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Attention Trajectories Predict Brand Choice

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ABSTRACT

Trajectories of attention during a complex brand choice task reflect the accumulation of utility and predict final choice before consumers implement it. Our findings reveal a "double attention lift" of the ultimately chosen brand towards the end of the choice task: it receives more attention than other brands do, and more of that attention is devoted to integrating information about the brand rather than to comparing it with other brands. Attention trajectories predict 85% of brand choices correctly out-of-sample, and 52% one period (29 secs.) before consumers reveal their brand choice. Attention during the choice task reflects sources of utility over and above those from brand ownership and knowledge effects. These results are obtained from a new multivariate attention-and-choice model, using K-fold Cross-Validation, and data from a large scale eye-tracking experiment among 325 regular consumers. The findings support notions from rational inattention theory, reveal the tight, potentially neurological, link between attention and utility accumulation, and have implications for consumer choice theory and managerial practice.

Keywords: Attention and Brand Choice, Complex Decision-Making, Utility Accumulation, Eye-Tracking, K-fold Cross-Validation.

Consumers make complex choices in information-rich environments, such as when choosing between different housing options, holiday destinations, household appliances, or smartphones. Even when all information is simultaneously available at a single location, such as a comparison website, consumers' limited attentional capacity prevents them from carefully devoting full attention to each of the choice options (Lohse and Johnson 1996; Shi, Wedel, and Pieters 2013; Willemsen, Böckenholt, and Johnson 2011). Early on, Simon (1971, pp. 40-41) expressed the challenge that consumers in an information-rich world face as follows "… the wealth of information means a dearth of something else: a scarcity of whatever it is that information consumes. What information consumes is rather obvious: it consumes the attention of its recipients. Hence a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it." Based on this notion of scarcity and costliness of attention, Rational Inattention (RI) theories (Gabaix 2019; Matějka and McKay 2015) posit that it is in the consumers' best interest to process the information and choice options that they find useful and ignore or pay less attention to those that seem less worth the effort. This implies a positive association between the attention that consumers devote to the options in a choice set and the choice likelihood of the options. There is indeed evidence for such a positive association (Atalay, Bodur, and Rasolofoarison 2012; Chandon et al. 2009; Krajbich et al. 2012; Pieters and Warlop 1999), presented in detail later. There is also evidence that consumers' attention during choice tasks, as measured by eye-movements, reflects key cognitive processes that consumers engage in prior to expressing their choice (Al-Moteri et al. 2017; Arieli, Ben-Ami, and Rubinstein 2011; Russo and Rosen 1975; Lohse and Johnson 1996). Moreover, accounting for the attention that consumers devote to specific attributes during repeated conjoint choice tasks has been shown to improve preference measurement (Meißner, Musalem, and Huber 2016; Yang, Toubia, and de Jong 2015).

Yet, what is still largely unknown is how eye-movements, attention, and the utility of brands during choice are linked. Specifically, three key questions are (1) how do *trajectories* of attention to each of the brands during the choice task contribute to the accumulation of utility and final choice, (2) which fundamental attention *processes* contribute to the accumulation of utility and brand choice, and (3) can trajectories of attention *predict* brand choice before it is made. Answering these questions is one step towards understanding the fundamental and possibly neurological links between attention, utility, and choice (Manohar and Husain 2013), and towards the more realistic, descriptive consumer choice theories that have been called for (Stüttgen, Boatwright, and Monroe 2012; Willemsen, Böckenholt, and Johnson 2011). The as-yet untapped potential of using eye-movement recording as a gateway to fundamental utility accumulation processes, as pointed out by Gabaix (2019, p. 328), is increasingly recognized in industry as well, as illustrated by the acquisition of manufacturers of eye-tracking hardware and software, such as SensoMotoric Instruments by Apple, EyeTribe by Facebook, and Eyefluence by Alphabet.

The present research follows up on this. Based on RI, we propose that trajectories of attention during a complex choice task, the accumulation of utility for each of the choice options, and final choice, are closely aligned. To address the questions and specific hypotheses to be derived, we conducted an eye-tracking experiment with a representative sample of 325 regular consumers across the continental US who made a complex choice for one of five brands of smartphones on a realistic comparison website. We estimate a new attention-and-choice model that describes the relationship between consumers' eye-movements during the choice task, trajectories of attention to each of the brands, utility and final brand choice. We refrain from making causal claims and emphasize the ability of attention trajectories to predict brand utility and choice.

We use new K-fold Cross Validation (CV) methodology to make out-of-sample and out-of-period predictions about brand choice based on attention from earlier periods during the choice task. We find that attention trajectories already mark the ultimate brand choice well before consumers implement their choice. In fact, the model correctly predicts brand choice of 52% of consumers one quarter of the time before (29 secs.), and 85% after the final quarter that they expressed their choice. Moreover, attention trajectories after the first quarter of the task already correctly predict brand choice for 92% of the consumers who chose a device of the brand they currently own (from now on referred to as “loyal”). This reveals a much earlier attention lift for the chosen brand than what has been reported before. The tight links between eye-movements, attention, and brand utility during the choice task are robust to differences in amount of information provided in the task and the time it took consumers to reveal their brand choice. The next section presents our theory and predictions. Then we describe the data, model, and the estimation and cross-validation results. The final section offers implications of the findings for consumer choice theory and marketing practice.

THEORY

Consumers move their eyes to inspect alternatives and their features when deciding which alternative to choose from a visual display such as a comparison website. These eye-movements comprise fixations and saccades. During a fixation, the eye is relative still (for about 200-400 msec.) and the gaze is directed to a specific location in the display to acquire information from it. Because visual acuity rapidly drops-off with increasing distance from the center of the gaze, people need to move their eyes to acquire information from different locations in the visual display. During such eye saccades, the gaze is rapidly redirected (20-50 msec.), while vision is actively suppressed to prevent blurring (Hutton 2008).

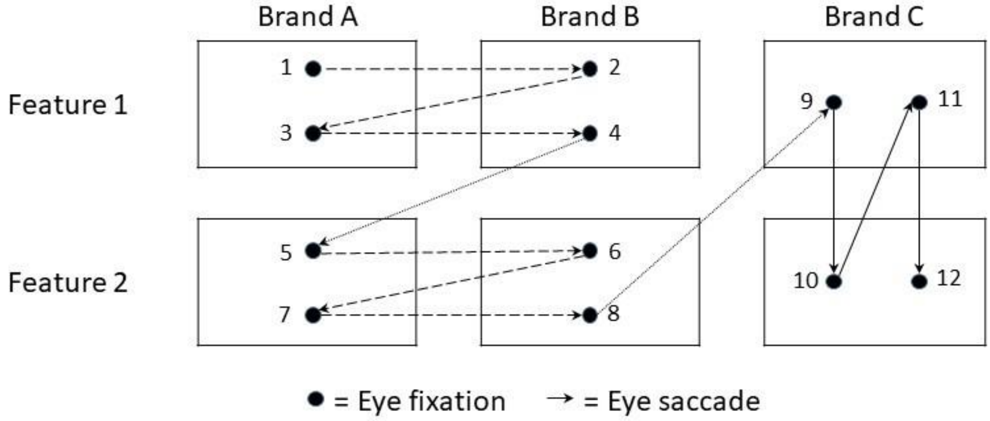
From a literature search, we identified 21 publications with 27 separate studies in which choice or consideration of consumer products, brands, or gambles were the dependent variable, and eye-movements were explanatory variables (Web Appendix A). We refer to these as “attention and choice” studies.

Eye-Movements and Attention

Eye-movements of consumers during choice tasks are overt, observed measures of the covert, latent attention processes that are fundamentally unobservable and that take place during these tasks (Glaholt and Reingold 2011; Orquin and Loose 2013). An eye fixation indicates with some measurement error (Hutton 2008; Reichle and Drieghe 2015) whether or not attention has been devoted to a specific location (*x,y* coordinates) or larger area-of-interest (AOI) in a visual display, such as a brand. The frequency of eye fixations reflects the quantity of attention for the brand, which contains information about the utility and choice probability of the brand (Orquin and Loose 2013; Pieters and Warlop 1999; Theeuwes and Belopolsky 2012). All 27 attention and choice studies examined eye fixations during choice, and seven studies also used eye saccades (Table A1, column G). Consistent with RI theory (Gabaix 2019; Matějka and McKay 2015), the chosen brand (option) received more attention than the non-chosen brands (column H).

Eye saccades during a choice task reflect specific types of attention to brands, which are not reflected in eye fixations. Figure 1 presents this idea. It shows a hypothetical pattern of eye-movements of a single person across a visual display with three brands (A to C) each with two features (1 and 2). Three fundamental types of eye saccades are (a) between different features of the same brand, labelled “within-brand saccades”, (b) between the same feature of two different brands, labeled “between-brand saccades”, and (c) between different features of different brands, labelled “other saccades.” In Figure 1, the saccade between fixations 11 and 12 is within brand C, the saccade between fixations 1 and 2 is between brands A and B, and the saccade between fixations 8 and 9 is from the “other” category.

FIGURE 1
EYE MOVEMENTS AND ATTENTION TRAJECTORIES DURING BRAND CHOICE



Measure	Brand A	Brand B	Brand C
Eye fixations:		Attention Quantity	
Sum	4	4	4
Eye fixations:		Attention Trajectory	
Quarter 1	2	1	0
Quarter 2	1	2	0
Quarter 3	1	1	1
Quarter 4	0	0	3
Eye saccades:		Attention Type	
Between-brand	4	2	0
Within-brand	0	0	3
Other	0	2	0

Patterns of observed within-brand and between-brand saccades have been described variously as, within-alternative and within-attribute (Lohse and Johnson 1996; Russo and Rosen 1975), between-alternative transitions (Stewart, Hermens, and Matthews 2016), product-based and attribute-based processing (Noguchi and Stewart 2014; Shi, Wedel, and Pieters 2013) or holistic and component processing (Arieli, Ben-Ami, and Rubinstein 2011). The underlying covert states have been termed, respectively, foraging for value and foraging for information (Manohar and Husain 2013), value construction and value encoding (Willemsen, Böckenholt, and Johnson 2011), and overall evaluation and attribute comparison (Mantel and Kardes 1999). We refer to the two covert states as integration and comparison attention. Integration attention is reflected in within-brands saccades that support the integration of different pieces of information about a single brand into an overall evaluation (e.g., Noguchi and Stewart 2014; Willemsen, Böckenholt, and Johnson 2011). Comparison attention is reflected in between-brand saccades that support comparison of attribute information across brands.

Notably, the same quantity of attention, reflected in eye fixations, can be due to different types of attention, reflected in eye saccades. Figure 1 illustrates this. Saccades are assigned to the brand they originate from, where the decision to move the eye is made (Hutton 2008). Three brands in Figure 1 each receive four eye fixations. If only the quantity of attention would contribute to utility, the three brands would have the same choice likelihood. Yet, whereas brand A and B receive, respectively, 4 and 2 between-brand saccades which reflect comparison attention, brand C receives 3 within-brand saccades which reflect integration attention.

We propose that these types of attention contain unique information about the utility of brands, over and above the information in the mere quantity of attention. Comparison attention aims to reduce uncertainty about performance of brands vis-à-vis each other (Arieli, Ben-Ami, and Rubinstein 2011; Willemsen, Böckenholt, and Johnson 2011), which may contribute to the utility of the brands involved in the comparison relative to those that are not. Likewise, integration attention aims to assess whether the benefits and strengths of brands outweighs their costs and relative weaknesses, which may be a precursor of final choice (Manohar and Husain 2013). The "other attention" type mostly fulfills "logistical" functions such as shifting attention to new locations of the display (Shi, Wedel, and Pieters 2013) which is not expected to have a role in the accumulation of utility.

Attention and choice studies have not yet simultaneously accounted for fixations and saccades which impedes firm conclusions about their independent contribution to choice. Still, there is initial evidence about the value carried by eye saccades. For instance, Yang, Toubia, and de Jong (2015) found that accounting for saccadic length (distance between fixations on different information elements in the display as a measure of effort) improved model fit in a choice-based conjoint task. Pieters and Warlop (1999) observed that the numbers of saccades within and between six brands of shampoo each with three visual elements were associated with brand choice. Stewart, Hermens, and Matthews (2016) found that the numbers of saccades within and between two choice options each were associated with choice, and Noguchi and Stewart (2014) that saccades between options did.

Taken together, this provides evidence for the tight link between (time-aggregated) attention and utility (Gabaix 2019; Orquin and Loose 2013; Theeuwes and Belopolsky 2012) and invites an analysis of the link between attention trajectories and choice.

Attention Trajectories and Choice

Attention to each of the brands evolves over the time course of the choice task and these attention trajectories carry information about the utility and ultimate choice of the brands. Specifically, the ultimately chosen option tends to receive progressively more attention, as reflected in eye fixations, towards the moment that choice is made. For instance, the last eye fixation in repeated, simple choices for snacks, 2-attribute gambles, or financial payoffs is more likely to be on the chosen option (Krajbich, Armel, and Rangel 2010; Manohar and Husain 2013; Reutskaja et al. 2011). Schotter et al. (2010) reported that photographs looked at longer in the final 1.6 seconds of a repeated choice task were more likely to be chosen. Atalay, Bodur, and Rasolofoarison (2012) observed that the frequency of fixations on the ultimately chosen brand of vitamins and food-replacement bars rose in the final five seconds before choice. Such selective attention to the ultimately chosen brand is consistent with the notion of RI theory (Gabaix 2019; Matějka and McKay 2015) that people focus their scarce attentional resources on the emerging winner(s) rather than spread these equally. Such selective attention may itself activate cognitive and motivational processes that amplify the accumulation of utility for the ultimately chosen brand (Janiszewski, Kuo, and

Tavassoli 2013; Shimojo et al. 2003; Tavassoli 2008). Although attention and choice studies have emphasized speeded choices for simple products and gambles, we expect the findings to generalize to complex choices with extended decision time. We propose:

Hypothesis 1: Quantity of attention, reflected in eye fixations, for the ultimately chosen brand as compared to non-chosen brands accumulates faster towards making the choice and thus increases its choice likelihood.

Two questions that arise are: (1) how is the increased attention for the ultimately chosen brand distributed between integration attention (within-brand saccades) and comparison attention (between-brand saccades), and (2) do integration and comparison attention contribute similarly to brand choice. Identifying the contribution of various types of attention to brand choice has been identified as an important area for theory development and research (Krajbich, Armel, and Rangel 2010; Meißner, Musalem, and Huber 2016, p. 16), but is still largely uncharted. This is a challenging issue because the type of attention allocated over time may depend on various stimulus factors such as perceptual salience of the stimuli (Towal, Mormann, and Koch 2013), size of the choice set (Reutskaja et al. 2011), features of the choice display (Atalay, Bodur, and Rasolofoarison 2012; Shi, Wedel, and Pieters 2013; Yang, Toubia, and de Jong 2015), and person factors such as brand knowledge (Chandon et al. 2009) or product involvement (Pieters and Warlop 1999). Still there is reason to believe that the ultimately chosen brand receives progressively more integration attention towards the end of complex choice tasks (Table A1). Such increased integration attention marks the evaluation stage of decision making (Russo and Leclerc 1994; Willemsen, Böckenholt, and Johnson 2011) where within-brand saccades are deployed to form an overall evaluation of specific brands. Such integration of information into an overall evaluation is costly (Bettman, Luce, and Payne 1998, Table 2) and is done when the penalty of missing out is high (Gabaix 2019). Stewart, Hermens, and Matthews (2016) report that about 61% of eye saccades in their study were within gambles, and that this percentage tended to increase in the second half of the task (average task duration 2.8 secs.). Shi, Wedel, and Pieters (2013) found that toward the final moment of choice between four personal computers each with twelve features (average task duration 67 secs.), most participants were in an attention state reflected in within-brand saccades. We expect this to hold in particular for the chosen brand:

Hypothesis 2: Integration attention, reflected in within-brand saccades, for the ultimately chosen brand as compared to non-chosen brands accumulates faster towards making the choice and thus increases its choice likelihood.

Joint support for hypotheses 1 and 2 would imply that consumers devote progressively more attention (eye-fixations) to their ultimately chosen brand and that an increasing share of this goes to integration attention (within-brand saccades) as compared to non-chosen brands. It would reveal a "double attention lift" for the chosen brand, and an increased choice likelihood.

Attention Trajectories and Brand Ownership

Attention and choice studies have emphasized tasks were all brands (options) are new or prior choices are unaccounted for (Table A1). In practice, consumers may already own one or more brands from the choice set or buy them repeatedly in case of packaged goods. This raises the question if and how ownership and prior choices influences attention trajectories and choice.

If initial attention after the start of the choice task would be mostly exploratory (Russo and Leclerc 1994) or random (Reutskaja et al. 2011) and irrespective of stimulus factors such as salience (Towal, Mormann, and Koch 2013) or person factors such as brand ownership, brands would receive similar amounts of attention early on. There are several reasons to predict, instead, that attention after the start of a choice task is initially higher for the currently owned brand.

First, the history of experiences with the owned brand as compared to other brands will create rich, value-laden memory representations. These are likely to be in working memory at the onset of the choice task, activating attention to the owned brand (option) (Theeuwes and Belopolsky 2012), regardless of salience and current goals (Anderson 2016).

Second, the mere act of having selected an option may increase the choice likelihood of the selected option in subsequent tasks, irrespective of the option's attributes and perceptual fluency. Tavassoli (2008) proposes a theory, and Janiszewski, Kuo, and Tavassoli (2013) provide evidence from five studies that this "mere selection effect" is due to biased competition for attention, which is expected to amplify neural activation of the selected option and to inhibit activation of neglected options. Such amplified activation increases, among others, the likelihood of perceptual pop-out of the earlier selected object from a subsequent choice display.

Third, the owned brand is the status quo or endowment option which may increase attention to it and choice likelihood. In line with this, Query Theory (QT) (Johnson, Häubl, and Keinan 2007) proposes that the endowment effect arises because sellers tend to start the task to keep-or-sell an object with a memory query for aspects that support the status quo. Such queries inhibit subsequent queries for evidence against the status quo. Using eye-movement recording, Ashby et al. (2016) found that sellers as opposed to buyers of lottery tickets focused attention preferentially and early on the benefits of the lottery tickets, and that such early attention influenced their later monetary valuations of the tickets. Dean, Kıbrıs, and Masatlioglu (2017) derive the optimality of preferential attention to the status quo option under conditions of limited attention and complex choice tasks.

Indirect evidence for ownership effects on initial attention comes from findings that consumers who bought a brand of pain reliever or bar soap "occasionally or regularly" versus "not" were more likely to fixate the brand at least once, to re-fixate and choose it (Chandon et al. 2009). In fact, Reutskaja et al. (2011) found that even for choice of snacks (choice sets of 4, 9, and 16) within a fixed 3 seconds, early eye fixations were already partly driven by person characteristics such as prior liking ratings of the snacks. Taken together, this suggests an ownership effect on attention and choice likelihood after the start of the choice task:

Hypothesis 3: More attention (quantity and integration), reflected in brand fixations and within-brand saccades, is devoted to the currently owned brand as compared to other brands initially after the start of the choice task and thus increases its choice likelihood.

Joint support for hypotheses 1, 2, and 3 has additional implications for consumers who currently own a device with the same brand name as one of the choice options on display. These consumers are expected to allocate more attention to the owned brand early in the choice task (H3). In line with RI, they continue to inspect the currently owned brand if this is a likely choice option, and otherwise switch their attention towards other brands on display. At the same time, consumers are expected to allocate increasingly more attention (quantity and integration) to the ultimately chosen brand towards the end of the choice task (H1 and H2), regardless of whether the eventually chosen brand is the same as the one they own. This would suggest that stickiness in choices is, at least partly, accounted for by attention to the owned and chosen option and by inattention to alternatives (Steiner, Stewart, and Matějka 2017), and would imply that:

Hypothesis 4: Attention trajectories account for brand ownership effects on brand choice.

DATA

Background and Sample

The context of our study is an on-line product comparison situation in which consumers evaluate a set of smartphones and choose one. Choice of smartphones is complex due to the multiple brands and attributes, and frequent product introductions and innovations. Participants were presented with a side-by-side comparison of five devices as is common on many wireless carrier, retailer, and reviewer websites. The choice set was the Apple iPhone 5 (brand A), Samsung Galaxy Note II (brand B), Nokia Lumia 920 (brand C), HTC One (brand D), Motorola Droid Razr Maxx HD (brand E). These were the most common devices in online product reviews and the most recent versions of each brand at the time of data collection (2013). Participants were instructed to review the presented information and chose the device that they would be most likely to purchase.

Tobii Insight, a dedicated eye-tracking research firm, conducted sampling and data collection for the study (https://www.tobiipro.com/insight/). It drew a stratified sample of 460 consumers who had indicated to be in the market for a new smartphone, from large, locally representative participant pools, from three locations in the continental US: Washington DC, Cincinnati, and San Diego. Stratification ensured representation of four user groups in the sample: users of the two leading brands in the product category (29% brand A, and 24% brand B), owners of other brands (27%), and current non-device users (21%). Data collection took place in dedicated research areas in shopping centers in each of the three locations. Participants were excluded due to technical complications during eye tracking (n = 2), if they did not complete or provided inconsistent responses in a separate questionnaire (n = 28), if trackability was less than 60% (n = 91) and if they did not intend to purchase a new smartphone in the next 9 months (n = 14) (details in Web Appendix B). The final sample comprised 325 participants.

Fifty-one percent of the sample was female, 53% had a college or a graduate degree, 69% was between 18 and 49 years. Of the 325 participants, 24 preferred not to answer the household income question, and 40% of those who did had a household income up to 49,999 USD (Question wordings and response scales are in Web Appendix B). Average rated product category knowledge was 5.0 (SD = 1.4, on 7-point scales), and brand knowledge, respectively, for brand A was 4.7 (SD = 1.8), for brand B was 4.1 (SD = 2.0), for brand C was 2.4 (SD = 1.6), for brand D was 2.9 (SD = 1.9), and brand E was 3.1 (SD = 1.8). Seventy-two percent of the sample (233 of 325) currently owned a device of one of the five brands in the choice set, respectively 93 owned brand A, 77 owned brand B, 2 owned brand C, 39 owned brand D, and 22 owned brand E. On average, participants indicated a 74% likelihood (0 to 100% scale) of purchasing a new device in the category in the next nine months. Participants received $50 to cover costs of commuting to one of the data collection facilities and volunteering their time.

Design and Stimuli

Participants were randomly assigned to one of three information conditions, varying in amount of information provided. These conditions were used to assess the robustness of the relationship between attention trajectories and brand choice across these. Final *n*s are 107 in the low (coded as -1), 115 in the medium (coded as 0), and 103 in the high information condition (coded as 1). Information conditions varied in the number of device features for each of the five brands on the computer screens (18 in low, 29 in medium, and 39 in high). Our low information condition still has more information elements than what is common in attention and choice studies (e.g., 6 brands and 3 features: Pieters and Warlop (1999); 3 brands and 6 features: Meißner, Musalem, and Huber (2016); 4 brands and 12 features: Shi, Wedel, and Pieters (2013); Web Appendix A, Table A1). Devices (brands) were shown in the columns and features in the rows of the display, with the device name/model, colors, and the price always displayed at the top of the page, as common in practice. Column position of the brands in the display was randomly sampled from five different column-order sequences, for each information condition (Web Appendix B, Figures B1 – B3 have sample stimuli for the three information conditions).

Eye-Movements and Brand Choice

Eye-movement recording was done for both eyes with Tobii 60XL infra-red eye-trackers integrated in 24 inch computer monitors (screen resolution: 1920 x 1200 pixels) on which the choice displays were shown, using a sampling rate of 60 Hz, with a typical accuracy of 0.5 degrees of visual angle. Participants were free to move their head in a virtual box of 44 cm width × 22 cm height.

Eye movements reflect attention with some measurement error. Measurement error may arise from dissociations between covert attention and overt eye movements in time and space (Hutton 2008), errors of the neural system in directing the eye to the intended location (Reichle and Drieghe 2015), and recording and processing of raw eye samples into fixations and saccades (van der Lans, Wedel, and Pieters 2011). We account for measurement error in three ways. First, we use the binocular individual threshold (BIT) algorithm (van der Lans, Wedel, and Pieters 2011) as in Yang, Toubia, and de Jong (2015). BIT identifies x,y fixation locations from the raw eye-movement recordings from both eyes and accounts for individual and stimulus differences in fixation thresholds. Second, we aggregate eye-movements into larger areas-of-interest (AOIs) than their exact x,y location, as other attention and choice studies (Web Appendix A, Table A1). We refer to these as brand (option) fixations, and within- and between-brand saccades as in Manohar and Husain (2013) and Pieters and Warlop (1999). Third, we decompose overt eye-movements that consumers make for each of the brands into covert attention and measurement error (Shi, Wedel, and Pieters (2013), as described in the Model section. Further, the sequence of eye fixations until choice is divided into four equal time bins for each participant, labelled Quarters 1 to 4. These periods cover, but are not equivalent to, stages of exploration (Q1), evaluation (Q2 and Q3), and verification and choice (Q4) (Russo and Leclerc 1994; Willemsen, Böckenholt, and Johnson 2011).

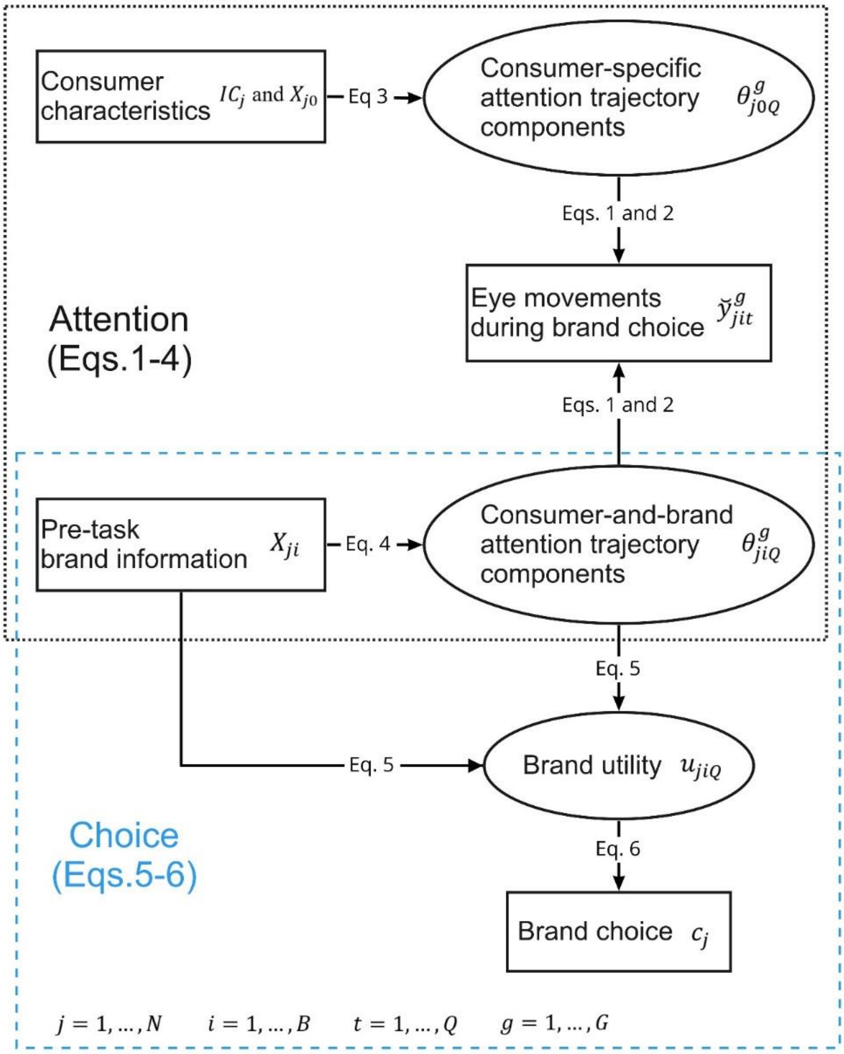
Choice shares were 25%, 28%, 8%, 22%, and 17% for, respectively, brands A to E. On average, participants inspected the information in the display for 116 seconds (SD = 95) before making their choice. As expected, information condition influenced the total time that participants took to make a choice ($F(2, 322) = 6.78$, $p = .001$, Cohen's $d = .29$), respectively 92 seconds (SD = 61) in the low information condition, 115 seconds (SD = 86) in the medium information condition, and 140 seconds (SD = 124) in the high information condition. User segments also differed in the total time they took to make a choice ($F(3, 321) = 4.58$, $p = .004$, $d = .34$), respectively 115 seconds (SD = 89) in the brand A segment, 97 seconds (SD = 84) in the brand B segment, 105 seconds (SD = 61) in the other brand segment, and 151 seconds (SD = 137) in the non-smartphone segment. The interaction between information condition and user segment was not statistically significant ($F < 1$). With 325 participants, 5 brands, 4 time periods, and 4 eye-movement measures, the dataset contains 26,000 eye-movement data points.

MODEL

We develop a multivariate attention and choice model to test our predictions. The model specifies that observable, overt eye-movements that consumers use to sample information from visual choice displays reflect unobservable, covert consumer-and-brand specific attention trajectories closely related to the accumulation of utility for each of the options on display. It is part of a broader effort to describe choice behavior and utility accumulation when the determinant processes are intrinsically unobservable (Gabaix 2019). The model is akin to but extends sequential sampling models (SSM) (Forstmann, Ratcliff, and Wagenmakers 2016; Otter et al. 2008) such as aDDM (Krajbich et al. 2012), which have been successfully used, among others, to describe repeated, simple, fast, binary or trinary decisions (see Mormann and Russo (2021) for a critical evaluation). The model goes beyond this by (a) simultaneously estimating covert attention trajectories for each of G types of observed eye-movements (here: four) for each of B choice options (here: five) and (b) using components of these trajectories to make out-of-sample and out-of-period brand choice predictions (using K-fold cross-validation), for (c) a single, complex, extended brand choice.

The model comprises an attention and a utility part, described next. Figure 2 summarizes its structure.

FIGURE 2
ATTENTION-AND-CHOICE MODEL



Attention Trajectories

The attention part links observed, overt eye-movements to covert attention (upper dotted box in Figure 2). It specifies that covert attention (η^g_{jiQ}) to brand i is reflected in observed eye-movements ($\breve{y}^g_{jit}$) that consumer j makes from the start of the choice task ($t = 1$) until brand choice is expressed ($t = Q$). Superscript g indicates the type of observable eye-movements ($\breve{y}^g_{jit}$), namely brand fixations ($g = 1$), within-brand saccades ($g = 2$), between-brand saccades ($g = 3$), and other saccades ($g = 4$). Eye-movements are natural-log transformed to normalize their distribution (Noguchi and Stewart 2014), after adding 1 to accommodate zero frequencies: $y^g_{jit} = ln(\breve{y}^g_{jit} + 1)$.

We use a multivariate latent trajectory specification (Meredith and Tisak 1990; Muthén 1997) to link observed eye-movements to covert attention:

(1) $$y^g_{jit} = \sum_{k=0}^{K_0-1} \eta^g_{jikQ}(x_t)^k + \epsilon^g_{j0t} + \epsilon^g_{jit}$$

(2) $$\eta^g_{jikQ} = \theta^g_{j0kQ} + \theta^g_{jikQ}$$

The parameter η reflects the tight, neurological link between eye movements and attention (Corbetta et al. 1998) and unobserved heterogeneity (ϵ) reflects that the link is not fully deterministic (Belopolsky and Theeuwes 2009) and contains various sources of measurement error (van der Lans, Wedel, and Pieters 2011).

Eq. 1 specifies that the sequence between $t = 1$ and $t = Q$ of observed eye-movements g is the weighted sum of three components of a latent attention trajectory, respectively, the initial level (η^g_{ji0Q}), linear change (η^g_{ji1Q}) and quadratic change (η^g_{ji2Q}), and time-varying unobserved heterogeneity for consumers (ϵ^g_{j0t}), and consumers and brands (ϵ^g_{jit}). Weights (time-scores) are specified as: $x_t = t - 1$, for all consumers ($j = 1, \dots, N$) and brands ($i = 1, \dots, B$).

Eq. 2 decomposes each attention trajectory component k for each eye-movement measure g into (a) consumer-specific attention (θ^g_{j0kQ}) which varies between consumers but is stable across brands, and (b) consumer-and-brand-specific attention (θ^g_{jikQ}) which varies between brands and consumers and which is of prime interest to predict brand choice.

Determinants of Attention Trajectories

Consumer characteristics (IC_j and X_{j0}) impact consumer-specific attention trajectory components (top-left of Figure 2):

(3) $$\theta_{j0kQ}^{g} = \gamma_{11k}^{g} + \gamma_{12k}^{g} IC_j + \sum_{l=3}^{K_1} \gamma_{1l}^{g} X_{j0l} + r_{j0k}^{g}$$

Eq. 3 specifies that consumer-specific attention trajectories (θ_{j0kQ}^{g}) are a function of a consumer-invariant attention trajectory (γ_{11k}^{g}), the manipulated information condition (IC_j) and other measured consumer characteristics (X_{j0}), respectively, current product ownership, product knowledge, gender, age, education, and income (coding in Web Appendix B and Data), and consumer-specific unobserved heterogeneity (r_{j0k}^{g}). Equation 3 ensures that the brand-and-consumer attention trajectories of key interest are comparable across experimental conditions and individual differences.

Pre-task information specific to consumer j and brand i impacts the consumer-and-brand attention trajectory components (middle left in Figure 2):

(4) $$\theta_{jikQ}^{g} = \sum_{h=1}^{K_2} \gamma_{2hk}^{g} X_{jih} + r_{jik}^{g}$$

Eq. 4 specifies that consumer-and-brand attention trajectories (θ_{jikQ}^{g}) are a function of brand and consumer characteristics (X_{ji} is a $1 \times K_2$ vector). These include: market-level brand preferences which are constant across consumers ($\sum_{l=1}^{4} \gamma_{2lk}^{g} BP_{il}$), brand column position in the choice display ($\sum_{l=1}^{4} \gamma_{2,l+4,k}^{g} BC_{jil}$), brand knowledge ($\gamma_{29k}^{g} BK_{ji}$), brand ownership ($\gamma_{2,10,k}^{g} BO_{ji}$), and brand-specific heterogeneity r_{jik}^{g}. Market-level brand preferences are captured by four fixed-effect dummy variables, with $BP_{il} = 1$ when $i = l + 1$ and 0 otherwise. Brand column position (BC_{jil}) is 1 if brand i for consumer j is in column l of the choice display and 0 otherwise. Brand ownership BO_{ji} indicates whether consumer j currently owns brand i (1 = yes, 0 = no), and brand knowledge coded as in the Data section. Heterogeneities in attention trajectories and eye-movement measures are assumed normally distributed with mean zero, and uncorrelated between the brand and consumer-levels. Eye-movements are allowed to correlate within each time period, and components of attention trajectories are allowed to correlate at the consumer and consumer-and-brand level. From our decomposition, the attention trajectories for each brand (eq. 4) can be directly related to brand utility and choice.

Accumulation of Utility

The utility part of the model (lower dashed box in Figure 2) links covert attention (θ^g_{jikQ}, eq. 4) to brand utility, while accounting for pre-task information (X_{ji}):

(5) $$u_{jiQ} = \sum_{g=1}^{4} \sum_{k=0}^{2} \beta_k^g \theta_{jikQ}^g + \sum_{h=1}^{K_2} \alpha_h X_{jih} + \varepsilon_{jiQ}$$

Eq. 5 specifies two sources of brand utility (u_{jiQ}) that contribute to the choice that consumer j expresses at time Q. The first source ($\beta_k^g \theta_{jikQ}^g$) reflects the tight link between attention and utility (Gabaix 2019; Orquin and Loose 2013; Theeuwes and Belopolsky 2012). Superscript g indicates that utility weights are potentially heterogeneous across attention types (Pieters and Warlop 1999). Subscript k indicates that the contribution of attention to utility is allowed to vary across the time course of the task. Specifically, the weight of initial attention (when $k = 0$, θ_{ji0Q}^g) on brand utility is captured by β_0^g, while the weight of attention reflected by eye movements later in the choice task is captured by β_1^g and β_2^g (corresponding to linear and quadratic attention trajectory components). The second source ($\alpha_h X_{jih}$) of brand utility is independent of attention during the task and accounts for intrinsic market-level brand preferences ($\sum_{l=1}^{4} \alpha_l BP_{il}$), position of the brand in the choice display ($\sum_{l=1}^{4} \alpha_{4+l} BC_{jil}$) (Atalay, Bodur, and Rasolofoarison 2012), knowledge effects ($\alpha_9 BK_{ji}$) (Chandon et al. 2009; Matějka and McKay 2015), and brand ownership effects ($\alpha_{10} BO_{ji}$). X_{ji} components (BP_{il}, BC_{jil}, BK_{ji}, and BO_{ji} are the same as in eq. 4). In eq. 5, ε_{jiQ} captures unobserved, exogenous utility shocks assumed to follow a logistic distribution, which gives a conditional logit formulation (McFadden 1973) for the probability $p(c_{jQ} = i)$ that consumer j chooses brand i from a set of B brands at time Q:

(6) $$p\left(c_{jQ} = i \middle| \alpha, \beta\right) = \frac{exp\,(u_{jiQ})}{\sum_{l=1}^{B} exp(u_{jlQ})}$$

Brand utilities are revealed by the choice (c_{jQ}) that participant j makes at moment Q. This means that the contributions (α and β) of the different sources of utility can only be estimated after observing the full sequence of eye-movements during the choice task ($t = 1, \dots, Q$). Assuming that the contributions to brand utility of attention trajectories (β) and other sources of utility that are independent of attention (α) are stable during the choice task, the only source of brand utility that varies over time is attention. This implies that the utility accumulated by brand i up to moment q (u_{jiq}) is a function of (θ_{jikq}^{g}) trajectories that capture the attention reflected by eye -movements (y_{jit}^{g}) observed from the start of the choice task until the current moment q ($t = 1, \dots, q$). Therefore, and importantly, trajectories θ_{jikq}^{g} do not rely on eye-movements that have not been observed yet, and that will only be observed in the future ($t = q + 1, \dots, Q$). In this way, the model affords inferences about brand utility before consumers reveal their choice.

Whereas causal relationships between eye-movements and attention (Belopolsky and Theeuwes 2009) and attention and utility (Theeuwes and Belopolsky 2012; Towal, Mormann, and Koch 2013) are fundamentally bidirectional and emergent (Mormann and Russo 2021), the proposed model rests on their predictive relations only. It uses eye-movements (G) observed in the course of a single, complex choice task ($t = 1, \dots, Q$) to infer components of latent attention trajectories ($k = 0, .., 2$) for each of B brands and uses those to predict brand choice, while accounting for other stimulus and person characteristics that might influence attention trajectories, brand choice or both.

Estimation and Validation

Let $\Gamma \equiv [\alpha, \beta, \eta, \gamma, \Sigma, \Psi]$ denote all parameters of the proposed model: utility weights (α, β), attention trajectories (η), brand- and consumer-level effects (γ), and variances of the unobserved heterogeneities in eye-movements (Ψ) and attention trajectories (Σ). We implement the model in RStan (Stan Development Team 2020) and assess convergence with a rank normalized measure of between- and within-chain variance (R-hat) (Vehtari et al. 2020). We report 95% Credible Intervals for parameter estimates and one-tailed Bayesian *p*-values (the smallest mass of the posterior distribution not including zero).

We use K-fold Cross-Validation (CV) to assess the model's out-of-sample predictive performance. This was originally developed in the machine learning and forecasting literatures (Browne 2000; Kuhn and Johnson 2013) to prevent overfitting and overoptimistic model performance when using the same data for model estimation (train, calibrate) and validation (test, predict), and to improve upon classic validation approaches that estimate and validate the model only once, which is often suboptimal (Steckel and Vanhonacker 1993). K-fold CV involves splitting the dataset into K folds, repeatedly (K-times) estimating the model on data from K-1 groups, validating it on observations in the Kth group, and aggregating the results across the folds.

We perform K-fold CV two times, using different splits of participants into folds. The first, random-split K-fold CV, randomly assigns participants into 10 approximately equal-sized groups (Kuhn and Johnson 2013; Marcot and Hanea 2020). The second, design-based K-fold CV, splits participants into 12 groups based on their information condition and user segment. This design-based CV puts the proposed model to a stronger test than random-split K-fold does. It predicts brand choice of participants in each of the 12 cells of the design from model estimates of the link between attention and choice in the other 11 cells. High model performance provides evidence of the robustness of the attention-choice link to important contextual and consumer variables. By assigning all observations for participant *j* to the same fold we ensure that both the random-split and design-based CVs meet the requirement of independence between estimation and validation samples (Varoquaux et al. 2017; Vehtari, Gelman, and Gabry 2017).

We predict the brand most likely to be chosen for each participant in the validation samples (out-of-sample) and in each of the four quarters, using information about eye-movements of that participant up to that quarter (out-of-period). Hit rates are percentages of participants predicted correctly out-of-sample and out-of-period, for each draw of the MCMC algorithm. Mean hit rates and 95% Bayesian Prediction Intervals (PIs) summarize the results (Hamada et al. 2004). We use these and the expected log predictive density (ELPD; larger values indicate better fit) (Vehtari, Gelman, and Gabry 2017) to assess model performance.

Web Appendix C and D provide details about model estimation and validation. Code to estimate all models (proposed and others), make brand choice predictions, and produce the tables and figures using a simulated dataset (Web Appendix I for more information) is available at https://github.com/*/attention_and_choice[1].

RESULTS

Table 1 has descriptive information about eye-movements during the choice task for the three experimental conditions, and for the chosen and non-chosen brands. To facilitate interpretation, it presents the shares of the three types of eye-saccades (sum to 1).

[1] GitHub username removed to preserve anonymity during the review process.

TABLE 1
EYE-MOVEMENTS DURING BRAND CHOICE

Eye Fixations and Shares of Saccades over Time	Information Condition: Low *M*	Low *SD*	Medium *M*	Medium *SD*	High *M*	High *SD*	Total *M*	Total *SD*	Choice-based: Chosen Brand *M*	Chosen Brand *SD*	Non-Chosen Brands *M*	Non-Chosen Brands *SD*
1st Quarter:												
Eye fixation frequency	57.23	38.22	73.91	53.38	90.20	82.87	73.58	61.79	16.99	17.96	14.15	16.52
Within-brand saccade share	.51	.32	.46	.30	.47	.29	.48	.30	.53	.30	.47	.30
Between-brand saccade share	.26	.29	.31	.28	.29	.25	.29	.28	.26	.26	.30	.28
Other saccade share	.23	.26	.23	.23	.24	.24	.23	.24	.21	.22	.24	.25
2nd Quarter:												
Eye fixation frequency	62.32	41.29	77.77	60.20	89.58	79.62	76.43	62.85	18.88	16.11	14.39	15.91
Within-brand saccade share	.46	.32	.41	.29	.39	.28	.42	.30	.50	.29	.39	.29
Between-brand saccade share	.31	.30	.33	.27	.36	.28	.33	.28	.29	.26	.35	.29
Other saccade share	.24	.25	.27	.24	.25	.23	.25	.24	.21	.21	.26	.25
3rd Quarter:												
Eye fixation frequency	62.59	39.70	75.24	57.54	90.17	77.20	75.81	60.67	22.56	20.83	13.31	15.00
Within-brand saccade share	.46	.31	.41	.30	.43	.29	.43	.30	.55	.27	.40	.30
Between-brand saccade share	.29	.30	.33	.30	.33	.27	.32	.29	.26	.24	.33	.30
Other saccade share	.25	.26	.26	.26	.24	.23	.25	.25	.19	.20	.27	.26
4th Quarter:												
Eye fixation frequency	66.91	44.52	82.11	60.71	95.82	80.43	81.45	64.17	36.01	27.17	11.36	14.17
Within-brand saccade share	.51	.33	.49	.31	.47	.30	.49	.31	.73	.19	.42	.31
Between-brand saccade share	.24	.28	.26	.27	.27	.26	.26	.27	.14	.15	.29	.29
Other saccade share	.25	.28	.25	.25	.26	.24	.25	.26	.13	.14	.29	.27
Total:												
Eye fixation frequency	249.05	16.38	309.04	228.02	365.77	313.86	307.27	244.8	94.43	69.86	53.21	51.58
Within-brand saccade share	.49	.24	.44	.23	.44	.21	.45	.23	.58	.19	.42	.23
Between-brand saccade share	.28	.20	.31	.21	.32	.19	.30	.20	.23	.14	.32	.21
Other saccade share	.24	.17	.25	.17	.25	.15	.24	.16	.18	.11	.26	.17
Task duration in seconds	92	61	115	86	140	124	116	95	--	--	--	--

Note – Total sample size for eye-fixation frequency is 325 across 5 brands (325 x 5 = 1625), with 107 (535) in low, 115 (575) in medium, and 103 (515) in the high information condition. For chosen brands *n* = 325, and for non-chosen brands *n* = 1300 (4 x 325). Average eye fixations frequency across 4 non-chosen brands shown.

Model Comparison

We compare performance of the proposed model with a naïve and three benchmark models (Table 2), using the results of the random-split K-fold CV. The naïve model (M0) assumes that information about market-level preferences and brand position in the choice display suffice to predict brand choice. The first benchmark (M1) adds brand ownership information. The second benchmark (M2) adds information about consumers' prior knowledge about each of the brands. The third benchmark (M3) assumes that over and above this information, which is known prior to the choice task ("pre-task brand information"), the accumulated sum of the eye-fixations to each of the brands up to the moment of choice predicts brand choice. It shares this assumption with sequential sampling models and studies that rely on time-aggregated eye movement data (Krajbich, Armel, and Rangel 2010; Noguchi and Stewart 2014; Pieters and Warlop 1999; Stewart, Hermens, and Matthews 2016). If this model were best, it would imply that trajectories of attention do not carry more information about brand utility than the accumulated sum of eye fixations does.

TABLE 2
MODEL SUMMARY

	Brand Choice Predictors						Random-Split K-fold CV		
	Market-level preferences,	Consumer Information							
Model	Display position	Brand Ownership	Brand Knowledge	Accumulated Eye-fixations	Attention Trajectories	# pars	ELPD	Hit Rate	95% PI
M0	x					8	-504	27%	[24; 31]
M1	x	x				9	-458	43%	[42; 45]
M2	x	x	x			10	-431	45%	[43; 47]
M3	x	x	x	x		11	-230	75%	[73; 77]
M4	x	x	x		x	22	-126	85%	[82; 87]

Note - # pars is number of model parameters. ELPD is Expected Log Predictive Density. Hit rate, with 95% Prediction Interval (PI) between brackets is percentage of participants for whom the model correctly predicts brand choice. Hit rate for random brand choice predictions is 20% (1 out of 5).

The proposed model (M4) outperforms the alternatives. It has the highest ELPD (-126) and highest hit rate (85%, with a 95% prediction interval (PI) from 82% to 87%). The 85% hit rate of the proposed model is impressive. It is 65 percentage points more than the 20% hit rate for random choice (1 out of 5 brands), 58 points more than the hit rate (27%) of the naïve model (M0), and 42 and 40 points more than the 43% and 45% hit rate of, respectively, the first (M1) and second (M2) benchmark which do not include observed eye movements or attention. It is also 10 percentage points more than the 75% hit rate of the third benchmark which relies on the cumulative sum of eye fixations.

Contribution of Attention Trajectories to Brand Choice

Table 3 gives the parameters estimates of the proposed model. Results for the second benchmark model (M2), which only contains pre-task information, are used as the baseline throughout. Estimates for the third benchmark (M3) are in Web Appendix E, Table E2.

In the baseline (M2), both brand ownership and knowledge predict brand choice (*p*s $< .001$). This reflects that consumers bring more knowledge to the table about the brand they eventually choose (M = 4.84, SD = 1.95) than about the other brands (M = 3.38, SD = 1.94, $F(1, 1163) = 104.9$, $p < .001$, $d = .60$), and that in addition to this, ownership predicts choice.

In support of the proposed model, the initial level of attention quantity (estimate is 6.68, $p < .001$), linear change (15.34, $p < .001$) and quadratic change (40.36, $p < .001$) for each brand contribute positively to predicting brand choice, over and above the information known prior to the choice task. This shows how the attention trajectory as a whole rather than just its final moments or end level align with brand utility. The significant, positive effect of the quadratic change supports **hypothesis 1** that a sharp rise towards the end of the task in the quantity of attention for a brand contributes positively to its utility and choice likelihood.

TABLE 3

ATTENTION TRAJECTORIES PREDICT BRAND CHOICE

Predictors		Estimate	p	2.5%	97.5%
		Baseline Model			
Brand B	α_1	.53	.002	.15	.92
Brand C	α_2	.21	.16	-.30	.74
Brand D	α_3	.83	<.001	.43	1.25
Brand E	α_4	.59	.002	.14	1.02
Column 1	α_5	.44	.01	.08	.83
Column 2	α_6	.33	.06	-.09	.75
Column 3	α_7	-.11	.52	-.54	.31
Column 4	α_8	.17	.16	-.25	.58
Brand knowledge	α_9	.38	<.001	.28	.49
Brand ownership	α_{10}	.90	<.001	.58	1.22
		Proposed Model			
Brand B	α_1	-.05	.71	-1.01	.88
Brand C	α_2	.09	.24	-.97	1.20
Brand D	α_3	1.20	.01	.16	2.29
Brand E	α_4	.15	.24	-.98	1.32
Column 1	α_5	-.93	.16	-3.07	1.24
Column 2	α_6	-1.09	.23	-3.50	1.40
Column 3	α_7	-.71	.37	-2.44	1.04
Column 4	α_8	-.38	.34	-1.91	1.18
Brand knowledge	α_9	.04	.53	-.19	.26
Brand ownership	α_{10}	.31	.40	-.41	1.05
Attention Quantity:					
Initial level	β_0^1	6.68	<.001	3.32	10.14
Linear change	β_1^1	15.34	<.001	11.20	19.69
Quadratic change	β_2^1	40.36	<.001	29.98	51.21
Attention Type:					
Integration:					
Initial level	β_0^2	-1.66	.27	-4.62	1.40
Linear change	β_1^2	4.08	.02	.38	8.11
Quadratic change	β_2^2	26.79	<.001	14.49	40.16
Comparison:					
Initial level	β_0^3	.38	.24	-3.57	4.28
Linear change	β_1^3	-.34	.69	-6.11	5.33
Quadratic change	β_2^3	-3.58	.53	-18.04	10.62
Other:					
Initial level	β_0^4	-1.18	.53	-6.12	3.81
Linear change	β_1^4	-1.53	.52	-7.76	4.65
Quadratic change	β_2^4	-2.92	.60	-20.00	13.81

Note – Brand fixed-effects relative to Brand A, and column effects relative to column 5. Baseline model is M2. 95% one-tailed Bayesian *p*-value, and 95% Credible Interval (CI) of parameter estimates.

Comparison attention, reflected in between-brand saccades, and other attention, reflected in between-brand saccades to different features, do not predict brand choice in this context (all *p*'s $\geq$ .24). Importantly, the quadratic change in integration attention, as reflected in within-brand saccades, is significant and positive (26.79, $p < .001$). This supports **hypothesis 2** that an increase in attention to integrate information about a brand towards the moment when choice is revealed increases the choice likelihood of that brand. Joint support for hypothesis 1 and 2 provides evidence for the "double attention lift" toward the ultimately chosen brand.

We use three pieces of evidence to support **hypothesis 4,** that attention trajectories account for brand ownership effects on brand choice. First, comparing the parameter estimates for M2 and M4 shows that whereas brand ownership significantly contributes to utility in the baseline model (.90, $p < .001$, Table 3), it no longer does so in the proposed model (.31, $p = .40$), which includes the contribution of attention trajectories to brand utilities. Second, the large difference in hit rates for M2 compared to M4 (45% vs 85%) implies that attention trajectories reflect sources of brand utility over and above those captured by brand ownership. Third, we test if attention trajectories not only reflect additional sources of brand utility, but also statistically account for sources of brand utility approximated by brand ownership, by comparing M4 against an additional follow-up model. This model (M6, Web Appendix E) contains only the attention trajectories and no "pre-task information". If brand ownership captured sources of brand utility that are not accounted for by consumer-and-brand specific attention trajectories, a model that excludes brand ownership and all other pre-task information variables (M6) would have a worse predictive performance compared to the proposed model. However, M4 and M6 have the same hit rate of 85% and overlapping PIs ([82; 87] and [83; 87], respectively). Together, these results show that heterogeneous attention trajectories statistically account for ownership effects on brand choice observed in models that do not account for attention during the task or for other sources of heterogeneity in consumer preferences (Dubé et al. 2008).

Quantifying the Double Attention Lift towards the Chosen Brand

We quantity the contribution of the "double attention lift" to choice in two ways. First, we use K-fold CV to make out-of-period predictions of brand choice. The out-of-period hit rate indicates how well the proposed model predicts final choice before out-of-sample participants reveal it. Results are in Table 4 and details in Web Appendix E. Up until half-way through the choice task (total completion time M = 116 sec., SD = 95), prediction performance of the proposed model (46%, PI [43; 48]) is similar to that of the baseline (45%, PI [43; 47]). However, attention trajectories up until the end of the third quarter already predict 52% [50; 55] of the final brand choices correctly. This is a significant 7 points higher hit rate than the baseline (95% PIs do not overlap). In the fourth quarter, the performance gap widens to 40 percentage points in favor of the proposed model: 85% [82; 87].

TABLE 4
PREDICTION PERFORMANCE

Model and Quarter	Out-of-Sample Hit Rate
Baseline Model	45% [43; 47]
Proposed Model	
Quarter 1	45% [43; 47]
Quarter 2	46% [43; 48]
Quarter 3	52% [50; 55]
Quarter 4	85% [82; 87]
Sample (*n*)	325

Note – Baseline model is M2. Mean percentage hit rate for random-split K-fold CV shown, with 95% Prediction Interval (PI) between square brackets.

Second, we test a follow-up of the proposed model without quadratic change in the attention trajectories (M5: initial level and linear change only; Web Appendix E). Hit rate of this model is 61% [58; 63]: the double attention lift towards choice improves hit rate by 24 points. Further analysis ruled out that the lift in attention quantity occurs because the ultimately chosen brand is the sole attention survivor. Even in the final quarter before choice, 83% of participants still examined three or more brands and 68% even examined all four non-chosen brands (Web Appendix H).

Attention Trajectories During Brand Choice

Support for hypothesis 1 and 2 so far came from the effects of attention trajectories on choice, using the choice part of the model (eq. 5). We use the attention part (eq. 4) to directly examine the double lift in attention trajectories towards the moment of choice, and to test hypothesis 3 about ownership effects on attention. To this aim, we slightly modify eq. 4 by including a dummy variable indicating whether a brand was ultimately chosen (1) or not (0), in addition to information on ownership and the other consumer and brand specific covariates. Table 5 and Figure 3 summarize the results. All results are in Web Appendix G.

The results support **hypothesis 3** that initially during choice participants devote more attention to the new device of the brand that they currently own as compared to devices of other brands, and that more of this attention is devoted to integrating information about the brand. Seventy-two percent of participants currently owned one of the brands in the choice display. The currently owned brand compared to other brands received a higher initial level of attention quantity (.13, $p < .01$) and integration attention (.11, $p = .02$) after the start of the task but did not have significant effects on the linear and quadratic growth in attention[2].

The results also support hypotheses 1 and 2 about the double attention lift towards

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[2] Brand ownership effects on initial attention were stronger in the model (eq. 4) without the chosen-brand dummy. Brand ownership increased initial level of attention quantity (estimate = .14, $p < .002$) but not the linear (.08, $p = .15$) and quadratic change (.00, $p = .25$). It also increased the initial level of integration attention (.14, $p = .005$) but not the linear (.11, $p = .10$) and quadratic change (-.01, $p = .60$). Details are in Web Appendix F.

the chosen brand. That is, the ultimately chosen brand gained attention towards the moment of choice (quadratic change of quantity .13, $p < .001$, and integration .16, $p < .001$) but did not shape initial attention or linear growth in attention. Brand ownership and chosen brand did not markedly shape attention trajectories for comparison and other attention, although there was a tendency for increased comparison attention towards the chosen brand ($p = .03$). Importantly, these effects on attention are independent of consumer-level factors (information condition, product ownership, product knowledge, gender, age, education, income), and brand-level factors (market-level preferences, brand position on the choice display, brand knowledge) which were all accounted for by the model (eqs. 3. and 4).

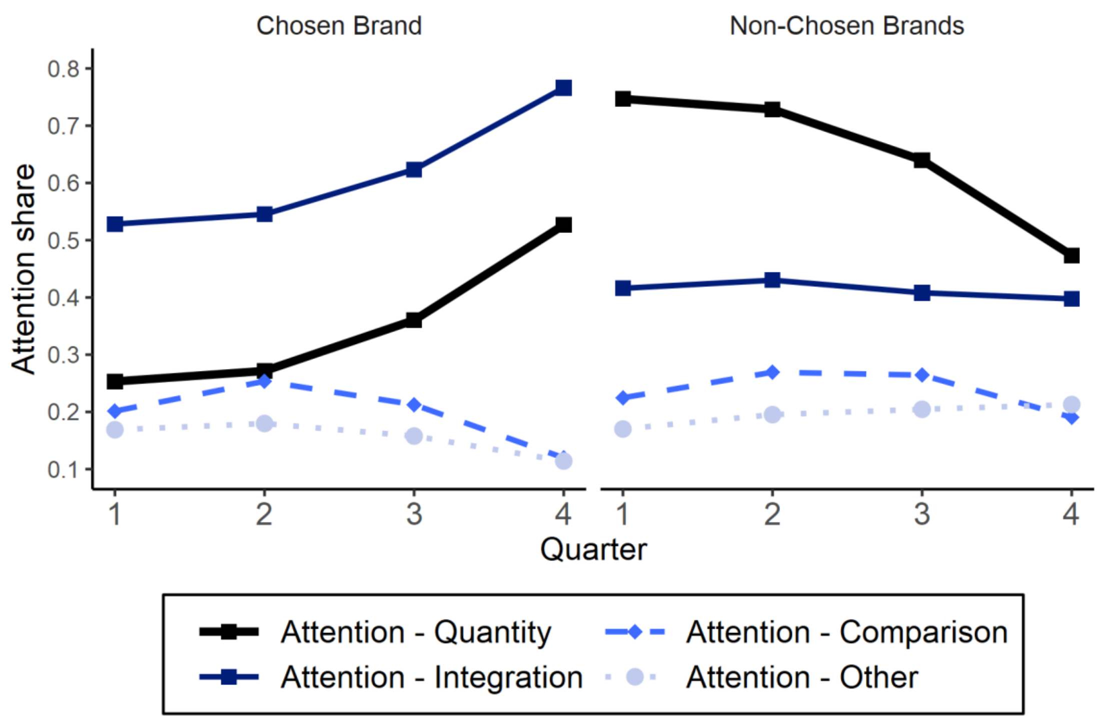
TABLE 5
ATTENTION TO THE BRAND OWNED AND BRAND CHOSEN

	Components of Attention Trajectories											
	Initial Level				Linear Change				Quadratic Change			
Predictors of Attention	*M*	*SD*	*p*	95% CI	*M*	*SD*	*p*	95% CI	*M*	*SD*	*p*	95% CI
Quantity:												
Brand owned	.13	.05	.01	[.03; .23]	.07	.09	.16	[-.10; .24]	-.04	.03	.18	[-.09; .02]
Brand chosen	.06	.04	.08	[-.02; .14]	.02	.07	.24	[-.12; .16]	.13	.02	<.001	[.09; .18]
Integration:												
Brand owned	.11	.05	.02	[.01; .22]	.11	.09	.09	[-.06; .29]	-.05	.03	.07	[-.11; .004]
Brand chosen	.08	.04	.03	[-.002;.17]	-.03	.07	.57	[-.17; .11]	.16	.02	<.001	[.11; .20]
Comparison:												
Brand owned	-.03	.04	.42	[-.10; .04]	.08	.06	.08	[-.03; .19]	-.02	.02	.24	[-.06; .01]
Brand chosen	.02	.03	.18	[-.03; .08]	.02	.05	.23	[-.07; .11]	.03	.01	.03	[-.001; .06]
Other:												
Brand owned	.03	.04	.18	[-.05; .10]	.05	.06	.16	[-.07; .16]	-.01	.02	.47	[-.05; .03]
Brand chosen	.01	.03	.22	[-.04; .07]	.01	.05	.24	[-.08; .11]	.02	.02	.08	[-.01; .05]

Note – Brand owned: yes = 1, no = 0. Brand chosen: yes = 1, no = 0. M is Mean estimate; SD is standard deviation; *p* is one-tailed Bayesian significance level, and 95% Confidence Interval (CI) of parameter estimates. All other effects at the brand and participant level are accounted for but not shown to save space.

Figure 3 depicts attention trajectories of the chosen and non-chosen brands. To facilitate interpretation, it shows attention quantity share relative to other brands, and integration attention share relative to comparison and other attention for the same brand. The double attention lift for the chosen brand towards choice is unmistakable. Share of attention quantity for the ultimately chosen brand is already 25% after the first quarter and grows to 53% just before choice. Share of attention quantity for the four non-chosen brands together has the reverse pattern (shares for chosen and non-chosen brands sum to 100): it starts at 75% and drops to 47%. Share of integration attention for the ultimately chosen brand (53%) as compared to non-chosen brands (42%) is already 11 points higher after the first quarter, which reflects the brand ownership effect. This gap widens towards the moment of choice when the chosen brand receives 77% but the non-chosen brands only 40% of integration attention as share of the total attention to the brand (a 33 points gap). Details are in Web Appendix H.

FIGURE 3
ATTENTION TRAJECTORIES FOR CHOSEN AND NON-CHOSEN BRANDS



Note – Estimated attention quantity shares sum to one for chosen and non-chosen brands combined. Parity share of attention quantity for the chosen brand is .20 per quarter (1/5). Estimated integration, comparison, and other attention shares sum to one for chosen brand and non-chosen brands separately. Parity share is .33 for each attention type per quarter (1/3)

Ownership Effects on Brand Choice and Attention Trajectories

Thirty-eight percent of participants chose a device with the same brand name as the one they currently own (loyals; *n* = 122), while 34% switched brands (switchers; *n* = 111). The remaining 28% (others; *n* = 92) did not yet own a device in the category or owned a brand not in the choice display. There were no differences between brands in their likelihood of being chosen by participants who currently own a device with the same brand name ($\chi^2(4) = 1.50$, $p = .83$).

As expected, loyals took less time to complete the complex choice task (M = 90 sec., SD = 77) as compared to switchers (M = 121 sec., SD = 81), and others (M = 143 sec., SD = 122; $F(2, 322) = 9.11$, $p < .001$, $d = .34$), but still longer than reported in other attention and choice studies, using simpler choice tasks or student samples (Web Appendix A, Table A1). For instance, time to choose was on average about 18 seconds in a study on choice of pain relievers and bar soaps by regular shoppers (Chandon et al. 2009), and 67 seconds in a study on choice of personal computers by students (Shi, Wedel, and Pieters 2013).

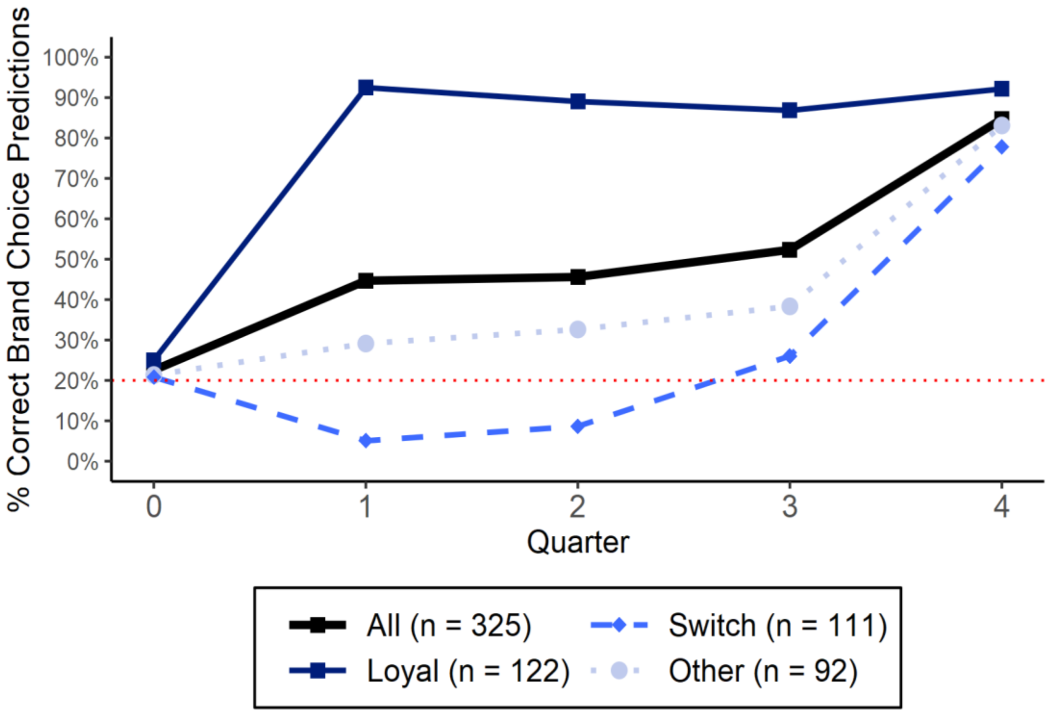
TABLE 6
PREDICTION PERFORMANCE:
BRAND LOYALS, SWITCHERS, AND OTHERS

Consumers	Before Choice Task	Periods During Choice Task: 1st Quarter	2nd Quarter	3rd Quarter	4th Quarter	Duration: *M* (*SD*) seconds
Loyal (*n* = 122)	25%	92%	89%	87%	92%	90 (77)
	[17; 34]	[89; 95]	[86; 93]	[84; 90]	[90; 94]	
Switch (*n* = 111)	21%	5%	9%	26%	78%	121 (81)
	[14; 28]	[2; 8]	[5; 13]	[22; 31]	[73; 83]	
Other (*n* = 92)	21%	29%	33%	38%	83%	143 (122)
	[15; 28]	[24; 35]	[27; 38]	[33; 43]	[79; 87]	
Overall (*n* = 325)	23%	45%	46%	52%	85%	116 (95)
	[18; 27]	[43; 47]	[43; 48]	[50; 55]	[82; 87]	

Note – Mean % hit rate, with 95% PI between square brackets.

The proposed model and K-fold CV make it possible to track how well attention trajectories predict each of the three groups (loyals, switchers, and others) over time. We calculate the hit rate for each group before the start (quarter 0, based on pre-task information) and after each of the four quarters in the choice task. Summary results are in Table 6 and Figure 4. The red dotted line in Figure 4 is the hit rate if brand choice would be random.

FIGURE 4
PREDICTION PERFORMANCE:
BRAND LOYALS, SWITCHERS, AND OTHERS



Note – Red dotted line indicates the 20% (1/5) hit rate in case of random brand choice predictions.

The pattern of results is notable. First, attention trajectories of brand loyals already predict their ultimate brand choice remarkably well after the first quarter (hit rate 92%) and consistent over time (89%, 87%, and 92% after quarters 2-4; all 95% PIs overlapping). It reflects sustained engagement of attention with the brand they own (H3) and choose (H1 and H2), for the final 68 seconds of the task, on average. Second, attention trajectories of brand switchers predict ultimate brand choice initially significantly *worse* (5% after quarter 1 and

9% after quarter 2) than if brand choice were random (PIs do not overlap 20%) but progressively better towards the moment of choice (78% after quarter 4). This early depressed hit rate is due to initial attention of switchers to the brand they own and that they ultimately do not chose. Specifically, in quarter 1, switchers allocate a larger share of attention quantity to the owned (.21) compared to the other three non-chosen brands in the set (.18, $p < .001$), with a similar pattern for share of integration attention (.22 vs .17, $p < .001$). This suggests that switchers did not come to the task with their mind (completely) set on choosing a different brand. Third, attention trajectories predict ultimate brand choice of "other" consumers, who do not own a brand on display, somewhat better (29% after quarter 1) than if choice were random and progressively so towards the end of the task (83% after quarter 4). This demonstrates how attention trajectories provide novel insights into decision processes of groups of consumers that differ on two dimensions, namely: ownership in the product category and brand switching behavior. Both loyals and switchers already own a device with the same brand name as one of the options in display, so they can choose between a brand with the same name or a competitor. Other consumers include both participants who are new to the product category and who own a brand in the product category that is not in the display. As a result, they make their choice from a set of brands they do not have prior experience with.

Robustness of the Attention-Choice Link

How robust are the identified links between attention trajectories and brand choice to various contextual factors? To answer this question, we report on three follow-up models (M7-M9) and the results of the design-based K-fold CV. The follow-up models include all the variables in the specification of M4 and add interaction variables between the attention trajectories and, respectively the three information conditions in the experimental design (M7), and completion time, indicated by the total number of eye fixations (M8) and the number of seconds that participants spend during the choice task (M9). If the strength of the attention-choice link would vary as a function of these factors, the follow-up models would outperform the proposed model. If anything, model performance was slightly worse in all cases: respective hit rates are 84% (M7), 84% (M8), and 83% (M9) (Web Appendix E).

For the design-based K-fold CV, we predicted brand choice of participants in each cell of the experimental design (3 information conditions x 4 user segments) from their attention to the brands and from the model estimates calibrated on participants in the other cells. If the strength of the attention-choice link were volatile, hit rates would vary greatly between the cells of the experimental design. The results provide a different picture (Web Appendix E). Final hit rates are remarkably similar. Deviations of this overall pattern occur for the non-user segment (no device yet) whose brand choices are initially predicted worse (e.g., 26% after quarter 1) than for other segments (all others 47% or better). Hit rates converge and do not differ when moving towards choice (average 85%). Results for the information conditions are equally supportive.

CONCLUSION

Our findings provides answers to the three questions that motivated the project: (1) how do *trajectories* of attention to each of the brands during the choice task contribute to the accumulation of utility and final choice, (2) which fundamental attention *processes* contribute to the accumulation of utility and brand choice, and (3) can trajectories of attention *predict* brand choice before it is made.

With respect to the first two questions, we found a robust "double attention lift" for the chosen brand towards the end of the choice task. The ultimately chosen brand received a progressively higher quantity of attention, as expressed in eye-fixations, and more integration attention, as expressed in eye saccades within the brand, presumably to integrate the brand's various strengths and weaknesses into an overall evaluation. This attention lift was *not* due to complete rejection of the non-chosen brands, since most of these still received some attention until the end. Also, the attention lift in integration attention towards the end only emerged for the ultimately chosen brand and *not* for the non-chosen brands.

Moreover, we identified a robust ownership effect on initial attention to the brand. That is, attention (quantity and integration) to the brand that consumers currently owned was higher during the first quarter of the task. Interestingly, the brand ownership effect on attention early during the task not only emerged for consumers who ultimately chose a new device of the brand they already owned (loyals), but also for consumers who chose a new device from a different brand than the brand they currently owned (switchers), which supports its generality in the present context. Moreover, brand ownership effects on brand choice seized to be statistically significant after accounting for attention trajectories. This suggests that, in our experiment, consumer-and-brand specific attention trajectories reflect sources of brand utility otherwise approximated by brand ownership effects on choice.

With respect to the third question, we found that attention trajectories predicted ultimate brand choice remarkably well: overall 85% of brand choices were predicted correctly out-of-sample, and 52% already on average about 29 seconds before the last quarter of the choice task set in.

These findings were obtained from a large-scale eye-tracking experiment (n = 325) with regular consumers who were in the market for a new smartphone and who choose from an information-rich visual brand display as is common in practice. We developed a new generally applicable attention-and-choice model, and used K-fold Cross-Validation to make out-of-sample and out-of-period predictions about brand choice. Jointly this affords new tests of specific hypotheses about attention trajectories and their effects on utility and choice, prevents overfitting, and enables assessing the predictive performance of models.

Implications and Future Directions

The proposed attention-and-choice model extends earlier models and research in five important ways. First, it decomposes overt eye-movement measures into covert attention and measurement error for each of the choice (brands) options. It is akin to the work by Shi, Wedel, and Pieters (2013) who distinguish individual-level attention states and eye-movements in a Hierarchical Hidden Markov Switching model. It extends this by providing estimates of the links between covert attention and brand utility, and over time. Second, it estimates attention trajectories and links these to utility and choice for any number of brands (options), in our application five. This extends earlier work limited to binary and trinary choice due to model structures assuming choice results when a pairwise comparison of choice options exceeds a threshold (Krajbich et al. 2010, 2012; Towal et al. 2013). Our straightforward conditional logit formulation is general and rooted in utility and rational inattention theory (Gabaix 2019). Third, it separates the quantity of attention, as reflected in eye fixations, from three types of attention, as reflected in saccades between successive eye fixations, respectively: integration attention, comparison attention, and other attention. Prior attention studies have emphasized eye-fixations and some have examined eye-saccades (Web Appendix A), but we are not aware of research on both. Our synthesis provides insight into higher-order cognitive processes that may contribute to brand utility, and which cannot be readily identified otherwise. Fourth, it decomposes attention trajectories into three key components, here, their initial level, linear and quadratic change. This makes it possible to monitor when attentional preferences for brands surface during the choice task, and to quantify the contribution that the earlier and later stages have to utility and final choice. Fifth, combined with K-fold cross-validation, the model affords out-of-sample and out-of-period predictions of participants not used to calibrate the model and before these reveal their brand choice. Our Bayesian K-fold CV produces precise Prediction Intervals, which enable straightforward tests of difference in predictive performance of models. This provides new tools for theory testing and managerial decision making, also outside the realm of attention and choice research.

In support of the central tenet of rational inattention (RI) theory, consumers indeed did not allocate their attention proportionally across the brands, but instead focused their attention toward the brand that they eventually chose, which has been documented before. Yet, a surprising result is how early during the choice task the eventually chosen brand already attracted more than its fair share of attention. Thus rational (in)attention was an emergent property that started much sooner than documented before. Prior research has reported a so-called "gaze cascade" where the finally chosen brand attracts a disproportionate amount of attention just before choice implementation. For instance, Shimojo et al. (2003) observed increased attention to the chosen alternative in the final second before choice. Atalay, Bodur, and Rasolofoarison (2012) reported a similar effect in the final five seconds of choice for vitamins and food-replacement bars. If such an attention lift for the chosen brand surfaces only late, it would be of theoretical but perhaps of lesser managerial and policy relevance. Our results are the first to document a "double attention lift" early on and later during an extended complex choice task in an information-rich environment.

The present findings are, to our knowledge, also the first to document the tight link between the accumulation of brand utility and trajectories of types of attention, in particular attention for information integration, over and above the mere quantity of attention. This extends RI and sequential sampling models which have emphasized quantity of attention as the dominant or sole predictor of utility. The final lift in integration attention is consistent with information integration across brands being costly (Bettman, Luce, and Payne 1998) and the optimality of reserving it for one or a few emergent options rather than deploying it throughout and for all options (Gabaix 2019).

Our work has important limitations which point to future research. First, our findings are contingent on the complex-choice context under study. The experiment concerned complex choice with a small choice set and large number of features, and consumers who were in the market for the target product. When the choice set is large and the feature set is small, or when consumers are not yet in the market for a (new) purchase, attention trajectories and their contribution to final choice might be different. For instance, in case of two-option, two-attribute choices, Noguchi and Stewart (2014) found a dominance of between-option saccades throughout the (brief) tasks. Future research can test the role of choice and feature set sizes, and other contextual factors on the contribution that the various attention trajectories have on choice.

Second, in an effort to keep the modeling tractable and to account for measurement error, we normalized the eye-movement data into four time bins for each consumer. This is consistent with prior research that has used up to four time bins (Meißner, Musalem, and Huber 2016; Willemsen, Böckenholt, and Johnson 2011), but limits the amount of detail about attention trajectories and utility accumulation. It also precludes modeling the time that consumers take to make a choice, which is an important caveat. Follow-up research which jointly models brand choice and individual decision time is called for.

Third, our model is agnostic about the causal processes linking attention and utility at each point in time, as other models are (Manohar and Husain 2013; Reutskaja et al. 2011). Thus, we cannot claim that attention causes utility, only that they are empirically strongly associated. The observed systematic links between trajectories of attention, utility and choice, informed by theory, do suggest such causal linkages, but our data and model do not permit strong inferences about these. It is reasonable to assume that attention and utility are part of a positive feedback loop (Shimojo et al. 2003), with utility driving attention (Anderson 2017;

Theeuwes and Belopolsky 2012; Yang, Toubia, and de Jong 2015), and attention driving utility (Towall et al. 2013), with sensible time-out mechanisms. Whereas both causal directions have been reported, we are not aware of research that directly examines and quantifies the moment-to-moment bidirectional effects between attention and utility, which is an important direction for future research. Linking work on attention and choice to the literature on sequential search for information and choice might prove useful in establishing such structural and causal links. Especially work on repeated search decisions leading to a single purchase decision would be relevant. There is initial work to formalize costly search for information before obtaining the rewards from a choice between multiple products or a choice of a single product with multiple features (e.g., Branco, Sun, and Villas-Boas 2016). Such work relies on various simplifying assumptions and as the number of attributes and options rise, estimating such models becomes intractable. Recent empirical work proposed and estimated a dynamic structural search model utilizing eye-tracking data (Ursu, Zhang and Erdem 2021). Integrating the proposed attention-and-choice model with search-and-choice models is challenging but a potentially fruitful area for cross-disciplinary work, novel theories and empirical findings.

Another interesting avenue for further research is to assess the effects of intra-task changes in the information structure and content of the choice options. Such changes can occur exogenously, when a new brand or offer pop-up during the choice task that consumers are engaged in, or endogenously as a consequence of the attention trajectories themselves. For instance, contingent on the brand currently garnering preferential attention, new information about that brand or about competing brands might accelerate or decelerate utility accumulation. Such applications might also be relevant to medical and moral decision making (Pärnamets et al. 2015) where intervention is especially desirable if normatively inferior choice options appear to gain early traction. In a recent review, Al-Moteri et al.

(2017, p. 63) conclude that "…the investigation of eye-movement behaviour in deliberate (analytical) decision-making modes does not appear to be a priority in eye-tracking studies in the medical field. This is an important area for future research." Our proposed model with K-Fold CV might help to understand how decision makers respond to from moment-to-moment changes in the decision environment and perhaps eventually to enable better choices.

Finally, given the possibility of early intervention that our model provides, our model can also be used to optimize the timing and type of targeted marketing messages and tactics. Such real-time marketing interventions would include promotions (e.g., providing a pop-up window with a coupon to encourage trial of an option that the firm wants the consumer to try) or dynamic web flow design where the firm can change in real-time the content provided to the consumer and the like.

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WEB APPENDICES

Web Appendix A. Eye Tracking in Decision Making Research

For the literature review on research about the role of eye movements in choice between options such as brands, we searched major marketing (Journal of Consumer Psychology, Journal of Consumer Research, Journal of Marketing, Journal of Marketing Research, Management Science, Marketing Science, and International Journal of Research in Marketing) from 1995 until 2020, the references in and to the “hits” from this search, and the references in and to a review of attention and choice (Orquin and Loose 2013). We used as search terms “attention” and/or “eye movements” and “choice” and /or “consideration” and/or “decision”. We used the following inclusion and exclusion criteria to sample final papers for the review. The final sample included all papers in which (1) the final dependent variable was choice or consideration of one or more choice options, (2) eye movements during the choice task are explanatory variables for the final choice or consideration, and where (3) choice is between consumer products or brands or gambles. The final sample excluded papers in which (1) eye movements are used to exclude tasks or participants, or eye movements are the final dependent variable (Arieli, Ben-Ami, and Rubinstein 2011; Bird, Lauwereyns, and Crawford 2012), (2) decision accuracy was the dependent variable (e.g. choose the most expensive item: Glaholt, Wu, and Reingold (2010)), (3) eye-movements were used to record the final choices of consumers (Milosavljevic et al. 2012), or (4) human coders observed and coded eye-movements of participants (Russo and Leclerc 1994). This led to the final set of 21 publications with a total of 27 individual studies on the role of eye-movements in decision making, summarized in Table A1.

TABLE A1

EYE TRACKING IN DECISION MAKING RESEARCH

A Source	B Participants	C Number of choice tasks	D Choice set size	E Stimuli and domain	F Stimulus exposure	G Eye movement data	H Key findings for choice or consideration probability	I Out-of-sample prediction
Atalay, Bodur, and Rasolofoarison (2012)	a: 63 mostly students	2	9	Pictures of fictitious brands of a: vitamin supplements, and a and b: meal replacement bars	Self-controlled (a: *"more than* 35 seconds", page 855, and b: not-reported	Fixation frequency and duration on left, center, right column of product display	Higher with larger log-sum of fixation durations on column, and more fixations on central column in final 0.5-5 sec.	No
	b: 64 mostly students	1						
Brandstätter and Körner (2014)	80 participants	11 (from set of 48)	2	Numeric information on 2-attribute gambles	Self-controlled (M=10 sec.)	Fixation and saccade frequency	Lower with more saccades on losses, and higher with final fixation on risky gamble	No
Chandon et al. (2007)	309 shoppers	1 (n=159)	16 (M=4.5 replicates each)	Pictures of shelves with existing brands of orange juice	Self-controlled (M=25 sec.)	Fixation and re-fixation yes/no at brand/sku level	Higher for each brand/sku with (re)fixation, aggregated across participants	No
		1 (n=150)	15 (1 replicate each)	Pictures of shelves with existing brands of detergents	Self-controlled (M=18 sec.)			
Chandon et al. (2009)	348 shoppers	2 (n=344) 1 (n=4)	12 (M=8 replicates each)	Pictures of shelves with existing brands of bar soaps, and pain relievers	Self-controlled (M=16 and 19 sec.)	Same as Chandon et al. (2007)	Same as Chandon et al. (2007)	No
Cohen, Kang, and Leise (2017)	a: 32 students	45 conjoint	3	Grids with apartment information	Self-controlled (M=9, 11, and 7 sec.)	Fixation frequency	Higher proportion of fixations on chosen option in final third part of task (p.59)	Predict each of 9 (in a) or 6 subsets (in b-c) from remaining subsets for same participants. No validation performance reported.
	b: 28 students	30	3	Grids with numeric gamble information				
	c: 11 students	300	3	Grids with textual gamble information				

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A Source	B Participants	C Number of choice tasks	D Choice set size	E Stimuli and domain	F Stimulus exposure	G Eye movement data	H Key findings for choice or consideration probability	I Out-of-sample prediction
Fisher (2017)	40 students and faculty	200	1 (accept-reject)	Pictures of snack (1 appetitive and 1 aversive) bundles	Self-controlled	Distribution of fixation durations	Total time to appetitive snack increases accept likelihood, aggregated across participants	Use estimates of even to predict odd trials for same participants
Krajbich, Armel, and Rangel (2010)	39 students	100	2	Pictures of snacks	Self-controlled (0.5 to 25 sec.)	Distribution of fixation durations	Higher with larger total fixation duration to option	Use estimates of even to predict odd trials for same participants
Krajbich et al. (2012)	30 students	300	1 (purchase–not)	Pictures of consumer electronics and household items with their price	Self-controlled 0.5 to 47 sec.)	Distribution of fixation durations	Slightly higher when last fixation on chosen product, across participants (p.7)	“same”
Manohar and Husain (2013)	17 participants	128	2	Grids with 2 attributes of numeric gamble information	Self-controlled	Fixation frequency and duration	Higher with more, longer, final fixation(s) (p.5)	No
Meißner, Musalem, and Huber (2016)	a: 60 participants b: 35 participants	12 conjoint 8 conjoint	3 + 1 (no choice) 5	Grids with information of existing brands of a: coffee machines, and of b: beach holidays	Self-controlled	Fixation frequency	Higher with more fixations; incidental fixations have little effect (p.15)	For a: predict each of 12 conjoint tasks from the 11 remaining tasks for same participants. M hit rate = 68%
Noguchi and Stewart (2014)	93 students	40	3	Displays with information on 2 attributes of cars, laptops, TVs	Self-controlled	Fixation and saccade frequency, fixation duration	Higher with more between-option saccades (p.49)	No
Pieters and Warlop (1999)	54 shoppers	1	6	Unknown brands of shampoo	Fixed 7 or 20 sec. depending on condition	Saccade frequency, fixation duration	Higher with more saccades and longer fixation durations	No

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A Source	B Participants	C Number of choice tasks	D Choice set size	E Stimuli and domain	F Stimulus exposure	G Eye movement data	H Key findings for choice or consideration probability	I Out-of-sample prediction
Reutskaja et al. (2011)	41 students	75	4, 9, or 16	Pictures of snacks	Fixed 3 sec.	Fixation freq., and y/n 1st fixation, re-fixation	Higher if item is first and/or last fixated	No
Russo and Rosen (1975)	12 students	45 conjoint	6	Textual information on used cars	Self-controlled	Fixation freq., duration and saccade freq.	Negative correlation time comparing options and their utility	No
Schotter et al. (2010)	32 students	25	2	Photographs	Self-controlled	Fixation duration and frequency on option	Higher when looked at longer in final 1.6 seconds	No
Shi, Wedel, and Pieters (2013)	108 students	1	4	Existing brands of personal computers	Self-controlled (M=67 sec.)	Sequence of eye saccades	Lower when more person-time in attribute-state, for 3-out-of-4 options	No
Smith and Krajbich (2018)	44 students	4 sets of 200	2	Pictures of snacks (2 sets), displays of gambles, and financial payoffs	Self-controlled (M=2.2 sec.)	Distribution of fixation durations	Higher with longer dwell time (p.1817) and last fixation (p.1818) to option	No
Stewart, Hermens, and Matthews (2016)	48 students	71	2	Grids with 2-attribute information of gambles	Self-controlled (M=2.8 sec.)	Fixation and saccade frequency	Higher with more within- and between-saccades, irrespective of attribute values	No
Stüttgen, Boatwright, and Monroe (2012)	64 students	15 conjoint	15 (each with 3 replicates)	Existing brands of instant noodles	Self-controlled (M=8-12 sec., estimated from Figure 3)	All cells on display fixated (yes/no)	Higher with more re-fixations on satisfactory brands	(1) Predict 3 tasks from remaining 12 tasks (72% hit rate), (2) as (1) for 20 from 44 people (hit rate not reported)

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A Source	B Participants	C Number of choice tasks	D Choice set size	E Stimuli and domain	F Stimulus exposure	G Eye movement data	H Key findings for choice or consideration probability	I Out-of-sample prediction
Towal, Mormann, and Koch (2013)	19 students	29-133 (median 95)	4	Snacks	Fixed 2 sec.	Fixation durations	Value of items on display predicts choice better than their visual saliency	No
Yang, Toubia, and de Jong (2015)	70 students	20 conjoint	4	6 (attribute) by 4 (choice options) information matrix for an existing brand of personal computers	Self-controlled	Fixation (yes/no) on information cells, distance of fixations between cells, revisits.	Accounting for fixated brand information improves efficiency of choice-based conjoint.	Use estimates of first 8-16 tasks to predict last 4 tasks for same participants

Notes: "Students" are undergraduate university students. Participants are "participants" if a publication does not provide information about the population from which participants are drawn. "Same" indicates the same information for this publication by the first author as in the row directly preceding in the table.

Web Appendix B. Data Collection and Preparation

DATA COLLECTION

Data collection took place June 17-26, 2013. A stratified sample of 460 participants were recruited for the study, in three locations in the continental US, respectively, Washington DC, Cincinnati, and San Diego. Data collection took place in dedicated research areas in shopping centers in each of the three locations.

Recruitment of Participants

Participants were identified and recruited by Tobii's partner organizations: Luth Research (San Diego), Various View Research (Cincinnati), Shugoll Research (Washington DC). Each of the Tobii's Recruiters followed the same screener guidelines across all locations. To qualify for the study, the participant: (a) needed to be 18 years or older, (b) did not have certain eye problems (e.g., lazy eye, nystagmus, etc.), (c) have had not completed any marketing research study in the past 6 months, (d) did not and do not work for a market research company, advertising/public relations agency, technology or Internet company such as Apple, Google, etc., as well as a company takes makes or sells consumer electronics such as Sony, Best Buy, etc., (e) own a cell phone (the cell phone could be a smartphone or not a smartphone), and (f) was intending to buy a smartphone in the next 9 months.

We designed the target sample to be drawn relatively equally from each of four major consumer segments based on smartphone ownership: Apple iPhone owners, Samsung smartphone owners, owners of other smartphone brands, and non-smartphone owners. The Apple smartphone owner segment includes participants who self-reported as owning a smartphone and indicated the smartphone's operating system (Apple iOS) and Apple as the manufacturer. The Samsung smartphone owner segment includes participants who self-reported as owning a smartphone and indicated the smartphone's operating system (Android) and Samsung as the manufacturer. Owners of other smartphone brands are participants who self-reported as owning a smartphone, and indicated the smartphone's operating system (Android, Blackberry, or Windows) and non-Apple/Samsung as the manufacturer. Non-smartphone owners are participants who own a cell phone with an operating system that is neither Android, iOS, Blackberry, nor Windows.

The recruited participants were scheduled to visit the Recruiter's facilities on a given day/time to participate in a study. The participants' appointments and the responses provided at the initial screening call were confirmed prior to the visit. Participants were paid $50 to cover the participant transportation costs of commuting to a focus group facility and volunteering their time.

Study Administration

Participants were recruited on the phone and scheduled to come in at a designated time to take part in an in-person study. On arriving at one of the recruiters' facilities, the recruiter's staff verified the participant's identification against a list of scheduled participants. Each participant was greeted by a Tobii eye tracking operator and escorted to a designated room of the recruiter's facility. Once seated in front of a computer, the participants received scripted verbal instructions from the Tobii technician. After that, the Tobii technician launched a 5-dot eye calibration exercise, the instruction for the Study Task, and the Stimuli for the Study Task on the participant's screen from a remote computer. The technician did not interact with the participants until the Study Task was completed, as marked by the launch of the "thank you" page. The Tobii technicians were not aware of the purpose of the research or the research sponsors.

The eye movements of the participants during the Study Task were recorded using Tobii's T60 XL Eye Tracker which is integrated into a high-resolution 24-inch TFT widescreen monitor. The Eye Tracker offers high-quality unobtrusive tracking over wide-screen gaze angles and allows for eye tracking studies of detailed stimuli. The participants sit in front of the display as they would usually in front of their home computer.

Participants were randomly assigned to one out of 15 the between-subject conditions: 3 information complexity levels (low, medium, high) x 5 brand order (the position of the five brands were rotated between participants). Figures B1-B3 show sample stimuli for the low, medium, and high information conditions.

FIGURE B1

CHOICE DISPLAY – LOW COMPLEXITY

Actual size on screen: vertical is 6.1 inches (48% of screen height), horizontal is 17.9 inches (88% of screen width)

		Apple iPhone 5	HTC One	Samsung Galaxy Note II	Nokia Lumia 920	Motorola Droid RAZR MAXX HD
						
	Colors Available	Click to Buy	Click to Buy	Click to Buy	Click to Buy	Click to Buy
Price	Price with 2-year Contract	$249.99	$199.99	$249.99	$99.99	$199.99
Wireless Capabilities	Band and Mode	|EDGE|GSM|Quad-band GSM|3G|UMTS|Quad-band UMTS|HSPA+|HSDPA|CDMA|4G LTE|Dual-band LTE|	|EDGE|GSM|Quad-band GSM|GPRS|3G|UMTS|HSDPA |CDMA|4G|4G LTE|Dual-band LTE|	|GSM|3G|UMTS|HSPA+|HSDPA |CDMA|4G LTE|Dual-band LTE|Quad-band|	|EDGE|GSM|Quad-band GSM|3G|Quad-band UMTS|HSPA+|HSDPA|4G|4G LTE|Dual-band LTE|	|EDGE|GSM|Quad-band GSM|3G|UMTS|HSPA+|HSDPA |CDMA|4G LTE|
	Bluetooth	4.0	4.0	4.0	3.0 + HS	4.0
	WiFi	802.11 a/b/g/n	802.11 a/b/g/n/ac	802.11 a/b/g/n	802.11 a/b/g/n	802.11 a/b/g/n
Operating System (OS) and Other Features	Mobile Operating System	iOS 6	Android 4.1 Jelly Bean	Android 4.1 Jelly Bean	Windows Phone 8	Android 4.1 Jelly Bean
	Supported Email	POP3, IMAP, Push email (Exchange, Gmail)	POP3, IMAP, Push email (Exchange, Gmail, Hotmail)	POP3, IMAP, Push email (Exchange, Gmail)	SMTP, POP3, IMAP4, Push email (Exchange, Gmail, Hotmail)	POP3, IMAP, Push email (Exchange, Gmail)
Size	Product Dimensions	4.87" x 2.31" x 0.30"	5.41" x 2.69" x 0.37"	5.95" x 3.17" x 0.37"	5.13" x 2.79" x 0.42"	5.19" x 2.67" x 0.37"
	Product Weight	3.95 oz.	5.04 oz.	6.44 oz.	6.53 oz.	5.54 oz.
Display	Screen Size	4.0 inches	4.7 inches	5.5 inches	4.5 inches	4.7 inches
Battery	Standby Time	Up to 9 days	Up to 20 days	Up to 19.5 days	Up to 13 days	Up to 16 days
	Talk Time	Up to 8 hours	Up to 18 hours	Up to 21 hours	Up to 7.5 hours	Up to 32 hours
Camera	Camera Resolution	8.0MP	HTC UltraPixel 4MP Camera	8.0MP	8.7MP	8.0MP
Memory	Internal Memory	32GB	32GB	16GB	32GB	32GB
	Memory Card	No	No	microSD up to 64GB	No	microSD up to 32GB
	RAM	1GB	2GB	2GB	1GB	1GB

FIGURE B2
CHOICE DISPLAY – MEDIUM COMPLEXITY

Actual size on screen: vertical is 9.3 inches (73% of screen height), horizontal is 17.9 inches (88% of screen width)

		Motorola Droid RAZR MAXX HD	Apple iPhone 5	HTC One	Nokia Lumia 920	Samsung Galaxy Note II
	Colors Available	 Click to Buy	 Click to Buy	 Click to Buy	 Click to Buy	 Click to Buy
Price	Price with 2-year Contract	$199.99	$249.99	$199.99	$99.99	$249.99
Battery	Battery Type	Lithium-ion Polymer	Lithium-ion	Lithium-polymer	Lithium-polymer	Lithium-ion
	Standby Time	Up to 16 days	Up to 9 days	Up to 20 days	Up to 13 days	Up to 19.5 days
	Talk Time	Up to 32 hours	Up to 8 hours	Up to 18 hours	Up to 7.5 hours	Up to 21 hours
Memory	Internal Memory	32GB	32GB	32GB	32GB	16GB
	Memory Card	microSD up to 32GB	No	No	No	microSD up to 64GB
	RAM	1GB	1GB	2GB	1GB	2GB
Wireless Capabilities	Band and Mode	|EDGE|GSM|Quad-band GSM|3G|UMTS|HSPA+|HSDPA |CDMA|4G LTE|	|EDGE|GSM|Quad-band GSM|3G|UMTS|Quad-band UMTS|HSPA+|HSDPA|CDMA|4G LTE|Dual-band LTE|	|EDGE|GSM|Quad-band GSM|GPRS|3G|UMTS|HSDPA |CDMA|4G|4G LTE|Dual-band LTE|	|EDGE|GSM|Quad-band GSM|3G|Quad-band UMTS|HSPA+|HSDPA|4G|4G LTE|Dual-band LTE|	|GSM|3G|UMTS|HSPA+|HSDPA |CDMA|4G LTE|Dual-band LTE|Quad-band|
	Bluetooth	4.0	4.0	4.0	3.0 + HS	4.0
	Built-In GPS	Yes	Yes	Yes	Yes	Yes
	WiFi	802.11 a/b/g/n	802.11 a/b/g/n	802.11 a/b/g/n/ac	802.11 a/b/g/n	802.11 a/b/g/n
Camera	Camera Resolution	8.0MP	8.0MP	HTC UltraPixel 4MP Camera	8.7MP	8.0MP
	Records Video	1080p Full HD	1080p Full HD	1080p Full HD	1080p Full HD	1080p Full HD
	Secondary Camera	1.3MP	1.2MP	2.1MP	1.2MP	1.9MP
Display	Pixel Density	313 PPI	326 PPI	468 PPI	332 PPI	267 PPI
	Screen Resolution	1280 x 720	1136 x 640	1920 x 1080	1280 x 768	1280 x 720
	Screen Size	4.7 inches	4.0 inches	4.7 inches	4.5 inches	5.5 inches
Size	Product Dimensions	5.19" x 2.67" x 0.37"	4.87" x 2.31" x 0.30"	5.41" x 2.69" x 0.37"	5.13" x 2.79" x 0.42"	5.95" x 3.17" x 0.37"
	Product Weight	5.54 oz.	3.95 oz.	5.04 oz.	6.53 oz.	6.44 oz.
Operating System (OS) and Other Features	CPU	1.5 GHz Dual Core	Not Specified by manufacturer	1.7 GHz Quad Core	1.5 GHz Dual Core	1.6 GHz Quad Core
	Media - Audio	AAC, AAC+, AMR-NB, AMR-WB, eAAC+, MIDI, MP3, OGG, WMA v9, WMA v10	AAC, HE-AAC, MP3, MP3 VBR, Audible, Apple Lossless, AIFF, and WAV	AAC, AMR, OGG, M4A, MID, MP3, WAV, WMA	MP3, QCELP, AMR-WB, AMR-NB, WMA 10 Pro, WMA 9, G.711, AAC-LC, AAC+/HEAAC, eAAC+/HEAACv2, ASF, MP4, AAC, M4A, 3GP, 3GZ	MP3, OGG, WMA, AAC, ACC+, eAAC+, AMR-NB, AMR-WB, MIDI, WAV, AC-3, Flac
	Mobile Operating System	Android 4.1 Jelly Bean	iOS 6	Android 4.1 Jelly Bean	Windows Phone 8	Android 4.1 Jelly Bean
	NFC	Yes	No	Yes	Yes	Yes
	QWERTY Keyboard	No	No	No	No	No
	Supported Email	POP3, IMAP, Push email (Exchange, Gmail)	POP3, IMAP, Push email (Exchange, Gmail)	POP3, IMAP, Push email (Exchange, Gmail, Hotmail)	SMTP, POP3, IMAP4, Push email (Exchange, Gmail, Hotmail)	POP3, IMAP, Push email (Exchange, Gmail)
	Voice Dial	Yes	Yes	Yes	Yes	Yes

FIGURE B3
CHOICE DISPLAY – HIGH COMPLEXITY

Actual size on screen: vertical is 12.4 inches (97% of screen height), horizontal is 17.9 inches (88% of screen width)

		HTC One	Nokia Lumia 920	Motorola Droid RAZR MAXX HD	Samsung Galaxy Note II	Apple iPhone 5
						
	Colors Available	Click to Buy	Click to Buy	Click to Buy	Click to Buy	Click to Buy
Price	Price with 2-year Contract	$199.99	$99.99	$199.99	$249.99	$249.99
Operating System (OS) and Other Features	CPU	1.7 GHz Quad Core	1.5 GHz Dual Core	1.5 GHz Dual Core	1.6 GHz Quad Core	Not Specified by manufacturer
	Media - Audio	AAC, AMR, OGG, M4A, MID, MP3, WAV, WMA	MP3, QCELP, AMR-WB, AMR-NB, WMA 10 Pro, WMA 9, G.711, AAC-LC, AAC+/HEAAC, eAAC+/HEAACv2, ASF, MP4, AAC, M4A, 3GP, 3GZ	AAC, AAC+, AMR-NB, AMR-WB, eAAC+, MIDI, MP3, OGG, WMA v9, WMA v10	MP3, OGG, WMA, AAC, ACC+, eAAC+, AMR-NB, AMR-WB, MIDI, WAV, AC-3, Flac	AAC, HE-AAC, MP3, MP3 VBR, Audible, Apple Lossless, AIFF, and WAV
	Media - Video	3GP, 3G2, MP4, WMV, AVI	H.264 / AVC, MPEG-4, VC-1, Windows video, H.263, WMV, AVI, 3GP, 3G2, M4V, MOV	MPEG-4, H.263, H.264, VC-1, VP8	MPEG4, H.263, H.264, VC-1, DivX, WMV, VP8, 3GP(MP4), AVI, FLV, MKV, WebM	h.264 / AVC, Motion JPEG, MPEG-4, Quicktime
	MMS	Yes	Yes	Yes	Yes	Yes
	Mobile Operating System	Android 4.1 Jelly Bean	Windows Phone 8	Android 4.1 Jelly Bean	Android 4.1 Jelly Bean	iOS 6
	NFC	Yes	Yes	Yes	Yes	No
	OS Support	Windows (7, Vista, XP), Mac OS	Windows (7, Vista, XP), Mac OS	Windows (7, Vista, XP), Mac OS	Windows (7, Vista, XP), Mac OS	Windows (7, Vista, XP), Mac OS (OS X)
	Phone Style	Bar phone	Bar phone	Bar phone	Bar phone	Bar phone
	QWERTY Keyboard	No	No	No	No	No
	Released (US)	4/19/2013	11/9/2012	10/18/2012	11/9/2012	9/21/2012
	Speakers	Stereo	Mono	Mono	Mono	Mono
	Supported Email	POP3, IMAP, Push email (Exchange, Gmail, Hotmail)	SMTP, POP3, IMAP4, Push email (Exchange, Gmail, Hotmail)	POP3, IMAP, Push email (Exchange, Gmail)	POP3, IMAP, Push email (Exchange, Gmail)	POP3, IMAP, Push email (Exchange, Gmail)
	TV-out	MHL / HDMI (micro-USB), Wireless with DLNA	Wireless with DLNA	Micro-HDMI, Wireless with DLNA	MHL / HDMI (micro-USB)	Lightning Digital AV Adapter, Lightning to VGA Adapter, Wirelessly
	Voice Dial	Yes	Yes	Yes	Yes	Yes
	Warranty (Labor/Parts)	1 Year	1 Year	1 Year	1 Year	1 Year
Memory	Internal Memory	32GB	32GB	32GB	16GB	32GB
	Memory Card	No	No	microSD up to 32GB	microSD up to 64GB	No
	RAM	2GB	1GB	1GB	2GB	1GB
Size	Product Dimensions	5.41" x 2.69" x 0.37"	5.13" x 2.79" x 0.42"	5.19" x 2.67" x 0.37"	5.95" x 3.17" x 0.37"	4.87" x 2.31" x 0.30"
	Product Weight	5.04 oz.	6.53 oz.	5.54 oz.	6.44 oz.	3.95 oz.
Wireless Capabilities	Band and Mode	|EDGE|GSM|Quad-band GSM|GPRS|3G|UMTS|HSDPA |CDMA|4G|4G LTE|Dual-band LTE|	|EDGE|GSM|Quad-band GSM|3G|Quad-band UMTS|HSPA+|HSDPA|4G|4G LTE|Dual-band LTE|	|EDGE|GSM|Quad-band GSM|3G|UMTS|HSPA+|HSDPA |CDMA|4G LTE|	|GSM|3G|UMTS|HSPA+|HSDPA |CDMA|4G LTE|Dual-band LTE|Quad-band|	|EDGE|GSM|Quad-band GSM|3G|UMTS|Quad-band UMTS|HSPA+|HSDPA|CDMA|4G LTE|Dual-band LTE|
	Bluetooth	4.0	3.0 + HS	4.0	4.0	4.0
	Built-In GPS	Yes	Yes	Yes	Yes	Yes
	WiFi	802.11 a/b/g/n/ac	802.11 a/b/g/n	802.11 a/b/g/n	802.11 a/b/g/n	802.11 a/b/g/n
Camera	Camera Resolution	HTC UltraPixel 4MP Camera	8.7MP	8.0MP	8.0MP	8.0MP
	Records Video	1080p Full HD	1080p Full HD	1080p Full HD	1080p Full HD	1080p Full HD
	Secondary Camera	2.1MP	1.2MP	1.3MP	1.9MP	1.2MP
Battery	Battery Type	Lithium-polymer	Lithium-polymer	Lithium-ion Polymer	Lithium-ion	Lithium-ion
	Standby Time	Up to 20 days	Up to 13 days	Up to 16 days	Up to 19.5 days	Up to 9 days
	Talk Time	Up to 18 hours	Up to 7.5 hours	Up to 32 hours	Up to 21 hours	Up to 8 hours
Display	Pixel Density	468 PPI	332 PPI	313 PPI	267 PPI	326 PPI
	Screen Resolution	1920 x 1080	1280 x 768	1280 x 720	1280 x 720	1136 x 640
	Screen Size	4.7 inches	4.5 inches	4.7 inches	5.5 inches	4.0 inches
	Screen Type	LCD (Active, Color, Backlit)	LCD (Active, Color, Backlit)	OLED (Active, Color, Backlit)	OLED (Active, Color, Backlit)	LCD (Active, Color, Backlit)
	Touch Screen	Yes	Yes	Yes	Yes	Yes

DATA PREPARATION

Data Exclusion

Participants were excluded from the analysis of the eye tracking data in case of (step 1) technical problems that prevented eye movement recording, (step 2) not completing the questionnaire or giving inconsistent responses, (step 3) eye movement trackability less than 60%, and (step 4) a stated purchase likelihood of 0%, despite initial screening, see Table B1. The final sample of participants meeting the inclusion criteria was 325, which compares favourably to other eye-movement research on decision-making that examined repeated choices (21 studies, M = 38, SD = 25, Web Appendix A, Table A1) or single choices from sets (7 studies, M = 135, SD = 105).

TABLE B1
DATA EXCLUSION PROCEDURE

Step	N_{start}	$N_{excluded}$	$N_{remaining}$	Exclusion criteria
1	460	2	458	Technical problems
2	458	28	430	Premature ending or inconsistent responses to the questionnaire
3	430	91	339	Trackability less than 60%
4	339	14	325	Stated purchase likelihood of 0%

For the 430 participants passing step 2, we used the eye samples recorded during the brand choice task. The Tobii 60XL eye trackers sample the left and right eye position at 60 Hz, giving for each participant and eye 60 measurements per second (one every 1/60 = 0.016 seconds = 16 milliseconds). For each “eye sample” the eye tracker records the timestamp, and the position of the eye on screen for both eyes in X and Y pixel coordinates. The eye samples were then processed into fixations using the Binocular-Individual Threshold (BIT) algorithm (van der Lans, Wedel, and Pieters 2011). The BIT algorithm labels each eye sample as being part of a fixation or not, using individual-level thresholds and information from both eyes which improves accuracy of fixation location detection over other (monocular, fixed-threshold) eye-movement algorithms. Trackability is calculated as the percentage of total eye samples labelled as part of a fixation. Trackability tends to be lower for participants with more eye blinking and longer eye lashes, such as females (Sforza et al. 2008), and for participants with reduced visual span and increased visual crowding sensitivity, such as older participants (Liu, Patel, and Kwon 2017). Out of the remaining 430 participants, 91 with a trackability less than 60% were excluded (21%). This compares favourably to other eye-movement studies of decision-making that report on participant exclusion from eye-movements. For instance, Meißner, Musalem, and Huber (2016) had to exclude 50 from the recruited 110 participants (45%), and Yang, Toubia, and de Jong (2015) 50 from the recruited 120 participants (42%).

We assessed whether the probability of being excluded from the analysis depends on study design and participant characteristics in two ways.

First, we examined whether the probability of being excluded from the analysis in steps 1 and 2 depends on the information condition that participants were assigned to. Person characteristics of these excluded participants (n = 30), such as age and gender, are missing since they did not complete the post-experimental questionnaire. We estimated a logistic regression model where the dependent variable is the status of the participant (1 = excluded in steps 1 or 2, 0 = otherwise) and the predictors are an intercept and two dummy variables, respectively, for the high (= 1) and medium (= 1) information conditions relative to the low information condition as base (= 0). The results show that information condition did not affect the probability of being excluded ($\chi^2(2) = .98$, $p = .61$).

Second, for the 430 participants remaining after step 2 we have information about their age, gender, brand ownership, and brand choice. For these participants we examined if the probability of being excluded from the analysis due to eye-movement quality (*n* = 91) depends on study design (information condition) and participant characteristics (age, gender, brand ownership and choice). We estimate a logistic regression model where the dependent variable is the status of the participant (1 = excluded in step 3, 0 = otherwise) and predictors are an intercept, and dummy variables for information condition (coded as before), gender (1 = female, 0 = otherwise), age (three variables for age groups 30-49, 50-64, and 65+, relative to the age group 18-29), brand ownership (four dummy variables for brands B to E, coded as 1 if the participant owns a device with the same brand name and 0 otherwise), and brand choice (four dummy variables for choice, coded as for brand ownership). The probability of being excluded (*n* = 91) depended, as expected, on gender ($\beta_{female} = .89$, $p = .001$; $\chi^2(1) = 10.8$, $p = .001$) and age ($\beta_{30-49} = .38$, $p = .31$; $\beta_{50-64} = 1.44$, $p < .001$; $\beta_{65+} = 1.95$, $p < .001$; $\chi^2(3) = 29.6$, p = <.001). More female (25% of 234) than male (16% of 196) participants, and more, older (34% of 160 being 50 years and older) than younger (13% of 270 being between 18 and 50 years) participants were excluded. Gender and age are added as covariates in all analyses at the participant level.

Importantly, the probability of being excluded due to low trackability did not depend on information condition ($\beta_{high} = .05$, $p = .86$; $\beta_{medium} = -.10$, $p = .75$; $\chi^2(2) = 0.24$, $p = .89$), brand ownership ($\beta_{brand\ 2} = -.39$, $p = .25$; $\beta_{brand\ 3} = -13.39$, $p = .98$; $\beta_{brand\ 4} = -.59$, $p = .24$; $\beta_{brand\ 5} = .40$, $p = .46$; $\chi^2(4) = 3.3$, $p = .50$), or brand choice ($\beta_{brand\ 2} = .001$, $p = .99$; $\beta_{brand\ 3} = .07$, $p = .88$; $\beta_{brand\ 4} = .12$, $p = .74$; $\beta_{brand\ 5} = -.24$, $p = .58$; $\chi^2(4) = .73$, $p = .95$), which indicates that data exclusions are Missing at Random (MAR). Using the estimated coefficients, we calculate the most likely outcome (inclusion or exclusion in step 3) for each of the 430 participants. For 80% of the participants the most likely outcome is the same as their actual inclusion/exclusion status. For comparison, a naïve model that predicts all participants are included has a hit rate of 79%, which further supports MAR for exclusions.

Processing of Eye Samples into Fixations and Saccades

For the 325 participants passing step 4, we have the location on the visual display in X and Y pixel coordinates for all fixations as determined by the BIT algorithm (van der Lans, Wedel, and Pieters 2011). We use these X and Y coordinates to assign fixations to areas-of-interest (AOI) on screen, which are the row-column-cells containing information about a specific brand on a specific attribute. Each fixation can fall either on one of the AOIs (brand-and-attribute cells), or on another area. For fixations that fall on an AOI, we record the brand and attribute cell they map onto. Then, we define saccades (transitions) as two fixations on different AOIs that are separated by at most one eye sample that is not part of a fixation. We identify three types of transitions: within-brand (when both fixations are on the same brand but different attributes), between-brand (fixations are on the same attribute but different brand), other-saccades (different brands and different attributes).

The density of attribute information could make it difficult to correctly differentiate between other-saccades and between-brand saccades. We investigated the potential impact from misclassifying between-brand saccades as other-saccades and the other way round. The total number of between-brand saccades (sum over all participants, quarters, and brands) is 13182. The total number of other-saccades (sum over all participants, quarters, and brands) is 10653. If the two attribute AOIs are too close, then there is a risk that: (1) a 'true' between-brand transition would be labelled incorrectly as "other", and (2) a 'true' transition between two brands on two different attributes would be incorrectly labelled as "between-brand". The probability of misclassification increases if AOIs are close to each other: for brands in adjacent columns and for attributes on adjacent rows. We checked how many transitions fall in this category: 12193 (92%) of between-brand saccades, and 6970 (65%) of other saccades.

We took the following steps to check how sensitive the results are to such misclassifications: (1) relabelled the potentially misclassified saccades (i.e., if a saccade was labelled as between-brand, we changed the label to ‘other’, and the other way round), and (2) estimated the proposed model using this data. There are only minor changes in the results (Table B2) that do not impact the substantive implications and theory tests. That is, all parameters keep their previously estimated magnitude and statistical significance levels.

Processing of Participant Responses to the Questionnaire

Information on the following consumer characteristics was available (with coding): gender (1 = female and 0 = male), age (0 = 18 to 29 years, 1 = 30 to 49 years, 2 = 50 to 64 years, 3 = 65 years and over), completed education (0 = high school, 1 = some education after high school, but no college degree, 2 = college degree, 3 = graduate degree), annual household income in USD (-4 = 14,999 or less, -3 = 15,000 to 24,999, -2 = 25,000 to 34,999, -1 = 35,000 to 49,999, 0 = 50,000 to 74,999 or “prefer not to answer”, 1 = 75,000 to 99,999, 2 = 100,000 to 149,999, 3 = 150,000 or more), and a dummy variable coded as 1 if “prefer not to answer”. Furthermore, information was available on current product category ownership (1 = yes and 0 = no), brand ownership (1 = brand currently owned is in the display, 0 = otherwise), knowledge about the product category (from 1 = “not at all knowledgeable” to 7 = “extremely knowledgeable”), knowledge about each of the brands in the display (from 1 = “nothing at all” to 7 = “a great deal”), and likelihood of purchasing a new device in the next nine months (0 = “no chance” to 100 = “completely certain”).

TABLE B2

ATTENTION TRAJECTORIES PREDICT BRAND CHOICE

(Sensitivity to misclassification of within-attribute and other transitions)

Predictors		Estimate	p	2.5%	97.5%
		Baseline Model			
Brand B	α_1	.53	.002	.15	.92
Brand C	α_2	.21	.16	-.30	.74
Brand D	α_3	.83	<.001	.43	1.25
Brand E	α_4	.59	.002	.14	1.02
Column 1	α_5	.44	.01	.08	.83
Column 2	α_6	.33	.06	-.09	.75
Column 3	α_7	-.11	.52	-.54	.31
Column 4	α_8	.17	.16	-.25	.58
Brand knowledge	α_9	.38	<.001	.28	.49
Brand ownership	α_{10}	.90	<.001	.58	1.22
		Proposed Model			
Brand B	α_1	-.03	.73	-1.09	.98
Brand C	α_2	.46	.17	-.69	1.61
Brand D	α_3	.98	.03	-.07	2.08
Brand E	α_4	-.10	.67	-1.18	.99
Column 1	α_5	-.68	.47	-2.83	1.40
Column 2	α_6	-.50	.59	-3.12	2.17
Column 3	α_7	-.32	.60	-2.01	1.43
Column 4	α_8	-.07	.71	-1.64	1.48
Brand knowledge	α_9	.11	.16	-.12	.35
Brand ownership	α_{10}	.39	.13	-.34	1.12
Attention Quantity:					
Initial level	β_0^1	7.03	<.001	3.65	10.58
Linear change	β_1^1	15.39	<.001	11.34	19.99
Quadratic change	β_2^1	40.28	<.001	29.95	51.36
Attention Type:					
Integration:					
Initial level	β_0^2	-1.53	.32	-4.68	1.61
Linear change	β_1^2	3.92	.02	.18	7.89
Quadratic change	β_2^2	26.79	<.001	14.54	39.40
Comparison:					
Initial level	β_0^3	-2.87	.22	-7.90	2.06
Linear change	β_1^3	-3.44	.27	-9.89	2.91
Quadratic change	β_2^3	.26	.25	-15.38	15.56
Other:					
Initial level	β_0^4	.08	.25	-3.91	4.09
Linear change	β_1^4	2.33	.18	-3.78	8.85
Quadratic change	β_2^4	-1.71	.65	-16.48	13.76

Note – Brand fixed-effects relative to Brand A, and column effects relative to column 5. Baseline model is M2. 95% one-tailed Bayesian *p*-value, and 95% Credible Interval (CI) of parameter estimates.

Web Appendix C. Model Estimation

LIKELIHOOD

Attention

Let attention a be reflected by n_a eye movements. Attention quantity ($a = quantity$) is reflected by eye fixations ($g = 1$). Attention type ($a = type$) is reflected by within-brand ($g = 2$), between-brand ($g = 3$), and other ($g = 4$) saccades. Therefore, $n_{quantity} = 1$ and $n_{type} = 3$. Then:

$$y_j^a = X_1^a \eta_j^a + X_2^a \epsilon_{j0}^a + \epsilon_j^a \tag{C.1}$$

In equation C.1:

y_j^a is a $BQn_a \times 1$ vector of log-transformed observed eye-movements (after adding 1 to accommodate zero frequencies: $y_j^a = \log(\breve{y}_j^a + 1)$) for participant j ($j = 1, \ldots, N$). Observations are grouped by brand ($i = 1, \ldots, B$): $y_j^a = \begin{bmatrix} y_{j1}^a & \ldots & y_{ji}^a & \cdots & y_{jB}^a \end{bmatrix}'$, quarter ($t = 1, \ldots Q$): $y_{ji}^a = \begin{bmatrix} y_{ji1}^a & \cdots & y_{jit}^a & \cdots & y_{jiQ}^a \end{bmatrix}'$, and eye movements: y_{jit}^a is $n_a \times 1$.

X_1^a is a $BQn_a \times (1 + B)K_0 n_a$ matrix, where $K_0 = 3$ (attention trajectory components: initial level, and linear and quadratic change):

$$X_1^a = [\mathbf{1}_B \quad I_B] \otimes (X \otimes I_{n_a}) \tag{C.2}$$

where X is a $Q \times K_0$ matrix with rows that contain the time scores ($[1 \quad x_t \quad x_t^2]$, $x_t = t - 1$) corresponding to the three attention trajectory components, $\mathbf{1}_B$ is a $B \times 1$ unit vector, and I_B and I_{n_a} are identity matrices of size B and n_a, respectively.

η_j^a is a $(1 + B)K_0 n_a \times 1$ vector that contains attention trajectory components for participant j (η_{j0}^a) and participant j and brand i (η_{ji}^a): $\eta_j^a = \begin{bmatrix} \eta_{j0}^a & \eta_{j1}^a & \ldots & \eta_{ji}^a & \cdots & \eta_{jB}^a \end{bmatrix}'$. η_{ji}^a is a $K_0 n_a \times 1$ vector: $\eta_{ji}^a = [\eta_{ji1}^a \quad \ldots \quad \eta_{jiK}^a]'$. η_{jik}^a has dimension $n_a \times 1$.

$$\eta_j^a = X_{3j}^a \gamma^a + r_j^a \tag{C.3}$$

X_2^a is a $BQn_a \times Qn_a$ matrix:

$$X_2^a = \mathbf{1}_B \otimes I_{Qn_a} \tag{C.4}$$

where $\mathbf{1}_B$ is a $B \times 1$ unit vector, and I_{Qn_a} is an identity matrix of size Qn_a.

ϵ_{j0}^a is a $Qn_a \times 1$ vector that contains measurement error at participant level. ϵ_j^a is a $BQn_a \times 1$ vector that contains measurement error at participant-and-brand (ϵ_{ji}^a) level: $\epsilon_j^a = [\epsilon_{j1}^a \quad \dots \quad \epsilon_{ji}^a \quad \cdots \quad \epsilon_{jB}^a]'$. ϵ_{j0}^a and ϵ_{ji}^a are distributed multivariate normal with mean zero and variance Ψ_0^a and Ψ_1^a, respectively. Ψ_0^a and Ψ_1^a are $Qn_a \times Qn_a$ block diagonal matrices, with each block of size $n_a \times n_a$ corresponding to one quarter. For example:

$$\Psi_0^{\mathrm{a}} = \begin{bmatrix} \Psi_{01}^{\mathrm{a}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \Psi_{0\mathrm{Q}}^{\mathrm{a}} \end{bmatrix} \tag{C.5}$$

In equation C.3:

X_{3j}^a is a $(1+B)K_0 n_a \times (K_0 n_a K_1 + K_0 n_a K_2)$ matrix of observed characteristics for participant j (X_{j0}) and brands $i = 1, \dots, B$ (X_{ji}). The matrix has two blocks of dimensions $K_0 n_a \times K_0 n_a K_1$ and $BK_0 n_a \times K_0 n_a K_2$, respectively:

$$X_{3j}^a = \begin{bmatrix} I_{K_0 n_a} \otimes X_{j0} & 0 \\ 0 & I_{K_0 n_a} \otimes X_{j1} \\ \dots & \dots \\ 0 & I_{K_0 n_a} \otimes X_{jB} \end{bmatrix} \tag{C.6}$$

γ^a is a $K_0 n_a (K_1 + K_2) \times 1$ vector that contains participant- (γ_1^a) and brand-specific effects (γ_2^a): $\gamma^a = [\gamma_1^{a\prime} \quad \gamma_2^{a\prime}]'$.

r_j^a is a $(1+B)K_0 n_a \times 1$ vector that contains unobserved heterogeneity at participant (r_{j0}^a) and at participant-and-brand level (r_{ji}^a): $r_j^a = [r_{j0}^a \quad r_{j1}^a \quad \dots \quad r_{ji}^a \quad \cdots \quad r_{jB}^a]'$. r_j^a is multivariate normally distributed with mean zero and variance Σ^a: $r_j^a \sim N(\mathbf{0}_{(1+B)K_0 n_a}, \Sigma^a)$. Σ^a is a block diagonal matrix:

$$\Sigma^a = \begin{bmatrix} \Sigma_0^a & 0 \\ 0 & I_B \otimes \Sigma_1^a \end{bmatrix} \tag{C.7}$$

where Σ_0^a and Σ_1^a are $K_0 n_a \times K_0 n_a$ matrices.

Let Θ denote the model parameters for attention quantity ($a = quantity$) and attention type ($a = type$). Specifically, Θ contains participant- and brand-specific: effects of observed characteristics (γ^a), attention trajectories (η_j^a), heterogeneity in attention trajectories (Σ_0^a and Σ_1^a), and variance of measurement errors (Ψ_0^a and Ψ_1^a).

In equation C.1, $\eta_j^a = \begin{bmatrix} \eta_{j0}^a & \eta_{j1}^a & \ldots & \eta_{ji}^a & \cdots & \eta_{jB}^a \end{bmatrix}'$ is a $(1+B)K_0 n_a \times 1$ vector that contains attention trajectories for participant j (η_{j0}^a) and participant j and brand i (η_{ji}^a), as reflected in eye movements observed at moments t up to and including Q ($t = 1, \ldots Q$). To simplify notation, we use θ_{jiQ} to denote trajectories of attention quantity ($\eta_{ji}^{quantity}$) and type (η_{ji}^{type}) for participant j and brand i, as reflected in eye movements observed at moments t up to and including Q ($t = 1, \ldots Q$).

Brand Choice

Let participant and brand utility at the moment when choice is expressed (u_{jiQ}) be revealed by the observed brand choice (c_j). At time Q, brand utility is:

$$u_{jiQ} = \alpha X_{ji}^c + \beta \theta_{jiQ} + \varepsilon_{jiQ} \tag{C.8}$$

where α is the effect of pre-inspection variables X_{ji}^c, β is the effect of attention trajectories θ_{jiQ}, and ε_{jiQ} is a random component that captures idiosyncrasies of consumer j's taste for brand i.

The probability that participant j chooses brand i at time Q is:

$$p\left(c_{jQ} = i \middle| \alpha, \beta\right) = \frac{exp\left(u_{jiQ}\right)}{\sum_{l=1}^{B} exp\left(u_{jlQ}\right)} \tag{C.9}$$

Let $\Phi = (\alpha, \beta)$ denote brand choice model parameters. The likelihood of the observed eye movements (EM) and brand choice (BC) given the attention (Θ) and brand choice (Φ) parameters is:

$$\mathcal{L}(BC, EM|\Theta, \Phi) = \prod_{j=1}^{N} p(c_{jQ}|\Phi) \prod_{j=1}^{N} \prod_{a=1}^{A} p(y_j^a|\eta_j^a, \Psi_0^a, \Psi_1^a) p(\eta_j^a|\gamma^a, \Sigma_0^a, \Sigma_1^a) \qquad \text{(C.10)}$$

PRIORS

The model is estimated using the following uninformative prior distributions (Carpenter et al. 2017; Gelman et al. 2013):

$$\begin{gathered}
\gamma^a \sim N(0, 5I_{K_0 n_a(K_1+K_2)}) \\
\Psi_{0t}^{\mathrm{a}} \sim Gamma(2, 3) \text{ (for } n_a = 1) \\
\Psi_{0t}^{\mathrm{a}} \sim Wishart(n_a + 2, I_{n_a}) \text{ (for for } n_a = 3) \\
\Sigma_0^a \sim Wishart(K_0 n_a + 2, I_{K_0 n_a}) \\
\Sigma_1^a \sim Wishart(K_0 n_a + 2, I_{K_0 n_a}) \\
\alpha \sim N(0, 10I_{B+1}) \\
\beta \sim N(0, 10I_{K_0 G})
\end{gathered} \qquad \text{(C.11)}$$

SAMPLING FROM POSTERIOR DISTRIBUTIONS

The model is estimated using the no-U-turn sampler (NUTS), a Markov chain Monte Carlo (MCMC) algorithm using the R interface to Stan (Carpenter et al. 2017; Gelman et al. 2013; Team 2018). We use two independent chains each with 50,000 iterations for the hierarchically-specified attention parameters, and 4,000 iterations for the single-level brand choice parameters. We use the second half of the iterations after the chains converge to summarize posterior distributions for attention and choice parameters ($S^a = 50{,}000$ and $S^c = 2{,}000$ samples from the posterior distribution of attention and brand choice parameters).

Web Appendix D. K-fold Cross-Validation

Despite its promise, K-fold CV is still seldom used in marketing and related disciplines (Yarkoni and Westfall 2017)[3]. Of the 27 attention and choice studies in the literature overview, one study reported on a classic 2-group validation (Stüttgen, Boatwright, and Monroe 2012), and six used subsets of repeated tasks to predict performance on other subsets for the same participants (Web Appendix A, Table A1, last column).

This appendix describes the steps in the two types of K-fold CV that we conduct.

Step 1: Split the total sample in K groups.

For each participant $j = 1, \ldots, N$, we have, respectively, observed eye movements (y_{jit}^{g}) and brand choice (c_j), participant- (X_{j0}) and brand-specific (X_{ji}) characteristics for $i = 1, \ldots, B$, $t = 1, \ldots, Q$, and $g = 1, \ldots, G$ ($B = 5$, $Q = 4$, and $G = 4$). The random-split K-fold CV splits participants in 10 groups, at random. The design-based K-fold CV splits participants into 12 groups, based on their information complexity condition ("low", "medium", and "high") and brand ownership segment ("owner of brand A", "owner of brand B", "owner of another smartphone brand", and "not owning a smartphone"). Both K-fold CV analyses (random-split and design-based) satisfy the independence assumption (Hastie, Tibshirani, and Friedman 2009; Varoquaux et al. 2017; Vehtari, Gelman, and Gabry 2017) that all observations of a participant are either in the estimation or in the validation sample, and not in both which could inflate predictive performance.

Step 2: Keep observations in one of the K groups separate (validation sample).

D_k contains all observations belonging to participants in group k. Let J_k contain the unique ids of participants in group k and N_k be the number of participants in group k.

[3] Five (< 1%) of the 701 papers published in JMR between 2010-2020 with the word-stem "predict" in the title, abstract or text, indicate to use "K-fold" validation (or k-fold, kfold, Kfold): (Blanchard, Aloise, and Desarbo 2017; Chan, Boksem, and Smidts 2018; Chen, Nelson, and Hsu 2015; Li and Xie 2020; Netzer, Lemaire, and Herzenstein 2019)

Step 3: Estimate the model on observations of the K-1 groups (estimation sample) (line 2 in Table D1).

D_{-k} contains all observations belonging to participants in groups other than k. Let J_{-k} contain the unique ids of the N_{-k} participants in groups other than k. No overlap between the estimation and validation samples requires that: $J_k \cap J_{-k} = \emptyset$ and $N_k + N_{-k} = N$.

The attention and choice parameters are estimated using the information contained in the estimation sample ($p(\Theta|D_{-k})$ and $p(\Phi|D_{-k})$, respectively). Attention parameters (Θ) include participant- and brand-specific: effects of observed characteristics (γ^a), latent attention trajectory components (η_j^a), heterogeneity in attention trajectories (Σ_0^a and Σ_1^a), and variance of measurement errors (Ψ_0^a and Ψ_1^a) (for attention quantity ($a = quantity$) and attention type ($a = type$)). Brand choice parameters ($\Phi = (\alpha, \beta)$) include brand- (α) and attention-specific (β) effects. Model estimation is described in detail in Web Appendix C.

Step 4: Use the parameter estimates from step 3 to predict the outcome of interest in the validation sample from step 2 (lines 4 to 26 in Table D1).

The outcome of interest is brand choice. The model predicts brand choice out-of-sample for participants J_k whose observations are not used in Step 3 to estimate attention and choice parameters. For each participant j in the validation sample, the model predicts brand choice "out-of-period", at five different moments: before the participant inspects the brands ($q = 0$), and then after each quarter ($q = 1, \dots, Q$, $Q = 4$). This is akin to multi-step cross-validation in time-series analysis where lagged variables are used to predict the same later variable, whereas here attention from earlier periods is used to predict later brand choice, out-of-sample. We do this both for random-split and design-based K-fold CV.

Before the participant inspects the brands ($q = 0$), brand utilities are calculated as a function of samples (S^c) from the posterior distribution of the effects (α) of pre-choice variables. After participant j in the validation sample starts inspecting the brands ($q \geq 1$), attention trajectories (η^a_{jqs}) are extracted conditional on sequentially observed eye movements ($t = 1, \dots, q$) and samples (S^a) from the posterior distributions of the attention parameters ($p(\Theta|D_{-k})$). For example, when $q = 2$ the model uses eye movements observed during the first two quarters (y^a_{jit} for $t = 1$ and $t = 2$) to extract attention trajectories (η^a_{jqs}). When $q = 3$, η^a_{jqs} are updated to incorporate information contained in eye movements observed in the first three quarters. Lines 15 to 17 in Table D1 provide the mean and variance of normally distributed attention trajectories (η^a_{jqs}). Brand choice utilities (u_{jiqs}) are calculated as a function of samples (S^c) from the posterior distribution of brand choice parameters ($p(\Phi|D_{-k})$) and attention trajectories reflected in eye movements observed up to q (line 22 in Table D1).

The model predicts that participants chose the brand with the highest utility in the set: $\hat{c}_{jqs} = i$, where $u_{jiqs} = \max_{l=1,\dots,B} u_{jlqs}$. To summarize, brand choice predictions ($\hat{c}_{jqs}$) are made out-of-sample (for participants included in the validation sample and not in the estimation sample) and out-of-period (for periods not yet observed). This implies that there are S^c (samples from the posterior distribution of the brand choice parameters $\Phi = (\alpha, \beta)$) predictions made for each $q = 0, \dots, Q$, for each of the participants in the validation sample.

Step 5: Compare the predicted outcome from step 4 with the actual outcome (lines 27 to 31 in Table D1)

The model correctly predicts brand choice if $\hat{c}_{jqs} = c_{jQ}$. Correct brand choice predictions are coded as 1 and incorrect predictions as 0.

Step 6: Repeat steps 2 to 5 for each of the K groups (lines 1 to 33 in Table D1).

Step 7: Summarize model performance across the K groups.

We use expected log predictive density (ELPD) (Vehtari, Gelman, and Gabry 2017) and brand choice hit rates to assess out-of-sample model performance. ELDP assesses the posterior predictive distribution of a model given the data, while taking the uncertainty of the brand choice predictions into account. The expected log predictive density of model m is:

$$\widehat{elpd}_m = \sum_{j=1}^{N} \log\left(\frac{1}{S}\sum_{s=1}^{S} p(c_{jQ}|\Phi_{-k,s})\right)$$

where $\Phi_{-k,s}$ is a sample $s = 1, \dots, S$ from the posterior distribution of brand choice model parameters calibrated on data (D_{-k}) that do not include the fold k that participant j is part of ($p(\Phi|D_{-k})$).

The hit rate quantifies the percent of participants for whom model m correctly predicts brand choice. The hit rate of model m at time q is calculated for every sample s from the posterior distribution of the brand choice parameters:

$$\widehat{Hit}_{mqs} = \frac{1}{N}\sum_{j=1}^{N} \mathbf{1}(\hat{c}_{jqs} = c_{jQ})$$

where $\mathbf{1}(\hat{c}_{jqs} = c_{jQ})$ is an indicator function that takes the value 1 for correct brand choice predictions ($\hat{c}_{jqs} = c_{jQ}$) and 0 otherwise.

The mean hit rate and lower and upper bounds of the prediction interval (PI) (Hamada et al. 2004) of model m at time q are, respectively, the average and the 2.5 and 97.5 percentiles of $\widehat{Hit}_{mqs}$ ($s = 1, \dots, S$).

Table D1: K-fold CV algorithm

for $k = 1$ to K **do**

Estimate attention $p(\Theta|D_{-k})$ and choice $p(\Phi|D_{-k})$ parameters

for $j \in J_k$ **do**

Predict brand choice before the participant inspects the brands ($q = 0$)

for $s = 1$ to S^c **do**

for $i = 1$ to B **do**

$u_{ji0s} = \alpha_s X_{ji}^c$

end for i

$\hat{c}_{j0s} = i$ where $u_{ji0s} = \max u_{jl0s}$, for $l = 1, \dots, B$

end for s

Predict brand choice from moment-to-moment as brands are inspected

for $q = 1$ to Q **do**

Observe y_{jq}^a **(**eye movements up to and including q for j)

for $s = 1$ to S^a **do**

$H_{qs}^a = \left(\left(X_{1q}^a\right)' \left(X_{2q}^a \Psi_{0s}^a \left(X_{2q}^a\right)' + I_B \otimes \Psi_{1s}^a\right)^{-1} X_{1q}^a + (\Sigma_s^a)^{-1}\right)^{-1}$

$h_{jqs}^a = \left(X_{1q}^a\right)' \left(X_{2q}^a \Psi_{0s}^a \left(X_{2q}^a\right)' + I_B \otimes \Psi_{1s}^a\right)^{-1} y_{jq}^a + (\Sigma_s^a)^{-1} X_{3j}^a \gamma_s^a$

$\eta_{jqs}^a \sim N(H_{qs}^a h_{jqs}^a, H_{qs}^a)$

end for s

$\theta_{jq}^a = (S^a)^{-1} \sum_s \eta_{jqs}^a$

for $s = 1$ to S^c **do**

for $i = 1$ to B **do**

$u_{jiqs} = \alpha_s X_{ji}^c + \sum_a \beta_s^a \theta_{jq}^a$

end for i

$\hat{c}_{jqs} = i$ where $u_{jiqs} = \max u_{jlqs}$, for $l = 1, \dots, B$

end for s

end for q

for $q = 0$ to Q **do**

for $s = 1$ to S^c **do**

$PredBC_{jqs} = \mathbf{1}(\hat{c}_{jqs} = c_j)$

end for s

end for q

end for j

end for k

Web Appendix E. Specification of Brand Choice Models

Let $u_{jiQ} = U_{jiQ} + \varepsilon_{jiQ}$ be the utility of brand i for consumer j at moment Q when brand choice is expressed, where U_{jiQ} is a non-stochastic utility component and ε_{jiQ} is a random component that captures the idiosyncrasies of consumer j's taste for brand i. Below, t indexes the four time periods ($t = 1, \ldots, Q$, $Q = 4$) during the task, and k the three trajectory components (initial, linear and quadratic change). We have the following models:

M0: $$U_{jiQ} = \sum_{l=1}^{B-1} \alpha_l BP_{il} + \sum_{l=1}^{4} \alpha_{4+l} BC_{jil}$$

M1: $$U_{jiQ} = \sum_{l=1}^{B-1} \alpha_l BP_{il} + \sum_{l=1}^{4} \alpha_{4+l} BC_{jil} + \alpha_9 BO_{ji}$$

M2: $$U_{jiQ}^{M1} = \sum_{l=1}^{B-1} \alpha_l BP_{il} + \sum_{l=1}^{4} \alpha_{4+l} BC_{jil} + \alpha_9 BK_{ji} + \alpha_{10} BO_{ji}$$

M3: $$U_{jiQ} = \beta_0^1 \sum_{t=1}^{Q} y_{jit}^1 + U_{jiQ}^{M_2}$$

M4: $$U_{jiQ} = \sum_{g=1}^{G} \sum_{k=0}^{2} \beta_k^g \theta_{jikQ}^g + U_{jiQ}^{M_2}$$

Follow-up Models:

M5: $$U_{jiQ} = \sum_{g=1}^{G} \sum_{k=0}^{1} \beta_k^g \theta_{jikQ}^g + U_{jiQ}^{M_2}$$

M6: $$U_{jiQ} = \sum_{g=1}^{G} \sum_{k=0}^{2} \beta_k^g \theta_{jikQ}^g$$

Robustness of Attention – Behavior Relationship:

M7: $$U_{jiQ} = \sum_{g=1}^{G} \sum_{k=0}^{2} \beta_k^g \theta_{jikQ}^g + \sum_{g=1}^{G} \sum_{k=0}^{2} \beta_{k+3}^g \theta_{jikQ}^g IC_j + U_{jiQ}^{M_2}$$

M8: $$U_{jiQ} = \sum_{g=1}^{G} \sum_{k=0}^{2} \beta_k^g \theta_{jikQ}^g + \sum_{g=1}^{G} \sum_{k=0}^{2} \beta_{k+3}^g \theta_{jikQ}^g NFIX_j + U_{jiQ}^{M_2}$$

M9: $$U_{jiQ} = \sum_{g=1}^{G} \sum_{k=0}^{2} \beta_k^g \theta_{jikQ}^g + \sum_{g=1}^{G} \sum_{k=0}^{2} \beta_{k+3}^g \theta_{jikQ}^g DT_j + U_{jiQ}^{M_2}$$

Where: $BP_{il} = 1$ for $l = i + 1$ and 0 otherwise; $BO_{ij} = 1$ if consumer j owns brand i, and 0 otherwise; BK_{ji} is consumer j's knowledge about brand i; $BC_{jil} = 1$ if brand i for consumer j is in column $l = 1, \ldots 4$ of the choice display and 0 otherwise; y^1_{jit} is the number of fixations on brand i at time t for consumer j; θ^g_{jikQ} is the brand i and consumer j attention trajectory k reflected in eye movements g observed during the choice task; IC_j is the information condition for consumer j ($IC_j = -1$ for "low", $IC_j = 0$ for "medium", and $IC_j = 1$ for "high"); $NFIX_j$ is the total number of fixations for consumer j ($NFIX_j = \sum_i^B \sum_q^Q y^1_{jiq}$); and DT_j is the total time (in seconds) that participant j inspected the brands.

All models are summarized here. Models M0 to M4 are presented in the text and summarized in Table 2. All models except M6 specify U_{jiQ} as a function that includes variables that are constant over time ("pre-inspection information").

Models M3 to M9 specify U_{jiQ} as a function of attention, which changes over time as more eye-movements are observed. This enables us to update out-of-sample brand choice predictions from moment-to-moment as the time-varying variables change. For M3, this refers to the sum of fixations up to current moment q: $\sum_{t=1}^{q} y^1_{jiq}$. For models that include θ^g_{jikQ} (M4-M10), attention trajectories are updated from moment-to-moment as eye movements are observed (updated y^a_{jq}), as specified in Web Appendix D (Table D1, lines 13-19).

Models M5 and M6 are follow-up models that provide tests of specific hypotheses by comparing their predictive performance with that of the proposed model (M4). Respectively, these models test if predictive performance improves when including information about: increasing attention in the final quarter (quadratic effect) (M4 versus M5); and pre-inspection information in addition to attention trajectories (M4 vs M6).

Models 7 to 9 assess the robustness of the attention-choice relationship across, respectively, the three information conditions (M7), the time that each participant took to express brand choice as indicated by the total number of eye fixations (M = 307, SD = 245) during inspection (M8), the time that each participant took to express brand choice (M = 116, SD = 95) as indicated by the difference between start and end time stamp of inspection (M9). These models assess the potential moderating effects of the experimental design and consumer-specific inspection-duration on the attention-choice relationship.

TABLE E1
MODEL PERFORMANCE

		Random-split K-fold			Design-based K-fold		
			Hit rate			Hit rate	
Model	# pars	ELPD	mean	PI	ELPD	mean	PI
M0	8	-504	27%	[24; 31]	-514	24%	[20; 29]
M1	9	-458	43%	[42; 45]	-460	43%	[42; 45]
M2	10	-431	45%	[43; 47]	-431	45%	[42; 47]
M3	11	-230	75%	[73; 77]	-226	75%	[72; 77]
M4	22	-126	85%	[82; 87]	-120	85%	[83; 87]
Follow-up Models:							
M5	18	-307	61%	[58; 63]	-305	61%	[59; 64]
M6	12	-126	85%	[83; 87]	-123	86%	[84; 88]
Robustness of Attention – Behavior Relationship:							
M7	34	-128	84%	[81; 86]	-123	84%	[82; 87]
M8	34	-127	84%	[82; 86]	-121	85%	[82; 87]
M9	34	-131	83%	[81; 86]	-125	84%	[82; 86]

Note – # pars is number of parameters in choice part. ELPD is Expected Log Predictive Density. Hit rate, with 95% Prediction Interval (PI) between brackets is percentage of participants for whom the model correctly predicts brand choice. Hit rate for random brand choice predictions is 20% (1 out of 5 brands).

Models M0 to M4 are detailed in the text. M0 performs much worse than M2, demonstrating the contribution of brand ownership and knowledge over and above intrinsic market preferences. M6, which only has the attention trajectories has the same hit rates as the proposed model M4 (85%), illustrating the contribution of the attention trajectories. M5, which only has the base and linear trajectory components and not the quadratic component (lift towards choice), does much worse than the proposed model (24 percentage points lower hit rate), showing the contribution to choice prediction of the lift in the final quarter. The three moderation models, M7 to M9 perform worse than the proposed model does, supporting the idea that the relationship between attention trajectories and brand choice is stable across different levels of information and the time consumers take to time to express their brand choice.

For completeness, parameter estimates for models M3, M6, and M7 are, respectively, in Tables E2, E3, E4, and E5. Tables E6, E7, and E8 present out-of-sample and out-of-period brand choice predictive performance for each of the 4 X 3 cells of the experimental design more the proposed model (M4), benchmark model M3, and follow-up model M6.

TABLE E2
BENCHMARK MODEL M3

		Benchmark Model M3: M2 with cumulative sum of fixations for each brand			
Predictors		Estimate	*p*	2.5%	97.5%
Brand B	α_1	.16	.20	-.32	.67
Brand C	α_2	-.25	.45	-1.00	.49
Brand D	α_3	.55	.03	-.02	1.12
Brand E	α_4	.20	.19	-.36	.79
Column 1	α_5	-1.97	<.001	-2.61	-1.37
Column 2	α_6	-1.29	<.001	-1.93	-.69
Column 3	α_7	-.91	<.001	-1.50	-.30
Column 4	α_8	-.30	.24	-.84	.23
Brand knowledge	α_9	.44	<.001	.29	.60
Brand ownership	α_{10}	.82	<.001	.42	1.23
Sum of eye fixations	β_0^1	.08	<.001	.07	.09

Note – Brand fixed-effects relative to Brand A. One-tailed Bayesian *p*-values, and 95% Credible Intervals.

TABLE E3

FOLLOW-UP MODEL M6

Predictors		Model M6: M4 without pre-choice task information			
		Estimate	*p*	2.5%	97.5%
Attention Quantity:					
Initial level	β_0^1	5.24	<.001	2.82	7.65
Linear change	β_1^1	14.08	<.001	10.23	18.01
Quadratic change	β_2^1	38.98	<.001	28.69	49.74
Attention Type:					
Integration:					
Initial level	β_0^2	-.53	.52	-2.70	1.75
Linear change	β_1^2	4.20	.01	.74	7.88
Quadratic change	β_2^2	24.67	<.001	13.61	36.05
Comparison:					
Initial level	β_0^3	-.45	.61	-3.25	2.38
Linear change	β_1^3	-.06	.75	-5.17	4.84
Quadratic change	β_2^3	-4.75	.44	-17.98	8.30
Other:					
Initial level	β_0^4	-.98	.47	-3.97	2.01
Linear change	β_1^4	-.21	.71	-4.98	4.89
Quadratic change	β_2^4	.77	.25	-13.92	15.40

Note – One-tailed Bayesian *p*-values, and 95% Credible Intervals.

TABLE E4
FOLLOW-UP MODEL M7

Predictors		Model 7: M4 with Potential Moderating Effect of Information Condition			
		Estimate	*p*	2.5%	97.5%
Brand B	α_1	-.02	.73	-.93	.94
Brand C	α_2	.20	.23	-.87	1.34
Brand D	α_3	1.35	.005	.27	2.47
Brand E	α_4	.12	.25	-1.10	1.31
Column 1	α_5	-1.35	.24	-3.78	.86
Column 2	α_6	-1.54	.23	-4.19	.88
Column 3	α_7	-1.22	.20	-3.12	.62
Column 4	α_8	-.75	.34	-2.41	.84
Brand knowledge	α_9	.05	.23	-.18	.29
Brand ownership	α_{10}	.31	.16	-.38	1.04
Attention Quantity:					
Initial level	β_0^1	7.46	<.001	3.77	11.07
Linear change	β_1^1	17.21	<.001	12.58	21.93
Quadratic change	β_2^1	44.12	<.001	32.43	56.10
Attention Type:					
Integration:					
Initial level	β_0^2	-1.98	.21	-5.13	1.28
Linear change	β_1^2	3.79	.03	-.36	8.02
Quadratic change	β_2^2	27.10	<.001	14.34	40.13
Comparison:					
Initial level	β_0^3	.77	.23	-3.48	4.90
Linear change	β_1^3	.11	.25	-5.65	6.19
Quadratic change	β_2^3	-2.91	.56	-17.30	12.45
Other:					
Initial level	β_0^4	-1.35	.51	-6.60	3.80
Linear change	β_1^4	-1.61	.53	-7.82	4.51
Quadratic change	β_2^4	-.01	.75	-16.15	15.81
Interactions with information condition					
Attention Quantity:					
Initial level	β_3^1	1.41	.15	-1.79	4.70
Linear change	β_4^1	4.30	.04	-.56	9.15
Quadratic change	β_5^1	6.51	.13	-5.56	18.96
Attention Type:					
Integration:					
Initial level	β_3^2	-.23	.69	-3.33	2.96
Linear change	β_4^2	-.09	.73	-4.43	4.37
Quadratic change	β_5^2	1.99	.24	-11.29	15.38
Comparison:					
Initial level	β_3^3	-.35	.69	-4.31	3.44
Linear change	β_4^3	-.56	.67	-6.46	5.31
Quadratic change	β_5^3	-5.74	.39	-20.85	10.24
Other:					
Initial level	β_3^4	-2.40	.23	-6.54	1.76
Linear change	β_4^4	-4.38	.17	-10.86	2.05
Quadratic change	β_5^4	.52	.25	-16.23	17.73

Note – Brand fixed-effects relative to Brand A. One-tailed Bayesian *p*-values, and 95% Credible Intervals. Information conditions coded -1 = low, 0 = moderate, 1 = high.

TABLE E5
K-FOLD CROSS-VALIDATION FOR PROPOSED MODEL M4 FOR ALL 4 X 3 CELLS IN THE EXPERIMENTAL DESIGN AND IN EACH OF THE 4 QUARTERS

Information Complexity	User segment	Baseline model	Proposed Model Q1	Q2	Q3	Q4	Sample (n)
Low	Brand A	44%	45%	48%	47%	80%	30
	Brand B	56%	52%	55%	57%	85%	28
	Other brand	38%	36%	40%	45%	82%	29
	Non-user	27%	29%	29%	37%	81%	20
Medium	Brand A	54%	50%	48%	58%	84%	33
	Brand B	47%	49%	48%	65%	90%	27
	Other brand	49%	52%	53%	53%	87%	29
	Non-user	26%	28%	30%	48%	86%	26
High	Brand A	53%	54%	51%	66%	86%	30
	Brand B	61%	63%	61%	56%	91%	22
	Other brand	47%	47%	48%	55%	90%	30
	Non-user	27%	23%	30%	32%	83%	21
Low		42%	41%	44%	47%	82%	107
Medium	All	45%	45%	45%	56%	87%	115
High		48%	47%	48%	54%	88%	103
	Brand A	50%	50%	49%	57%	84%	93
All	Brand B	54%	54%	54%	59%	88%	77
	Other brand	45%	45%	47%	51%	86%	88
	Non-user	27%	26%	30%	40%	83%	67
All	All	45%	45%	46%	52%	85%	325

Note – Cell numbers are row percentage hit rates. Other brand users own another brand. Non-users currently do not own a device in the product category. Baseline model is M2. Proposed Model is M4. Q is time period (Quarter) during the choice task.

TABLE E6
K-FOLD CROSS-VALIDATION FOR MODEL M3 FOR ALL 4 X 3 CELLS
IN THE EXPERIMENTAL DESIGN AND IN EACH OF THE 4 QUARTERS

Information Complexity	User segment	Baseline model	M3: M2 with total number of eye fixations per brand				Sample
			Q1	Q2	Q3	Q4	(n)
Low	Brand A	44%	37%	47%	55%	73%	30
	Brand B	56%	43%	45%	53%	86%	28
	Other brand	38%	35%	48%	47%	67%	29
	Non-user	27%	28%	34%	40%	77%	20
Medium	Brand A	54%	47%	43%	51%	70%	33
	Brand B	47%	41%	56%	69%	82%	27
	Other brand	49%	42%	42%	49%	70%	29
	Non-user	26%	25%	29%	37%	65%	26
High	Brand A	53%	54%	51%	60%	74%	30
	Brand B	61%	53%	54%	63%	88%	22
	Other brand	47%	41%	46%	46%	85%	30
	Non-user	27%	24%	26%	39%	57%	21
Low	All	42%	36%	44%	50%	76%	107
Medium	All	45%	40%	43%	51%	72%	115
High	All	48%	44%	45%	52%	76%	103
All	Brand A	50%	46%	47%	55%	72%	93
All	Brand B	54%	45%	51%	62%	85%	77
All	Other brand	45%	39%	46%	47%	74%	88
All	Non-user	27%	26%	29%	38%	66%	67
All	All	45%	40%	44%	51%	75%	325

Note – Cell numbers are row percentage hit rates. Other brand users own another brand. Non-users currently do not own a device in the product category. Baseline model is M2.

TABLE E7

K-FOLD CROSS-VALIDATION FOR FOLLOW-UP MODEL M6 FOR ALL 4 X 3 CELLS IN THE EXPERIMENTAL DESIGN AND IN EACH OF THE 4 QUARTERS

Information Complexity	User segment	Baseline model	M6: Proposed model without pre-inspection information				Sample
			Q1	Q2	Q3	Q4	(n)
Low	Brand A	44%	45%	46%	44%	80%	30
	Brand B	56%	51%	54%	58%	85%	28
	Other brand	38%	35%	38%	45%	84%	29
	Non-user	27%	26%	32%	35%	80%	20
Medium	Brand A	54%	52%	47%	59%	83%	33
	Brand B	47%	49%	50%	62%	90%	27
	Other brand	49%	51%	49%	52%	88%	29
	Non-user	26%	27%	33%	49%	89%	26
High	Brand A	53%	57%	52%	68%	91%	30
	Brand B	61%	64%	62%	58%	87%	22
	Other brand	47%	47%	50%	60%	93%	30
	Non-user	27%	22%	26%	35%	82%	21
Low		42%	40%	43%	46%	82%	107
Medium	All	45%	45%	45%	56%	87%	115
High		48%	49%	48%	57%	89%	103
	Brand A	50%	51%	49%	57%	85%	93
All	Brand B	54%	54%	55%	59%	87%	77
	Other brand	45%	44%	46%	52%	88%	88
	Non-user	27%	25%	31%	41%	84%	67
All	All	45%	45%	46%	53%	86%	325

Note – Cell numbers are row percentage hit rates. Other brand users own another brand. Non-users currently do not own a device in the product category. Baseline model is M2.

Web Appendix F. Consumer- and Brand-Specific Effects on Attention

TABLE F1
ATTENTION QUANTITY

Predictors	Components of Attention Trajectories								
	Initial Level (*k* = 0)			Linear Change (*k* = 1)			Quadratic Change (*k* = 2)		
	M	*SD*	*p*	*M*	*SD*	*p*	*M*	*SD*	*p*
Consumer-level (*j*):									
Brand eye fixations (g = 1):									
Intercept	1.28	.16	<.001	.15	.13	.11	-.04	.04	.35
Information condition	.18	.05	<.001	-.02	.03	.53	.00	.01	.24
Product ownership	-.05	.12	.56	-.08	.08	.30	.01	.02	.22
Product knowledge	-.10	.04	.004	.00	.02	.69	.00	.01	.25
Gender	.24	.09	.004	-.03	.06	.55	.01	.02	.23
Age	-.01	.05	.63	.03	.03	.13	-.01	.01	.51
Education	.19	.05	<.001	-.02	.03	.44	.00	.01	.25
Income not disclosed	.20	.16	.10	-.06	.11	.50	.00	.03	.25
Income category	.02	.03	.16	-.01	.02	.45	.00	.01	.16
Variance	.50	.05	<.001	.02	.01	<.001	.00	.00	<.001
Brand-level (*i*):									
Brand eye fixations (*g* = 1):									
Brand B	-.02	.05	.62	.20	.09	.01	-.03	.03	.31
Brand C	.01	.06	.24	.05	.09	.21	.00	.03	.74
Brand D	.05	.05	.16	.12	.09	.08	-.02	.03	.37
Brand E	.04	.05	.17	.06	.09	.19	.00	.03	.25
Column 1	1.35	.05	<.001	-.59	.08	<.001	.02	.01	.01
Column 2	.88	.05	<.001	-.19	.08	.03	.10	.03	<.001
Column 3	.37	.05	<.001	.18	.08	.01	.03	.03	.11
Column 4	.15	.05	<.001	.24	.08	.002	-.05	.03	.04
Brand knowledge	.03	.05	.02	-.01	.02	.52	-.05	.03	.05
Brand ownership	.14	.05	.002	.08	.08	.15	.00	.03	.25
Variance	.16	.04	<.001	.27	.07	<.001	.02	.01	<.001

Note – *M* = Mean estimate; *SD* = Standard deviation; *p* = one-tailed Bayesian significance level. All eye-movement measures transformed natural log +1 prior to analysis. Information condition: -1 = low, 0 = medium, 1 = high. Product -, and brand ownership: 1 = yes, 0 = no. Product knowledge mean-centered between participants. Brand knowledge mean-centered within participant. Gender: 1 = female, 0 = male. Age: 0 = “18-29”, 1 = “30-49”, 2 = “50-64”, and 3 = “65+”. Education: 0 = high school, 1 = associate degree, 2 = college degree, 3 = graduate degree. Income not disclosed: 1 = participant did not disclose income, 0 = otherwise. Income category: -4 = “$14,999 or less”, -3 = “$15,000 to $24,999”, -2 = “$25,000 to $34,999”, -1 = “$25,000 to $49,999”, 0 = “$50,000 to $74,999”, 1 = “$75,000 to $99,999”, 2 = “$100,000 to $149,999”, 3 = “$150,000 or more”. Brand B to E are brand fixed effects. Column 1 to 4: 1 = brand is shown in the respective column, 0 = otherwise.

TABLE F2
INTEGRATION ATTENTION

Predictors	Components of Attention Trajectories								
	Initial Level (k = 0)			Linear Change (k = 1)			Quadratic Change (k = 2)		
	M	*SD*	*p*	*M*	*SD*	*p*	*M*	*SD*	*p*
Consumer-level (j):									
Within saccades (g = 2):									
Intercept	.52	.12	<.001	-.08	.14	.50	.05	.04	.12
Information condition	.10	.04	.01	-.06	.04	.12	.02	.01	.05
Product ownership	-.04	.09	.56	-.02	.08	.63	-.01	.03	.64
Product knowledge	-.05	.03	.06	-.03	.03	.24	.01	.01	.14
Gender	.21	.07	<.001	-.10	.06	.10	.03	.02	.09
Age	-.03	.04	.40	.04	.04	.11	-.01	.01	.31
Education	.13	.04	<.001	-.05	.04	.20	.01	.01	.14
Income not disclosed	.16	.12	.09	.00	.12	.74	-.02	.04	.51
Income category	.00	.02	.24	-.02	.02	.32	.01	.01	.11
Variance	.23	.03	<.001	.04	.01	<.001	.00	.00	<.001
Brand-level (i):									
Within saccades (g = 2):									
Brand B	-.03	.06	.53	.28	.09	.001	-.05	.03	.06
Brand C	.01	.06	.24	.14	.10	.07	-.03	.03	.30
Brand D	.04	.06	.18	.21	.10	.01	-.05	.03	.11
Brand E	-.01	.06	.64	.18	.10	.03	-.03	.03	.27
Column 1	1.04	.05	<.001	-.61	.08	<.001	.11	.03	<.001
Column 2	.46	.05	<.001	-.05	.09	.52	-.01	.03	.66
Column 3	.08	.05	.05	.19	.08	.01	-.05	.03	.05
Column 4	-.02	.05	.58	.25	.09	.002	-.06	.03	.04
Brand knowledge	.02	.01	.10	-.01	.02	.51	.01	.01	.02
Brand ownership	.14	.05	.005	.11	.09	.10	-.01	.03	.60
Variance	.24	.04	<.001	.35	.06	<.001	.02	.01	<.001

Note – *M* = Mean estimate; *SD* = Standard deviation; *p* = one-tailed Bayesian significance level. All eye-movement measures transformed natural log +1 prior to analysis. Information condition: -1 = low, 0 = medium, 1 = high. Product -, and brand ownership: 1 = yes, 0 = no. Product knowledge mean-centered between participants. Brand knowledge mean-centered within participant. Gender: 1 = female, 0 = male. Age: 0 = “18-29”, 1 = “30-49”, 2 = “50-64”, and 3 = “65+”. Education: 0 = high school, 1 = associate degree, 2 = college degree, 3 = graduate degree. Income not disclosed: 1 = participant did not disclose income, 0 = otherwise. Income category: -4 = “$14,999 or less”, -3 = “$15,000 to $24,999”, -2 = “$25,000 to $34,999”, -1 = “$25,000 to $49,999”, 0 = “$50,000 to $74,999”, 1 = “$75,000 to $99,999”, 2 = “$100,000 to $149,999”, 3 = “$150,000 or more”. Brand B to E are brand fixed effects. Column 1 to 4: 1 = brand is shown in the respective column, 0 = otherwise.

TABLE F3
COMPARISON ATTENTION

Predictors	Components of Attention Trajectories								
	Initial Level (k = 0)			Linear Change (k = 1)			Quadratic Change (k = 2)		
	M	*SD*	*p*	*M*	*SD*	*p*	*M*	*SD*	*p*
Consumer-level (j):									
Between saccades (g = 3):									
Intercept	.15	.11	.08	.16	.11	.08	-.04	.04	.25
Information condition	.18	.04	<.001	.00	.03	.25	-.01	.01	.53
Product ownership	.01	.09	.25	-.12	.08	.12	.02	.02	.15
Product knowledge	-.06	.03	.01	-.01	.02	.54	.00	.01	.20
Gender	.09	.06	.07	.00	.06	.25	.01	.02	.20
Age	-.06	.04	.11	-.01	.03	.65	.01	.01	.16
Education	.14	.04	<.001	-.01	.03	.59	.00	.01	.69
Income not disclosed	.12	.12	.13	-.01	.11	.72	-.01	.03	.65
Income category	.03	.02	.04	.01	.02	.18	.00	.01	.34
Variance	.24	.03	<.001	.07	.02	<.001	.01	.00	<.001
Brand-level (i):									
Between saccades (g = 3):									
Brand B	.02	.04	.22	.02	.06	.24	.00	.02	.74
Brand C	.02	.04	.22	.04	.06	.20	-.01	.02	.42
Brand D	.00	.04	.75	.10	.06	.05	-.03	.02	.10
Brand E	.01	.04	.24	.04	.06	.19	-.01	.02	.50
Column 1	.50	.03	<.001	.08	.05	.06	-.07	.02	<.001
Column 2	.62	.03	<.001	.16	.06	.002	-.07	.02	<.001
Column 3	.40	.03	<.001	.26	.05	<.001	-.08	.02	<.001
Column 4	.36	.03	<.001	.13	.06	.01	-.04	.02	.01
Brand knowledge	.01	.01	.06	.00	.01	.24	.00	.00	.24
Brand ownership	-.02	.03	.50	.08	.06	.07	-.01	.02	.40
Variance	.05	.01	<.001	.10	.02	<.001	.01	.00	<.001

Note – *M* = Mean estimate; *SD* = Standard deviation; *p* = one-tailed Bayesian significance level. All eye-movement measures transformed natural log +1 prior to analysis. Information condition: -1 = low, 0 = medium, 1 = high. Product -, and brand ownership: 1 = yes, 0 = no. Product knowledge mean-centered between participants. Brand knowledge mean-centered within participant. Gender: 1 = female, 0 = male. Age: 0 = “18-29”, 1 = “30-49”, 2 = “50-64”, and 3 = “65+”. Education: 0 = high school, 1 = associate degree, 2 = college degree, 3 = graduate degree. Income not disclosed: 1 = participant did not disclose income, 0 = otherwise. Income category: -4 = “$14,999 or less”, -3 = “$15,000 to $24,999”, -2 = “$25,000 to $34,999”, -1 = “$25,000 to $49,999”, 0 = “$50,000 to $74,999”, 1 = “$75,000 to $99,999”, 2 = “$100,000 to $149,999”, 3 = “$150,000 or more”. Brand B to E are brand fixed effects. Column 1 to 4: 1 = brand is shown in the respective column, 0 = otherwise.

TABLE F4
OTHER ATTENTION

Predictors	Components of Attention Trajectories								
	Initial Level (k = 0)			Linear Change (k = 1)			Quadratic Change (k = 2)		
	M	*SD*	*p*	*M*	*SD*	*p*	*M*	*SD*	*p*
Consumer-level (j):									
Other saccades (g = 4):									
Intercept	.17	.10	.04	.12	.10	.11	-.02	.03	.42
Information condition	.13	.03	<.001	-.02	.03	.46	.01	.01	.20
Product ownership	-.04	.07	.53	-.03	.07	.54	.00	.02	.74
Product knowledge	-.05	.02	.02	-.01	.02	.51	.00	.01	.24
Gender	.07	.05	.09	.01	.05	.25	.00	.02	.70
Age	-.01	.03	.55	.04	.03	.10	-.01	.01	.25
Education	.10	.03	<.001	.02	.03	.19	-.01	.01	.40
Income not disclosed	.05	.10	.21	-.11	.09	.22	.03	.03	.12
Income category	.00	.02	.24	.01	.01	.21	.00	.00	.71
Variance	.16	.02	<.001	.05	.01	<.001	.00	.00	<.001
Brand-level (i):									
Other saccades (g = 4):									
Brand B	-.01	.04	.66	.03	.06	.22	.00	.02	.68
Brand C	.01	.04	.24	-.03	.06	.57	.01	.02	.19
Brand D	.01	.04	.24	-.03	.06	.57	.02	.02	.18
Brand E	.01	.04	.23	-.12	.06	.05	.05	.02	.01
Column 1	.41	.03	<.001	-.17	.06	.002	.02	.02	.08
Column 2	.64	.04	<.001	-.16	.06	.005	.03	.02	.05
Column 3	.36	.03	<.001	.11	.05	.02	-.03	.02	.09
Column 4	.25	.03	<.001	.09	.06	.06	-.01	.02	.42
Brand knowledge	.01	.01	.05	-.01	.02	.34	.01	.00	.08
Brand ownership	.03	.04	.16	.05	.06	.15	-.01	.02	.60
Variance	.06	.02	<.001	.08	.02	<.001	.01	.00	<.001

Note – *M* = Mean estimate; *SD* = Standard deviation; *p* = one-tailed Bayesian significance level. All eye-movement measures transformed natural log +1 prior to analysis. Information condition: -1 = low, 0 = medium, 1 = high. Product -, and brand ownership: 1 = yes, 0 = no. Product knowledge mean-centered between participants. Brand knowledge mean-centered within participant. Gender: 1 = female, 0 = male. Age: 0 = "18-29", 1 = "30-49", 2 = "50-64", and 3 = "65+". Education: 0 = high school, 1 = associate degree, 2 = college degree, 3 = graduate degree. Income not disclosed: 1 = participant did not disclose income, 0 = otherwise. Income category: -4 = "$14,999 or less", -3 = "$15,000 to $24,999", -2 = "$25,000 to $34,999", -1 = "$25,000 to $49,999", 0 = "$50,000 to $74,999", 1 = "$75,000 to $99,999", 2 = "$100,000 to $149,999", 3 = "$150,000 or more". Brand B to E are brand fixed effects. Column 1 to 4: 1 = brand is shown in the respective column, 0 = otherwise.

Web Appendix G. Attention to the Chosen Brand

TABLE G1
QUANTITY OF ATTENTION TO THE CHOSEN BRAND

	Components of Attention Trajectories								
	Initial Level (k = 0)			Linear Change (k = 1)			Quadratic Change (k = 2)		
Predictors	*M*	*SD*	*p*	*M*	*SD*	*p*	*M*	*SD*	*p*
Consumer-level (*j*):									
Brand eye fixations (g = 1*)*:									
Intercept	1.27	.16	<.001	.15	.13	.11	-.05	.04	.23
Information condition	.18	.05	<.001	-.02	.03	.54	.003	.01	.24
Product ownership	-.04	.12	.59	-.08	.08	.30	.02	.02	.18
Product knowledge	-.10	.04	.003	.00	.02	.69	.001	.01	.25
Gender	.24	.09	.004	-.03	.06	.55	.01	.02	.23
Age	-.01	.05	.62	.03	.03	.14	-.01	.01	.49
Education	.19	.05	<.001	-.02	.03	.44	.001	.01	.25
Income not disclosed	.20	.16	.10	-.06	.11	.51	.003	.03	.25
Income category	.02	.03	.16	-.01	.02	.46	.004	.01	.16
Variance	.49	.05	<.001	.02	.01	<.001	.002	.00	<.001
Brand-level (*i*):									
Brand eye fixations (*g* = 1):									
Brand B	-.02	.05	.57	.20	.09	.01	-.04	.03	.15
Brand C	.01	.06	.25	.05	.09	.21	-.01	.03	.56
Brand D	.04	.05	.19	.12	.09	.09	-.04	.03	.13
Brand E	.04	.05	.19	.06	.09	.19	-.01	.03	.52
Column 1	1.34	.05	<.001	-.59	.08	<.001	.08	.03	<.001
Column 2	.88	.05	<.001	-.19	.08	.03	.02	.03	.15
Column 3	.37	.05	<.001	.18	.08	.01	-.05	.03	.047
Column 4	.15	.05	.001	.24	.08	.002	-.05	.03	.04
Brand knowledge	.02	.01	.049	-.01	.02	.50	.01	.01	.13
Brand ownership	.13	.05	.01	.07	.09	.16	-.04	.03	.18
Chosen brand	.06	.04	.08	.02	.07	.24	.13	.02	<.001
Variance	.16	.04	<.001	.27	.07	<.001	.02	.01	<.001

Note – *M* = Mean estimate; *SD* = Standard deviation; *p* = one-tailed Bayesian significance level. All eye-movement measures transformed natural log +1 prior to analysis. Information condition: -1 = low, 0 = medium, 1 = high. Product -, and brand ownership: 1 = yes, 0 = no. Product knowledge mean-centered between participants. Brand knowledge mean-centered within participant. Gender: 1 = female, 0 = male. Age: 0 = “18-29”, 1 = “30-49”, 2 = “50-64”, and 3 = “65+”. Education: 0 = high school, 1 = associate degree, 2 = college degree, 3 = graduate degree. Income not disclosed: 1 = participant did not disclose income, 0 = otherwise. Income category: -4 = “$14,999 or less”, -3 = “$15,000 to $24,999”, -2 = “$25,000 to $34,999”, -1 = “$25,000 to $49,999”, 0 = “$50,000 to $74,999”, 1 = “$75,000 to $99,999”, 2 = “$100,000 to $149,999”, 3 = “$150,000 or more”. Brand B to E are brand fixed effects. Chosen brand: 1 = yes, 0 = no. Column 1 to 4: 1 = brand is shown in the respective column, 0 = otherwise.

TABLE G2
INTEGRATION ATTENTION TO THE CHOSEN BRAND

	Components of Attention Trajectories								
	Initial Level (k = 0)			Linear Change (k = 1)			Quadratic Change (k = 2)		
Predictors	*M*	*SD*	*p*	*M*	*SD*	*p*	*M*	*SD*	*p*
Consumer-level (j):									
Within saccades (g = 2):									
Intercept	.51	.12	<.001	-.08	.14	.50	.03	.04	.17
Information condition	.10	.04	.01	-.06	.04	.12	.02	.01	.05
Product ownership	-.04	.09	.57	-.02	.08	.64	.00	.03	.25
Product knowledge	-.05	.03	.06	-.03	.03	.24	.01	.01	.14
Gender	.21	.07	<.001	-.10	.06	.10	.03	.02	.09
Age	-.03	.04	.40	.04	.04	.11	-.01	.01	.29
Education	.13	.04	<.001	-.05	.04	.20	.01	.01	.14
Income not disclosed	.16	.12	.09	.00	.12	.73	-.02	.04	.52
Income category	.00	.02	.24	-.02	.02	.32	.01	.01	.10
Variance	.23	.03	<.001	.04	.01	<.001	.00	.00	<.001
Brand-level (i):									
Within saccades (g = 2):									
Brand B	-.03	.06	.46	.28	.09	.001	-.07	.03	.02
Brand C	.00	.06	.25	.15	.10	.06	-.04	.03	.15
Brand D	.03	.06	.22	.21	.10	.01	-.07	.03	.02
Brand E	-.02	.06	.56	.18	.10	.03	-.05	.03	.10
Column 1	1.03	.05	<.001	-.61	.09	<.001	.10	.03	<.001
Column 2	.45	.05	<.001	-.04	.09	.53	-.01	.03	.53
Column 3	.08	.05	.048	.19	.08	.01	-.05	.03	.06
Column 4	-.02	.05	.57	.25	.09	.002	-.06	.03	.03
Brand knowledge	.01	.01	.16	-.01	.02	.56	.00	.01	.20
Brand ownership	.11	.05	.02	.11	.09	.09	-.05	.03	.07
Chosen Brand	.08	.04	.03	-.03	.07	.57	.16	.02	<.001
Variance	.23	.04	<.001	.34	.06	<.001	.02	.01	<.001

Note – *M* = Mean estimate; *SD* = Standard deviation; *p* = one-tailed Bayesian significance level. All eye-movement measures transformed natural log +1 prior to analysis. Information condition: -1 = low, 0 = medium, 1 = high. Product -, and brand ownership: 1 = yes, 0 = no. Product knowledge mean-centered between participants. Brand knowledge mean-centered within participant. Gender: 1 = female, 0 = male. Age: 0 = “18-29”, 1 = “30-49”, 2 = “50-64”, and 3 = “65+”. Education: 0 = high school, 1 = associate degree, 2 = college degree, 3 = graduate degree. Income not disclosed: 1 = participant did not disclose income, 0 = otherwise. Income category: -4 = “$14,999 or less”, -3 = “$15,000 to $24,999”, -2 = “$25,000 to $34,999”, -1 = “$25,000 to $49,999”, 0 = “$50,000 to $74,999”, 1 = “$75,000 to $99,999”, 2 = “$100,000 to $149,999”, 3 = “$150,000 or more”. Brand B to E are brand fixed effects. Chosen brand: 1 = yes, 0 = no. Column 1 to 4: 1 = brand is shown in the respective column, 0 = otherwise.

TABLE G3
COMPARISON ATTENTION TO THE CHOSEN BRAND

	Components of Attention Trajectories								
	Initial Level (k = 0)			Linear Change (k = 1)			Quadratic Change (k = 2)		
Predictors	*M*	*SD*	*p*	*M*	*SD*	*p*	*M*	*SD*	*p*
Consumer-level (j):									
Between saccades (g = 3):									
Intercept	.16	.12	.08	.16	.11	.08	-.04	.04	.22
Information condition	.18	.04	<.001	.00	.03	.25	-.01	.01	.53
Product ownership	.01	.08	.25	-.12	.08	.13	.02	.02	.14
Product knowledge	-.06	.03	.01	-.01	.02	.54	.00	.01	.20
Gender	.09	.06	.07	.00	.06	.25	.01	.02	.20
Age	-.06	.04	.11	-.01	.03	.64	.01	.01	.16
Education	.14	.04	<.001	-.01	.03	.58	.00	.01	.69
Income not disclosed	.12	.12	.13	-.01	.11	.72	-.01	.03	.65
Income category	.03	.02	.03	.01	.02	.18	.00	.01	.34
Variance	.24	.03	<.001	.07	.02	<.001	.01	.00	<.001
Brand-level (i):									
Between saccades (g = 3):									
Brand B	.01	.04	.22	.02	.06	.24	.00	.02	.68
Brand C	.02	.04	.23	.03	.06	.21	-.02	.02	.37
Brand D	.00	.04	.71	.09	.06	.06	-.04	.02	.07
Brand E	.00	.04	.25	.04	.06	.19	-.01	.02	.43
Column 1	.50	.03	<.001	.08	.05	.07	-.07	.02	<.001
Column 2	.62	.03	<.001	.16	.06	.002	-.07	.02	<.001
Column 3	.40	.03	<.001	.26	.05	<.001	-.08	.02	<.001
Column 4	.36	.03	<.001	.13	.06	.01	-.04	.02	.01
Brand knowledge	.01	.01	.08	.00	.02	.25	.00	.00	.68
Brand ownership	-.03	.04	.42	.08	.06	.08	-.02	.02	.24
Chosen brand	.02	.03	.18	.02	.05	.23	.03	.01	.03
Variance	.05	.01	<.001	.10	.02	<.001	.01	.00	<.001

Note – *M* = Mean estimate; *SD* = Standard deviation; *p* = one-tailed Bayesian significance level. All eye-movement measures transformed natural log +1 prior to analysis. Information condition: -1 = low, 0 = medium, 1 = high. Product -, and brand ownership: 1 = yes, 0 = no. Product knowledge mean-centered between participants. Brand knowledge mean-centered within participant. Gender: 1 = female, 0 = male. Age: 0 = “18-29”, 1 = “30-49”, 2 = “50-64”, and 3 = “65+”. Education: 0 = high school, 1 = associate degree, 2 = college degree, 3 = graduate degree. Income not disclosed: 1 = participant did not disclose income, 0 = otherwise. Income category: -4 = “$14,999 or less”, -3 = “$15,000 to $24,999”, -2 = “$25,000 to $34,999”, -1 = “$25,000 to $49,999”, 0 = “$50,000 to $74,999”, 1 = “$75,000 to $99,999”, 2 = “$100,000 to $149,999”, 3 = “$150,000 or more”. Brand B to E are brand fixed effects. Chosen brand: 1 = yes, 0 = no. Column 1 to 4: 1 = brand is shown in the respective column, 0 = otherwise.

TABLE G4
OTHER ATTENTION TO THE CHOSEN BRAND

	Components of Attention Trajectories								
	Initial Level (*k* = 0)			Linear Change (*k* = 1)			Quadratic Change (*k* = 2)		
Predictors	*M*	*SD*	*p*	*M*	*SD*	*p*	*M*	*SD*	*p*
Consumer-level (*j*):									
Other saccades (g = 4*):*									
Intercept	.17	.10	.04	.12	.10	.11	-.03	.03	.40
Information condition	.13	.03	<.001	-.02	.03	.45	.01	.01	.19
Product ownership	-.04	.07	.52	-.03	.07	.55	.00	.02	.25
Product knowledge	-.05	.02	.02	-.01	.02	.50	.00	.01	.24
Gender	.07	.05	.10	.01	.05	.25	.00	.02	.70
Age	-.01	.03	.54	.04	.03	.10	-.01	.01	.25
Education	.10	.03	<.001	.02	.03	.19	-.01	.01	.40
Income not disclosed	.05	.10	.21	-.11	.09	.22	.03	.03	.12
Income category	.00	.02	.23	.01	.01	.21	.00	.00	.71
Variance	.16	.02	<.001	.05	.01	<.001	.00	.00	<.001
Brand-level (*i*):									
Other saccades (*g* = 4):									
Brand B	-.01	.04	.64	.03	.06	.22	.00	.02	.64
Brand C	.01	.04	.24	-.03	.06	.56	.01	.02	.21
Brand D	.01	.04	.24	-.03	.06	.55	.02	.02	.20
Brand E	.01	.04	.23	-.12	.06	.05	.05	.02	.01
Column 1	.41	.03	<.001	-.17	.06	.002	.02	.02	.09
Column 2	.64	.04	<.001	-.16	.06	.005	.03	.02	.05
Column 3	.36	.03	<.001	.11	.05	.02	-.03	.02	.10
Column 4	.25	.03	<.001	.08	.06	.06	-.01	.02	.41
Brand knowledge	.01	.01	.07	-.01	.02	.33	.01	.00	.13
Brand ownership	.03	.04	.18	.05	.06	.16	-.01	.02	.47
Chosen brand	.01	.03	.22	.01	.05	.24	.02	.02	.08
Variance	.06	.02	<.001	.08	.02	<.001	.01	.00	<.001

Note – *M* = Mean estimate; *SD* = Standard deviation; *p* = one-tailed Bayesian significance level. All eye-movement measures transformed natural log +1 prior to analysis. Information condition: -1 = low, 0 = medium, 1 = high. Product -, and brand ownership: 1 = yes, 0 = no. Product knowledge mean-centered between participants. Brand knowledge mean-centered within participant. Gender: 1 = female, 0 = male. Age: 0 = “18-29”, 1 = “30-49”, 2 = “50-64”, and 3 = “65+”. Education: 0 = high school, 1 = associate degree, 2 = college degree, 3 = graduate degree. Income not disclosed: 1 = participant did not disclose income, 0 = otherwise. Income category: -4 = “$14,999 or less”, -3 = “$15,000 to $24,999”, -2 = “$25,000 to $34,999”, -1 = “$25,000 to $49,999”, 0 = “$50,000 to $74,999”, 1 = “$75,000 to $99,999”, 2 = “$100,000 to $149,999”, 3 = “$150,000 or more”. Brand B to E are brand fixed effects. Chosen brand: 1 = yes, 0 = no. Column 1 to 4: 1 = brand is shown in the respective column, 0 = otherwise.

Web Appendix H. Attention to Chosen and Non-Chosen Brands

This appendix describes how attention trajectories of the chosen and non-chosen brands are used to calculate attention shares and strategies.

Step 1: Estimate differences in attention between chosen and non-chosen brands.

We estimate a slightly modified version of the attention model specified in the paper. We refer to this modified version as the Attention to the Chosen Brand (ACB) model. The only difference is that the ACB model accounts for differences in attention between chosen and non-chosen brands by adding a dummy for the chosen brand (1 = consumer j chooses brand i, 0 = otherwise) and its corresponding effect (γ) on participant-and-brand attention trajectories (equation 4 in the paper). We estimate the posterior distributions of the ACB model parameters as described in Web Appendix C.

Step 2: Calculate model-based attention measures ($\hat{y}_j^g$), free of measurement-error:

$$\hat{y}_j^g = X_1^g \hat{\eta}_j^g$$

where $\hat{y}_j^g$ is a $BQ \times 1$ vector for participant j ($j = 1, \ldots, N$) that contains attention type g for brands $i = 1, \ldots, B$ and quarters $t = 1, \ldots Q$; X_1^g is a $BQ \times (1 + B)K_0$ matrix of time-scores corresponding to attention trajectory components ($K_0 = 3$: initial, linear and quadratic change); and $\hat{\eta}_j^g$ is the posterior mean of the attention trajectories.

Step 3: Calculate model-based number of eye-movements ($\hat{\hat{y}}_j^g$), free of measurement-error:

The dependent variable in the attention model is the log transformed number of eye movements of type $g = 1, \ldots, G$. To calculate the measurement-free number of eye-movements we inverse-log transform the value obtained in step 2 ($\hat{y}_j^g$): $\hat{\hat{y}}_j^g = \exp(\hat{y}_j^g) - 1$

Step 4: Calculate attention strategy as:

$$Attention\ Strategy_{jit} = \frac{\hat{\hat{y}}_{jit}^2}{\hat{\hat{y}}_{jit}^2 + \hat{\hat{y}}_{jit}^3}$$

where $\hat{\hat{y}}_{jit}^{2}$ is the model-based number of within-brand saccades, free of measurement-error, and $\breve{y}_{jit}^{3}$ is the estimated number of between-brand saccades, free of measurement-error.

We calculate $Attention\ Strategy_{jit}$ for all participants ($j = 1, \dots, N$), brands ($i = 1, \dots, B$), and quarters ($t = 1, \dots, Q$). For participant j and quarter t:

$$Attention\ Strategy_{jt}^{chosen} = Attention\ Strategy_{jit}$$

$$Attention\ Strategy_{jt}^{non-chosen} = \frac{1}{B-1}\sum_{l \neq i} Attention\ Strategy_{jlt}$$

where $c_{jQ} = i$ (participant j chooses brand i).

Step 5: Calculate share of attention-quantity as:

$$Attention\ Share_{jit}^{1} = \frac{\hat{\hat{y}}_{jit}^{1}}{\sum_{l=1}^{B} \hat{\hat{y}}_{jlt}^{1}}$$

where $\hat{\hat{y}}_{jit}^{1}$ is the model-based number of eye fixations for participant j, brand i, and quarter t.

Step 6: Calculate share of attention type g ($g = 2, 3, 4$):

$$Attention\ Share_{jit}^{g} = \frac{\hat{\hat{y}}_{jit}^{g}}{\hat{\hat{y}}_{jit}^{2} + \hat{\hat{y}}_{jit}^{3} + \hat{\hat{y}}_{jit}^{4}}$$

where $\hat{\hat{y}}_{jit}^{g}$ is the model-based number of saccades of type g for participant j, brand i, and quarter t.

Table H1 summarizes the attention strategy index for the chosen and non-chosen brands, their difference, and all brands.

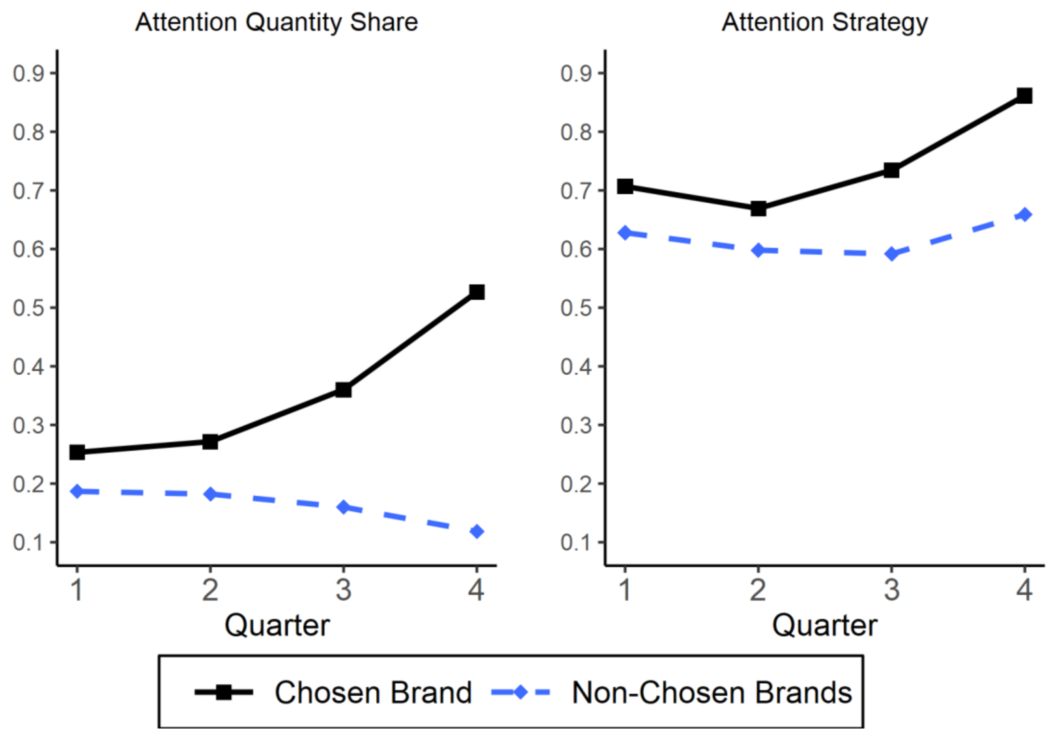
TABLE H1
ATTENTION STRATEGY

	Inspection Periods: Time Quarters During Choice Task							
	Quarter 1		Quarter 2		Quarter 3		Quarter 4	
Brand	M	SD	M	SD	M	SD	M	SD
Chosen	.71	.23	.67	.20	.73	.16	.86	.08
Non-chosen	.63	.26	.60	.24	.59	.25	.66	.24
Difference	.08	--	.07	--	.14	--	.20	--
All brands	.64	.26	.61	.23	.62	.24	.71	.23

Note – *n* = 325, with one chosen and four non-chosen brands. Attention strategy is the ratio of within-brand saccades and the sum of within- and between-brand saccades, free of measurement error. It ranges from 0 = all saccades are between-brands to 1 = all saccades are within-brands.

FIGURE H1

DOUBLE LIFT: ATTENTION QUANTITY AND STRATEGY



Note – Average attention share for the four nonchosen brands shown. Parity share of attention quantity (fixations) for each brand is .20 per quarter (1/5). Attention strategy is ratio of integration attention (within-brand) to the sum of integration and comparison attention (between-brand), which range from 0 (no within-brand saccades) to 1 (only within-brand saccades). Parity attention strategy is .50 (within-saccades = between-saccades).

TABLE H2
INSPECTING NON-CHOSEN BRANDS

	Number of non-chosen brands fixated				
	All brands				No brands
Period	4	3	2	1	0
1st Quarter:	78%	8%	10%	5%	0%
2nd Quarter:	83%	10%	4%	2%	1%
3rd Quarter:	77%	10%	7%	6%	0%
4th Quarter:	68%	15%	11%	4%	2%

Note – cell values are % of participants (*n* = 325) who fixate at least once on the indicated number of non-chosen brands (column) during each quarter (row).

Web Appendix I. Pseudo-Code to Generate Simulated Data

Let the original brand choice and eye movements dataset be $D = BC, EM$, where $BC = c_j$ ($j = 1, \dots, N$) contains the brand choices made by participants, and $EM = \breve{y}_{jit}^{g}$ ($j = 1, \dots, N$, $i = 1, \dots, B$, $t = 1, \dots, Q$, $g = 1, \dots, G$, and $N = 325$, $B = 5$, $Q = 4$, $G = 4$) contains the number of observed eye-movements. A non-disclosure agreement (NDA) precludes making the original dataset publicly available. Therefore, we generate and make available, at researchbox.org[4], a simulated dataset that principally reproduces the attention and choice results reported in the manuscript. The simulated dataset, ($D^{sim} = BC^{sim}, EM^{sim}$) contains simulated values, thus preserving confidentially of the original data and obeying the NDA.

To generate the simulated dataset we follow these three steps:

Step 1: Simulate eye movements (EM^{sim}) by sampling from:

$$p(EM^{sim}|X^a, EM) \propto p\left(EM^{sim}\middle|\Theta\right)p(\Theta|X^a, EM)$$

where Θ denotes the posterior distribution of the attention model parameters calibrated on the original dataset, and X^a denotes the explanatory variables included in the attention model. Web Appendix C describes in detail the specification and estimation of the attention model.

Step 2: Estimate attention growth parameters for participants in the simulated dataset:

$$p(\Theta^{sim}|EM^{sim}) \propto p\left(EM^{sim}\middle|\Theta^{sim}\right)p(\Theta^{sim})$$

where Θ^{sim} denotes the posterior distribution of the attention model parameters calibrated on the simulated eye movements (EM^{sim}). Θ^{sim} includes participant-and-brand specific attention growth factors (θ^{sim}).

Step 3: Simulate brand choice (BC^{sim}) by sampling from:

$$p\left(BC^{sim}\middle|\theta^{sim}, X^c, BC\right) \propto p\left(BC^{sim}\middle|\theta^{sim}, \Phi\right)p(\Phi|X^c, \theta, BC)$$

[4] https://researchbox.org/129&PEER_REVIEW_passcode=SLWYGF

where X^c denotes explanatory variables (pre-inspection information) included in the choice model in addition to attention growth factors, Φ denotes the posterior distribution of the proposed choice model parameters, and θ are attention growth factors for the participants in the original dataset.

Tables I1-I3 below present the results obtained with this simulated dataset.

TABLE I1 (simulated dataset)
EYE-MOVEMENTS DURING BRAND CHOICE

Eye Fixations and Shares of Saccades over Time	Information Condition: Low *M*	Low *SD*	Medium *M*	Medium *SD*	High *M*	High *SD*	Total *M*	Total *SD*	Choice-based: Chosen Brand *M*	Chosen Brand *SD*	Nonchosen Brands *M*	Nonchosen Brands *SD*
1st Quarter:												
Eye fixation frequency	60.93	42.28	80.90	60.78	97.17	91.05	79.48	68.62	20.40	18.83	14.77	16.85
Within-brand saccade share	.58	.27	.51	.24	.52	.23	.54	.25	.61	.23	.52	.25
Between-brand saccade share	.23	.21	.28	.20	.27	.17	.26	.20	.22	.16	.27	.20
Other saccade share	.19	.17	.20	.13	.21	.15	.20	.15	.17	.13	.21	.16
2nd Quarter:												
Eye fixation frequency	63.40	42.94	82.11	62.65	98.26	90.56	81.07	69.02	21.11	16.99	14.99	14.63
Within-brand saccade share	.59	.23	.52	.22	.50	.21	.54	.22	.59	.20	.53	.23
Between-brand saccade share	.22	.17	.27	.17	.29	.16	.26	.17	.24	.14	.27	.17
Other saccade share	.18	.12	.21	.11	.21	.11	.20	.11	.18	.09	.21	.12
3rd Quarter:												
Eye fixation frequency	67.98	44.65	86.23	65.48	103.42	92.31	85.67	71.04	25.05	19.03	15.16	14.63
Within-brand saccade share	.58	.22	.55	.22	.51	.20	.55	.22	.61	.17	.53	.22
Between-brand saccade share	.22	.17	.25	.16	.27	.15	.25	.16	.22	.12	.26	.17
Other saccade share	.20	.12	.20	.11	.21	.11	.20	.11	.17	.08	.21	.12
4th Quarter:												
Eye fixation frequency	69.01	45.39	87.47	64.90	103.94	89.78	86.61	69.94	31.01	22.65	13.90	14.78
Within-brand saccade share	.66	.22	.62	.22	.61	.21	.63	.22	.72	.14	.61	.23
Between-brand saccade share	.15	.14	.18	.13	.19	.13	.17	.13	.14	.09	.18	.14
Other saccade share	.19	.15	.20	.15	.21	.13	.20	.14	.14	.08	.21	.15
Total:												
Eye fixation frequency	261.32	173.56	336.71	252.6	402.79	361.96	332.83	277.13	97.56	73.72	58.82	57.55
Within-brand saccade share	.61	.19	.56	.19	.54	.17	.57	.19	.64	.15	.55	.19
Between-brand saccade share	.21	.13	.24	.13	.25	.12	.23	.13	.19	.09	.24	.13
Other saccade share	.19	.10	.20	.09	.21	.09	.20	.09	.16	.07	.21	.10

Note – Total sample size 325 across 5 brands (325 x 5 = 1625), with 107 (535) in low, 115 (575) in medium, and 103 (515) in high information condition. For chosen brands *n* = 325, and for nonchosen brands *n* = 1300 (4 x 325). Average brand eye fixations across 4 nonchosen brands shown.

TABLE I2 (simulated dataset)
MODEL SUMMARY

	Brand Choice Predictors						Random-Split K-fold CV		
	Market-level preferences, Display position	Consumer Information							
Model		Brand Ownership	Brand Knowledge	Accumulated Eye-fixations	Attention Trajectories	# pars	ELPD	Hit Rate	95% PI
M0	x					8	-513	25%	[20; 29]
M1	x	x				9	-448	46%	[45; 48]
M2	x	x	x			10	-412	48%	[45; 50]
M3	x	x	x	x		11	-199	78%	[76; 80]
M4	x	x	x		x	22	-50	93%	[91; 95]

Note - # pars is number of parameters to predict choice. ELPD is Expected Log Predictive Density. Hit rate, with 95% Prediction Interval (PI) between brackets is percentage of participants for whom the model correctly predicts brand choice. Hit rate for random brand choice predictions is 20% (1 out of 5 brands).

TABLE I3 (simulated dataset)
ATTENTION TRAJECTORIES PREDICT BRAND CHOICE

Predictors		Estimate	p	2.5%	97.5%
		Baseline Model			
Brand B	α_1	.32	.05	-.08	.70
Brand C	α_2	.33	.10	-.17	.86
Brand D	α_3	.79	<.001	.37	1.23
Brand E	α_4	.51	.01	.08	.96
Column 1	α_5	.86	<.001	.50	1.25
Column 2	α_6	.40	.03	-.02	.84
Column 3	α_7	-.12	.53	-.58	.35
Column 4	α_8	-.07	.60	-.56	.39
Brand knowledge	α_9	.40	<.001	.29	.51
Brand ownership	α_{10}	1.07	<.001	.76	1.40
		Proposed Model			
Brand B	α_1	-.81	.20	-2.04	.48
Brand C	α_2	.25	.22	-.91	1.41
Brand D	α_3	1.21	.03	-.03	2.50
Brand E	α_4	.18	.24	-1.11	1.42
Column 1	α_5	-.65	.53	-3.59	2.43
Column 2	α_6	-1.72	.29	-5.09	1.81
Column 3	α_7	-1.41	.20	-3.64	.77
Column 4	α_8	-1.60	.12	-3.66	.52
Brand knowledge	α_9	.17	.10	-.10	.44
Brand ownership	α_{10}	.54	.08	-.25	1.34
Attention Quantity:					
Initial level	β_0^1	4.50	<.001	1.58	7.48
Linear change	β_1^1	11.86	<.001	7.68	15.97
Quadratic change	β_2^1	33.07	<.001	23.32	43.54
Attention Type:					
Integration:					
Initial level	β_0^2	2.43	.09	-1.36	6.20
Linear change	β_1^2	7.28	<.001	2.86	11.99
Quadratic change	β_2^2	29.78	<.001	15.49	43.61
Comparison:					
Initial level	β_0^3	.16	.25	-5.51	5.51
Linear change	β_1^3	-.20	.73	-7.65	7.39
Quadratic change	β_2^3	2.49	.24	-14.12	19.05
Other:					
Initial level	β_0^4	1.74	.21	-4.41	7.96
Linear change	β_1^4	2.28	.20	-4.82	9.75
Quadratic change	β_2^4	1.37	.25	-16.68	20.14

Note – Brand fixed-effects relative to Brand A, and column effects relative to column 5. Baseline model is M2. Proposed model is M4. 95% one-tailed Bayesian p-value, and 95% Credible Interval (CI) of parameter estimates.

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