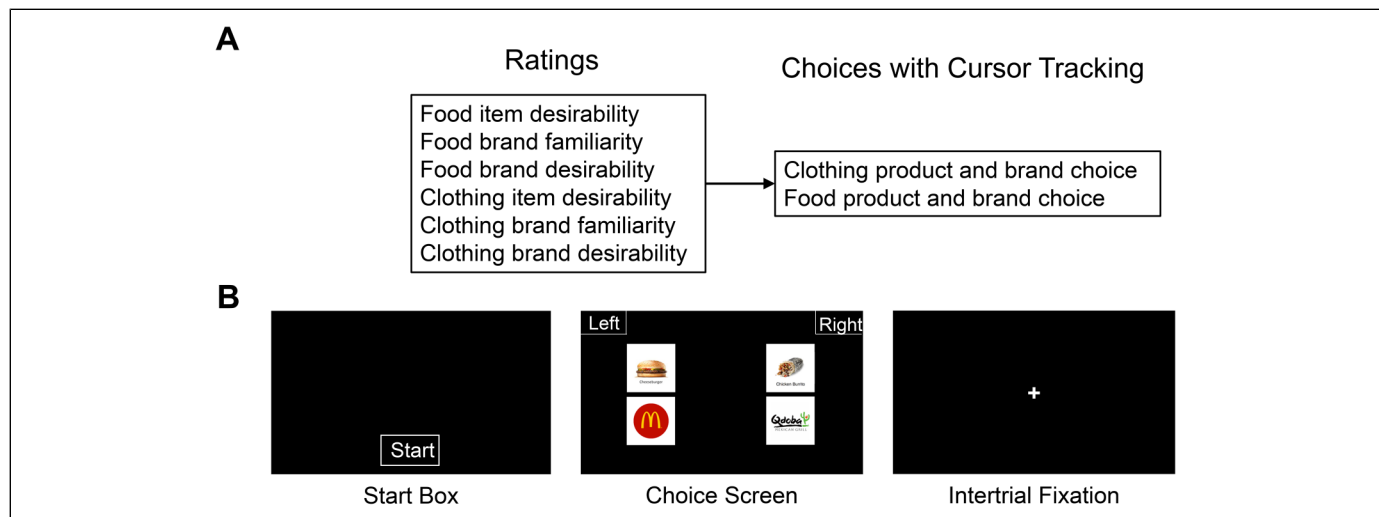


Figure 2. Study Design.

Notes: Panel A: The study consisted of eight tasks: six rating tasks followed by two choice tasks that utilized mouse cursor tracking. Panel B: Example trial of the food product and brand choice task: Participants first clicked on the start box, then moved the mouse cursor to an upper box labeled “left” or “right” and clicked in the box to make a choice. Importantly, the choice screen with the branded products was only visible after the cursor was in motion. An intertrial fixation appeared between trials.

affected by spatial location of information, an intervention that influences the visual prominence of attributes. We predicted that presenting brands in a more prominent location would increase relative brand consideration time, offering causal evidence that processing brand desirability relatively earlier than product desirability leads to more brand-based choice.

Method

Participants. We preregistered Study 1 (aspredicted.org/ki9xv.pdf; for all data, preregistrations, sample analysis, and materials, see <https://osf.io/ja8v2/>) and recruited 46 students and community members for a lab study ($M_{age} = 32.39$ years, range = 18–65 years; 76.1% female, 23.9% male).⁵ We required all participants to fast for three hours prior to the study. Participants could not have any dietary restrictions and must have lived in the United States for at least five years to participate. They received a \$5 show-up fee and \$30 upon completion of the study.

Ratings task. Participants completed the following three tasks twice, once for food items and once for clothing items (Figure 2, Panel A). Participants viewed an image⁶ of a

product or brand and indicated (1) product desirability (food product: “How much would you like to eat that food, and ONLY that food?”; clothing product: “How much would you like to receive that clothing item, and ONLY that item?”; $-2 = \text{“strongly dislike,”}$ and $2 = \text{“strongly like”}$), (2) brand familiarity (yes/no), and (3) brand desirability (“How much do you like each particular brand?”; $-2 = \text{“strongly dislike,”}$ and $2 = \text{“strongly like”}$). We counterbalanced whether food or clothing ratings were the first three tasks, but within each of these categories the order of tasks was always (1) product desirability, (2) brand familiarity, and (3) brand desirability ratings.

We used brands that offered a wide array of products and used food and clothing items absent distinguishing brand features to facilitate product–brand pairings, in line with conjoint measurement studies where various attributes, such as products and brand, may be varied across participants (Green and Rao 1971). For example, we used a picture of a generic donut that could be paired with different coffee shop brands (all images used are provided in a link in Web Appendix B). Food products fit into only one of the following categories: fast-food chain, fast casual chain, coffee shop, or Mexican restaurant. Food brands were also chosen to reflect these restaurant categories. Overall, there were 48 food products and 25 food brands that participants rated. For clothing ratings, we showed male and female participants different clothing products contingent on their gender. Men rated 15 pants, 17 shirts, 15 sweaters. Women rated 15 dresses, 15 pants, 17 shirts, and 15 sweaters. Both genders rated 39 brands.

Cursor-tracking paradigm. After the ratings task, participants completed two separate cursor-tracking tasks. In the food task, participants made 200 choices between two different foods from two different brands (e.g., Figure 2, Panel B); in the clothing task, they made 200 choices between two different clothing

⁵ In our analyses, we removed two participants from the food–brand task: one for exhibiting no variance in brand ratings (leaving us unable to estimate attribute consideration time) and one for exhibiting no conflict between product and brand in the choice sets. Additionally, we removed one participant from the clothing–brand task who showed no variance in brand ratings. The remaining sample size is consistent with prior research using process tracing to explore the behavioral mechanisms underlying choice.

⁶ Image size for food products and food brands: 300×300 pixels; image size for clothing products: 298×431 pixels; image size for clothing brands: 296×193 pixels. The screen resolution was 1080×1920 pixels.

items from two different brands. Product–brand combinations were selected to span the set of all possible product–brand combinations as much as possible. On average, participants viewed over 40 unique product–brand pairs and viewed each pair only eight times throughout the choice task. Participants were not shown any products or brands they rated as neutral (i.e., 0). For additional details, see Web Appendix B.

We designed pairings to enhance realism for both clothing and food products. For example, a participant might see a food–brand pairing of a doughnut from Starbucks but would never be offered a doughnut from Burger King since such a product is not likely to be served there. To further increase realism, if a product appeared in multiple trials, it was always paired with the same brand. Participants made choices in 25-trial blocks with short rests between each block. Participants completed all trials of one choice class task (i.e., food–brand task or clothing–brand task) before moving to the other one (task order was counterbalanced).

To choose the product–brand pairing they preferred, participants moved the mouse cursor to the upper box labeled “left” or “right.” Figure 2, Panel B, depicts a typical trial. Each trial began with a box containing the word “START” displayed at the bottom center of a black screen. Once participants clicked the START box, the trial began. The screen remained black until the participant began to move the cursor. Once participants moved the cursor, the two choice options were revealed. This encouraged smooth and natural cursor movements to ensure that we captured the decision process as it unfolded (Gold and Shadlen 2007; Song and Nakayama 2009; Spivey and Grosjean 2005). The location of each product–brand pairing (left vs. right) was randomized. In the food–brand task, we randomized the location of the foods and brands (top vs. bottom) in each trial, but in the clothing–brand task, the clothing item always appeared at the top of the screen to reduce noise, given that clothing product and brand images were different sizes. Choice trials were separated by an intertrial interval of one second where a black screen was shown.

Participants’ choices were incentive compatible; all participants received a \$10 gift card to one of the clothing brands they selected in the clothing–brand task. Additionally, participants also received one of the food items they chose in the food–brand task.

Cursor tracking. The cursor’s position was tracked using Psychophysics Toolbox (Kleiner, Brainard, and Pelli 2007) with a temporal resolution of approximately 60 Hz. Tracking for each trial started when participants clicked in the start box and ended when they clicked in the upper-left or upper-right box to indicate a choice. Following best practices from prior research (Dotan et al. 2019), we shifted and normalized coordinates so that the point at which the cursor clicked in the start box was $(x,y)=(0,0)$, the pixel clicked to select the left option was $(-1,1)$, and the pixel clicked to select the right option was $(1,1)$. We instructed participants to (1) respond naturally by moving the cursor continuously from the start button toward the top side of the screen of the desired choice option

and (2) respond as quickly and accurately as possible. Once the cursor was in motion, all choice options appeared.

We highlight two important considerations regarding the cursor-tracking data. First, given that participants made continuous cursor movements and that both choice options were only revealed once the cursor began its initial movement, these cursor paths allow us to measure intermediate processing stages (Dotan, Meyniel, and Dehaene 2018; Erb et al. 2016; Friedman, Brown, and Finkbeiner 2013; Pinheiro-Chagas et al. 2017). Second, these paths provide richer data beyond response time, which acts as a summary of the cognitive processes used in the decision process. Specifically, cursor paths enable us to identify the order in which different processing stages occur (e.g., whether an initial stage utilizes only information about the product and whether this is followed by a later stage that utilizes both product and brand information).

Data preprocessing. As preregistered, and in line with prior research (Lim et al. 2018; Sullivan et al. 2015), we followed two preprocessing steps to reduce noise (Web Appendix B).

Cursor trajectory analyses. First, to analyze cursor trajectories, we normalized time to compare similar decision process stages across participants who may have different underlying processing latencies, consistent with previous research (Dotan et al. 2019).⁷ Every trial was divided into 100 equal-sized time bins. The start position was denoted as time $t=1$, and the time when a choice was entered was denoted as time $t=100$. The mean x and y positions of the cursor during each time bin were then computed. Thus, the data for cursor trajectories for each trial consisted of 100 horizontal and vertical cursor locations.

Second, we conducted linear regressions to examine how participants’ product and brand desirability ratings influenced the cursor trajectory angle at every normalized time point. In these regressions, the dependent variable, trajectory angle at time t , was normalized such that -45° indicated a direct movement toward choosing the left option, 0° indicated a movement directly upward, and $+45^\circ$ indicated a direct movement toward choosing the right option. The independent variables were (1) the difference in product desirability (i.e., $\text{food}_{\text{right}} - \text{food}_{\text{left}}$ or $\text{clothing}_{\text{right}} - \text{clothing}_{\text{left}}$) and (2) the difference in brand

⁷ In addition to being a standard practice when analyzing cursor paths, normalizing time is appropriate for two reasons. First, it allows for a simple way to compare across trials that have differences in response times from the same individual. For example, if an individual takes two seconds on one trial, and three seconds on another, it is difficult to compare absolute times across the individual’s trials, since the first trial does not have data between two and three seconds. Second, normalized time permits a method to control for large differences in response times across participants, which could reflect differences in underlying cognitive-processing speeds. These differences could lead to problems when conducting analysis on absolute times, as such times would reflect different stages of cognitive processing in different participants. Using time-normalized analyses removes these problems. We also find similar results in additional analyses utilizing raw time (see the “Alternative Consideration Time Metrics” subsection).

desirability (i.e., $\text{brand}_{\text{right}} - \text{brand}_{\text{left}}$). We conducted these regressions at the individual level for each of the 100 normalized time points. Note that each normalized time point included a participant's data from all trials in the study at that particular time point of the trial.

Finally, as a test of our primary hypothesis, we used the results from these regressions to identify the earliest normalized time point at which attribute (i.e., product or brand) desirability had a significant and lasting influence on trajectory angles, which we denote as an attribute's consideration time. This analysis allows us to identify the relative time during the choice process at which product or brand desirability begins to affect decisions. We did this by computing the time point at which brand or product desirability positively influenced trajectories at the 5% level (two-sided test) and continued to remain significant for the remainder of the time units. Importantly, this test requires that an attribute maintain its significance from that time point through the end of the trial. This allows us to compare the relative time at which product versus brand desirability first influences the decision process and how this consideration time is correlated with brand-based choice, directly testing our primary hypothesis.⁸

Formally, we write the regression for each participant as:

$$\text{CursorAngle}_{it} = \beta_{0t} + \beta_{1t}\text{Product}_i + \beta_{2t}\text{Brand}_i,$$

where CursorAngle_{it} is the normalized angle the mouse cursor takes relative to its consideration point at time t in trial i , Product is the difference between the right and left product ratings, and Brand is the difference between the right and left brand ratings. A linear regression is run for each t in $t=1$ to 100. Then, we say that the consideration time of attribute j is t^* if t^* is the earliest time such that the p -value associated with β_{jt^*} is less than .05 for all $t \geq t^*$. We denote this as the time-to-significance metric, as this method estimates an initial time at which an attribute remains significantly correlated with cursor trajectories for the remainder of the decision process. These regressions are at the participant level (i.e., individual-specific estimates of consideration time).

To see how this time-to-significance metric relates to our hypotheses, consider the results for two hypothetical consumers. First, suppose a simple case of a consumer who immediately uses both product and brand desirability to make decisions. This consumer recognizes the value of both products and brands the instant they are first displayed. Given that product and brand desirability are processed and utilized in decision making, they will affect cursor movements from the

earliest normalized time point ($t=1$) throughout the duration of the trial. Thus, our analysis would identify time point 1 as the consideration time of both product and brand.

For the second case, suppose a more realistic scenario in which a consumer takes some time to identify and utilize both product and brand desirability. In this case, the results of the regression analysis would reveal that product and brand desirability differences only predict cursor movements after some delay in normalized time, as it takes the consumer time to process the product and brand values. If product attributes affect decisions relatively earlier than brand attributes, product desirability would have an earlier consideration time relative to brand desirability for this consumer. Using the estimated consideration times from the regression results allows us to quantify *how much* earlier products influence choice compared with brands.

Results

Choices. We first investigated how properties of the choice set affect choices. As expected, both the relative product desirability (i.e., $\text{product}_{\text{right}} - \text{product}_{\text{left}}$) and relative brand desirability (i.e., $\text{brand}_{\text{right}} - \text{brand}_{\text{left}}$) predicted choices, as evidenced by the fixed effects from a logistic mixed-effects regression of choosing the right-side option on the relative product and brand differences (food task: $\beta_{\text{product}} = .99$, $p < .001$, $\beta_{\text{brand}} = .49$, $p < .001$; clothing task: $\beta_{\text{product}} = .93$, $p < .001$, $\beta_{\text{brand}} = .36$, $p < .001$; see Web Appendix Figure B1ab).

To examine whether participants exhibited sizeable variation in the propensity to exhibit brand-based choices (i.e., individual-specific component), we computed a measure of brand-based choice for each participant and each task as follows. First, we restricted the data set to trials in which participants faced a conflict between their preferred brand and their preferred product. We defined a conflict as occurring when participants' product and brand desirability ratings suggested that one option dominated in the product and the other option dominated in the brand (e.g., left product rated as 1, right product rated as 2, left brand rated as 2, right brand rated as 1), meaning that we identified conflict trials at the participant level. As detailed in Web Appendix B, a conflict occurred in approximately 25% of the trials, on average. We calculated each participant's brand-based ratio (BBR) as the fraction of conflict trials in which each participant chose the option they identified as having a better brand.

We find substantial variation in brand-based choice across participants (food: $M = 32.4\%$, $SD = 19.7\%$; clothing: $M = 28.6\%$, $SD = 23.2\%$; Web Appendix Figure B1cd). This allowed us to examine the extent to which differences in brand-based choice are associated with differences in product and brand consideration time.

Differential consideration time of product and brand desirability in the choice process. Moving to hypothesis testing, we examined whether the desirability of products and brands predicted decision making at different times in the choice process.

⁸ Some working papers have suggested potential flaws in this analysis (Zhang et al. 2018, 2019; however, see a compelling response by Sullivan et al. [2019]). The central criticism is that such a method may not provide clear evidence for a causal role of consideration time in choice. This highlights the importance of the parts of our studies that explicitly test for a causal link from the extent of time spent considering an attribute to the choice itself. Moreover, we supplement this analysis with two additional measures of consideration time and find that the results are robust to these alternative metrics (Web Appendix B).

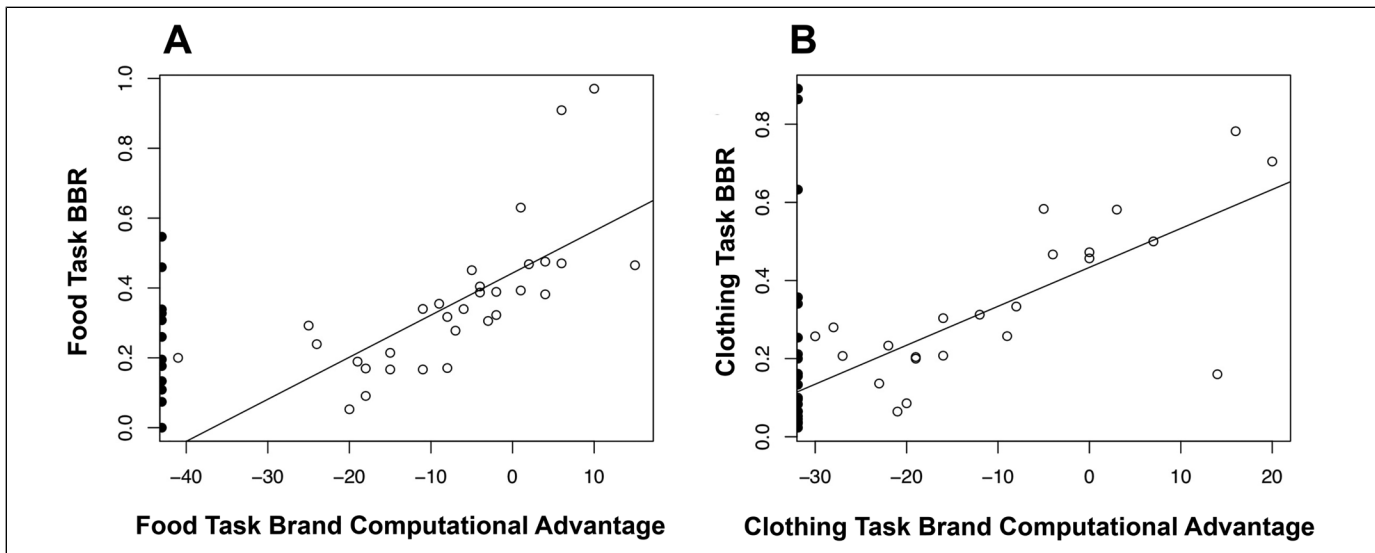


Figure 3. Brand-Based Choice and Attribute Consideration Time (Study 1).

Notes: Scatterplots present the BBR as a function of the brand's computational advantage, defined as the consideration time of the product and the consideration time of the brand, for the food-brand task (Panel A) and the clothing-brand task (Panel B). White circles depict participants who had both product and brand significantly correlate with cursor movements. Black semicircles depict the BBRs of participants with at least one attribute not significantly correlated with cursor movements. The linear regression line for each task is displayed.

First, we estimated attribute consideration time via the time-to-significance metric detailed previously for each participant in the food task. We found that product had a significantly earlier consideration time than brand ($M_{\text{product}} = 62.1$, $SD = 7.5$; $M_{\text{brand}} = 70.3$, $SD = 10.7$; $t(30) = 3.46$, $p = .002$).⁹ Second, we repeated this analysis for the clothing task and again found that product had a significantly earlier consideration time than brand ($M_{\text{product}} = 57.3$, $SD = 10.4$; $M_{\text{brand}} = 67.7$, $SD = 11.7$; $t(22) = 3.14$, $p = .005$).¹⁰ Overall product desirability influenced the choice process 8%–10% earlier than brand desirability, equivalent to a 160 ms advantage for the product. Web Appendix B provides an additional group-based analysis supporting the average individual consideration time differences between brand and product detailed here.

Relationship between attribute consideration time and brand-based choices. Having demonstrated that product and brand desirability start influencing choices at different times, we next

examined whether these relative differences in consideration time predict consumers' propensity to make brand-based choices.

We examined this by computing a participant-specific metric of the brand's consideration time advantage. We denote this as the brand computational advantage, defined as the difference between when product and brand desirability start to influence the choice process. A brand computational advantage of x implies that the brand's consideration time was x time units before the product's consideration time. To test for an association between consideration time and choice, we then conducted a linear regression of each participant's BBR (defined as the fraction of trials in which the option with the more preferred brand was chosen over the option with the more preferred product) on their brand computational advantage.

This regression resulted in a positive correlation between consideration time and choice for the food task ($R^2 = .49$, $p < .001$; Figure 3, Panel A) and clothing task ($R^2 = .55$, $p < .001$; Figure 3, Panel B), suggesting that the earlier the brand was initially considered compared with the product, the more likely participants were to exhibit a brand-based choice. Indeed, differences in attribute consideration time predicted approximately half the variation in observed decisions.¹¹

This analysis computed consideration time and choice from the same data. However, we find that consideration time also

⁹ Note that this analysis excludes participants for whom either product (4.6% of participants) or brand (27.9% of participants) did not influence cursor movements and thus did not influence choice (following Sullivan et al. [2015]). An alternative analysis designed to include all participants assigned a time point of 101 (i.e., time point after the choice process ended) for product or brand if product or brand never significantly influenced cursor movements. This analysis yielded a similar result ($M_{\text{product}} = 63.9$, $SD = 11.1$; $M_{\text{brand}} = 78.9$, $SD = 16.6$; $t(42) = 5.41$, $p < .001$).

¹⁰ As with the food task, this analysis excluded participants for whom either product (6.8% of participants) or brand (40.9% of participants) did not influence cursor movements (following Sullivan et al. [2015]). To include all participants in this analysis, we assigned a time point of 101 for product or brand if product or brand never significantly influenced cursor movements. This analysis yielded a similar result ($M_{\text{product}} = 60.3$, $SD = 15.0$; $M_{\text{brand}} = 81.3$, $SD = 18.8$; $t(43) = 5.07$, $p < .001$).

¹¹ Since brand/product desirability never became significant for some portion of participants, we also conducted a similar analysis that included participants who never had a consideration time for product or brand by setting the consideration time for that feature at a normalized time of 101, just after the end of the process. This yielded a similar result to the previous analysis (food choice task: $R^2 = .41$, $p < .001$; clothing choice task: $R^2 = .75$, $p < .001$).

predicts decisions in out-of-sample data. For this additional analysis, we estimated consideration time from the first set of 100 trials and used this to predict the proportion of brand-based choices (BBR) in the second set of 100 trials. We find a positive relationship such that the earlier the brand started to influence the decision process in the first half of trials, the greater the choice share of the option with the better brand in the second half of trials (food task: $\beta = .008$, $p < .001$, $R^2 = .50$; clothing task: $\beta = .005$, $p < .001$, $R^2 = .44$).

Alternative consideration time metrics. We conducted two robustness checks (detailed in full in Web Appendix B) to determine the extent to which an attribute's decision weight (i.e., subjective importance) might have biased the estimate of consideration time and led to a spurious correlation between the BBR and consideration time. In both robustness checks, we estimated consideration time using an alternative metric that explicitly controlled for attribute weight. The results, detailed in Web Appendix Table B1, found that these alternative consideration time estimates were both correlated with the time-to-significance metric and were also both correlated with the BBR. Given that we continue to find strong evidence for our predicted effects under these additional metrics and, thus, that the time-to-significance metric did not appear to be biased, we continued the remainder of the analysis with this time-to-significance metric.

Consideration time and product–brand decision weights. The results so far suggest that considering brand desirability before product desirability predicts brand-based choice. In line with prior research (Dotan et al. 2019), we reasoned that this positive relationship occurs because attributes processed earlier are integrated into the decision for a longer period of time and thus receive a greater weight in the final choice. To examine this hypothesis, as specified in our preregistration, we next investigated the relationship between consideration time and the decision weights assigned to brands and products.

First, we examined how decision weights relate to the propensity to exhibit brand-based choice. We conducted logistic regressions where we regressed choice of the right-side option on relative product desirability and relative brand desirability. This allowed us to estimate the participant-specific weights that brand and product desirability received in decisions for the food and clothing tasks. From this, we took the difference in the product and brand's decision weight in both tasks and ran a linear regression using this difference to predict the BBR. We found significant effects, such that the difference between the product and brand attribute weights predicted a sizeable amount of variance in the BBR for the food task ($\beta = .25$, $p < .001$, $R^2 = .67$) and clothing task ($\beta = .32$, $p < .001$, $R^2 = .86$). That is, the extent to which brand received a larger weight than product predicted choice of the option with the dominant brand.

Second, we examined whether consideration time of product and brand desirability was associated with differences in attribute weights. We regressed the difference in product and brand weights on the computational advantage of the brand using the time-to-significance metric, which resulted in a

significant and sizable correlation (food task: $\beta = .02$, $p < .001$, $R^2 = .33$; clothing task: $\beta = .02$, $p < .001$, $R^2 = .66$). That is, we find that weighting the brand more than the product is correlated with processing brands relatively earlier than products.

Moreover, we found that the difference in attribute weights mediated the relationship between consideration time and brand-based choice (Web Appendix Figure B6). Additionally, as reported in Web Appendix B, consideration time still predicted BBR when controlling separately for the weight placed on product and brand, rather than only their difference. These results suggest that the relationship between earlier processing of attributes and brand-based decisions is mediated by increased weight of the attribute in the final decision.

Finally, another analysis reported in Web Appendix B3 reveals that an attribute's relative importance, as derived via a conjoint analysis of the data, is correlated with attribute consideration time, but that consideration time has independent predictive power beyond conjoint part-worths. This analysis thus demonstrates that the cursor trajectory method we present is better at explaining consumers' decisions than relying solely on conjoint analysis.

Spatial location influences attribute consideration time. The previous analysis treats attribute consideration time as a participant-specific constant, but choice contexts, such as the presentation format or the spatial location of attributes, may alter consideration time by influencing how participants access their memory. In the food task, we counterbalanced the spatial location of product and brand images, comparing the outcomes that occur when placing the brand image at either the top or the bottom of the screen. This allowed us to test the exploratory hypothesis that making brand desirability more prominent causes people to make more brand-based decisions (i.e., context-specific component). Specifically, we tested whether altering attributes' spatial location influenced (1) decision weights and (2) consideration time, and whether consideration time mediated the effect of spatial location on decision weights. This provides a causal test of the effect of attribute consideration time on decision making.

First, we computed the difference in attribute weights for the product and brand for each participant separately when (1) the brand was at the top of the screen and the product was on the bottom and (2) when the brand was on the bottom and the product was at the top. When the brand was at the top (vs. bottom) of the screen, there was a smaller negative difference between product and brand weights (i.e., brand weight – product weight) ($M_{\text{top}} = -.41$, $SD = .60$; $M_{\text{bottom}} = -.54$, $SD = .55$; $t(42) = 2.49$, $p = .017$). This result suggests that brands were relatively more important in decisions when positioned at the top rather than when they were positioned at the bottom of the screen, consistent with an influence of spatial location on choice.

Second, we computed attribute consideration time for each of the two spatial location arrangements. When the brand was at the top (vs. bottom) of the screen, there was a smaller negative difference between the consideration time of the product (vs. brand) ($M_{\text{top}} = -10.7$, $SD = 17.3$; $M_{\text{bottom}} = -17.3$,

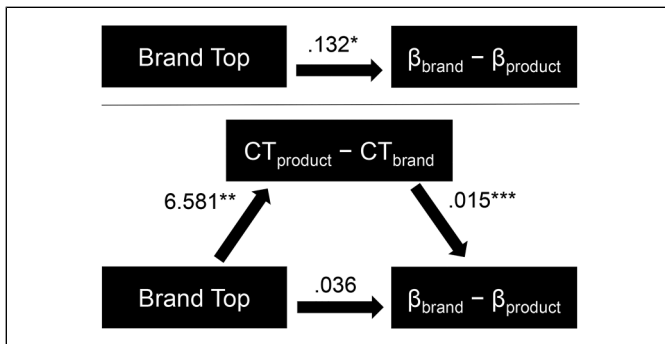


Figure 4. Relationship Between Spatial Location and Attribute Weights Is Mediated by Consideration Time (Study 1).

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Notes: This figure depicts mediation of spatial location on attribute in the food task through relative consideration time (CT). CT represents the consideration time of product (CT_{product}) and brand (CT_{brand}); β represents attribute weight for products (β_{product}) and brands (β_{brand}); Brand Top takes a value of one when brands were displayed at the top of the computer screen and value of zero when brands were displayed at the bottom.

$SD = 18.8$; $t(42) = 3.51$, $p = .001$). This result indicates that brand desirability began to influence the decision process relatively earlier when brands were positioned at the top (vs. bottom) of the screen. Whereas both spatial locations had an earlier estimated consideration time for the product than the brand, the spatial location of the attributes still significantly altered their relative consideration times.

Third, we find that relative consideration time significantly mediated the relationship between spatial location and decision weights (Figure 4).

Next, we reasoned that if spatial location affects attribute consideration time, this should affect consumers' propensity to exhibit brand-based choice. That is, the computational advantage of the brand when brands are positioned at the top (vs. bottom) of the screen should correlate with differences in consumers' propensity to select the option with the preferred brand over the one with the preferred product (i.e., differences in BBR). As hypothesized, we found a positive association between the difference in brand-based ratios ($BBR_{\text{top}} - BBR_{\text{bottom}}$) and the difference in the computational advantage of the brand (computational advantage of brand when brand is on top – computational advantage of brand when brand is on bottom; $\beta = .004$, $p = .048$).

We thus find that speeding up the relative consideration time of brand desirability via a spatial location manipulation causes people to make more brand-based choices. A natural question that arises is whether the opposite pathway occurs. Do preferences influence relative consideration time? Although such a relationship would not contradict the existence of the mechanism in the direction we have tested, it might offer an alternative path that could bias the size of some of the previously observed effects. Notably, our two robustness checks detailed previously explicitly controlled for decision weight and still found a relationship between consideration time and choice. However, an additional factor that can influence preference strength is the

value of the stimuli themselves (i.e., product and brand stimulus values as elicited during the initial ratings task). In Web Appendix B4, we detail an additional test that addresses this concern. Specifically, we find that these stimulus values do not strongly influence consideration time. Overall, this suggests that the causal direction we explore here is stronger than the effect of preferences on consideration time.

Discussion

Supporting our hypothesis, Study 1 found that attribute consideration time can arise from both (1) a stable, individual-specific component and (2) a context-specific component. Regarding the first component, we find that consumers have a baseline tendency to consult their memory to prioritize brand and product attributes relevant to the decision. Consumers' tendency to process brand desirability relatively earlier was associated with resolution of product–brand conflicts in favor of the preferred brand. At the same time, we provide evidence for the second component, revealing that attribute consideration time is malleable and affects brand-based choice. Specifically, influencing the visual prominence of brand information via a spatial manipulation affects consideration time, exogenously shifting the order in which memories are consulted. Further, relative consideration time mediates the relationship between spatial location of brand and product information and decision weights.

One contribution of our research is the demonstration of the cognitive processes underlying the influence of marketing actions on consumer decisions. Indeed, a variety of marketing actions may influence decisions by altering consideration time. Study 1 examined an intervention whereby brand (vs. product) desirability increased in visual prominence. We tested an additional intervention in a preregistered supplemental study reported in Web Appendix A. Participants read a promotional marketing message increasing the prominence of either brands or products, depending on condition. Similar to Study 1, an ad increasing brand prominence caused consumers to consider desirability of brand attributes relatively earlier than product attributes, which increased brand-based choice.

Study 2: Examining Choice over Fewer Trials

Study 2 generalized the results of Study 1 to fewer choice trials.¹² We also measured product and brand desirability *after* participants made their decisions, ensuring that prior

¹² An additional way to investigate the generalizability of these results with fewer trials is to analyze an initial subset of data from Study 1 (i.e., first 50 choices). Indeed, we found that the main relationship between consideration time and choice held using a subset of early-stage data: there was a positive relationship such that the earlier the brand (vs. product) started to influence the decision process, the greater the choice share of the option with the better brand ($\beta = .007$, $p < .001$, $R^2 = .50$). In this subset of choice trials, as in the analysis of the full sample of data, spatial location influenced both consideration time and decision weights, and the relationship between spatial location and decision weights was mediated by relative consideration time (see Web Appendix Figure B7).

exposure to the products and brands does not drive results. Lastly, we again tested whether a spatial manipulation making brand information more prominent than product information causes consumers to consider brand attributes relatively earlier than product attributes, increasing consumers' likelihood of choosing in favor of preferred brands.

Method

Participants. We recruited 299 participants from Amazon's Mechanical Turk ($M_{\text{age}} = 42.71$ years, range = 20–83 years; 45.1% female, 54.2% male, .7% nonbinary). We excluded participants with missing mouse cursor data (e.g., participants using a touchscreen), leaving a final sample of 290 participants.

Cursor-tracking paradigm and rating task. We converted the lab paradigm from Study 1 for use online using PsychoPy (Peirce et al. 2019) and Pavlovia (<https://pavlovia.org>) software. Participants completed a survey in Qualtrics and opened a link to a Pavlovia study, which had a design similar to Study 1. Participants made a series of food–brand choices as in Study 1, with two key changes: First, participants made only ten food-brand choices while we tracked their cursor trajectories. These choices were identical across participants, with order randomized. We substantially decreased the number of choice trials to generalize Study 1 results to choices over fewer trials. This had the added benefit of allowing us to display each product and brand pairing only once during the study. Second, participants rated product and brand desirability *after* making choices in the food–brand task. This rules out an alternative explanation that the results in Study 1 are due to cognitive processing of brands and products in advance of decisions.

Results

Next, we present an overview of results, which followed a similar pattern to Study 1. For full details, see Web Appendix C.

Relationship between attribute consideration time and brand-based choice. First, we regressed BBR on relative consideration time (i.e., product consideration time – brand consideration time), which revealed a positive and significant relationship ($R^2 = .21$, $p < .001$). As in Study 1, choices were associated with differences in relative consideration time.

Spatial location influences attribute consideration time. As in the food task in Study 1, half the trials had products located at the top of the screen and the other half had brands located at the top of the screen. Since we observed choices over ten trials, this meant that only five trials for each spatial location condition were presented to each participant. For this reason, we adapted the estimation strategy to account for the decrease in trials and increase in participants (detailed in full in Web Appendix C). We used this exogenous variation in spatial

location to investigate whether such changes influenced both decision weights and relative consideration time.

Consistent with Study 1, this analysis revealed that an attribute's consideration time was influenced by spatial location. When brand was at the top of the screen, the brand's consideration time was 40 time units and the product's consideration time was 56 time units, for a relative difference of 16. When the product was at the top, the brand's consideration time was 51 time units and the product's consideration time was 44 time units, for a relative difference of -7 . Thus, the difference in the relative consideration time across spatial locations was 23 time units (i.e., $[56 - 40] - [44 - 51]$). As described in Web Appendix C, we generated confidence intervals on this 23-time-unit estimate (95% CI = [6, 57]; 99% CI = [3, 64]). This provides evidence that spatial location can influence consideration time in this setting and is consistent with Study 1's findings documenting the relationship between attribute consideration time and choice, as the relative consideration time of the brand was earlier when the brand was displayed at the top (vs. bottom) of the screen.

Second, we examined how final attribute weights varied as a function of spatial location. We conducted a mixed-effects logistic regression where we regressed a binary variable for choosing the right-side option on the difference in product values (i.e., product right – product left), the difference in brand values (i.e., brand right – brand left), an indicator variable for whether the brand was located at the top of the screen, and interactions of the indicator variable with the difference in product and brand values. Consistent with an effect of spatial location, the brand weight significantly increased when brand was located at the top (vs. bottom) of the screen ($\beta = .22$, $SE = .06$, $z = 3.82$, $p < .001$). We found a similar effect for product weight when product was located at the top (vs. bottom) of the screen ($\beta = -.13$, $SE = .05$, $z = -2.56$, $p = .010$). Finally, Web Appendix C reports an analysis demonstrating that these differences in weights translate to differences in choice proportions, as measured by the BBR. Altogether, these findings conceptually generalize the key findings in Study 1 over fewer choice trials.

Study 3: Three-Attribute Choice

Having demonstrated that the key results from Study 1 extend to choices over only ten trials in Study 2, we conducted Study 3 to examine choice over three attributes (i.e., product, brand, and price) to test whether consideration time operated similarly in a more complex, externally valid decision environment.

Method

Participants. We recruited 60 university students, alumni, and community members to participate in this lab study ($M_{\text{age}} = 35.05$ years, $SD = 14.36$; 76.7% female, 23.3% male). We required that participants had lived in the United States for five years and did not have any dietary restrictions. Participants received \$25 for their participation.

Procedure. The study consisted of three tasks similar to those in Studies 1 and 2 (i.e., food ratings, brand ratings, choices with cursor tracking), with the following caveats.

First, in the choice task, participants made decisions over food–brand–price combinations rather than food–brand pairs. That is, each choice option now had a third relevant attribute: price. We displayed prices to participants across four levels of the attribute to place it on the same four-point scale as the product and brand attributes. Specifically, price was shown as a number of dollar signs (i.e., \$, \$\$, \$\$\$, or \$\$\$\$) and the instructions informed participants how these symbols corresponded to the price of the option (e.g., \$ corresponded to a “very inexpensive option,” \$\$\$\$ corresponded to a “very expensive option”). In the analysis, we transformed the price display to a quantitative scale that matched the product and brand attribute ratings (\$ = +2, \$\$ = +1, \$\$\$ = -1, \$\$\$\$ = -2) and described the desirability of a lower price value.

Second, we fixed the spatial location of attributes across trials. In each trial, the product appeared at the top of the screen, the brand appeared in the middle, and the price appeared at the bottom. We chose not to alter the spatial location of the attributes in Study 3 for two reasons. First, Studies 1 and 2 already provided convincing evidence that contextual factors influence consideration time. The key motivation for this study was to extend the paradigm to a larger number of attributes. Second, altering the location of attributes here might lead to increased difficulty for participants, given the larger number of attributes. For this reason, we chose to model the design after standard choice-based conjoint designs, which typically do not alter attribute location (e.g., Meißner, Musalem, and Huber 2016).

Cursor trajectory analyses. The cursor trajectory analyses and associated consideration time estimates are highly similar to those that emerged in the analyses of Studies 1 and 2. The key change is that we extended the analyses to account for three attributes, rather than two, as detailed in Web Appendix D.

Results

Choices. As expected, participants utilized all three attributes when making decisions. Choices were predicted by the relative product desirability, relative brand desirability, and relative price desirability, as evidenced by the fixed effects from a logistic mixed-effects regression of choosing the right-side option on the relative product, brand, and price differences ($\beta_{\text{product}} = .86$, $p < .001$; $\beta_{\text{brand}} = .40$, $p < .001$; $\beta_{\text{price}} = .24$, $p < .001$).

We next examined whether there was variation in the propensity to resolve attribute conflicts in favor of one attribute. To do this, we examined the three possible combinations of conflicts between two attributes (i.e., product–brand, product–price, and brand–price) while omitting the value of the third attribute; we chose this approach because there were relatively few trials in which two attributes conflicted with one another

and had an identical value for the third attribute. When there was a conflict between the preferred product and the preferred brand, and the price attribute was allowed to take any value, participants chose the option with the preferred brand 36.1% (SD = 22.0%) of the time. This is comparable to the results reported in Studies 1 and 2 for the BBR. When there was a conflict between the preferred product and a lower price, participants chose the option with the preferred product 64.5% (SD = 25.5%) of the time. When there was a conflict between preferred brand and a lower price, participants chose the option with the preferred brand 53.1% (SD = 21.9%) of the time. Overall, there was variation across each of these three choice metrics.

Differential consideration time of product, brand, and price desirability in the choice process. Using the time-to-significance metric, we estimated the consideration time for the product ($M = 65.2$, $SD = 15.9$), the brand ($M = 79.3$, $SD = 21.5$), and the price ($M = 84.5$, $SD = 23.3$). Replicating Studies 1 and 2, on average, product desirability began to influence the decision process before brand desirability ($t(59) = 4.46$, $p < .001$). Product desirability also influenced the decision process earlier than price ($t(59) = 4.59$, $p < .001$), with no significant difference between brand and price ($t(59) = 1.23$, $p = .223$).

Relationship between attribute consideration time and choice. Next, we investigated whether differences in attribute consideration time were associated with differences in participants' choices. For each participant, we computed the difference between the consideration time of two attributes and regressed this on the propensity to resolve conflicts in favor of one attribute (Figure 5). In all three cases, we found a sizable correlation between this relative consideration time and choices (product–brand: $R^2 = .58$, $p < .001$; price–product: $R^2 = .81$, $p < .001$; price–brand: $R^2 = .64$, $p < .001$). Moreover, in Web Appendix D, we estimate two alternative consideration time metrics and find that each is correlated with the time-to-significance metric as well as choice. Finally, similar to Study 1, we report an analysis in Web Appendix D detailing that cursor trajectories from the first half of the trials serve as a strong predictor for choices in the second half of the trials, demonstrating that consideration time predicts decisions in out-of-sample data.

Computation time and decision weights. We next investigated the relationship between attribute consideration time and the final decision weight an attribute received in choice.

First, we examined how decision weights relate to the likelihood of making a choice in favor of an attribute. To estimate participant-specific decision weights, we conducted a logistic regression of whether the right-side option was chosen on relative product desirability, relative brand desirability, and relative price desirability. Next, for each type of decision, we regressed choice on the difference in the associated weights. We found a strong correlation for product–brand decisions ($\beta = .30$, $p < .001$, $R^2 = .66$), price–product decisions ($\beta = .36$, $p < .001$, $R^2 = .80$), and price–brand decisions ($\beta = .40$, $p < .001$, $R^2 = .77$).

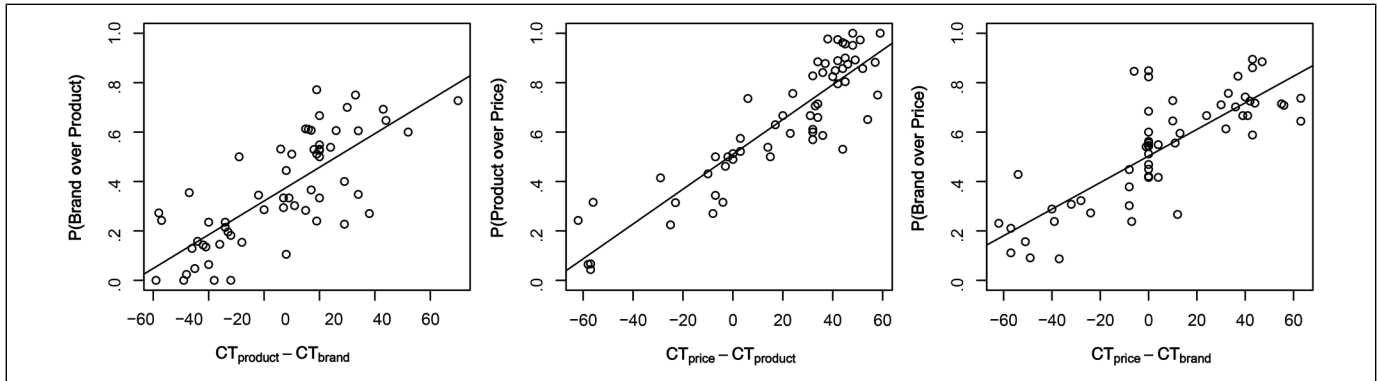


Figure 5. Choice and Attribute Consideration Time (Study 3).

Notes: Scatterplots present the likelihood of resolving a particular type of choice conflict as a function of consideration time (CT) differences in Study 3. Possible combinations of all choice conflicts are presented on the vertical axis. Consideration time differences between the associated attributes of a choice conflict are presented on the horizontal axis. The linear regression line for each analysis is plotted.

Second, we examined whether differences in attribute consideration time were associated with differences in attribute decision weights. To test this, we regressed the difference in decision weights on the differences in consideration time and found a relationship for product–brand comparisons ($\beta = .02$, $p < .001$, $R^2 = .48$), price–product comparisons ($\beta = .02$, $p < .001$, $R^2 = .62$), and price–brand comparisons ($\beta = .01$, $p < .001$, $R^2 = .70$).

Third, we tested whether the difference in weights assigned to each attribute mediated the relationship between consideration time and choice (Web Appendix Figure D1). We find evidence for mediation for each of the three choice cases. Moreover, as detailed in Web Appendix D, relative consideration time was still a significant predictor for most choice conflicts, even after separately controlling for attribute weights rather than only controlling for their difference.

Finally, Web Appendix D replicates the finding from Study 1 that an attribute's relative importance, as derived via a conjoint analysis of the data, is correlated with attribute consideration time, but that consideration time has independent predictive power beyond conjoint part-worths.

General Discussion

Four studies investigated the relationship between attribute consideration time and choice, utilizing cursor tracking to capture consumers' decision process in real time. We demonstrate that differences in the relative time that choice attributes (e.g., product, brand) enter the decision process predict brand-based choices. Specifically, attribute consideration time is a function of (1) a stable individual-specific component and (2) a context-dependent component.

With regard to the first component, Studies 1–3 and the supplemental study demonstrate that individual differences in consumers' decision-making circuitry are associated with the initial time at which decision-relevant attributes begin to influence the decision process. This first component reflects a baseline tendency for how consumers systematically consult their memory and prioritize certain attributes (e.g., brand, product, price)

relevant to the decision (Shadlen and Shohamy 2016; Weber et al. 2007).

With regard to the second component, attribute consideration time is affected by contextual cues in the environment that marketers often manipulate (e.g., positioning of brand information, promoting brand value). Specifically, in Study 1 (food task) and Study 2, a manipulation of product and brand spatial location affected the relative consideration time at which product and brand desirability first influenced decisions. When the product (brand) was presented at the top of the screen, such that it was processed earlier, product (brand) desirability was computed relatively earlier and received greater weight in the decision process. Beyond varying attribute spatial location, the supplemental study reported in Web Appendix A found that a promotional message advertising the value of brands (vs. products) increased the relative consideration time for brand (vs. product) desirability, increasing brand-based choice. These decisions were consequential, as participants received a gift card to a clothing brand (Study 1) and a food product to eat (Study 1 and supplemental study) based on their decisions.

In identifying the relationship between attribute consideration time and choice, we advance research in cursor tracking, as we are the first to compute attribute consideration time from a relatively low number of trials (only ten choice trials in Study 2) and to examine choices over three attributes: product, brand, and price (Study 3). Overall, we uncover how consumers integrate attribute desirability into their choices over branded products, highlighting the applicability of cursor tracking for examining the psychological drivers of consumer choice as they unfold in real time.

Contributions and Future Directions

As its primary contribution, this research highlights the applicability of cursor tracking as a methodological tool to study questions related to consumer choice. Prior research has utilized different types of cursor-tracking techniques from the one employed here to study implicit attitudes (Wojnowicz et al. 2009), emotion

(Mattek et al. 2016), memory (Papesh and Goldinger 2012), and intertemporal decisions (Dshemuchadse, Scherbaum, and Goschke 2013; Reeck, Wall, and Johnson 2017), among others. More relevant to our studies, research has examined how consideration time of processing the health and taste of food affects self-control decisions (Sullivan et al. 2015), wherein there is a biological predisposition to prioritize taste (i.e., sugar, salt, fats; Brooks, Simpson, and Raubenheimer 2010; Leshem 2009). We demonstrate insights from this cursor-tracking paradigm for how branding influences choice, wherein it is not clear what attribute (e.g., product, brand, price) will have an earlier consideration time, or whether there is heterogeneity across consumers in *when* these choice attributes first influence the decision.

In highlighting this cursor-tracking technique as a methodological tool for consumer researchers, we make several advancements beyond prior research. First, we demonstrate that attribute consideration time can serve as an additional metric to understand how consumers deploy attention. Second, we derive consideration time via multiple estimation strategies (e.g., the time-to-significance, intercept, and modified DDM metrics) to demonstrate that we can accurately capture this psychological construct as consumers' make choices naturally, in real time, and that this can easily be exported to additional contexts (e.g., digital analysis of e-commerce platforms, research on different stages of the decision process).

Third, we advance research focused on detailing computations in two-attribute choice (Lim et al. 2018; Philastides and Ratcliff 2013; Sullivan et al. 2015). We demonstrate applicability of this paradigm for decisions with more than two attributes and demonstrate that differences in when attributes are first considered strongly predict decisions in out-of-sample data. Lastly, we find that factoring in attribute consideration time improves on the predictions of more "standard" sequential sampling models that do not allow attribute consideration time to differ and also provides information independent of conjoint weights, thus offering marketers a more robust tool for understanding choice processes beyond traditional marketing metrics. Cursor metrics are passive and straightforward to collect, such that they may be a low-cost complement to traditional marketing tools. Overall, we advance previous work in cursor tracking and highlight it as a methodological tool that can improve predictive accuracy of choice models and shed light on underlying decision mechanisms in marketing (Hui, Fader, and Bradlow 2009).

Beyond these methodological advancements, our results also allow us to examine the predictions and assumptions of various models from the decision-making literature. For example, much previous work has proposed that decision models are either static or dynamic. Static models typically take the features within a choice set and convert them to a measure of value that predicts choice (e.g., the weighted additive model from Keeney and Raiffa [1993]) or propose some simplifications of attribute weighting and comparison (e.g., Huber 1979; Tversky 1969). In contrast, dynamic models note how value changes over time as information is sampled and individuals make a choice when enough evidence has accumulated (e.g.,

Bussemeyer and Diederich 2002; Bussemeyer and Townsend 1993; Ratcliff 1978; Ratcliff et al. 2016). Within the class of dynamic models, most models have assumed that information aggregation begins with the first piece of information sampled, but others have argued that information aggregation does not begin until all pieces of information are sampled (Edmunds et al. 2020; Russo and LeClerc 1994; Shi, Wedel, and Pieters 2013). Our findings are consistent with the former class of models suggesting that evidence accumulation is impacted by some attributes before it is impacted by all attributes, as we find differential timing in when mouse trajectories are influenced by attributes. Overall, this article leans more toward the first proposal, that information aggregation can begin before all features are sampled, but more work is needed to tease these two possibilities apart.

Moreover, our findings contribute to research on how consumers process and attend to information during decision making (Beatty and Smith 1987; Urbany, Dickson, and Wilkie 1989) and how they retrieve information from memory (Bartels and Johnson 2015). Classic work has studied how attention and memory interact with construction and execution of the decision process (Bettman 1979; Johar, Maheswaran, and Peracchio 2006). Additional work has focused on the order in which information is processed, demonstrating that this can alter decision-making strategies (Feldman and Lynch 1988; Johnson, Häubl, and Keinan 2007; Tavassoli and Lee 2004; Weber et al. 2007), lead certain information to receive a higher weighting in final choice (Legrenzi, Girotto, and Johnson-Laird 1993; Schwarz et al. 1991), and bias later interpretations of information (Russo, Medvec, and Meloy 1996; Russo, Meloy, and Medvec 1998). Related work finds that the order in which one considers information can influence information assessment (Woolley and Liu 2021) and can alter the influence of underlying goals (Carlson, Meloy, and Miller 2013), which affects purchase rates (Gao and Simonson 2016). Our work advances this literature by estimating differences in the time at which attributes of the decision process are integrated from natural movements in real-time decisions.

More broadly, our investigation into individual heterogeneity underlying brand-based decisions advances prior research (Plassmann and Weber 2015), with insight into segmenting consumers (Camerer and Yoon 2015). We empirically demonstrate that such differences are manifested in the consideration time of processing attribute desirability. Cataloging how individual consumer-specific factors interact with brand messaging to affect choice is an important contribution of the present research.

This research is also practically relevant. Current e-commerce analytics firms and online advertisers actively track consumers' cursor movements on numerous websites (e.g., Oracle Moat) but only perform basic analyses with the data. Collecting cursor-tracking data is accessible, cheap, and scalable (Dotan et al. 2019; Goldstein et al. 2014). Integrating the tools we introduce here could result in an increased ability to segment customers by identifying those who are likely to initially attend to brand-relevant features. Our results that demonstrate the

ability for cursor trajectories to predict out-of-sample decisions may prove particularly useful here, as firms can make inferences about consumers based on their prior cursor pathways.

Conclusion

The current research highlights the utility of cursor tracking for consumer researchers. We demonstrate that differences in the extent to which brands drive consumer choice is explained, in part, by the relative point in time when consumers first consider relevant product attributes; this timing is in turn influenced by individual differences among consumers and by contextual factors marketers use to draw attention to their offerings. Across multiple studies, we uncover how consumers integrate attribute desirability into their choices among branded products. More broadly, we highlight the applicability of cursor tracking for examining the psychological drivers of consumer choice as they unfold in real time.

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