Attention in Motion: Using Scroll Tracking to Measure the Dynamics of Preferential Choice

Ilkka Leppänen
School of Business, Aalto University

Author accepted manuscript (9 January 2026)

Cite as: Leppänen, I. (in press) Attention in Motion: Using Scroll Tracking to Measure the Dynamics of Preferential Choice. *Management Science*.

Permalink: ...

Data, analysis scripts, and the Online Appendix are openly available at the project's Open Science Framework page at https://osf.io/25fu7.

Correspondence should be addressed to Ilkka Leppanen, School of Business, Aalto University, Ekonominaukio 1, 02150 Espoo, Finland. Email: ilkka.j.leppanen@aalto.fi

Abstract

Understanding how preferences are formed in commonplace and natural situations is highly valuable for researchers and practitioners. Here, I develop scroll tracking, a process-tracing method that uses a touch-scroll-based responsive mobile web design well-suited for studying the cognitive processes behind decision making. The method follows the decision maker's scrolling behaviour and records a response curve in the pixel-millisecond coordinate space. To demonstrate the value of response curve analysis in decision research, different metrics are proposed that are derived from the response curve and rooted in the motor response and gaze dwell metrics presented in the literature. An experimental study framed as a consumer choice problem is used to validate the method and test predictions made by attentional evidence accumulation models using the response curve metrics. The way the decision maker interacts in the app can be used to predict subjective valuations as well as latent individual difference measures and risk attitudes, as a complementary risky choice study shows. I then compare the predictive ability of different drift diffusion models, stocked with the scroll-tracking response metrics. The scroll tracking metrics improve all the models. These findings show the potential of naturalistic process-tracing methods in responsive digital applications. These designs can be used to covertly study decision processes and are applicable to different practical settings.

1 Introduction

In this paper I introduce scroll tracking, a method that uses mobile websites to trace decision processes. Scroll tracking utilises data on how people interact with virtual elements, such as on-screen boxes, that respond to touch-scroll gestures. Research on attention and motor response dynamics is combined to build a method that models the human computational process that compares and integrates decision values over time.

Decision neuroscience often studies the following kind of problem, which here is adapted from Callaway et al. (2021). A decision maker (DM) is choosing a product to buy on a supermarket shelf. They sample information on the available alternatives, and, at some point, they arrive at a decision. This process is noisy, so it takes some time for the DM to find the item they want (Ratcliff et al., 1999; Gold and Shadlen, 2007; Shadlen and Kiani, 2013). Moreover, it takes longer to decide when many options are nearly similar than when one option stands out. The DM's neural system creates perceptual representations of the options, which compete for attention (Desimone and Duncan, 1995). Options that receive more attention experience a boost in the rate at which the DM sorts out their relative differences (Krajbich et al., 2010; Cavanagh et al., 2014; Smith and Krajbich, 2018). The literature is well-versed in this link between attention and choice (Shimojo et al., 2003; Glaholt et al., 2009; Arieli et al., 2011; Schotter et al., 2012; Orquin and Loose, 2013; Pärnamets et al., 2015). Sequential sampling models propose that choice is affected by the relative desirability of the options and that it is biased by where attention is allocated. The models predict that the DM makes a commitment and moves their hand towards the target once they have sampled enough evidence on the options.

However, the real picture is richer than this. Shoppers move their hands while they look at options, and at least some of this movement is non-arbitrary and goal-directed. For instance, the DM may gaze at option A while reaching towards option B. Alternatively, the DM may already hold option C in their hands while looking at B. This raises questions about the modelling of movement in the choice process. For instance, could the model that predicts what the DM chooses benefit from knowing where hand movements are directed? Could the movements the DM displays between the options reveal something about their tastes?

Mounting neural evidence suggests that movement is important to decision making. The brain does not strictly follow a serial process of perceptual coding, target selection, and motor action when making decisions. Likewise, movement itself is not strictly separated into planning and execution. Many motor plans can be made while perceptual information is processed (Hommel et al., 2001; Cisek, 2007; Cisek and Kalaska, 2010). Human movement is flexible and adaptive because our bodies possess more degrees of freedom than required (Todorov and Jordan, 2002), and we can achieve the same goals by orchestrating movements in several different ways (Haggard, 2008). In common language, people use motion-related metaphors to describe their decision processes. We are often "between" options, or we "step back" to re-evaluate. We may "lean into" a good option, or "walk away" from a bad option.[1] It should be uncontroversial to state that our decision processes involve movement planning and execution. Goal-directed movement should be considered a real part of the process such that it precedes commitment (Lepora and Pezzulo, 2015; Calalo et al., 2025). The literature based on the attention-choice paradigm describes how to model how visual perception biases economic decision making, but, in general, it lacks unified ways that model how motor movements influence the process with attention. Because hand movements are, in principle, overt and trackable, such methods have practical implications.

In the present study I show how to record patterns of attention and movement using the mobile application ("app") presented in Figure 1. Scroll tracking follows how the DM moves between options and slows down or stops to look at those options. The method exploits *responsiveness* of modern web design. A web page is responsive when its layout automatically scales to the size of the device. On handheld devices, this means that only a few options are visible on the screen at one time, and the DM must use scrolling to make comparisons. The DM indicates their choice by a button tap. The options are contained in a scrollable element, and the app records how it moves. Movement is represented as a response curve in the pixel-millisecond coordinate space. The response curve recordings can be converted into analysis metrics that are used to model the decision process. Based on these ideas, I propose that scroll tracking captures not only where attention is allocated but also how movement is executed during preference formation.

Touchscreen digital interfaces allow exploring the link between motor response dynamics and decision making. These interfaces are ubiquitous: most web browsing is based on touch-scroll gestures on handheld devices, which means that most digital consumption decisions are made using such devices.[2] In 2024, almost 60% of global internet traffic came from mobile devices (Statista, 2024). Although the example presented above is from a physical supermarket, shoppers in virtual marketplaces use motor responses as well, especially when browsing on tablets or smartphones.[3]

Scroll tracking is part of a larger family of responsive methods that rely on touch-scroll gestures. Responsive methods can model preference formation by measuring both attention and movement from the decision process. Understanding preferences forms the basis of data-driven econometric applications. Eye tracking provides a precise way to track attentional allocation during choice (Glaholt et al., 2009; Orquin and Loose, 2013), but it may be overcostly or inaccessible and may underemphasise the role of actions in the process. Mouse tracking provides a dynamic approach to mental processing (Freeman et al., 2011) but fails to capture attention and how it amplifies decision values. Scroll tracking offers a new perspective on the study of decision processes, even if it cannot substitute eye tracking due to its limited capability to track nuanced shifts in attention.

The next three subsections provide more detail on the three tenets of scroll tracking: that decisions are formed when attention and motion interact in the cognitive subsystems, that the sequential sampling of decision information is biased by response dynamics, and that response curves can quantify the spatial attraction effect.

1.1 Attention in motion

It is widely known that attention is part of choice. For instance, measurements of eye fixations are frequently used to model the computation of decision value in evidence accumulation models (Krajbich et al., 2010; Krajbich and Rangel, 2011; Krajbich et al., 2012; Konovalov and

Krajbich, 2016; Smith and Krajbich, 2018; Zilker, 2022). Increased gaze dwell time on an option predicts an increased rate of relative evidence accumulation towards that option, which also increases the probability of choosing it (Cavanagh et al., 2014). Increased gaze dwell time amplifies the option's subjective value in some instances (Smith and Krajbich, 2019). When there are many attributes, attention to an attribute increases its relative weight and decreases the weight of a non-fixated one (Fisher, 2017, 2021). Overall, the literature has found that the time that one attends to information on choice options affects choice probabilities and option values.[4]

Another well-known link exists between motion and response competition. Movement often begins before final selections are made (Freeman et al., 2011; Selen et al., 2012; Gallivan et al., 2018; Kim et al., 2021; Priorelli et al., 2025), as people can keep multiple goals in mind and maintain the flexibility to re-evaluate options during choice (Chapman et al., 2010; Stewart et al., 2013). Neural recordings show that decisions are computed and represented in the neural structures that guide behavioural responses, such as the parietal cortex (Sugrue et al., 2005; Wispinski et al., 2020). The perception of an object, such as a teapot, activates simulations of potential actions related to the object, such as grasping its handle (Tucker and Ellis, 1998). Shared representation theories propose that attention and motion are intertwined, as perceptions and motor actions use a common representational format (Hommel et al., 2001). Thus, it is evident that decision making should be interpreted as the parallel operation of perception, inference, and motor action.[5]

The brain uses parallel planning to prepare many competing actions at the same time (Gallivan et al., 2017), which is reflected in intermediate motor movements (Kim et al., 2021). These are movements "between" the available options (Spivey and Dale, 2006; McKinstry et al., 2008; Chapman et al., 2010; Koop and Johnson, 2011; Freeman, 2018; Dotan et al., 2018). An example of an intermediate movement is a hand reach that travels along an average trajectory between two options that are in front of the DM. When the options are more similar, there are more intermediate movements between them. It has been proposed that moving along these average trajectories is optimal because it preserves the flexibility to re-evaluate options (Kim et al., 2021). Intermediate movement is shown in the trajectory as curvature towards the non-chosen option, which has been termed the *spatial attraction effect* in the literature.

The spatial attraction effect can be illustrated by a virtual shopping example. Consider that the DM observes two options, A and B, from the website's layout and the way it cues movement between the options. The perceptions of these options are shared with action plans that specify how to move to view the options. The possibilities for performing actions with choice options are termed affordances in the previous literature, and each option has its own affordance (Gibson, 1986; Tucker and Ellis, 1998; Symes et al., 2007; Pezzulo and Cisek, 2016). While looking at option A, the affordance competition from option B creates spatial attraction that is not necessarily registered as reduced attention to option A but that may be observed as initiated motor movement away from it. In this sense, the DM is "pulled towards" the competing option (McKinstry et al., 2008). After viewing option B for some time, the DM may feel the spatial attraction of option A, which is again registered as motor movement. When A and B are subjectively more similar, spatial attraction between them is stronger.

1.2 Computational modelling

Scroll tracking is a computational method that assumes that a sequential sampling process calculates a relative decision value (RDV) that determines choice (Gold and Shadlen, 2007). The model is estimated from data that includes choices, response times (RTs), and the response metrics specified in Subsection 2.2.

I use the bounded drift diffusion model (DDM; Ratcliff, 1978; Ratcliff et al., 1999) as the basic framework to model the RDV. The DDM is increasingly used in preference-based decision making research (Milosavljevic et al., 2010; Krajbich et al., 2010; Frydman and Nave, 2017; Clithero, 2018). As detailed, for instance, in Milosavljevic et al. (2010), the evolution of the RDV over discrete time t is described by a difference equation

$$\mathrm{RDV}_t = \mathrm{RDV}_{t-1} + \nu + \epsilon_t. \tag{1}$$

The parameter $\epsilon_t \sim \mathcal{N}(0, \sigma^2)$ describes Gaussian noise that is added after each transition, with standard deviation σ. The drift rate ν is related to the numerical values assigned to the options V_i and V_{-i}. In the notation used throughout this paper, $-i$ denotes the option other than i. Drift rate is then defined as

$$\nu = k(V_i - V_{-i}) \tag{2}$$

and it models the relative speed of evidence accumulation towards option i. Value difference is translated into drift rate by the constant $k > 0$. The DDM, therefore, predicts how choice probabilities and RTs depend on subjective value differences. A choice is made when RDV_t exceeds either threshold a for option i or a normalised threshold 0 for option $-i$. Assuming a neutral starting point value $z = a/2$ for RDV_0, the probability of choosing option i is

$$P(\text{choose } i) = (1 + \exp(-a\nu/\sigma^2))^{-1} \tag{3}$$

and the expected RT is

$$E[\mathrm{RT}] = t_0 + \frac{a}{2\nu}\tanh(a\nu/(2\sigma^2)) \tag{4}$$

where t_0 is a non-decision time component that represents the length of the time interval during which RDV_t remains unchanged (Ratcliff et al., 1999).

The DDM yields logistic choice probabilities (Eq. 3), and it is equivalent with the logit model (Woodford, 2014; Smith et al., 2019). However, using the joint distribution of choices and RTs in the DDM improves out-of-sample predictions (Clithero, 2018) and reduces variance in utility estimates (Webb, 2019) over the logit approach. Logit models are widely used in applications that assume random utility based data-generation processes. DDMs, and bounded evidence accumulation models more broadly, are valuable in econometric applications (Webb, 2019; Xiang Chiong et al., 2024).

In the basic DDM, the drift rate parameter ν is constant across the decision process and proportional to the value difference, but it has also been proposed that ν can change within the process. Perhaps the most common way to bias ν is by attention allocation (Krajbich et al., 2010; Krajbich and Rangel, 2011; Cavanagh et al., 2014; Smith and Krajbich, 2019; see also Callaway et al., 2021 for a normative analysis). Attention allocation is quantified in gaze dwells on different regions of the stimuli, which have been measured in prior research using eye trackers. In the DDM, an increased dwell time over option i biases the drift rate towards that option. When the fixations change to option $-i$, the biasing effect changes. The biasing effect can be described by an additive or a multiplicative model. An additive relationship between drift rate and attention is written

$$\nu = k(V_i - V_{-i} + \eta), \tag{5}$$

where η presents a constant attention bias that is independent of the values of the options (Cavanagh et al., 2014; Thomas et al., 2019; Smith and Krajbich, 2018, 2019). The additive bias parameter η receives a new measured value each time attention changes between the options, and this changes the course of the drift process if the options' value difference is not too large. It is straightforward to verify that increasing η increases ν and causes both an increased probability of choosing option i (Eq. 3) and a leftward shift in the RT distribution (Eq. 4) at all levels of the options' value difference $V_i - V_{-i}$.

The biasing effect can also be modelled in the attentional DDM (Krajbich et al., 2010; Krajbich and Rangel, 2011; Krajbich et al., 2012) using a multiplicative relationship between drift rate and attention,

$$\nu = k(V_i - \theta V_{-i}). \tag{6}$$

Here $\theta > 0$ represents a modulative bias of attention. When the multiplicative bias parameter $\theta < 1$, attention towards option i amplifies its value V_i relative to V_{-i}. The modulative effect vanishes when θ approaches unity. The multiplicative model predicts qualitatively the same modulative effect of attention on choice probabilities and RTs as the additive model.

Movement is not currently used in models of the biasing effect of attention; DDMs view motor movement as a non-decision component that does not directly affect the RDV (Krajbich et al., 2012; Wispinski et al., 2020). However, we know that decision making is affected by processing that occurs after movement initiation (Resulaj et al., 2009; van Den Berg et al., 2016), implying that the relative evidence continues to accumulate towards an option even while motor action is ongoing.[6]

1.3 Motor response dynamics

Interactive choice tasks have previously been used to study how people produce movement patterns in two and three-dimensional spaces (Spivey et al., 2005; Spivey and Dale, 2006). These response trajectories track the motion of the hand from a starting point to a point that marks the chosen option. In previous research, methods that track mouse pointer movements[7] have proven sensitive to detecting mixtures of mental states (Spivey and Dale, 2006) in various domains, such as in spoken words (Spivey et al., 2005), social categorisation cues (Freeman et al., 2008), dietary attributes (Sullivan et al., 2015) and subjective utilities of risky options (Stillman et al., 2020).

Mouse tracking quantifies the spatial attraction effect with metrics derived from the response trajectory. The most common metrics include the degree of curvature in the response trajectory (where a steeper curve means more attraction from the unchosen option; Spivey et al., 2005; McKinstry et al., 2008), maximum deviation away from the chosen option and towards the unchosen option (Freeman and Ambady, 2010), and the area under the curve, or the polygon area drawn by the trajectory and closed by an ideal straight line (Freeman et al., 2008; Koop and Johnson, 2011; Stillman et al., 2020). The spatial attraction effect is graded: if the competing option is rendered gradually less desirable, the effect diminishes. In the recent literature, the shape of the motor response trajectory has been seen as a manifestation of the evidence accumulation process (Dotan et al., 2018; Stillman et al., 2020; Molano-Mazón et al., 2024). However, as argued above, while response trajectories can model the spatial attraction effect, they are insufficient to model the biasing effects of attention in evidence accumulation.

1.4 Purpose and organisation of the paper

The main purpose of this paper is to demonstrate that scroll tracking can detect the spatial attraction effect in movement patterns while also providing measurements of attention. To validate the method as fit for purpose, metrics that model the biasing effect of scrolling on the relative decision value are first identified, after which the method is tested empirically.

Section 2 presents how the response curve is constructed from the measurements of scroll bar movements and discusses different response metrics that quantify the attention-motion dynamics. Section 3 reports the results of a consumer choice experiment that tests the model predictions. Section 4 discusses the relevance of scroll tracking as a process-tracing method, its limitations, and practical implications. The Online Appendix reports the results of robustness tests, supplementary analyses, and an additional risky choice experiment.

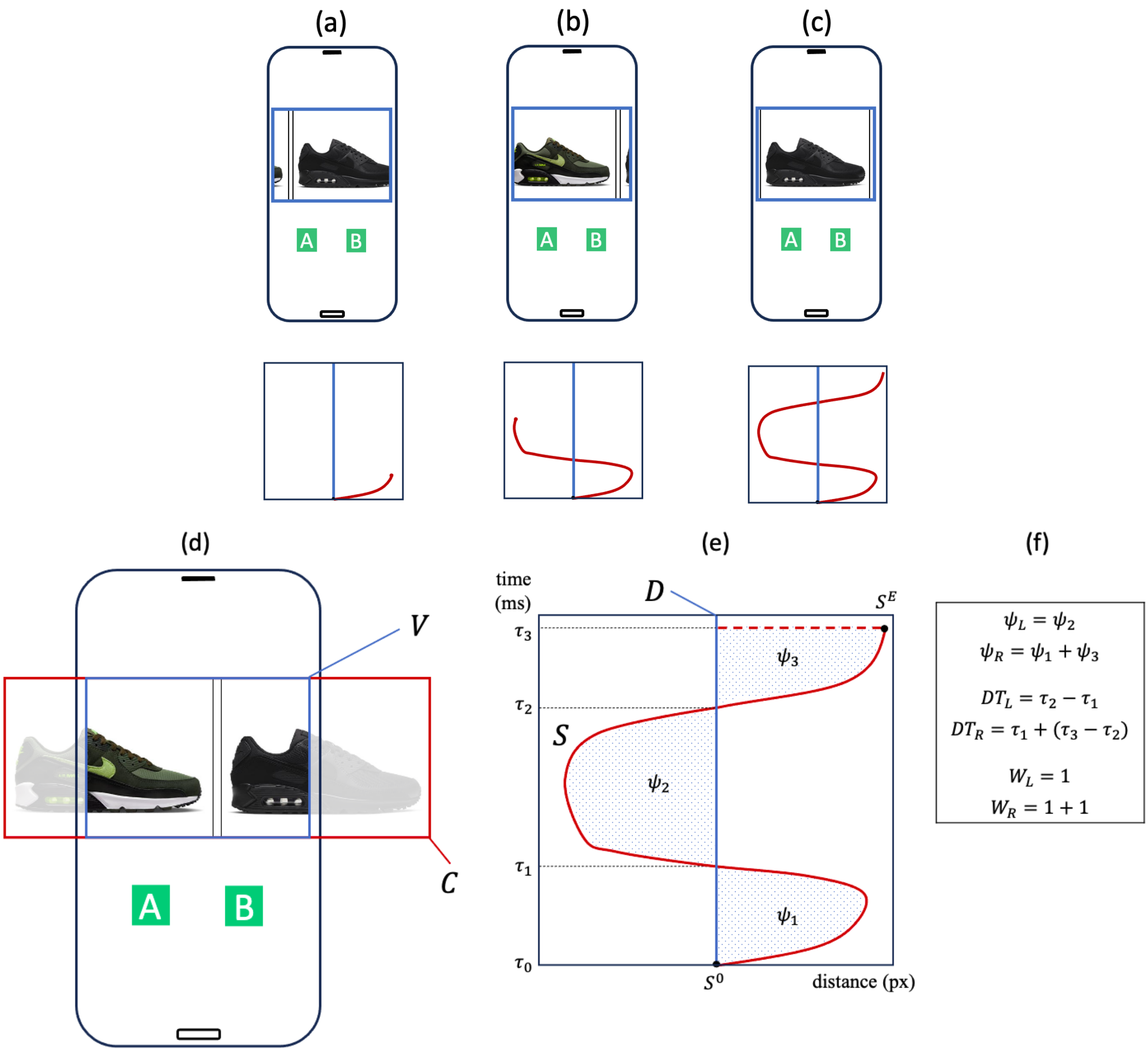
2 Method

2.1 The response curve

Scroll tracking is implemented in an app where the decision stimuli are contained in web elements. The app is designed for mobile web browsers.[8] The user interacts with the elements using touch-scroll gestures (Figure 1). The motor response is manifested in a response curve S in the pixel-millisecond coordinate space. To generate S, the app covertly records the horizontal position of the scroll bar whenever it moves and combines this with time stamps. The response curve is a time-series of scroll bar locations. Each new round of decision making begins with the scroll bar placed at the middle position. At the start of each round, the decision stimuli and the choice buttons are hidden, but they become visible when screen touching is first detected. RT recording begins at the initial movement of the scroll bar and ends when one of the choice buttons are tapped.

When the DM is scrolling so that option $i \in \{L, R\}$ (Left, Right) is visible, the motor response recorded by the moving scroll bar is registered as bias towards that option. The "amount of scrolling" can be calculated from the part of S that is on side i of the mid-line D, which divides the 300-pixel wide viewport (the visible part of the web page on screen, see Figure 1). Once the scroll bar passes the mid-line, the relative decision value changes from accumulating towards option i to accumulating towards option $-i$.

Scroll bar movement is interpreted in the same way as changing gaze dwell locations in eye tracking (Krajbich et al., 2010). In the scroll-tracking app, the first position of the scroll bar is



Note: The top row demonstrates scrolling between the options, and the boxes below show how the response curve is drawn from scrolling. (a) Scrolling right to option B. (b) Scrolling left to option A. (c) Scrolling back right to option B. (d) V = 300 px wide viewport. C = scrollable container for the stimuli where both options cannot be viewed simultaneously. Squares with A and B = choice buttons for the left and right-hand side options, respectively. (e) The response curve S in pixel (px)-millisecond (ms) space, S^0 = starting point, S^E = ending point. D = mid-line in the centre of the viewport. In this example trajectory, the left-hand side option has been viewed once, and the right-hand side option has been viewed twice. The first movement of the scroll bar from S^0 counts as the first switch. The thick dashed line at the top is not part of S but it is added for the calculation of ψ_3. (f) How the different response metrics are calculated in this example.

Figure 1: **Illustration of scroll tracking**

in the centre (Figure 1), and the DM initiates the round by scrolling left or right. The design imitates eye-tracking setups where the inter-stimulus interval presents a fixation cross in the centre of the screen, minimising the possibility of a starting point bias in first fixations.

2.2 Response metrics

To quantify the biasing effect of scrolling, measurement benchmarks are used from the motor response dynamics literature (e.g. Schoemann et al., 2021). The response curve S is directly used to determine the response metrics.

Let the sequence $\tau_0, \tau_1, ..., \tau_N$ denote the time-values where S intersects with D (Figure 1). Scrolling starts at $\tau_0 = 0$. There are m measurement points within each interval $(\tau_j, \tau_{j+1}]$, and we include point τ_{j+1} in these m measurements, but not point τ_j. The end point of the final measurement interval is not an intersection point (e.g. τ_3 in Figure 1e), but it is included in the calculation of the metrics. The metrics M_L, M_R are defined for the left-hand side (L) and right-hand side (R), respectively. The set of metrics $M \in \{DT, \psi, W\}$ consists of:

- **Dwell times (DT)** over the options, which calculate how long each option has been observed. These are analogous to the gaze dwell times obtained from eye-tracking data and used to study the attention-choice link (Krajbich et al., 2010). Dwell times can be calculated from the sequence $\tau_1 - \tau_0, \tau_2 - \tau_1, ...$ and totalled as DT_L and DT_R for the total time of looking at the Left and Right options, respectively.

- **Polygon areas (ψ)**, or areas determined by the segments of S that belong to either the left or the right-hand side of the mid-line D. Each interval $(\tau_j, \tau_{j+1}]$ determines one polygon (e.g. $(\tau_0, \tau_1]$ defines ψ_1 in Figure 1e). The polygon is determined by a sequence of vertices $(S(t_0), t_0), (S(t_1), t_1), ..., (S(t_m), t_m)$ such that $t_0 = \tau_j$, $t_m = \tau_{j+1}$, and $\tau_j < t_1 < t_2 < ... < t_{m-1} < \tau_{j+1}$. The area is calculated using Gauss's formula $\frac{1}{2}\sum_{k=1}^{m-1}\big(S(t_k)t_{k+1} - t_k S(t_{k+1})\big)$. Each term in this formula is a cross-multiplication between the vertical and the horizontal coordinates that are diagonal to each other. When scrolling over the left-hand side option, the polygon is negatively oriented and the area is multiplied by -1. Total polygon areas are ψ_L and ψ_R. It should be noted that because area is calculated using both the spatial extent of scrolling and the temporal extent, the polygon area measurements in principle contain all the information contained in dwell time measurements.

- **Switches** (W) between the options in both directions. A switch at τ_j is considered left-to-right if S is increasing when it crosses the midline at this point, or if $\exists \epsilon > 0$ such that $\forall h \in (0, \epsilon)$, $S(\tau_j) < S(\tau_j + h)$. Otherwise, if S is decreasing when it crosses the midline, it is considered a right-to-left switch. These switches are then totalled by type: W_L indicating the number of right-to-left switches over the course of the decision, and W_R indicating the number of left-to-right switches.

For statistical analyses, it is practical to use **proportional response metrics**, defined as

$$\mathrm{PRM}_i^M = M_i/(M_L + M_R), \qquad \text{for} \qquad i \in \{L, R\} \tag{7}$$

where $M \in \{DT, \psi, W\}$. For instance, when the metric of interest is dwell time, the proportional response metric $\text{PRM}_L^{DT} > 0.5$ if the subject has viewed the Left option most of the time. In the illustrative example of Figure 1, the proportional response metrics are calculated as follows: the proportional dwell time on Left is $\text{PRM}_L^{DT} = (\tau_2 - \tau_1)/\tau_3$ because the total dwell time is equal to τ_3; the proportional polygon area on Left is $\text{PRM}_L^{\psi} = \psi_2/(\psi_1 + \psi_2 + \psi_3)$; and $\text{PRM}_L^W = 1/(1+2)$ because there is one switch to the left and two switches to the right. While the first two proportional metrics are continuous between 0 and 1, the proportional metrics for the switches, PRM_i^W, are fractional numbers attaining values from the sequence $\frac{1}{3}, \frac{2}{3}, \frac{2}{4}, \dots$ (and also $0, 1$).

Aggregate response metrics are also studied that are not separate for the left and right-hand sides, including response time $RT = DT_L + DT_R$, total number of switches $W_{tot} = W_L + W_R$, length of S, and the total distance that the scroll bar travels in the x-direction.

2.3 Using response metrics in computational modelling

To take advantage of scroll tracking when building DDMs, the present study follows research in the literature that incorporates process tracing to model the value comparison process (Krajbich et al., 2010; Cavanagh et al., 2014; Smith and Krajbich, 2019; Fisher, 2021). The main purpose of the DDMs is to model the drift rate ν, i.e. the relative rate of evidence accumulation, towards the Left option so that it is biased by scrolling. Drift rate depends on value differences and differences in proportional response metrics (i.e. the additive model, Eq. 5), defined as

$$\nu \sim \beta_0 + \beta_1 \Delta V + \beta_2 \Delta \text{PRM}, \tag{8}$$

where $\Delta\text{PRM} = \text{PRM}_L - \text{PRM}_R$ and $\Delta V = V_L - V_R$. Given that the beta coefficients are positive, Eq. 8 predicts that the drift rate is increased when V_L increases relative to V_R, or when the response metric M_L increases relative to M_R (see Eq. 7), and that these two effects are independent. Thus, Eq. 8 states that the relative average speed of evidence accumulation can be raised by an increase in either the value difference or the relative amount of scrolling.

Cavanagh et al. (2014) derive the following representation for the drift rate in the multiplicative model (Eq. 6) using process tracing. We use product terms that include the proportional response metrics and option values,

$$\nu \sim \gamma_0 + \gamma_1(\text{PRM}_L V_L - \text{PRM}_R V_R) + \gamma_2(\text{PRM}_R V_L - \text{PRM}_L V_R) \tag{9}$$

when setting $\theta = \gamma_2/\gamma_1$ in Eq. 6. Because the modulative parameter $\theta < 1$, i.e. value of the currently scrolled option is integrated at a higher rate than the competing option, we should observe that $\gamma_1 > \gamma_2$ for the data to be consistent with the multiplicative model.

2.4 Choice-scrolling link

The attentional DDM links process tracing to choice (Krajbich et al., 2010; Cavanagh et al., 2014; Smith and Krajbich, 2018, 2019). It predicts that increased gaze dwell time on an option increases the likelihood of choosing that option when the options' subjective values are equal. Using scroll tracking and the proportional response metrics (Eq. 7), it can be predicted that choice and scrolling have the following relationship:

$$\text{choose } i \sim \beta_0 + \beta_1 \text{PRM}_i, \qquad \text{when } V_i = V_{-i}, \tag{10}$$

where β_0 and β_1 are the intercept and slope coefficients, respectively, of the linear equation. The link can be understood in terms of the attention-choice relationship: when the values are equal, the more one attends to option i by scrolling over that option, in proportion to the total amount scrolled over both options, the higher is the value of PRM_i and the higher is the likelihood of choosing option i. This is a consequence of the bias in the drift rate (Eqs. 8 and 9), which leads to an increase in choice probability (Eq. 3).

Another choice-bias prediction is the link between value difference and the probability that the last-attended option is the chosen one (Krajbich et al., 2010; Smith and Krajbich, 2018). The last-attended option has a higher probability of being chosen than the other option, but this probability is decreased if the last-attended option is significantly worse than the other. Hence, the DM may choose option i while attending to option $-i$ because the former has higher value than the latter. This relationship can also be imported into the scroll-tracking context by studying whether choice probability is predicted by the last-scrolled option.

2.5 Value-scrolling link

It was argued earlier that motor movement data reflect the dynamic preference formation process. An example from the literature is how the metric "area-under-the-curve" quantifies spatial competition in mouse tracking. Stillman et al. (2020) show that such measurements correlate, at the level of single trials, with risk preferences estimated from observed choices. They argue that the motor response measurement provides preferential diagnostic information that could be useful in addition to information on choices and RTs. Observing conflict from the response metric provides a window into the latent psychological factor, which, in their case, is a risk preference parameter.

The DM should experience increasing difficulty, or choice conflict, in deciding between options as the values of these options become more equal. Choice conflict should increase intermediate movements, or spatial competition from the non-selected option. In the scroll-tracking app, there should be more scrolling between the options, as manifested by longer dwell times, larger polygon areas, and more switches, when the subjective values become more equal. This raises the possibility of using the proportional response metrics to represent the relative subjective value difference. In other words, when option i is judged as better than option $-i$, option i should receive a higher proportion of scrolling. Thus, we should observe a link between value and scrolling,

$$V_i \sim \beta_0 + \beta_1 \text{PRM}_i, \qquad \text{when } V_{-i} \text{ fixed}, \tag{11}$$

where β_0 and β_1 are the intercept and slope coefficients, respectively. Eq. 11 models subjective value as a linear function of the measurements that we obtain from scroll tracking, but conceptually we also know that subjective value influences the proportional response metrics.

It is important to note the following caveats when scroll tracking is used to index valuations of decision options. First, only imperfect measurements of subjective value can be obtained (Chen and Risen, 2010). In Section 3, these are product ratings on a numerical scale, which are useful but not definitive measurements of preference. There may be some unmeasured components of subjective value, or measurement error, that influence the response metrics. For instance, the DM may change their mind about a previously expressed rating of a product, and scroll over that product more (or less) than we would expect based on the previous measurement. Second, the two links discussed above do not, as such, predict causal relationships. Eq. 10 is derived from the attentional DDM. Eq. 11 presents a diagnostic link that makes it possible to investigate relative value through scrolling measurements. While the typical view would be that choice processes affect attentional processes, the literature also supports the idea that attention has a causal effect on choice (Krajbich, 2019).

3 Empirical validation

Understanding consumer choices in digital marketplaces is valuable for theorists and practitioners. It helps develop efficient techniques for modelling choice probabilities and algorithms for optimising assortments of product and service offerings. Consumer choice processes have previously been investigated using computational decision models (Busemeyer and Johnson, 2004; Krajbich et al., 2012; Philiastides and Ratcliff, 2013; Enax et al., 2016; Fisher, 2017, 2021). Here I demonstrate how an understanding of the DM's response dynamics obtained with scroll tracking can be integrated into computational choice modelling. Scroll tracking is tested in an experiment with choices between pairs of ordinary consumer lifestyle products. The next subsections describe the data collection procedure and present an analysis of the predicted choice-scrolling relationships. The paper then proceeds to computational modelling using the DDM and the additive model (Eq. 5). Model comparison is performed using cross-validation, and the multiplicative model (Eq. 6) is also studied.

3.1 Data collection

The pre-registered experiment consisted of a product rating task and a choice task (see Figure 2). In Part 1, the subjects rated 115 consumer products, which were either Nike trainers (athletic shoes) or Longines watches, on a Likert scale from -3 to 3. The subjects were instructed that a rating of 3 (respectively -3) meant that they would be extremely likely (unlikely) to wear the product. No information other than a single lateral (trainers) or frontal (watches) picture of each product was presented. Product k's rating provided a measurement for its subjective value V_k. To match the stimuli with the subjects' gender preferences, at the beginning of Part 1, the subjects were asked whether they wished to see men's or women's products. In Part 2, the subjects made 120 binary choices between paired products from Part 1. A pairing algorithm (modelled after Philiastides and Ratcliff, 2013) assigned each product i a pair $-i$ and a random location L = Left or R = Right, and ensured that $|V_i - V_{-i}| \leq 3$. Otherwise, the pairing was random.

The experiment was conducted online using the Prolific subject pool (20 to 50-year-old UK residents). Each subject was compensated with a £5 monetary reward, and typical completion

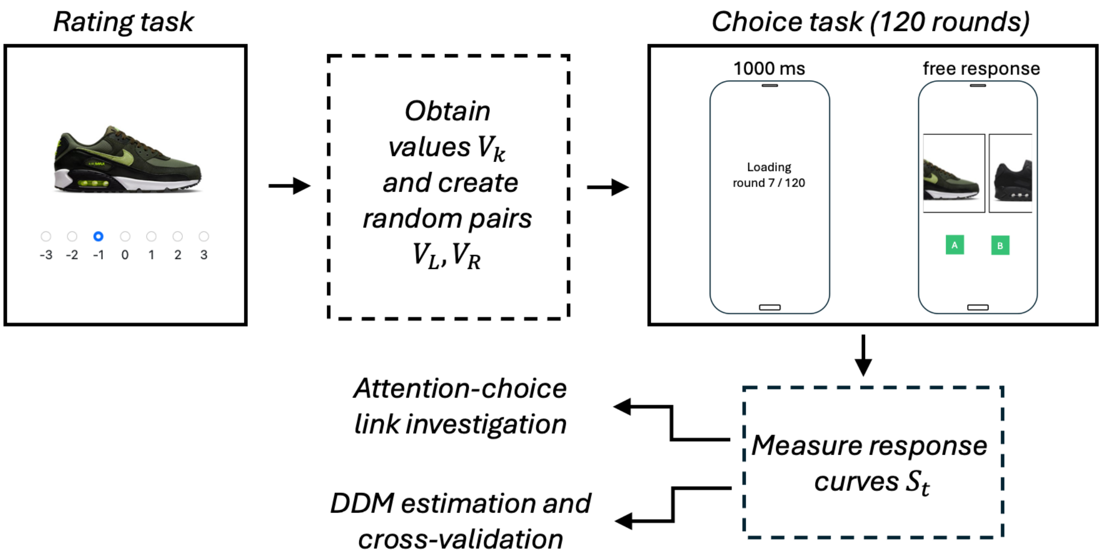


Figure 2: **Experimental design for the consumer choice study**

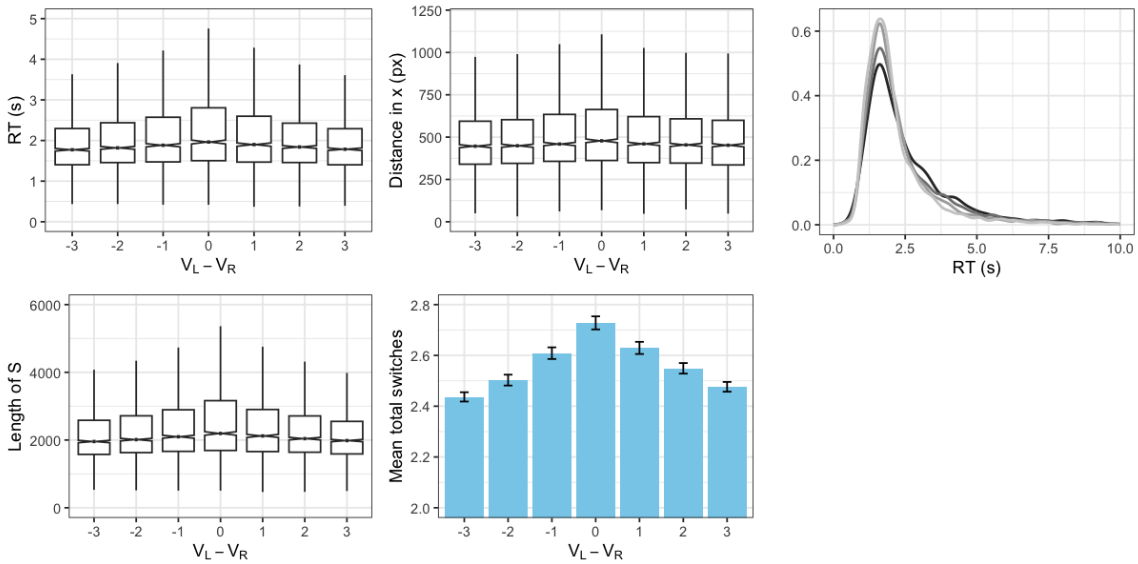
time was 20 minutes. Half the subject pool were assigned shoes and the other half watches as the experimental stimuli (see Online Appendix for additional screenshots). All decision rounds shorter than 0.3 seconds or longer than 15 seconds were discarded; the discarded rounds represent about 0.6% of the total data. Overall, 120 subjects participated, but one subject's data was removed because a large number of their rounds were excluded based on pre-registered criteria. Therefore, the final sample size is 119 subjects.

All data, pre-registration documents, and analysis scripts are available as supplementary data and at the Open Science Framework.[9] In the statistical analyses reported here, continuous predictors were scaled and centred around their mean values when used in multiple regressions.

3.2 Choices and response metrics

It is instructive to first understand how choices change as a function of value differences $\Delta V = V_L - V_R$ and how aggregate response metrics (see Section 2.2) react to such differences. Using a Generalised Linear Mixed Model (GLMM) with the logistic link function and subjects as random intercepts, we can see that ΔV significantly predicts choice of the left-hand side option (log-odds 1.27, 95% CI = $[1.23, 1.32]$, $p < 0.001$) even when round is added as a covariate (log-odds 0.00039, 95% CI = $[-0.038, 0.039]$, $p = 0.98$; fixed intercept log-odds -0.041, $p = 0.15$; random intercept SD = 0.22).

Figure 3 displays how the aggregate metrics of RT, total distance that the scroll bar moves (in the x-direction), total length of the response curve S, and the total number of switches, change as value difference $V_L - V_R$ changes from -3 to 3. The total switches metric is count data, unlike the other aggregate response metrics, which are approximately continuous. Therefore, total switches is presented using a bar plot in Figure 3, while box plots are used for the others. The median number of total switches is 2. All four metrics reflect decision conflict, a "core feature" of sequential sampling models (Smith and Krajbich, 2018), in that the amount of deliberation is highest for choices where value differences are small and choice is difficult, and lowest for choices where value differences are large. Mean RT is 2.40 s (SD = 1.62 s), which is somewhat higher than some binary consumer choice studies using laboratory desktop setups (Philiastides and Ratcliff, 2013), although more similar to others (Tavares et al., 2017). Figure 3 also includes a density plot of RTs, which shows that the distribution experiences a slight shift to the right when $|V_L - V_R|$ approaches zero, indicating that choice difficulty increases when value difference decreases.



Note: Box plots: notches are 95% CIs for medians. Bar plot: whiskers are standard errors. Density plot: darker lines mean that $|V_L - V_R|$ is closer to zero.

Figure 3: **Aggregate response metrics**

3.3 Predicting choice from scrolling

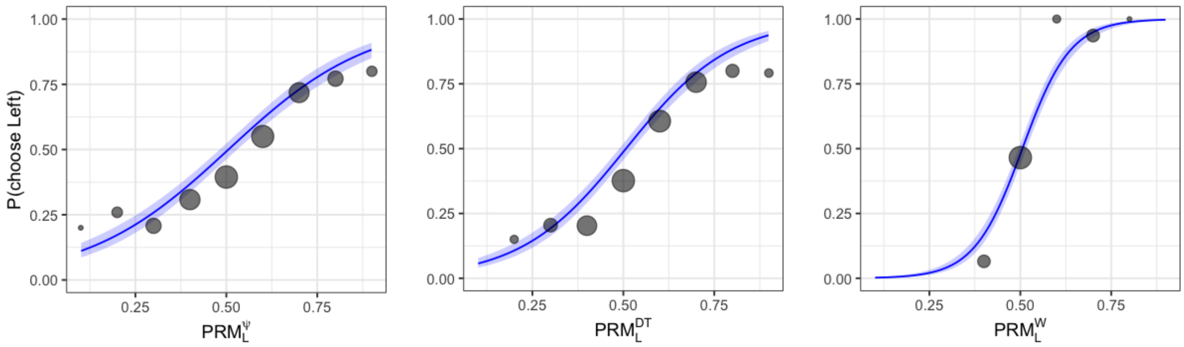
The choice-scrolling relationship discussed in Subsection 2.4 is now studied using scroll tracking and the proportional response metrics.

First, a restricted dataset is used where $V_L = V_R$ to test whether choice has an increasing relationship with the proportional response metrics. Figure 4 presents the results from logistic GLMMs that link choice of Left to scrolling over Left. The results confirm that the probability of choosing Left increases in all proportional response metrics. As indifference in values is required, this model represents the strictest test for the choice-scrolling relationship. However, it should be noted that the ratings V_i are only a proxy for subjective value; thus there could be latent, unmeasured components of subjective value that affect scrolling behaviour.

As a second test, subjective value difference ΔV is used as a covariate in a GLMM to predict the choice of the Left option with PRM_L using the full dataset, including those rounds where $V_L \neq V_R$. The regression equation is the following:

$$\text{choose Left} \sim \beta_0 + \beta_1 \Delta V + \beta_2 \text{PRM}_L^M \qquad \text{for } M \in \{\psi, DT, W\}, \tag{12}$$

where β_0 is the regression intercept and β_1, β_2 are slope coefficients. The coefficient estimates are presented in log-odds in Table 1. As expected, the intercept coefficients β_0 are zero, as the subjects were assigned random pairings of their rated products. Choice is affected by changing value difference, as predicted by the β_1 coefficients. The β_2 coefficients confirm the strong link between choice and scrolling. The strength of this link is comparable to the choice-attention relationship established in previous studies using eye tracking (Krajbich et al., 2010; Cavanagh et al., 2014; Smith and Krajbich, 2018, 2019).



Note: The blue curve represents logit-GLMM estimations when the data are restricted by condition $V_L = V_R$, see Table 1 for results with the full dataset. Shaded ribbons are 95% CIs. In each panel, points depict group means of choice probabilities in 9 different bins of PRM values at increments of 0.1, and each point is plotted at the bin's upper boundary. The right panel contains fewer points because the data are concentrated on fewer bins. Point size represents the relative size of each bin. In the middle panel, one point is omitted because its bin contained only a single value.

Figure 4: **Link between choice probability and scrolling when $V_L = V_R$**

	(1)	(2)	(3)
Intercept (β_0)	-0.036 $[-0.14, 0.065]$	-0.039 $[-0.15, 0.071]$	-0.017 $[-0.19, 0.16]$
ΔV (β_1)	1.25 [1.20, 1.30] ***	1.25 [1.20, 1.30] ***	1.25 [1.20, 1.30] ***
PRM_L^{ψ} (β_2)	1.05 [0.99, 1.11] ***		
PRM_L^{DT} (β_2)		1.19 [1.13, 1.25] ***	
PRM_L^{W} (β_2)			1.95 [1.85, 2.045] ***
RE: subject (SD)	0.51	0.57	0.94
Num. obs.	14 200	14 200	14 200
AIC	13 675	13 350	12 573

Note. Coefficients expressed in log-odds. RE = random effects (intercept), AIC = Akaike information criterion. 95% CIs in brackets, significance level: $p < .001$ ***.

Table 1: **GLMMs (Eq. 12) predicting choices of Left using proportional response metrics**

Scroll tracking uses spatial and temporal measurements, and these measurements may yield different sensitivities to detect the relationships investigated here. Recall from Subsection 2.2 that while the dwell time metric DT is temporal, the area metric ψ is calculated as the polygon area in the pixel-millisecond space (spatio-temporal metric), and the switches metric W is based on counting the back-and-forth movement of the scroll bar (spatial metric). Therefore, comparing the performance of the statistical models that rely on these metrics is a diagnostic of the accuracy of the metric. One criterion of model comparison that may be used is the Akaike information criterion (AIC), which is shown for each model in Table 1. The GLMM using PRM_L^W has the lowest AIC at 12573, implying that the switches-based proportional response metric is the best at minimising the log-likelihood in the logistic model of choice. A model that uses both PRM_L^{DT} and PRM_L^{W} to predict choice improves AIC to a value of 12381, as Table 2 shows. These two metrics, DT and W, are independent from each other unlike ψ, which includes the temporal and spatial dimensions. This result suggests that the combined metrics provide a marginal improvement in the model's ability to explain the statistical relationship.

Intercept (β_0)	-0.019 [$-0.19, 0.15$]
ΔV (β_1)	1.24 [1.19, 1.29] ***
PRM_L^{DT} ($\beta_{2,1}$)	0.52 [0.45, 0.60] ***
PRM_L^{W} ($\beta_{2,2}$)	1.54 [1.43, 1.64] ***
RE: subject (SD)	0.89
Num. obs.	14 200
AIC	12 381

Note. Coefficients are expressed in log-odds. RE = random effects (intercept), AIC = Akaike information criterion. 95% CIs are indicated in brackets, significance level: $p < .001$ ***.

Table 2: **GLMM similar to Eq. 12 but adding PRM_L^{DT} and PRM_L^{W} as predictors of choices of Left**

3.4 First and last scrolls

Given that one option is revealed first by scrolling, that option potentially exerts an increased influence on the DM's choice. Therefore, we next test whether choice probability is affected by the first scroll direction or by the time the DM spends scrolling over the first option. This is assessed using a logit-GLMM where an indicator variable "first scroll direction" (1 = Left, 0 = Right) and the duration of the first dwell predict choice of Left. This GLMM also includes the interaction term between the indicator variable and first dwell duration. The log-odds are significantly positive for first scroll direction (coefficient = 0.077, 95% CI = $[0.002, 0.15]$, $p = 0.044$; fixed intercept log-odds -0.073, 95% CI = $[-0.13, -0.015]$, $p = 0.013$; random subject intercept SD = 0.13), but not for first dwell time (log-odds 0.023, 95% CI = $[-0.029, 0.075]$, $p = 0.39$) or the interaction term (log-odds -0.064, 95% CI = $[-0.13, 0.006]$, $p = 0.072$). This result indicates that there is an increased probability of $e^{0.077} \approx 8.0\%$ of ultimately choosing Left if the first scroll is in that direction. However, the duration of the first scroll does not affect choice probability, regardless of its direction (non-significant interaction term). It should also be noted that 55.8% of all first scrolls are to the left; however, all else being equal, the probability of choosing Left is not significantly different from 50%, as seen from the β_0 coefficients in Table 1.

Another possibility is that the last viewed option exerts a higher impact on choice probability. The attention-based DDM (Eqs. 5 and 6) nudges the evidence accumulation process towards the currently-viewed option, which implies that the chosen option has a high probability of being the last option viewed. Because this effect is observed in eye-tracking research (Krajbich et al., 2010; Smith and Krajbich, 2018; Krajbich, 2019), it may also be present in the scroll-tracking data. The literature also predicts that the relationship between the last-seen option and the chosen option is dependent on the relative value difference. Hence, the DM might choose the last viewed option if it is better than the alternative, but not if it is worse.

To formalise the above, we may investigate the relationship between value difference and incongruent choices, which are those choices of option i where option $-i$ received the last scroll. As mentioned in Section 2.4, the attentional DDM predicts that the last-attended option has a higher probability of being chosen, unless it is significantly worse than the other option. To test this relationship, I estimate a logistic regression in which the value difference predicts an indicator for an incongruent choice. The prediction is that the odds of an incongruent choice of option i increase as the value difference $V_i - V_{-i}$ increases; hence, the odds of an incongruent choice of i are high only if V_i is sufficiently larger than V_{-i}. Of all choices in the current study, 23.9% are incongruent. Then, the indicator variable "choose Right while last scroll is Left" is used and regressed on value difference $\Delta V = V_L - V_R$ using a logit GLMM on the conditional dataset where all choices are Right. The odds ratio is significant at -0.077 (95% CI = $[-0.15, -0.0017]$, $p = 0.041$; fixed intercept log-odds -2.46, $p < 0.001$; random subject intercept SD = 2.31). This implies that increasing ΔV, or the relative desirability of Left, decreases the probability that the choice of Right is preceded by the last dwell that is Left. To study the converse case, the indicator variable "choose Left while last scroll is Right" is used and regressed on ΔV using data where all choices are Left. The log-odds of 0.073 are non-significant (95% CI = $[-0.0035, 0.15]$, $p = 0.057$; fixed intercept log-odds -2.04, 95% CI = $[-2.56, -1.57]$, $p < 0.001$; random subject intercept SD = 2.51). However, in both results, the fixed effect CIs have one boundary close to zero, and a cautious interpretation would be that the incongruent choice, overall, is not strongly moderated by value difference.

The findings reported here regarding the first and last scrolls are somewhat mixed but generally in line with previous research using eye tracking. Cavanagh et al. (2014) find that first dwell time predicts choice in 1 out of 3 conditions, while the present study does not find this. Cavanagh et al. (2014) also find a last dwell bias on choice in 2 out of 3 conditions. In turn, Smith and Krajbich (2018) find that there is about a 70% chance of choosing the last-seen option when value difference is zero. In the scroll-tracking data, the corresponding figure is 79.6%.

3.5 Linking subjective value to scrolling

Next, the link between subjective value and scrolling (Eq. 11) is investigated without using data on choices. Let us focus on rounds where $V_R = 0$; the DM is indifferent about the Right option in all these rounds. The question here is whether, in that case, the amount of scrolling over the Left option is related to the subjective value placed on that option. Following Eq. 11 we can write linear mixed models (LMMs) with random subject intercepts proposing that

$$V_L \sim \beta_0 + \beta_1 \mathrm{PRM}_L^M \qquad \text{for } M \in \{DT, \psi, W\} \text{ and } V_R = 0. \tag{13}$$

Table 3 shows the estimated βs; all relationships between value and proportional scrolling metrics are significantly positive. We see that, for instance, a one-unit increase in the proportional dwell time metric over the Left option is related to an increase of 0.42 in the subjective value of that option.

Scroll tracking applications are likely to find combinations of spatially and temporally

	(1)	(2)	(3)
Intercept (β_0)	-0.13 [$-0.36, 0.10$]	-0.13 [$-0.35, 0.10$]	-0.13 [$-0.37, 0.10$]
PRM_L^{ψ} (β_1)	0.39 [0.31, 0.47] ***		
PRM_L^{DT} (β_1)		0.42 [0.34, 0.50] ***	
PRM_L^{W} (β_1)			0.40 [0.31, 0.48] ***
RE: subject (SD)	1.12	1.13	1.16
RE: residual (SD)	1.71	1.71	1.71
Num. obs.	2270	2270	2270

Note. RE = random effects, 95% CIs in brackets, significance level: $p < .001$ ***.

Table 3: **LMMs predicting V_L when $V_R = 0$ (Eq. 13)**

constructed response metrics useful in representing subjective value, but based on the previous analysis, strong conclusions cannot be drawn on which metric stands out from the others. This stems from the similarity of the metrics, and one way of confirming this similarity is to directly compare how each metric responds to changes in value difference. Figure 3 shows that these approaches to quantify the response curve are apparently similar in their sensitivity to detect value difference to the classical approach using RTs. Figure 3 also indicates that the different metrics might be highly correlated. Table 4 quantitatively studies how each aggregate metric correlates with the others, separately when $\Delta V = 0$ and when $\Delta V \neq 0$. As expected, correlations between the metrics are rather strong and stronger when the value difference is zero than when it is non-zero.

	RT	Length of S	Switches	Dist. in x
RT		*0.997*	*0.732*	*0.656*
Length of S	0.997		*0.752*	*0.701*
Switches	0.684	0.707		*0.785*
Dist. in x	0.613	0.663	0.743	

Table 4: **Correlation tables for aggregate metrics; the upper diagonal elements (italics) are correlations when $\Delta V = 0$, and the lower diagonal elements are correlations when $\Delta V \neq 0$**

3.6 Computational modelling of choices and RTs

This section investigates the latent parameter distributions from DDMs where the scroll-tracking datastream predicts the relative rate of value comparisons. To compare DDMs that use different response metrics, I study their ability to predict out-of-sample data. I follow research in the literature that has demonstrated that incorporating process tracing, typically eye-tracking data, in evidence accumulation modelling improves the models' predictive accuracy (Krajbich et al., 2010; Cavanagh et al., 2014; Smith and Krajbich, 2019; Fisher, 2021). The purpose is to demonstrate that computational modelling of choice probabilities and RT distributions can benefit from response metrics, which can be ultimately used in decision science applications.

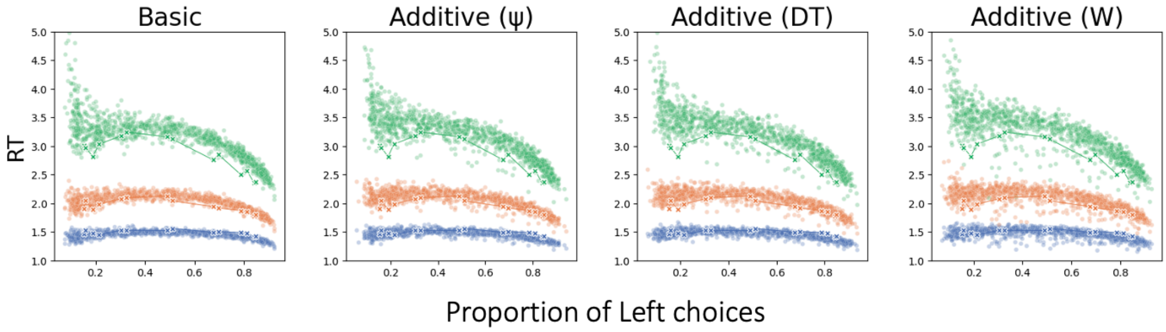
The DDM modelling investigates what affects the drift rate ν. The DDMs are formulated such that the drift rate is regressed on value differences and differences in proportional metrics using all $M \in \{DT, \psi, W\}$, following the additive model in Eq. 8. The other DDM parameters (starting point z, boundary separation a, non-decision time t_0) are formulated without the regression or hierarchical formats. These parameters are not assumed to vary between subjects, rounds or levels of value differences. The basic DDM, where the drift rate depends only on one fixed effect, value difference, is defined by erasing the term $\beta_2\Delta$PRM from Eq. 8.

The DDMs are estimated with hierarchical Bayesian modelling and Markov Chain Monte Carlo (MCMC) sampling.[10] The hierarchical Bayesian model produces a set of parameters for each subject such that these individual parameters are governed by group-level distributions. Thus, the subjects are modelled as random effect intercepts. The estimated fixed effects are, depending on the regression format, intercept and coefficients for the drift rate ν. In addition to the DDM parameters, the procedure produces posterior estimates for the standard deviation of the subject-level random intercepts (i.e. variation in subject intercepts of drift rate). See the Online Appendix for more details on the prior distributions. The DDMs are estimated by running 4 Markov chains of 4,000 samples each, with initial 2,000 burn-in samples that are discarded. The scale reduction factor (Gelman and Rubin, 1992) is $\hat{r} \leq 1.01$, and the effective sample size is > 400 for all group-level parameters for all the DDMs, indicating that the chains have converged to stable posteriors.

The Bayesian approach produces posterior predictive distributions for choices and RTs that can be used for model comparisons. The posterior predictive distribution expresses the variability in the model's ability to predict choices and RTs, given the observed data and its hierarchical structure. Figure 5 presents quantile probability plots that show predicted RT quantiles (data points) using the basic and additive DDMs (Eq. 8), as a function of Left-choice proportions. The predictions are laid over observed RT quantiles, which are denoted by the "x"-markers. Each "x" pair marks the observed RT quantile for a specific condition given by ΔV, and the line connects those condition-level points for readability. The first "x" in each pair corresponds to a Left and the second to a Right choice. A value difference of $\Delta V = 1$, for instance, is indicated by the 5th pair of markers from the left. We can extrapolate that the proportion of Left choices is close to 0.7 when $\Delta V = 1$ and that 50% of RTs are 2 s or less for this proportion. Conversely, a proportion of about 0.3 are Right choices when $\Delta V = 1$ and 50% of RTs are about 2.1 s or less.

We can make two observations from the quantile probability plots of Figure 5, and these are based on the DDM literature (Ratcliff and McKoon, 2008). First, there is more variance in predictions for smaller proportions of Left choices, as seen in the left-hand side of each plot. This is a known feature of DDM predictions where less-preferred (incorrect) responses, or choosing Left when $\Delta V < 0$, have slower RTs. Second, the basic DDM and the additive models predict variance in the RTs differently. The latter seemingly exhibit more variance, especially in higher RT quantiles. The additive models contain one more regressor, the term $\beta_2\Delta$PRM in Eq. 8, than the basic model, which increases variability in the drift rate. Therefore, adding proportional response metrics as predictors of drift rate increases the variance of the predicted RTs in higher quantiles, which is expected as changes in drift rate affect the higher RT quantiles more than the lower ones.

The DDM coefficient estimates are produced by the marginal posterior distributions. Figure 6 presents the distributions for drift rate coefficients that follow the basic and additive models



Note. Markers connected by solid lines show observed RT quantiles at levels 25%, 50%, and 75% from bottom to top, respectively. Markers are in pairs of Left and Right choices, and each pair denotes the level of value differences $\Delta V = V_L - V_R$. Datapoints indicate draws from the posterior predictive distributions. Datapoints are arranged in the same quantiles as observed RTs.

Figure 5: **Quantile probability plots for observed and predicted RTs from the posterior predictive distributions of the Basic and Additive DDMs**

(Eq. 8). All regressor distributions are sufficiently to the right to exclude the possibility that the 95% highest density interval contains zero. The result confirms what the additive model predicts: drift rate ν is affected by the differences in $\Delta V = V_L - V_R$ and differences in ΔPRM^M for all $M \in \{DT, \psi, W\}$. Summary statistics for the other DDM parameters are presented in the Online Appendix Table S3. An interesting observation from Figure 6 is that the β_2 coefficient for the DDM with switches is significantly higher than the β_2s for the other two additive DDMs, implying that drift rate is more responsive to a unit change in ΔPRM^W than in the others. Otherwise, the posterior means of β coefficients are similar in magnitude to those in the literature (e.g. Cavanagh et al., 2014 who find $\beta_1 = 0.44$ and $\beta_2 = 0.29$ using gaze dwell times).

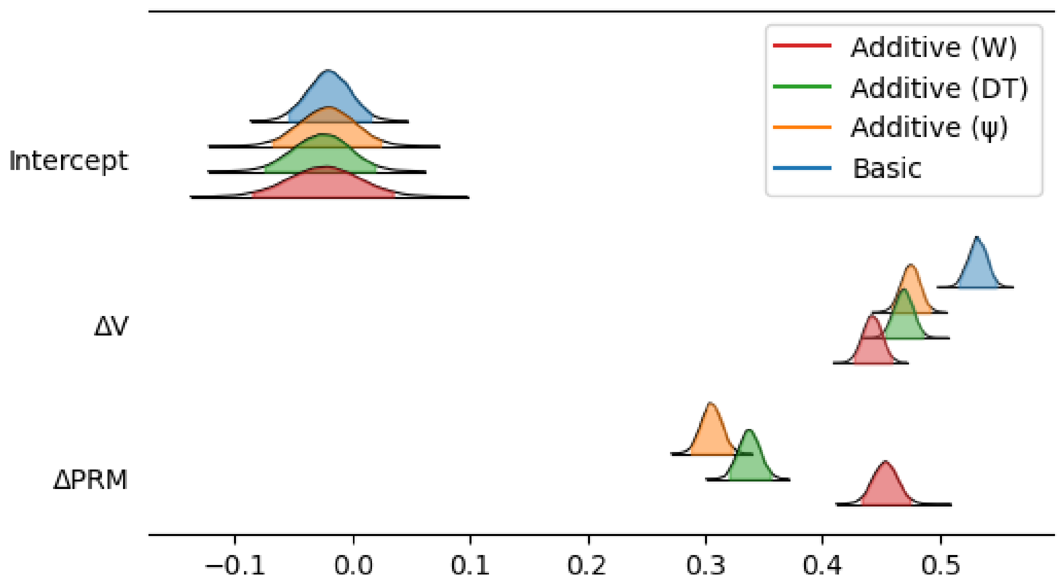


Figure 6: **Marginal posterior distributions for the basic and additive model coefficients (Eq. 8)**

Next, cross-validation is performed using re-estimated DDMs with observations from oddnumbered rounds. These models produce new posterior predictive distributions for choices on even-numbered rounds. Then, a set of predicted choices from multiple draws is compared to observed choices on even rounds (hold-out evaluation), and the number of predicted choices that correspond to observed choices is calculated. The comparisons are summarised in correctness scores that calculate shares of correctly predicted choices in each draw and in each chain. There are 4 chains × 4,000 draws = 16,000 correctness scores, which are summarised in Table 5. All the scroll-DDMs demonstrate better predictive power than the basic model, while the additive model with switches W as the proportional response metric exhibits the best predictive power.

DDM	Score
Basic	64.2%
Additive (ψ)	67.5%
Additive (DT)	68.1%
Additive (W)	69.4%

Note. Score = mean % of even round choices predicted correctly.

Table 5: **Predictive correctness of DDMs estimated using odd rounds data**

3.7 Multiplicative effects

Both the additive and the multiplicative model predict that attention to an option boosts the relative rate of evidence accumulation towards it, but the multiplicative model is sensitive to reference points. This means that the biasing effect of attention on drift rate is different for appetitive and aversive options. Recall that in the multiplicative model (Eq. 6), the biasing parameter θ discounts the value of the non-attended option V_{-i}. If both options are appetitive ($V_i, V_{-i} > 0$), the model predicts that attention on option i will inflate its choice probability. However, if both options are aversive ($V_i, V_{-i} < 0$), attention on i will deflate its choice probability (Armel et al., 2008).

The same estimation procedure as with the additive model (Subsection 3.6) is used to estimate multiplicative effects. This produces marginal posterior distributions for the DDM parameters. The multiplicative case contains two drift rate coefficients in Eq. 9. Table S4 in the Online Appendix presents the summary statistics from these marginal posterior distributions, and there we see that the prediction $\gamma_1 > \gamma_2$ (see Subsection 1.2) holds for all proportional response metrics M. The result means that the modulative parameter $\theta < 1$ as required by the model (Eq. 6). Based on the posterior mean estimates, θ is within $[0.76, 0.80]$, a range that is somewhat higher than in previous studies. Using dwell time data based on eye tracking, Krajbich et al. (2010) find that $\theta = 0.52$ (mean of individual-level fits), while Cavanagh et al. (2014) find $\theta = 0.56$, and Smith and Krajbich (2018) find $\theta = 0.48$ (mean of group-level fits).

It should be noted, however, that the experiment discussed here did not aim to distinguish multiplicative-attentional effects from additive effects, a goal that has been extensively pursued in the recent literature (Cavanagh et al., 2014; Smith and Krajbich, 2019). One reason for this is how the ratings were used in the stimulus presentations. Krajbich et al. (2010) and Smith and Krajbich (2018), for instance, use only stimuli that are rated appetitive by the subjects. By contrast, the pairing algorithm used in the consumer choice study produced a balance of appetitive and aversive options.

In the cross-validation procedure the multiplicative models do not reach the same level of predictive correctness as the additive models (Table 5), and the correctness of each of the three multiplicative models is 64.2%, equal to that of the basic DDM without the attentional component. Previous studies with gaze-dwell data, such as Cavanagh et al. (2014), find that the additive model contains a higher deviance information criterion (a measure of improved model fit) than the multiplicative model, a result aligned with our cross-validation based on correctness scores. On the other hand, Smith and Krajbich (2019) find that the amplifying effect in the multiplicative model is stronger (lower modulative parameter θ) in food-choice tasks where subjects were familiar with the stimuli.

3.8 Additional validation

3.8.1 Risky choice experiment

The Online Appendix reports a complementary validation experiment using a risky choice task modelled after the "money-risk" task studied by Smith and Krajbich (2018) (henceforth, SK18). SK18 used the task to investigate attention and choice using eye tracking. In this task, subjects choose between two gambles, one of which is lower risk than the other, with the relative riskiness of the options varying randomly from round to another. The gambles are two-outcome lotteries, where each outcome has a 50% probability of being realised. The gambles are presented in the scroll-tracking app in a similar way to the options in the consumer choice experiment.

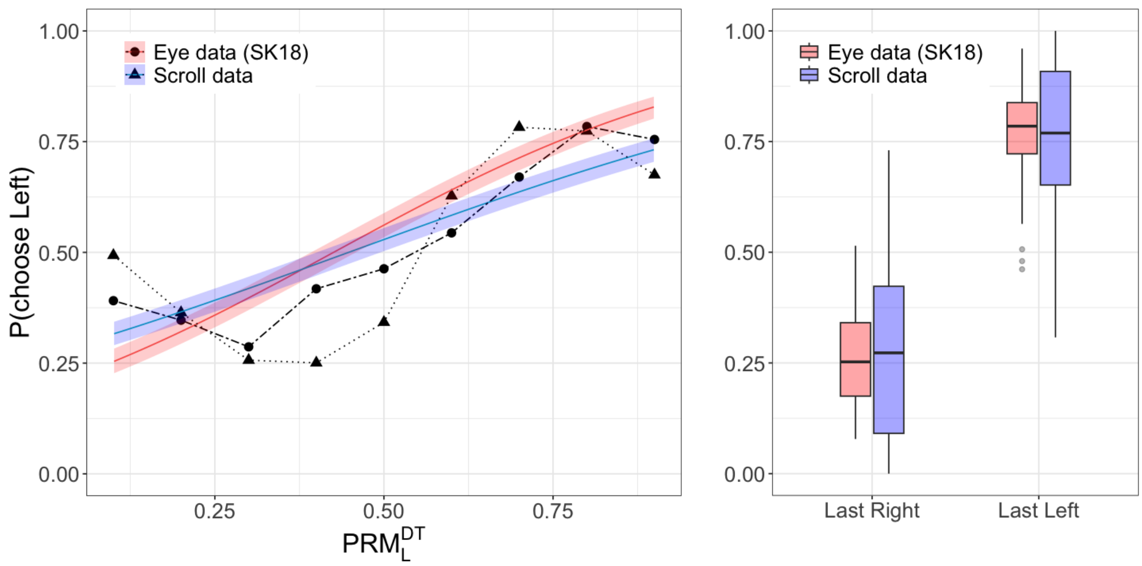
The lotteries used in the money-risk task are reproduced from the SK18 dataset. Essentially, each subject-wise series of lotteries in the SK18 money-risk dataset has an equal chance of being allocated to a subject in the current study. To model each subject's latent risk attitude, a general risk question (GRQ; Dohmen et al., 2011) is added at the end of the study. To create a measure of relative utility difference, subjective utilities are estimated with the constant relative risk-aversion (CRRA) framework (Prelec, 1998) using maximum likelihood, which produces the degree of relative risk aversion parameter ρ for each subject. Then, the money-risk task is used to study the two links elaborated in Subsections 2.4 and 2.5, namely the choice-scrolling and value-scrolling links. The computational DDM analyses are also repeated.

The Online Appendix presents the full results, which can be summarised as follows. First, the choice-scrolling link is confirmed, as scrolling over the Left option heightens the probability of choosing Left (log-odds range $[0.56, 0.64]$) while controlling for utility difference (see Figure 7 and Table S5). Nonetheless, this link is weaker than in the consumer choice study reported in Table 1. Second, the value-scrolling link is confirmed, as the risk-aversion parameter ρ can be predicted from the mean amount of scrolling on the less-risky option (log-odds range $[0.80, 0.83]$), and the self-reported risk attitude GRQ can likewise be predicted from how much the less-risky option is scrolled (log-odds range $[-3.45, -3.28]$, negative because risk-seeking behaviour increases in GRQ). Third, the cross-validation exercise shows that the additive and multiplicative DDMs exhibit slightly better predictive power (correctness scores in the range of $[58.7, 59.6]$%; Table S8) than the basic model (correctness score 56.9%). However, there are no notable differences in the predictive correctness scores between the additive and multiplicative

DDMs. Therefore, while adding the proportional response metrics in the DDMs improves predictions, the modelling does not differentiate between the types of metrics used.

The SK18 dataset is used to reproduce analyses of the PRM_L^{DT} metric and estimate CRRA ρs and utility differences (see the Online Appendix for more details). This allows direct comparisons between eye tracking and scroll tracking. Figure 7 (left panel) shows the comparison between choice-response links in the scroll data and the eye data. Figure 7 (right panel) shows how the last gaze dwell or scroll is related to choice. A strong link between the last-seen option and choosing that option is present in both datasets.

The SK18 data is also used to estimate the basic, additive and multiplicative DDMs with the dwell time metric and perform the cross-validation procedure. The additive model with DT predicts 64.1% of even round choices in the SK18 dataset, while the basic model predicts 55.8% and the multiplicative model with DT predicts 54.6% of choices. However, as the SK18 dataset contains a smaller sample of 36 subjects, the results are not directly comparable with the scroll-tracking money-risk data, which is produced by a larger sample of 98 subjects. The number of subjects is relevant in hierarchical modelling because a model with more levels enhances the reliability of the estimates by reducing uncertainty in the subject-level effects and provides a more robust representation of individual-level variability.



Note. Left: The solid curves represent logit-GLMM estimations with Eq. 12 using ΔU as a covariate (see the Online Appendix for full tables of results). Shaded ribbons = 95% CIs, datapoints = group means of choice probabilities in 9 bins of PRM values at increments of 0.1. Dashed lines are datapoint connectors. Right: Box plots summarising mean Left choices for each subject, conditional on whether the last dwell was on Right or Left. In both panels, the eye data uses the first 120 rounds of the SK18 dataset.

Figure 7: **Link between choice and response using money-risk data from 2 studies**

The analysis procedure followed in the money-risk task involves the additional step of estimating utility differences from choice data, but the consumer choice study used value differences calculated from the direct rating task. This may be the reason for the weaker predictive power of modelling based on utility differences, as demonstrated by the posterior predictiveness check scores (Online Appendix Table S8). The Online Appendix provides posterior predictive RT distributions along with observed RTs for different binned levels of utility difference (Figures S12 and S13). The comparison shows that extreme utility differences worsen the fit compared to moderate utility differences, but this observation is partly an artifact of the analysis process. There are 7 subjects with $\rho < -4$ (risk seeking) in the scroll data, and, for these subjects, the utility function is compressed towards zero. Their mean utility of the Left option is 0.28, whereas for all subjects the mean utility of Left is 0.53 (recall that utility is scaled in $[0, 1]$).

Finally, we can compare how similar the scrolling patterns are across the two studies. Figure S14 in the Online Appendix displays aggregate response metric distributions for both studies. We see that, overall, there is more scrolling in the consumer choice task than in the money-risk task. It is likely that this discrepancy is a result of the relative complexity of stimuli in the consumer choice task (product pictures).

3.8.2 Robustness checks

Two robustness checks are performed to investigate how sensitive the main results are to the definitions of the response metrics. These checks are conducted because the way that the response metrics are currently calculated may introduce bias in them.

Recall that the DT and ψ metrics are calculated entirely based on the asymmetric portions of the response curve relative to the mid-line, and the W metric is calculated based on how many times the response curve crosses the mid-line (Figure 1). Possible bias in these metrics could arise because (1) some scroll bar movements can be fast, ballistic "saccades" when moving between the options, as opposed to "smooth-pursuit" scrolling (thus it is plausible that the time spent in saccadic movements should not be accounted for when calculating attention), and (2) some scrolls may be "U-turns", or quick reversals of scrolling direction just after crossing the mid-line so that the option is visible only for a very short duration of time. Thus, the dwell times are re-analysed such that only sufficiently slow scroll bar movement is counted towards dwell time. Then a similar analysis is repeated for switches; namely, a scroll bar making a quick U-turn does not produce a switch count. The Online Appendix presents measurement details and results from these robustness checks: some of the strength in choice-scrolling and value-scrolling links is attributable to the portion of dwell time recorded during fast scrolling, and removing quick U-turn switches strengthens the relationships. The main conclusions are, for the most part, qualitatively the same as in Sections 3.3 and 3.5, which report the main results.

4 Discussion

In this paper I have presented ways to study how dynamic motor responses and attention interact in the computational process that determines choices. The results show that choice probabilities and subjective valuations can be linked to using metrics derived from response curves. The response curves are recorded with a mobile application that represents a natural choice situation. I now discuss the wider methodological relevance, limitations and challenges, and practical domains of scroll tracking.

4.1 Scroll tracking as a process-tracing method

Motor planning is present in trivial tasks, such as choosing which candy to eat. It is also present in abstract, cognitively demanding tasks, such as playing Candy Crush Saga. Motor responses do not solely report choices; rather, they belong to the choice process that reflects the way we build decision values (Lepora and Pezzulo, 2015; Gordon et al., 2021; Priorelli et al., 2025). As discussed in Subsection 1.1, perceptions and action plans are based on the presentation features of objects. In an online shopping environment, for instance, product browsing creates perceptual and attentional representations from gazing at pictures and text as well as representations for intentions and action plans. The latter specify how choice is operationalised, i.e. how to scroll or swipe the page to view the products.[11] Methods that trace both attention and movement enable us to capture this link between the two in preference formation.

Previous studies have modelled attention in preference formation using dynamic eye fixation distributions (Krajbich, 2019). However, there are two drawbacks to relying on eye tracking alone. First, eye tracking overlooks the role of action representations in the process, a role that was extensively analysed in the previous section. Second, the eye is a sensory organ, and people rarely make choices solely using their eyes (Cisek and Kalaska, 2005). Methods in the action dynamics literature, such as mouse cursor tracking (Stillman et al., 2018; Schoemann et al., 2021), can sensitively detect movement in choice, but these methods ultimately reject the role of perception and attention (for recent exceptions, see Fisher, 2023 and 2025). Moreover, some movement-tracing methods may be invasive enough to alter the way people acquire information from response options (Lohse and Johnson, 1996).

In the classical DDM, motor action is a non-decision component of the choice process (Ratcliff et al., 1999; Krajbich et al., 2012) and goal-directed movement occurs only after the decision has been made. The current study differs from these previous studies in that it recognises that spatial movement in a digital application can proxy attentional processes. The study uses simple metrics derived from the response curve. Figure 3 provides an overview of how the aggregate response metrics relate to value difference.

Much work remains to understand how movement best fits within the evidence accumulation framework that aims to explain RT-accuracy tradeoffs (Wispinski et al., 2020; Molano-Mazón et al., 2024). Studying naturalistic movements allows the consideration of evidence integration across other modalities than just time (Shadlen and Kiani, 2013). Pixel regions could be treated as one (spatial) modality, and it could be possible to create a model with one accumulator that integrates evidence across time and another accumulator that integrates evidence across pixels. Future work should also study optimal ways of scrolling. Previous research has assumed that information sampling (Drugowitsch et al., 2012; Fudenberg et al., 2018) and gaze dwells and fixation switches (Callaway et al., 2021) are costly. A similar normative analysis could be conducted with scrolling patterns that assume the notion of costliness quite naturally.

4.2 Limitations of and challenges to scroll tracking

A clear limitation of the current implementation of scroll tracking is that the stimuli must be relatively simple. For instance, if an option contains many attributes or many regions of interest, such as quality and price, the method may not yield the desired resolution. In the money-risk task, each option consists of two possible outcomes. Scroll tracking assumes that each outcome pair elicits the spatial attraction effect and attentional bias, but unlike eye tracking used by Smith and Krajbich (2018), the method does not measure attention allocated to each outcome separately.

Even with single-attribute options, such as the products used in the consumer choice study, scroll tracking may not entirely capture attention dynamics. Eye tracking is evidently superior for capturing overt attention and millisecond precision in attention shifts. As the scroll bar movement reveals information gradually, one cannot be sure which part of the stimuli the DM is attending to. On the other hand, looking at something does not equate perceiving it, and gaze measurements can only be a proxy for overt attention, rather than a direct measure of perception (Holmqvist et al., 2011). It is possible to design setups where scrolling is both horizontal for option comparisons and vertical for attribute comparisons (similar to many e-commerce platforms), or laboratory designs where response curve analysis complements eye tracking.

In addition, there may be options with unbalanced information content, such as a product picture versus a numerical value, which may elicit different comparison dynamics within each viewing (Khaw et al., 2018). Scroll tracking may also be sensitive to option layout: intermediate movements (see Subsection 1.1) are diminished when the spatial distance between the options increases, or when the options are separated by virtual barriers (Kim et al., 2021). Therefore, one might arrive at the wrong conclusions about the spatial attraction effect if the layout is not carefully designed to track this effect.

Based on the DDM modelling reported in Subsection 3.6, the relative evidence accumulates at a somewhat slower rate when the intake is modelled using scrolling than when it is modelled using gaze dwell durations. However, without direct comparisons using identical stimuli, it is impossible to discern whether this difference should be attributed to the complexity of the stimuli, or to the scrolling method. DDM non-decision times are likewise slower than in comparable experiments in the literature. The posterior means of non-decision times are in the range of $[689, 708]$ ms in the consumer choice study (see Tables S3 and S4 in the Online Appendix), and in the range of $[472, 477]$ ms in the money-risk task (Tables S6 and S7). Non-decision time reflects stimulus encoding and motor execution (Myers et al., 2022), where the latter means the time it takes to lift one's finger off the scrollable element and move it to tap the choice button. Both factors are likely at play in our posterior estimations. Moreover, some experimental paradigms used in eye-tracking research might not be directly applicable in the scroll-tracking context. For example, exogenous time pressure might impose a limitation because scroll bar movements are slower than saccadic eye movements. Furthermore, biometric analyses that are conducted with an eye-tracker, such as pupillometry, are not transferable to the scroll-tracking context.

The sampling frequency of scroll tracking is variable, with a mean of 33.3 Hz (SD = 16.8 Hz, median 34.6 Hz). This figure is lower than in eye tracking, which commonly has a sampling frequency above 200 Hz. Thus, low sampling frequency may be considered a limitation to experimental setups that require high resolution. The sampling frequency is low because datapoints are recorded only when the scroll bar is moving. The response curve S (Figure 1) remains constant when the scroll bar does not move. Hence, the sampling frequency is "endogenous" and dependent on the DM's behaviour. Decision rounds with relatively few samples (low average resolution) often contain pauses at some time point during the response. As this tendency to pause scrolling may be subject-specific, future work could study a DDM with varying boundary and non-decision time parameters for each subject. This would allow for the possibility that a pause in the process, at least near the completion of a decision round, marks termination of evidence accumulation.

It should also be noted that the data stream recorded by scroll tracking is of a fundamentally different nature to the gaze dwell distributions acquired with eye tracking. The spatio-temporal response curve is a time series signal, and its analysis can be enhanced with signal processing methods such as smoothing and interpolation if a higher resolution is required.

Furthermore, this paper studies only a handful of possible response metrics, and, as the literature on mouse tracking demonstrates, there may be more ways to calculate aggregate metrics from response data. The response curve S (Figure 1) describes scroll bar dynamics within the choice process, but the metrics that are drawn from S in this paper may not be specific enough to capture its full potential. For example, the proportional metric PRM^{ψ} measures the spatio-temporal attraction between the two options but does not count how many times the sides are switched. On the other hand, the metric PRM^{W} tallies the switches but does not recognise the time dimension or how far the scroll bar moves from the switching point. One way to develop the metrics would be to incorporate data analytic methods where the analysis unit is S itself (or segments of S). For example, Stillman et al. (2025) use functional data analysis to classify mouse pointer trajectories, and in a mobile web context, this method could be used to classify reject/accept swipe trajectories in sequential decision tasks.

4.3 Managerial and practical applications

The DDM can be seen as a preferential choice model that provides a framework for incorporating response times as inputs (see Subsection 1.2). Responsive methods such as scroll tracking allow the use of "clickstream" data (Chen and Yao, 2017; Aouad et al., 2025; Lu and Hutchinson, 2025) collected from e-commerce applications, and here it has been demonstrated how this datastream can inform the DDM. One immediate econometric avenue for responsive methods is the prediction of choice probabilities in field applications such as pricing, capacity planning, and optimal product assortments. Even though the attentional DDM is binary, it can be extended to model choices between three or more alternatives (Krajbich and Rangel, 2011) or choices where each alternative contains more than one attribute (Fisher, 2021; Yang and Krajbich, 2023).

Scroll tracking can be used to index subjective values, such as product ratings and risk attitudes, if there are sufficient observations of a DM's scrolling behaviour. This opens the possibility for applications where preferences are elicited without observing choices. For instance, a DM who is scrolling more over an item is more likely to choose that item than a less-scrolled item. Such knowledge could be used to build a consideration set for that DM (Aouad and Segev, 2021). The marketing literature has for long recognised that consumers distinguish between considering and choosing (Hauser and Wernerfelt, 1990). Another practical benefit of responsive process-tracing methods is related to studying the optimality of goal-directed movement within a website. Studies on sensorimotor control show that people optimise intermediate movements (Haith et al., 2015; Gallivan et al., 2018). The optimality of movements within consideration sets, such as those built by online search engines, could thus be investigated. A related possible application area is digital interventions, which are increasingly used in healthcare (Trella et al., 2022). These applications use online reinforcement learning that updates recommendations based on user behaviour, and response curves that show movements within the apps could potentially be informative for their algorithms.

Touch-scroll gestures belong to the immediate action repertoire of choice in mobile web applications. These gestures are also increasingly used in a range of other digital interfaces, including self-service and checkout kiosks, point-of-sale interfaces, smart appliances, fitness wearables, in-vehicle systems, interactive learning devices, medical and diagnostic equipment, and different behavioural biometric solutions (Gupta et al., 2023). Many of these environments could benefit from linking responsive touch-scroll-based methods to preferential choice process modelling, the first steps of which are demonstrated in this paper.

Notes

[1]Decision making is not the only avenue where such metaphors are used to convey abstract meanings. Statements such as "investors embrace AI" or "graduates kickstart their careers" are rooted in movement. Our understanding of the world at large is embodied (Lakoff and Johnson, 1980; Glenberg and Kaschak, 2002).

[2]Modern web-design standards aim to ensure that websites are accessible with mobile devices, as outlined by the W3 Consortium (2015). Since 2020, the dominant search engine, Google, has indexed websites primarily based on their mobile versions, meaning that developers are incentivised to design websites such that they are responsive and can be used with touch-scroll gestures. See `https://developers.google.com/search/blog/2020/03/announcing-mobile-first-indexing-for` (accessed 11 July 2025).

[3]Early smart devices used a variety of input methods, but finger movements have become the established way to use them. Upon launching the first iPhone in San Francisco in 2007, the former Apple CEO, Steve Jobs, famously said that the finger is the "best pointing device in the world".

[4]Most of this literature focuses on endogenously allocated attention. Exogenous attention manipulations are also known to increase choice probabilities, see e.g. Armel et al. (2008) and Gossner et al. (2021).

[5]In addition to visual information, neural representations may be based on other sensory modalities, such as auditory or gustatory (Hommel et al., 2001). For instance, hearing a busker play across the street might generate an action plan to move closer, and tasting wine a plan to consume more. The visual pathway is arguably the most relevant in the digital context discussed in this paper.

[6]Being optimally responsive to a changing environment necessitates movement within decision processes. It would be counterproductive to pause movement while waiting for the decision process to complete, restart movement once it has completed, and then, when the environment changes, begin the process anew and again pause movement (Wispinski et al., 2020).

[7]Some studies use devices other than computer mice. Examples include Dale et al. (2008), who use a Nintendo Wiimote game controller, and Dotan et al. (2018) and Zuk et al. (2025), who use touchscreen devices. Dotan et al. (2019) argue that touchscreens that track finger movements are more natural and contain less variance than mouse movements. Gomez et al. (2015) find that DDM drift rates are not differentially affected by response modes

(keypress vs. touchscreen).

[8]The app is built using the open-source experiment platform oTree (Chen et al., 2016). Response curve recording is based on the JavaScript HTML Document Object Model. Technical documentation, a link to a demo version, and downloadable source code are available at the project's OSF page at https://osf.io/25fu7/wiki/Scrolltracking/.

[9]https://osf.io/25fu7.

[10]The HSSM toolbox in Python, version 0.2.4 (Fengler et al., 2025).

[11]Accepting that choice involves movement leads to new interpretations of consumer choice processes. For instance, online shoppers are not finished with their choice when they click products into shopping carts, because the action plan contains a longer chain of intended movements. Indeed, cart abandonment rates are extremely high, sometimes in excess of 90% (Wang et al., 2023). One way to explain cart abandonment is to understand that adding products to, and removing them from, carts are actions that interact with perceptions. Using the terminology of Subsection 1.1, cart abandonment happens when the "pull" from competing options gets strong enough.

References

Aouad, A., Feldman, J., Segev, D., and Zhang, D. J. (2025). The click-based mnl model: A framework for modeling click data in assortment optimization. *Management Science*, 71(8):6319–7222.

Aouad, A. and Segev, D. (2021). Display optimization for vertically differentiated locations under multinomial logit preferences. *Management Science*, 67(6):3519–3550.

Arieli, A., Ben-Ami, Y., and Rubinstein, A. (2011). Tracking decision makers under uncertainty. *American Economic Journal: Microeconomics*, 3(4):68–76.

Armel, K. C., Beaumel, A., and Rangel, A. (2008). Biasing simple choices by manipulating relative visual attention. *Judgment and Decision Making*, 3(5):396–403.

Busemeyer, J. R. and Johnson, J. G. (2004). Computational models of decision making. *Blackwell Handbook of Judgment and Decision Making*, pages 133–154.

Calalo, J. A., Ngo, T. T., Sullivan, S. R., Strand, K., Buggeln, J. H., Lokesh, R., Roth, A. M., Carter, M. J., Kurtzer, I. L., and Cashaback, J. G. (2025). Online movements reflect ongoing deliberation. *Journal of Neuroscience*, 45(31).

Callaway, F., Rangel, A., and Griffiths, T. L. (2021). Fixation patterns in simple choice reflect optimal information sampling. *PLoS Computational Biology*, 17(3):e1008863.

Cavanagh, J. F., Wiecki, T. V., Kochar, A., and Frank, M. J. (2014). Eye tracking and pupillometry are indicators of dissociable latent decision processes. *Journal of Experimental Psychology: General*, 143(4):1476.

Chapman, C. S., Gallivan, J. P., Wood, D. K., Milne, J. L., Culham, J. C., and Goodale, M. A. (2010). Reaching for the unknown: multiple target encoding and real-time decision-making in a rapid reach task. *Cognition*, 116(2):168–176.

Chen, D. L., Schonger, M., and Wickens, C. (2016). otree—an open-source platform for laboratory, online, and field experiments. *Journal of Behavioral and Experimental Finance*, 9:88–97.

Chen, M. K. and Risen, J. L. (2010). How choice affects and reflects preferences: revisiting the free-choice paradigm. *Journal of Personality and Social Psychology*, 99(4):573.

Chen, Y. and Yao, S. (2017). Sequential search with refinement: Model and application with click-stream data. *Management Science*, 63(12):4345–4365.

Cisek, P. (2007). Cortical mechanisms of action selection: the affordance competition hypothesis. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 362(1485):1585–1599.

Cisek, P. and Kalaska, J. F. (2005). Neural correlates of reaching decisions in dorsal premotor cortex: specification of multiple direction choices and final selection of action. *Neuron*, 45(5):801–814.

Cisek, P. and Kalaska, J. F. (2010). Neural mechanisms for interacting with a world full of action choices. *Annual Review of Neuroscience*, 33(1):269–298.

Clithero, J. A. (2018). Response times in economics: Looking through the lens of sequential sampling models. *Journal of Economic Psychology*, 69:61–86.

Dale, R., Roche, J., Snyder, K., and McCall, R. (2008). Exploring action dynamics as an index of paired-associate learning. *Plos One*, 3(3):e1728.

Desimone, R. and Duncan, J. (1995). Neural mechanisms of selective visual attention. *Annual Review of Neuroscience*, 18(1):193–222.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J., and Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, 9(3):522–550.

Dotan, D., Meyniel, F., and Dehaene, S. (2018). On-line confidence monitoring during decision making. *Cognition*, 171:112–121.

Dotan, D., Pinheiro-Chagas, P., Al Roumi, F., and Dehaene, S. (2019). Track it to crack it: dissecting processing stages with finger tracking. *Trends in Cognitive Sciences*, 23(12):1058–1070.

Drugowitsch, J., Moreno-Bote, R., Churchland, A. K., Shadlen, M. N., and Pouget, A. (2012). The cost of accumulating evidence in perceptual decision making. *Journal of Neuroscience*, 32(11):3612–3628.

Enax, L., Krajbich, I., and Weber, B. (2016). Salient nutrition labels increase the integration of health attributes in food decision-making. *Judgment and Decision making*, 11(5):460–471.

Fengler, A., Bera, K., Omar, A., and Frank, M. (2025). Hssm: A generalized toolbox for hierarchical bayesian estimation of computational models in cognitive neuroscience. in preparation.

Fisher, G. (2017). An attentional drift diffusion model over binary-attribute choice. *Cognition*, 168:34–45.

Fisher, G. (2021). A multiattribute attentional drift diffusion model. *Organizational Behavior and Human Decision Processes*, 165:167–182.

Fisher, G. (2023). Measuring the factors influencing purchasing decisions: Evidence from cursor tracking and cognitive modeling. *Management Science*, 69(8):4558–4578.

Fisher, G. (2025). Triangulating decision-making via choices, eye fixations, and reaching trajectories. *Organizational Behavior and Human Decision Processes*, 189:104421.

Freeman, J. B. (2018). Doing psychological science by hand. *Current Directions in Psychological Science*, 27(5):315–323.

Freeman, J. B. and Ambady, N. (2010). Mousetracker: Software for studying real-time mental processing using a computer mouse-tracking method. *Behavior Research Methods*, 42(1):226–241.

Freeman, J. B., Ambady, N., Rule, N. O., and Johnson, K. L. (2008). Will a category cue attract you? motor output reveals dynamic competition across person construal. *Journal of Experimental Psychology: General*, 137(4):673.

Freeman, J. B., Dale, R., and Farmer, T. A. (2011). Hand in motion reveals mind in motion. *Frontiers in Psychology*, 2:59.

Frydman, C. and Nave, G. (2017). Extrapolative beliefs in perceptual and economic decisions: Evidence of a common mechanism. *Management Science*, 63(7):2340–2352.

Fudenberg, D., Strack, P., and Strzalecki, T. (2018). Speed, accuracy, and the optimal timing of choices. *American Economic Review*, 108(12):3651–3684.

Gallivan, J. P., Chapman, C. S., Wolpert, D. M., and Flanagan, J. R. (2018). Decision-making in sensorimotor control. *Nature Reviews Neuroscience*, 19(9):519–534.

Gallivan, J. P., Stewart, B. M., Baugh, L. A., Wolpert, D. M., and Flanagan, J. R. (2017). Rapid automatic motor encoding of competing reach options. *Cell Reports*, 18(7):1619–1626.

Gelman, A. and Rubin, D. B. (1992). Inference from iterative simulation using multiple sequences. *Statistical Science*, 7(4):457–472.

Gibson, J. J. (1986). *The Ecological Approach to Visual Perception*. Lawrence Erlbaum Associates.

Glaholt, M. G., Wu, M.-C., and Reingold, E. M. (2009). Predicting preference from fixations. *PsychNology J.*, 7(2):141–158.

Glenberg, A. M. and Kaschak, M. P. (2002). Grounding language in action. *Psychonomic Bulletin & Review*, 9(3):558–565.

Gold, J. I. and Shadlen, M. N. (2007). The neural basis of decision making. *Annual Review of Neuroscience*, 30(1):535–574.

Gomez, P., Ratcliff, R., and Childers, R. (2015). Pointing, looking at, and pressing keys: A diffusion model account of response modality. *Journal of Experimental Psychology: Human Perception and Performance*, 41(6):1515.

Gordon, J., Maselli, A., Lancia, G. L., Thiery, T., Cisek, P., and Pezzulo, G. (2021). The road towards understanding embodied decisions. *Neuroscience & Biobehavioral Reviews*, 131:722–736.

Gossner, O., Steiner, J., and Stewart, C. (2021). Attention please! *Econometrica*, 89(4):1717–1751.

Gupta, S., Maple, C., Crispo, B., Raja, K., Yautsiukhin, A., and Martinelli, F. (2023). A survey of human-computer interaction (hci) & natural habits-based behavioural biometric modalities for user recognition schemes. *Pattern Recognition*, 139:109453.

Haggard, P. (2008). Human volition: towards a neuroscience of will. *Nature Reviews Neuroscience*, 9(12):934–946.

Haith, A. M., Huberdeau, D. M., and Krakauer, J. W. (2015). Hedging your bets: intermediate movements as optimal behavior in the context of an incomplete decision. *PLoS Computational Biology*, 11(3):e1004171.

Hauser, J. R. and Wernerfelt, B. (1990). An evaluation cost model of consideration sets. *Journal of Consumer Research*, 16(4):393–408.

Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., and Van de Weijer, J. (2011). *Eye tracking: A comprehensive guide to methods and measures*. Oxford University Press.

Hommel, B., Müsseler, J., Aschersleben, G., and Prinz, W. (2001). The theory of event coding (tec): A framework for perception and action planning. *Behavioral and Brain Sciences*, 24(5):849–878.

Khaw, M. W., Li, Z., and Woodford, M. (2018). Temporal discounting and search habits: evidence for a task-dependent relationship. *Frontiers in Psychology*, 9:2102.

Kim, H. E., Avraham, G., and Ivry, R. B. (2021). The psychology of reaching: action selection, movement implementation, and sensorimotor learning. *Annual Review of Psychology*, 72(1):61–95.

Konovalov, A. and Krajbich, I. (2016). Gaze data reveal distinct choice processes underlying model-based and model-free reinforcement learning. *Nature Communications*, 7(1):12438.

Koop, G. J. and Johnson, J. G. (2011). Response dynamics: A new window on the decision process. *Judgment and Decision Making*, 6(8):750–758.

Krajbich, I. (2019). Accounting for attention in sequential sampling models of decision making. *Current opinion in psychology*, 29:6–11.

Krajbich, I., Armel, C., and Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, 13(10):1292–1298.

Krajbich, I., Lu, D., Camerer, C., and Rangel, A. (2012). The attentional drift-diffusion model extends to simple purchasing decisions. *Frontiers in Psychology*, 3:23998.

Krajbich, I. and Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences*, 108(33):13852–13857.

Lakoff, G. and Johnson, M. (1980). *Metaphors We Live By*. University of Chicago press.

Lepora, N. F. and Pezzulo, G. (2015). Embodied choice: how action influences perceptual decision making. *PLoS Computational Biology*, 11(4):e1004110.

Lohse, G. L. and Johnson, E. J. (1996). A comparison of two process tracing methods for choice tasks. *Organizational Behavior and Human Decision Processes*, 68(1):28–43.

Lu, J. and Hutchinson, J. W. (2025). Information search within a web page: Modeling the full sequence of eye movement decisions, subjective value updating, and first clicks. *Management Science*, 71(3):2332–2359.

McKinstry, C., Dale, R., and Spivey, M. J. (2008). Action dynamics reveal parallel competition in decision making. *Psychological Science*, 19(1):22–24.

Milosavljevic, M., Malmaud, J., Huth, A., Koch, C., and Rangel, A. (2010). The drift diffusion model can account for the accuracy and reaction time of value-based choices under high and low time pressure. *Judgment and Decision making*, 5(6):437–449.

Molano-Mazón, M., Garcia-Duran, A., Pastor-Ciurana, J., Hernández-Navarro, L., Bektic, L., Lombardo, D., de la Rocha, J., and Hyafil, A. (2024). Rapid, systematic updating of movement by accumulated decision evidence. *Nature Communications*, 15(1):10583.

Myers, C. E., Interian, A., and Moustafa, A. A. (2022). A practical introduction to using the drift diffusion model of decision-making in cognitive psychology, neuroscience, and health sciences. *Frontiers in Psychology*, 13:1039172.

Orquin, J. L. and Loose, S. M. (2013). Attention and choice: A review on eye movements in decision making. *Acta psychologica*, 144(1):190–206.

Pärnamets, P., Johansson, P., Hall, L., Balkenius, C., Spivey, M. J., and Richardson, D. C. (2015).

Biasing moral decisions by exploiting the dynamics of eye gaze. *Proceedings of the National Academy of Sciences*, 112(13):4170–4175.

Pezzulo, G. and Cisek, P. (2016). Navigating the affordance landscape: feedback control as a process model of behavior and cognition. *Trends in cognitive sciences*, 20(6):414–424.

Philiastides, M. G. and Ratcliff, R. (2013). Influence of branding on preference-based decision making. *Psychological Science*, 24(7):1208–1215.

Prelec, D. (1998). The probability weighting function. *Econometrica*, pages 497–527.

Priorelli, M., Stoianov, I. P., and Pezzulo, G. (2025). Embodied decisions as active inference. *PLOS Computational Biology*, 21(6):e1013180.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, 85(2):59.

Ratcliff, R. and McKoon, G. (2008). The diffusion decision model: theory and data for two-choice decision tasks. *Neural Computation*, 20(4):873–922.

Ratcliff, R., Van Zandt, T., and McKoon, G. (1999). Connectionist and diffusion models of reaction time. *Psychological Review*, 106(2):261.

Resulaj, A., Kiani, R., Wolpert, D. M., and Shadlen, M. N. (2009). Changes of mind in decision-making. *Nature*, 461(7261):263–266.

Schoemann, M., O'Hora, D., Dale, R., and Scherbaum, S. (2021). Using mouse cursor tracking to investigate online cognition: Preserving methodological ingenuity while moving toward reproducible science. *Psychonomic Bulletin & Review*, 28(3):766–787.

Schotter, E. R., Gerety, C., and Rayner, K. (2012). Heuristics and criterion setting during selective encoding in visual decision making: Evidence from eye movements. *Visual Cognition*, 20(9):1110–1129.

Selen, L. P., Shadlen, M. N., and Wolpert, D. M. (2012). Deliberation in the motor system: reflex gains track evolving evidence leading to a decision. *Journal of Neuroscience*, 32(7):2276–2286.

Shadlen, M. N. and Kiani, R. (2013). Decision making as a window on cognition. *Neuron*, 80(3):791–806.

Shimojo, S., Simion, C., Shimojo, E., and Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature Neuroscience*, 6(12):1317–1322.

Smith, S. M. and Krajbich, I. (2018). Attention and choice across domains. *Journal of Experimental Psychology: General*, 147(12):1810.

Smith, S. M. and Krajbich, I. (2019). Gaze amplifies value in decision making. *Psychological Science*, 30(1):116–128.

Smith, S. M., Krajbich, I., and Webb, R. (2019). Estimating the dynamic role of attention via random utility. *Journal of the Economic Science Association*, 5(1):97–111.

Spivey, M. J. and Dale, R. (2006). Continuous dynamics in real-time cognition. *Current Directions in Psychological Science*, 15(5):207–211.

Spivey, M. J., Grosjean, M., and Knoblich, G. (2005). Continuous attraction toward phonological competitors. *Proceedings of the National Academy of Sciences*, 102(29):10393–10398.

Statista (2024). Share of mobile internet traffic in global regions 2024. Accessed 30 December 2024.

Stewart, B. M., Baugh, L. A., Gallivan, J. P., and Flanagan, J. R. (2013). Simultaneous encoding of the direction and orientation of potential targets during reach planning: evidence of multiple competing reach plans. *Journal of Neurophysiology*, 110(4):807–816.

Stillman, P. E., Krajbich, I., and Ferguson, M. J. (2020). Using dynamic monitoring of choices to predict and understand risk preferences. *Proceedings of the National Academy of Sciences*, 117(50):31738–31747.

Stillman, P. E., Shen, X., and Ferguson, M. J. (2018). How mouse-tracking can advance social cognitive theory. *Trends in Cognitive Sciences*, 22(6):531–543.

Stillman, P. E., Wilson, J. D., Kalkstein, D. A., and Ferguson, M. J. (2025). The temporal dynamics of self-control. *Proceedings of the National Academy of Sciences*, 122(45):e2501425122.

Sugrue, L. P., Corrado, G. S., and Newsome, W. T. (2005). Choosing the greater of two goods: neural currencies for valuation and decision making. *Nature Reviews Neuroscience*, 6(5):363–375.

Sullivan, N., Hutcherson, C., Harris, A., and Rangel, A. (2015). Dietary self-control is related to the speed with which attributes of healthfulness and tastiness are processed. *Psychological Science*, 26(2):122–134.

Symes, E., Ellis, R., and Tucker, M. (2007). Visual object affordances: Object orientation. *Acta Psychologica*, 124(2):238–255.

Tavares, G., Perona, P., and Rangel, A. (2017). The attentional drift diffusion model of simple perceptual decision-making. *Frontiers in Neuroscience*, 11:468.

Thomas, A. W., Molter, F., Krajbich, I., Heekeren, H. R., and Mohr, P. N. (2019). Gaze bias differences capture individual choice behaviour. *Nature Human Behaviour*, 3(6):625–635.

Todorov, E. and Jordan, M. I. (2002). Optimal feedback control as a theory of motor coordination. *Nature Neuroscience*, 5(11):1226–1235.

Trella, A. L., Zhang, K. W., Nahum-Shani, I., Shetty, V., Doshi-Velez, F., and Murphy, S. A. (2022). Designing reinforcement learning algorithms for digital interventions: pre-implementation guidelines. *Algorithms*, 15(8):255.

Tucker, M. and Ellis, R. (1998). On the relations between seen objects and components of potential actions. *Journal of Experimental Psychology: Human Perception and Performance*, 24(3):830.

van Den Berg, R., Anandalingam, K., Zylberberg, A., Kiani, R., Shadlen, M. N., and Wolpert, D. M. (2016). A common mechanism underlies changes of mind about decisions and confidence. *elife*, 5:e12192.

W3 Consortium (2015). Mobile accessibility: How wcag 2.0 and other w3c/wai guidelines apply to mobile. Retrieved from `http://www.w3.org/TR/mobile-accessibility-mapping/`.

Wang, S., Cheah, J.-H., and Lim, X.-J. (2023). Online shopping cart abandonment: A review and research agenda. *International Journal of Consumer Studies*, 47(2):453–473.

Webb, R. (2019). The (neural) dynamics of stochastic choice. *Management Science*, 65(1):230–255.

Wispinski, N. J., Gallivan, J. P., and Chapman, C. S. (2020). Models, movements, and minds: bridging the gap between decision making and action. *Annals of the New York Academy of Sciences*, 1464(1):30–51.

Woodford, M. (2014). Stochastic choice: An optimizing neuroeconomic model. *American Economic Review*, 104(5):495–500.

Xiang Chiong, K., Shum, M., Webb, R., and Chen, R. (2024). Combining choice and response time data: A drift-diffusion model of mobile advertisements. *Management Science*, 70(2):1238–1257.

Yang, X. and Krajbich, I. (2023). A dynamic computational model of gaze and choice in multi-attribute decisions. *Psychological Review*, 130(1):52.

Zilker, V. (2022). Stronger attentional biases can be linked to higher reward rate in preferential choice. *Cognition*, 225:105095.

Zuk, A. A. O., Bertrand, J. K., and Chapman, C. S. (2025). Continuous measures of decision-difficulty captured remotely: Mouse-tracking sensitivity extends to tablets and smartphones. *Computers in Human Behavior*, 162:108450.