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RESEARCH ARTICLE

Order in multi-attribute product choice decisions: Evidence from discrete choice experiments combined with eye tracking

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Abstract

Over time, research on order effects during information searching and choice tasks has received thorough attention in marketing, psychology, and economics. When early information search influences choice in favor of that information, it is called *primacy*; the equivalent for later information search is called *recency*. However, research that disentangles primacy and recency effects during multi-attribute product choice, as well as studies on the cognitive processes underlying primacy and recency effects are lacking. I address this gap with two choice-based conjoint experiments combined with eye tracking and by means of multilevel mediation analysis. Consistent with my prediction that to counterbalance the impact of decision irrelevant information on choice through early information search by later information search is mentally too costly, I find that “spatial position” biases choice due to primacy rather than recency. This bias, however, is small. This suggests that for decision irrelevant information, the causal influence of attention on choice generalizes to more complex decisions, though with little impact. Consistent with my prediction that the level of information elaboration moderates the mediation process, increasing task motivation decreases the dominance of primacy.

KEYWORDS

bounded rationality, conjoint, consumer decision-making, eye tracking, multi-attribute, order, primacy, recency

1 | INTRODUCTION

Over time, research on order effects during information searching and choice tasks has received thorough attention in marketing (Bagchi & Davis, 2012; Carlson et al., 2006; Ein-Gar et al., 2012; Haugtvedt & Wegener, 1994) and psychology literature (Hogarth & Einhorn, 1992; Petty et al., 2001; Russo et al., 2006). Extant research typically has not monitored exactly what information decision-makers were searching for; rather, prior research has manipulated the order of information pieces according to the reading order. These researchers have often used the terms primacy and recency. The former refers to initial

information search influencing choice in favor of that information, the latter refers to later information search influencing choice in favor of that information.

Recently, researchers in business and economics, as well as in psychology, have started to analyze the information search process during search and product choice tasks with the use of eye-tracking methodology (Orquin & Mueller Loose, 2013; Zuschke, 2020a). In most of these studies, disentangling primacy and recency was not the main focus; rather, they focused on understanding and modeling consumers' eye movements and choice behavior (Wedel et al., 2022). Nonetheless, these studies provide evidence that initial (Gluth

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et al., 2020; Krajbich et al., 2010; Krajbich & Rangel, 2011; Reutskaja et al., 2011; Willemsen et al., 2011) and later (Atalay et al., 2012; Gluth et al., 2020; Krajbich et al., 2010; Krajbich & Rangel, 2011; Russo & Leclerc, 1994; Shi et al., 2013; Willemsen et al., 2011) information search indicate the final product choice. Some of these studies even propose that information search causally influences choice in contrast to a simple correlation. This means decision-makers choose the item they look at longer due to being influenced by the looking action itself. Indeed, together with studies using stimuli other than typical consumer products (Cavanagh et al., 2014; Gluth et al., 2018; Shimojo et al., 2003; Stewart et al., 2016) and with studies that exogenously manipulate information search (Bhatnagar & Orquin, 2022), there is converging evidence for this claim. This claim is important as it helps to better understand how a decision context unrelated to the decision-makers' underlying values may bias choice through initial or final information search.

However, as pointed out by Mormann and Russo (2021), it remains unclear whether this claim also holds for more complex decisions that require more mental resources as, for example, in multi-attribute product choice where consumers repeatedly make various choices. Further, as insight on primacy and recency often were a byproduct rather than the main focus, prior studies predominantly analyzed the effects early and later information searches have on choice in isolation and/or they focused on the predictive nature of initial and final information searches rather than explaining the cognitive processes underlying these effects. In contrast, marketing and psychology studies that focused on primacy and recency without using eye-tracking methodology acknowledged that presentation order influences choice through information search but, typically, they did not explicitly comment on information search potentially having a causal role in determining choice. They based their arguments on theories and concepts such as anchoring (Tversky & Kahneman, 1974), freezing (Webster et al., 1996), predecisional distortion (Russo et al., 1996), or the elaboration likelihood model (Petty & Cacioppo, 1986).

To shed further light on the cognitive processes underlying primacy and recency effects during multi-attribute choice, I synthesize the causal claim with research in marketing and economics that focused on the impact "spatial position," a factor unrelated to decision-makers' underlying values, has on information search and product choice (Atalay et al., 2012; Meißner et al., 2016; Reutskaja et al., 2011). Specifically, I propose a serial mediation model, with spatial position as focal antecedent, product choice as outcome, and initial and later information search as intervening variables. Following previous research suggestions (Zuschke, 2020a), I embed the mediation analysis into the theoretical framework of bounded rationality (Simon, 1955). I then argue that primacy and recency effects emerge as consumers adapt their information search behavior by trading off mental effort and accuracy (Payne et al., 1993) to such an extent that the decision becomes prone to information search induced biases.

Research has also documented that spatial position during more complex choices does not affect product choice likelihood (Meißner et al., 2016). One reason may be that for some consumers spatial

position exerts an effect on choice likelihood through information search, while for other consumers it does not. Depending on the ratio of these consumer types in the sample, the sample's total effect of spatial position on product choice might be non-significant. Hence, the aforementioned indirect effect could be conditional on a moderator (Preacher et al., 2007). Based on bounded rationality theory, I speculate that the level of information elaboration, as expressed by differing task motivation, serves as moderator. Additionally, if spatial position's indirect effect on product choice through information search is conditional on task motivation, the moderation's temporal dynamics can shed further light on order effects during consumer decision-making.

I therefore propose extending the serial mediation model outlined above by testing for moderation of the spatial position and information search relationship. This is a moderated serial mediation analysis in a multi-attribute product choice context. To the best of my knowledge, research has not covered this approach yet. Further, using this kind of experimental setup follows the call of Mormann and Russo (2021) to investigate the potential causal role of information search on choice during more complex decisions. This study answers the following questions:

- Does spatial position exert an effect on product choice through early and/or later information search?
- Does the magnitude of the effect spatial position has on choice through initial and/or later information search depend on consumers' level of information elaboration?
- Does the total indirect effect spatial position has on choice through information search translate into a total effect?

2 | THEORETICAL FRAMEWORK

2.1 | The impact of spatial position on initial and later eye fixations

Previous research has documented that decision-makers fixate on information serially, in a repeating left-to-right scan path fashion, with fixations most likely falling on adjacent locations (Liechty et al., 2003; Russo & Leclerc, 1994; Shi et al., 2013; van der Lans et al., 2008a, 2008b). I therefore expect that in a multi-attribute choice setting where consumers choose between five products that are arranged horizontally, they will repeatedly and serially fixate on the product information in a left-to-right scan path. This implies, as Chandon et al. (2009) pointed out, that consumers who fixate on information on the right and want to move their fixation to information to the left are likely to fixate on information in between, giving fixation advantage to information at the center and fixation disadvantage to information located at the edges. With advantage (disadvantage), I mean an effect that positively (negatively) differs from the mean across positions.

There is evidence from vision research and product choice research that early in the viewing process, consumers more frequently

fixate on information in the center and toward the left rather than to information toward the right (Atalay et al., 2012; Foulsham et al., 2013, 2018; Ossandón et al., 2014; Reutskaja et al., 2011; Tatler, 2007). Later in the viewing process, consumers were found to fixate more frequently on information in the center (Atalay et al., 2012; Meißner et al., 2016). Further, extending vision research (Ossandón et al., 2014), Meißner et al. (2016) showed that toward the end of the viewing process, consumers gradually shift their fixations to information on the right, at the expense of information on the left.

Two types of asymmetries therefore characterize consumers' viewing process. On the one hand, consumers repeatedly and serially fixate on information from left to right, leading to fixation advantages for information in the center and disadvantages for information at the edges. On the other hand, they show a tendency to initially fixate more intensely on the center and to the left and later more intensely on the center and to the right. The reason for this behavior could be learned left-right reading patterns (Ryan et al., 2018), biological factors (Ossandón et al., 2014) or a combination of both (Shi et al., 2013).

Consequently, I expect consumers to fixate most on information about products located at the center during the initial viewing process, followed by information about products located to the left. Accordingly, I expect that consumers initially fixate least on product information placed toward the right edge. Later in the viewing process, I expect consumers to fixate more frequently on product information placed at the center and toward the right. Accordingly, later in the viewing process, I expect that consumers fixate the least on product information placed toward the left edge.

2.2 | The causal claim from a bounded rationality point of view

One rationale behind bounded rationality is that consumers' preferences depend on the mental resources required to reach a decision (Simon, 1955). Indeed, various laboratory studies (Bettman et al., 1998; Payne et al., 1993), choice-based conjoint studies (Meißner et al., 2019; Toubia et al., 2012), field studies (Levav et al., 2010; Wästlund et al., 2015), and large-scale studies (Nikolova & Inman, 2015) have demonstrated that in many situations, consumers tend to simplify their information search and by implication also their information processing. This results in preferences being constructed on the spot, not merely being revealed.

In a multi-attribute choice context, I expect that consumers search for information about products and choose products in line with their underlying values (Meißner et al., 2016). Further, I expect that consumers adapt their information search behavior according to their goals. With "adapt," I mean they simplify information processing by trading off effort and accuracy (Payne et al., 1993), for example, by using a decision heuristic such as satisficing (Stüttgen et al., 2012). Consumers who simplify still largely make choices in line with their goals (Bettman et al., 1998) but I assume that accuracy drops to a level

where the choice becomes prone to information that does not reflect consumers' underlying values. Specifically, Levav et al. (2010) suggest that consumers spend relatively more effort on each additional piece of information they wish to process. Therefore, I expect that counterbalancing the impact of decision irrelevant information on choice through early information search by later information search is mentally too costly. This reasoning is consistent with previous primacy and recency accounts that suggest consumers "freeze" on early information (Petty et al., 2001; Webster et al., 1996); however, the reasoning outlined above provides a finer grained view on the phenomenon than earlier studies give.

2.3 | The impact of spatial position on choice through initial and later information searching

2.3.1 | Methodological triangulation

I access the information search behavior of consumers choosing between different products' images by using eye-tracking methodology and by measuring the consumers' eye fixations. Consumers' information search can reflect information processing (Johnson et al., 1988; Pieters & Warlop, 1999). As Orquin and Holmqvist (2018) point out, inferences drawn from information searches must be proven, not assumed. Mediation analysis enables this possibility, since it combines the search for information about products and the products' choice likelihood, as indicated by an indirect effect. Specifically, if a certain spatial position exerts its positive (negative) effect on product choice through information search, choice likelihood for products placed at that spatial position increases (decreases) indirectly. Depending on the direction and magnitude of the corresponding direct effect, the choice model, that is, the outcome model, may or may not yield a total effect that positively (negatively) differs from chance (MacKinnon et al., 2007).

2.3.2 | Predictions

I assume that spatial position exerts its effect on product choice through initial and final information search. Further, I expect both the initial and final searches to be positively related to product choice. Hence, I expect the signs of the specific indirect effects through initial and final information search to correspond with the signs of the effects mentioned in the previous sections. However, to understand the total effect of spatial position on choice, the sum of the specific indirect effects, that is, the total indirect effect, is crucial. I, therefore, outline my predictions for the total indirect effect for each spatial position. Throughout the manuscript, I use the terms "specific indirect effect through initial (later) information search" and "initial (later) indirect effect" interchangeably. Additionally, I use the term negative (positive) indirect effect in referring to an indirect effect that is smaller (greater) than zero. Hence, an indirect effect that decreases (increases) choice likelihood.

As outlined above, for the “center” I expect the strongest fixation advantage initially and later. This results in a positive initial and positive later indirect effect. Since later information processing requires more effort, I predict the positive initial indirect effect to be of greater magnitude than the corresponding positive later indirect effect. Consequently, I predict a dominance of primacy. Dominance of primacy (recency) in this context means that the initial (later) indirect effect takes the major share of the total indirect effect.

Recall that for “right,” I expect the strongest fixation disadvantage initially and some fixation advantage later. This results in a negative initial and positive later indirect effect through information search. Since later information processing requires more effort, I predict that during later information search, it is mentally too costly for consumers to keep the negative initial and the positive later indirect effects in balance, leading to a negative total indirect effect. For “left,” I expect a reversed fixation pattern. Specifically, as already outlined, I expect some fixation advantage initially and the strongest fixation disadvantage later. This results in a positive initial and negative later indirect effect. Since later information processing is mentally more costly than early processing, I predict that during later information search, it is mentally too costly for consumers to keep the positive initial and the negative later indirect effects in balance, again leading to a negative total indirect effect.

Thus, for both spatial edge positions during later information search, it is mentally too costly to keep the initial and later indirect effects in balance. Due to the different signs of the indirect effect through later information search between both spatial edge positions, the dominating mechanisms for “left” and “right” differ. For “left,” the negative later indirect effect carries the major share of the negative total indirect effect, that is, recency dominates. For “right,” the negative initial indirect effect carries the major share of the negative total indirect effect, that is, primacy dominates.

For information searches regarding products placed in “center-left” and “center-right,” neither theory nor previous research suggests whether the initial or later indirect effects dominate in such a setup. I therefore explore these spatial positions' total indirect effects and their dominant mechanisms without making predictions.

Besides the indirect effects, it is worthwhile to briefly comment on the direct and total effects. Spatial position effects have been researched in various contexts such as Instagram and Twitter (Hartmann et al., 2021), store shelf layout (Chandon et al., 2009; Christenfeld, 1995; Drèze et al., 1994; Valenzuela & Raghuram, 2009; van Nierop et al., 2008), vending machine choices (Reutskaja et al., 2018), or artworks (Kreplin et al., 2014). However, these studies' settings are too different from the current study's, which disallows predictions about most spatial positions' direct and total effects. At least for the “center” previous research suggests a direct effect opposite in sign. However, the prior research does not provide a consistent picture of whether it can offset the total indirect effect through information search (Chandon et al., 2009; Meißner et al., 2016; Reutskaja et al., 2011). Moreover, as I outline in the next section, the total effect may be conditional on some moderator due to moderated indirect effects. Thus, again, I explore

rather than predict the different spatial positions' direct and total effects.

2.4 | Moderation of spatial position effects through information search

Consistent with the notion of constructive preferences (Bettman et al., 1998) and based on the idea that motivation is a determinant of the level of information elaboration (Cacioppo & Petty, 1982; Petty & Cacioppo, 1986), research has documented that motivated consumers search for more (Celsi & Olson, 1988; Toubia et al., 2012) and more relevant (Bialkova et al., 2014; Bialkova & van Trijp, 2010; Pieters & Warlop, 1999; van Herpen & van Trijp, 2011) information. Also, consumers motivated by incentive alignment processed product attributes differently than those not motivated by incentive alignment during repeated conjoint choices (Ding, 2007; Ding et al., 2005; Dong et al., 2010). Related to this, research documented that initial information search tends to serve exploration and orientation purposes, while later information search more heavily relates to task-relevant information (Meißner et al., 2016; Shi et al., 2013; Willemsen et al., 2011).

Thus, there is evidence that consumers with a high task motivation are more willing to invest mental effort and, therefore, rely less on simplified information processing than consumers with a low task motivation. This leads to a higher accuracy for motivated consumers than for less motivated consumers (Payne et al., 1993). Consequently, I expect motivated consumers to use later information search to counterbalance the impact of decision irrelevant information on choice through early information search.

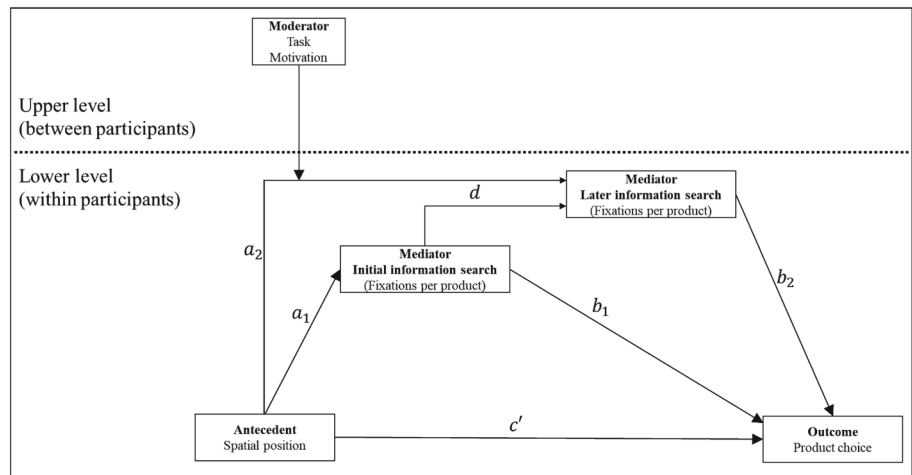
Depending on the dominant mechanism per spatial position, I predict a decreasing dominance of primacy or recency as task motivation increases, as expressed by total indirect effects that are closer to zero. The conceptual model is depicted in Figure 1.

3 | METHOD

3.1 | Choice

I accessed participants' preferences when they choose between different products by means of a choice-based conjoint experiment, which is a special type of discrete choice experiment. I modeled their choices under the assumption of utility maximizing behavior (McFadden, 1974). Hence, I assume that participants choose the product that provides the greatest subjective utility. As participants can only choose one product per choice task, different models such as a conditional fixed effect logistic regression model (McFadden, 1974) or mixed logit (McFadden & Train, 2000; Revelt & Train, 1998) can be estimated. Because I assume preference heterogeneity in the population, I choose the mixed logit model. The utility that individual i obtains from alternative j can be expressed as follows:

FIGURE 1 Conceptual model. Note: Upper level and lower level refer to the multilevel nature of the data.



$$U_{ij} = b_{ij}X_{ij} + \epsilon_{ij}, \text{ where} \quad (1)$$

- X_{ij} = a vector of observed variables for individual i and alternative j
- b_{ij} = the corresponding vector of coefficients for X that is unobserved for each i and varies in the population with density $f(\beta_i | \theta)$, where θ specifies the distribution of β_i
- ϵ_{ij} = a random term that is independently, identically distributed (i.i.d), also called Gumbel and type I extreme value.

Conditional on β_i , the probability that individual i chooses alternative j from the available alternatives k in choice set S is standard logit:

$$p_{ij}(\beta_i) = \frac{e^{b_i X_{ij}}}{\sum_{k=1, k \in S}^5 e^{b_i X_{ik}}}, \quad j = 1, \dots, 5. \quad (2)$$

Note that due to the conditioning, the constant cancels out and therefore will not be estimated. I treat all product attributes as random as long as they contain sufficient heterogeneity in the population. I treat the position variables, which technically are alternative specific constants, and both information search variables as fixed coefficients. I estimate a mixed logit model under the initial assumption that the random effects are independently normally distributed in the population. All standard errors are robust.

I used Stata Version 17 to analyze the choice data and estimate the choice models with the user-written command *mixlogit* (Hole, 2007). I used the command's option *robust* to calculate robust standard errors.

3.2 | Information search

In line with previous research (Atalay et al., 2012), I eliminated fixations below 100 ms. I used Tobii Studio in both studies. Fixations were classified based on the software's velocity threshold algorithm (I-VT).

To capture the dynamics of the information search, I divided the process into two equidistant segments based on the total number of fixations per choice task. I used multilevel models with random effects to account for the repeated measure design and the hierarchical structure in the data. Due to the count data and because the fixation variance exceeds the mean in both segments in both studies, I chose generalized linear mixed models with a negative binomial distribution and a log link function. These models better fit the data than generalized linear mixed models with a Poisson distribution and log link function, a normal distribution with an identity link or log link function, or than a negative binomial fixed effect regression model with clustered robust standard errors as assessed by Bayesian information criteria (BIC). The models each have the form

$$M \sim \text{Negative Binomial}(\lambda_{isj}), \quad (3)$$

where M represents the observed number of fixations for individual i in choice situation s on alternative j in the first (second) half of the information search process, following a negative binomial distribution governed by the parameter λ_{isj} . In turn, this parameter is modeled using a log link function characterized as follows:

$$\ln \lambda_{isj} = (a + \beta_i) * X_{isj} + \epsilon_{isj}, \quad (4)$$

where

- X_{isj} is a vector of observed variables encompassing the spatial position variables, a task experience variable, and product attribute variables. The task experience variable indicates whether the choice task belongs to the first, second, third, or fourth quarter of the experiment.
- a is a vector of unobserved fixed effects (population-level effects), including a constant a_0 .
- β_i is a vector of random effects (individual-level effects), and ϵ_{isj} is the random error.

I estimated generalized linear mixed models under the initial assumption that the random effects are independently normally distributed in the population. I specified all product attributes as random effects if they contained sufficient heterogeneity in the population. I specified initial information search when it was used to predict the final information search as fixed. All standard errors were robust. I used SPSS Version 27 and the command *GENLINMIXED* for model estimation and calculation of the robust standard error.

3.3 | Moderated mediation analysis

The principle of mediation analysis is that a variable *X* exerts its effect on an outcome *Y* via one or more mediators *M*, also called intervening variables (Baron & Kenny, 1986). Moderated mediation analysis describes the conditions by which the variable *X* exerts its effect on *Y* via *M*. For a contemporary discussion of this topic and information on the analytical procedure, refer to (Edwards & Lambert, 2007; Hayes & Rockwood, 2020; Krull & MacKinnon, 1999; Preacher et al., 2007; Zhang et al., 2009).

In contrast to the indirect effect in linear models, the indirect effect in non-linear models depends on the actual level of the focal antecedent. As Geldhof et al. (2018) pointed out, when researchers are only interested in the significance of the indirect association in non-linear models with count and binary outcomes, significance can be tested with Markov chain Monte Carlo (MCMC) simulation by multiplying the information search and choice models' raw coefficients. In the current study's experimental setup, this approach, however, provides limited insight. To overcome this problem, I took a two-step approach.

First, I relied on the partial derivative framework (Geldhof et al., 2018; Hayes & Preacher, 2010; Stolzenberg, 1980) since the non-linear models introduced in the previous sections are linear in its parameters. To support the so-called "instantaneous indirect effects" (Hayes & Preacher, 2010) with an inferential test, I used 10,000 MCMC simulations to derive 95% confidence intervals (Preacher & Selig, 2012). Appendix A gives more details on the analytical procedure. For ease of readability, I refer to the instantaneous indirect effect throughout the article as "indirect effect."

Second, the specific indirect effect in serial varies with the actual level of the mediator that is used as predictor for the other mediator. Therefore, I conditioned the specific indirect effect in serial on three levels. The average within participants mean value per participant, task, and product is labeled "avg." The average 16th percentile value is labeled "few," and the average 84th percentile value is labeled "many." However, it is desirable to have an average single point estimate for the total indirect effect. In this particular case, a parallel mediation model is useful. As Pieters (2017) demonstrated, from a statistical point of view, serial and parallel mediation are equivalent. Hence, I used a parallel mediation model to derive a single total indirect effect and the serial mediation model to investigate the dominating mechanism, that is, primacy or recency.

Since "logic, theory, and prior research findings" (Pieters, 2017) dictate which mediation model is appropriate, this topic should be commented on. Both models consider correlation between the mediators; however, serial mediation assumes that initial information search causally influences later information search. I argue that serial mediation is appropriate since research has variously demonstrated that information search is guided by both bottom-up control of attention and personal relevance, which means it is a non-random process (Orquin et al., 2021; Orquin & Mueller Loose, 2013). Moreover, research has shown that during initial information search consumers already focus on task-relevant information and that this focus increases as the task progresses (Gluth et al., 2020; Meißner et al., 2016; Willemsen et al., 2011). Initial information and later information searches stem from the same entity, making the directionality straightforward. That is, initial information search precedes later information search. Thus, initial and later information searches are not simply correlated; rather, the former predicts the latter. Accordingly, spatial position influences consumer's information search for various product images, after which they make a choice. Hence, the mediator–outcome relation is also straightforward. That is, information search predicts product choice rather than vice versa.

4 | STUDY 1

4.1 | Participants

One hundred and ninety persons at a large European university participated in the experiment. Each of them received compensation of EUR 5 for taking part in the study. Due to measurement errors and incomplete data, 123 remained for analysis ($m_{age} = 28.5$; $SD_{age} = 7.9$; number of male participants = 22; number of female participants = 100; number of genders not captured = 1).

4.2 | Design

Participants were asked to choose between budgie food products that were adapted from the same kind of products that are available at the local market (Figure 2). Participants were generally unfamiliar with the products due to not being budgie owners. However, they were familiar with the product attributes, as these were similar to attributes otherwise used in grocery shopping. Hence, preferences could be accessed while brand familiarity effects were minimized. Choice task order was fixed across participants and prior to each choice task a 2-s white fixation cross was presented in the middle of a black screen. An area of interest (AOI) comprised the entire product.

In line with the number of alternatives typically used in choice-based conjoint studies (Pinnel & Englert, 1997), participants chose between five product images. Each product was characterized by nine attributes with two features each. The design followed Burgess and Street (2003, p. 2202) who introduced a fractional factorial design for five alternatives and nine attributes with two features each. The



FIGURE 2 Products presented in Study 1, Choice Task 6. Attributes and features: Number of birds (two vs. one); size (large package [1 kg] vs. small package [500 g]); brand (fictitious vs. real); bird color (blue vs. yellow); package color (blue/green vs. ocher/yellow); product window (available vs. not available); ingredients (with tasty honey vs. with vitamins); ingredients' background color (red vs. no color); appeal (hard vs. soft).

design consisted of 80 product images distributed across 16 choice tasks. Participants were forced to choose between the five product images. This design was 100% efficient, implying that each attribute occurred with equal frequency, namely, 80 times. Further, each feature mentioned in Figure 2 occurred with equal frequency, namely, 40 times, and each feature repeated itself with minimum frequency in a choice task. For example, participants could choose between three large and two small products, and vice versa.

The product attributes, such as size, key visual etc. were uncorrelated. More importantly, product attributes were uncorrelated with spatial position. Thus, the design provides an isolated view on the effects spatial position has on information search and choice, while simultaneously providing a realistic choice environment. Moreover, this design allowed for disclosing the importance of spatial position across the entire set of product attributes. The position of the product images from left to right was “left,” “center-left,” “center,” “center-right,” and “right.” The data consist of 9840 observations (123 participants * 16 choice tasks * 5 products).

4.3 | Coding and mean centering

I used effect coding. The nine product attributes were coded 1 and -1 . The variable “size,” for example, is coded 1 when a product is large and -1 when a product is small. Spatial position is a multi-categorical variable consisting of five categories. Hence, four variables were used for model estimation. I coded a spatial position variable with 1, when the respective position was present, -1 when the reference category was present, and 0 when the remaining three products were present.

By design, each product attribute and each spatial position variable has a mean of zero within each participant. I group mean center the number of fixations variable in the first half of the information search process when used as predictor for fixations in the second half of the information search process (Zhang et al., 2009). Across all information search models, the constant therefore represents the grand

mean. The grand mean represents the average “amount of information search” (Meißner et al., 2019) per product.

Because each single spatial position is of interest, I repeated the analysis and changed the reference category to obtain a standard error for each spatial position variable. Since the spatial position variables were specified as fixed, the respective coefficient estimates and standard errors were identical under different reference category specifications.

4.4 | Experimental procedure

Participants sat approximately 70 cm in front of a 24-in. screen with a resolution of 1920 * 1200 pixels. They were informed and gave consent that their eye movements would be tracked with a Tobii X60 eye tracker, mounted below the screen, while they were conducting the choice experiment. Prior to each recording, participants had to follow a moving dot to calibrate the eye tracker. Before the experiment started, participants completed a warm-up trial to familiarize them with the choice buttons and how the products were presented in the choice task. For exploratory purposes, participants had two electrodes stuck to their faces for measuring facial muscle activity. This, however, goes beyond the scope of the present article and will, therefore, not be described in more detail. The experiment started with an initial on-screen instruction that participants had to select the budgie food product they would buy in the supermarket. Participants reviewed the stimuli and could terminate a presentation without any time constraints by pressing a keyboard button to indicate their choice.

4.5 | Results

Excepting the subsequent section, I refer to the indirect, direct, and total effects of the position variables only. The information search and choice models' raw coefficients including standard errors and p values are given in Tables A.1 and A.2, respectively.

4.5.1 | Information search–choice relationship

Before getting into the mediation details, I first present results on the information search–choice relationship. Both initial ($\beta = .281, p < .001$) and later ($\beta = .716, p < .001$) information searches per product significantly predict product choice. In line with previous research, the predictive power increases (confidence intervals between both time segments do not overlap) as the task progresses (Willemssen et al., 2011). Further, this finding corroborates previous research that shows participants search more heavily for task-relevant information later in the information search process (Gluth et al., 2020; Meißner et al., 2016).

The next section discloses whether participants' search for information about products placed at different spatial positions, everything else being equal, carries through to product choice. Put differently, I analyze whether indirect effects of spatial position on choice through information search are prevalent.

4.5.2 | Indirect effects

As Figure 3 illustrates, the edge positions exert a negative effect on product choice through information search, as indicated by a negative total indirect effect ($\beta_{totalindirect-left} = -.045$; $\beta_{totalindirect-right} = -.049$) with 95% confidence intervals that do not straddle zero. The three center positions, in turn, exert a positive effect on product choice through information search as the positive total indirect effects indicate ($\beta_{totalindirect-centerLeft} = .012$; $\beta_{totalindirect-center} = .058$; $\beta_{totalindirect-centerRight} = .024$). For “center” and “center-right,” 95% confidence intervals do not straddle zero while for “center-left” 90% confidence intervals do not straddle zero. For more details on the total indirect effects, see Table A.3.

Before giving the statistics of the various specific indirect effects for the five spatial positions, Table 1 provides a simplified version of the results. This facilitates both the comprehension of empirical

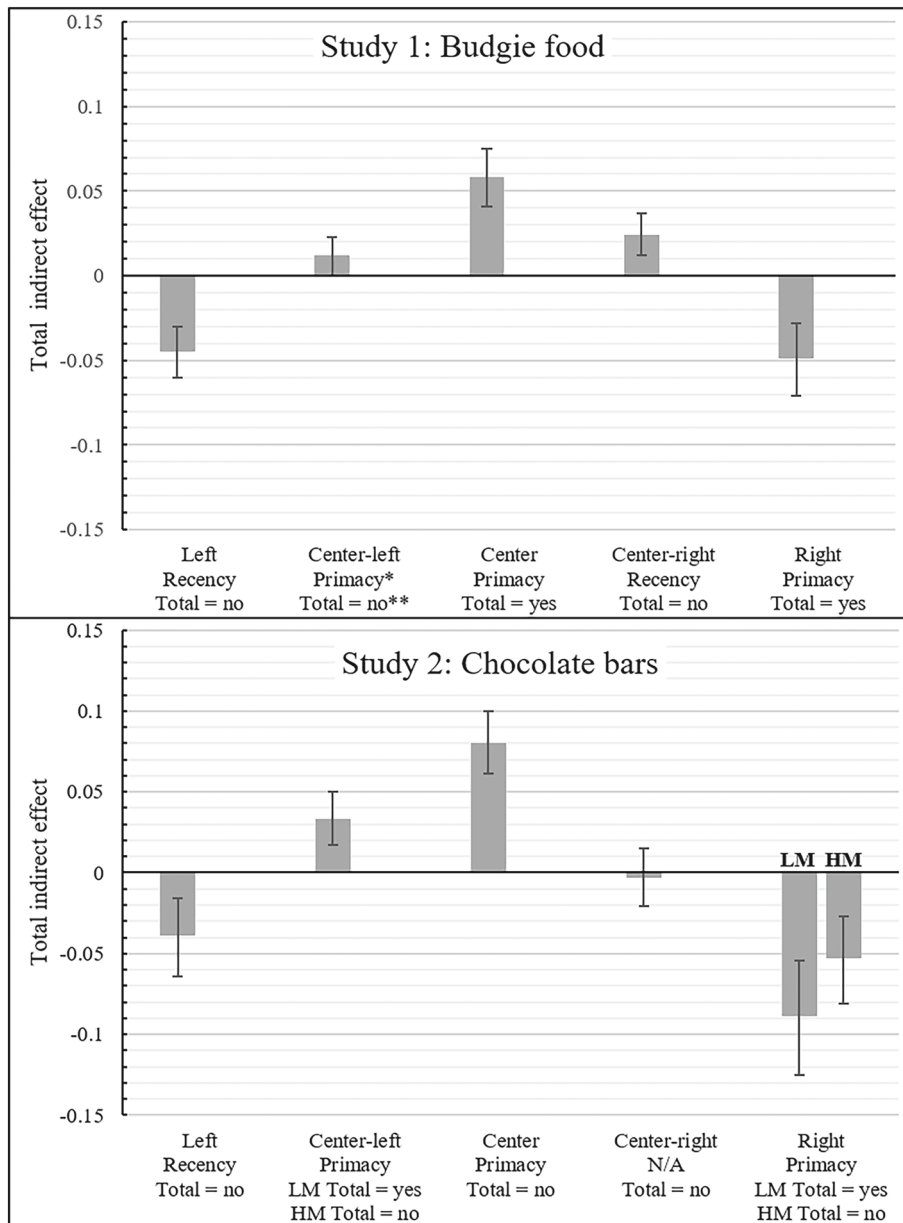


FIGURE 3 Results across both studies. Note: Error indicators represent 95% confidence intervals based on 10,000 MCMC simulations. The dominant mechanism, that is, primacy or recency, is written below each spatial position. Total = yes (no) means that the total indirect effect does (not) translate into a corresponding total effect. * = total indirect effect based on 90% confidence interval. ** = total effect with $p = .106$. LM = low motivation. HM = high motivation. N/A = not applicable as the total indirect effect is non-significant. “Center-left” total effects in Study 2 differ due to moderated direct effects.

TABLE 1 Predictions and results.

	Results	Study	Moderation condition	Specific indirect effect through initial information search	Specific indirect effect through initial information search, which causally influences later information search	Specific indirect effect through later information search	Total indirect effect	Dominant mechanism
Left	Predicted	N/A	N/A	+	+	–	–	Recency
	Measured	Bird food	N/A	ns.	ns.	–	–	Recency
		Chocolate	ns.	ns.	ns.	–	–	Recency
Center-left	Predicted	N/A	N/A	+	+	–	?	?
	Measured	Bird food	N/A	+	+	–	+	Primacy
		Chocolate	ns.	ns.	+	+	–	+
Center	Predicted	N/A	N/A	+	+	+	+	Primacy
	Measured	Bird food	N/A	+	+	ns.	+	Primacy
		Chocolate	ns.	ns.	+	+	+	+
Center-right	Predicted	N/A	N/A	–	–	+	?	?
	Measured	Bird food	N/A	–	–	+	+	Recency
		Chocolate	ns.	ns.	–	–	+	ns.
Right	Predicted	N/A	N/A	–	–	+	–	Primacy
	Measured	Bird food	N/A	–	–	+	–	Primacy
		Chocolate	LM	LM	–	–	ns.	–
			HM	HM	–	+	–	Primacy

Note: + (–) = positive (negative) specific indirect effect, that is, a specific indirect effect that is >0 (<0) based on 95% confidence intervals. ? = I explore rather than predict the effect. Dominant = for primacy, the specific indirect effects through initial information search carry the major share of the total indirect effect. For recency, the indirect effect through final information search carries the major share of the total indirect effect. N/A = not applicable. ns. = $p > .10$.

*Based on 90% confidence intervals.

findings and judgment of the match between prediction and empirical findings. As the table shows, predictions and results are largely congruent.

For the left edge position, the specific indirect effect through initial information search is close to zero ($\beta = .002$, $p > .05$). Similarly, the three specific indirect effects through initial and later information search in serial are close to zero ($\beta_{few} = .001$; $\beta_{average} = .001$; $\beta_{many} = .002$, $p > .05$). Thus, the major share of the total indirect effect ($\beta_{totalindirect-left} = -.045$) can be attributed to the specific indirect effect through later information search ($\beta = -.044$, $p \leq .05$). Thus, recency dominates. For a detailed overview of the specific indirect effects and their confidence intervals, see Table A.4.

For the “right” edge position, the major share of the total indirect effect ($\beta_{totalindirect-right} = -.049$) can be attributed to the specific indirect effects through initial information search ($\beta = -.047$, $p \leq .05$) and initial and later information searches in serial ($\beta_{few} = -.016$; $\beta_{average} = -.024$; $\beta_{many} = -.037$, $p \leq .05$) as the indirect effect through later information search is positive ($\beta = .025$, $p \leq .05$). Thus, primacy dominates.

For “center-left” ($\beta_{totalindirect-centerLeft} = .012$), primacy dominates as both the indirect effect through initial ($\beta = .016$) and the indirect effects through initial and later information searches in serial ($\beta_{few} = .005$; $\beta_{average} = .008$; $\beta_{many} = .013$, $p \leq .05$) differ positively from

zero, while the indirect effect through later information search differs negatively from zero ($\beta = -.015$, $p \leq .05$).

For the “center” ($\beta_{totalindirect-center} = .058$), primacy dominates too as both the indirect effect through initial ($\beta = .039$, $p \leq .05$) and the indirect effects through initial and later information searches in serial ($\beta_{few} = .013$; $\beta_{average} = .020$; $\beta_{many} = .030$, $p \leq .05$) differ positively from zero, while the indirect effect through later information search is close to zero and non-significant ($\beta = -.006$, $p > .05$).

In turn, for “center-right” ($\beta_{totalindirect-centerRight} = .024$), recency dominates as both the indirect effect through initial ($\beta = -.010$, $p \leq .05$) and the indirect effects through initial and later information searches in serial ($\beta_{few} = -.004$; $\beta_{average} = -.006$; $\beta_{many} = -.009$, $p \leq .05$) differ negatively from zero, while the indirect effect through later information search differs positively from zero ($\beta = .039$, $p \leq .05$).

4.5.3 | Direct effects

For product images placed “right” and “center-left,” no significant direct effect emerged ($\beta_{right} = -.053$, $p = .611$; $\beta_{centerLeft} = -.001$, $p = .994$), while for the other spatial positions direct effects opposite in sign are prevalent ($\beta_{left} = .481$, $p < .001$; $\beta_{center} = -.135$, $p = .099$; $\beta_{centerRight} = -.292$, $p = .001$).

4.5.4 | Total effects

As illustrated in Figure 3, the negative total indirect effect for product images placed “right” translates into a negative and significant total effect ($\beta = -.320, p < .001$). Similarly, the positive total indirect effect for product images placed in the “center” translates into a positive and significant total effect ($\beta = .240, p < .001$). For the remaining positions, the total indirect and direct effects offset each other as the total effects are non-significant ($\beta_{\text{left}} = -.09, p = .229$; $\beta_{\text{centerLeft}} = .109, p = .106$; $\beta_{\text{centerRight}} = .062, p = .314$).

Computing attribute importance weights from both partial log likelihood analysis (Lancsar et al., 2007) and from part-worth utilities at the individual level and averaging these weights across individuals (Cattin & Wittink, 1982; Meißner et al., 2016) both reveal that among the 10 possible ranks in preference space, spatial position is the eighth most important attribute.

4.6 | Discussion

In line with my predictions (see Table 1) and as illustrated in Figure 3, product images placed “center-left,” “center,” and “center-right” exert a positive effect, while product images placed at the edges exert a negative effect on choice through information search. Importantly, the indirect effects associated with product images placed in the “center” and at the “right” translate into total effects on choice. As predicted, these effects are dominated by primacy. The other spatial positions' total indirect effect is offset by a direct effect opposite in sign and similar in magnitude, which leads to a non-significant total effect.

4.7 | Limitations

In line with previous studies (Krajbich et al., 2010; Reutskaja et al., 2011), to provide the same starting conditions for each participant, a 2-s white fixation cross was presented in the middle of a black screen prior to each choice set. Recalling that participants were less likely to choose product images placed in the “center” and at the “right” edge due to a primacy effect, the identified causal relationship might be a methodological artifact. Additionally, choice task order was fixed across participants. However, prior research has demonstrated that order effects between choice tasks could affect consumers' choice behavior (Levav et al., 2010; Swait & Adamowicz, 2001). The presented products were quasi-realistic designs that did not control for visual saliency, yet visual saliency was found to influence consumers' choices (Milosavljevic et al., 2012). Brand familiarity effects were controlled for indirectly in that participants were familiar with the products' attributes but unfamiliar with the product category. This might have induced a low task motivation in participants. Therefore, it is important to replicate the findings while controlling for these limitation factors. I address these issues in the next study.

5 | STUDY 2

In this study, I used data from Zuschke (2020b). That study's purpose was to investigate how typical in-store marketing activities, such as enlarging a product and improving the visual saliency of a product, impact choice. Additionally, the study analyzed boundary conditions, that is, task motivation (high vs. low) and task complexity (three product images vs. five product images to choose from). The results showed that both in-store activities exert an effect on product choice through information search.

The data follows the same experimental setup and has the same statistical properties as Study 1. Consequently, and importantly, identical to Study 1, the product attributes were not correlated with one another, nor with spatial position. Hence, this study can be considered a replication of Study 1 for another product type, namely, chocolate bars, while simultaneously addressing the limitations of the first study. For ease of comparison, I use data on the five product images condition only. In the following exposition, I outline details on Study 2, which are important for the current study. For more information, I refer the reader to the original article.

5.1 | Participants

The data comprises 77 right-handed participants ($m_{\text{age}} = 27.2$; $SD_{\text{age}} = 7.7$; number of male participants = 25; number of female participants = 52) who were recruited at a large European university. Of the participants, 40 were assigned to a low task motivation condition and 37 to a high task motivation condition. Each participant received compensation of EUR 10 for taking part in the study.

5.2 | Design

Participants had to choose between five chocolate bars that were adapted from the same kind of products that were available at the local market. The size of a bar on screen approximated the size of such a bar on the retail shelf. Brand familiarity was controlled for by using a fictitious brand name and modified design features. Saliency was controlled for by changing the opacity of certain design elements. In contrast to Study 1, this study did not use a fixation cross prior to stimulus onset. As in Study 1, the AOI encompassed the entire product image. The data consisted of 6160 observations (77 participants * 16 choice tasks * 5 products). Task motivation was manipulated by task instructions (Pieters & Warlop, 1999; Pieters & Wedel, 2007). Moreover, the choice task in the high task motivation condition was incentive-aligned in that participants were promised a bar of chocolate that best matched their choices. I coded task motivation with 1 = high motivation and -1 = low motivation, followed by a grand mean centering to keep the constant interpretable. For each participant, the order of the choice tasks was randomized, thereby preventing order effects that could arise between choice tasks.

5.3 | Experimental procedure

Participants sat approximately 70 cm in front of a 24-in. screen with a resolution of 1920 * 1200 pixels. They were informed and gave consent that their eye movements could be tracked with a Tobii X60 eye tracker, mounted below the screen, while conducting the choice experiment.

The experiment started with an initial on-screen instruction. In both conditions participants were instructed to select a product they would buy at the grocery store, followed by an instruction that differed for the two conditions. Participants in the high task motivation condition read that the study's purpose was to test several products about to be introduced in the local market and that their input would be very helpful in developing a product that sells well. Participants in the low task motivation condition read that the study was part of developing a new product test. Participants reviewed stimuli and, without any time constraints, could terminate every choice set's presentation by pressing the space bar. Afterwards, they indicated their choice by a keyboard button. Participants repeated this procedure 16 times.

5.4 | Model estimation procedure

In both the information search and choice models, I included interaction terms between the proposed moderator, that is, task motivation, and the product attributes, as well as between the five spatial positions and task motivation in the initial model estimation. Following suggestions of Hayes and Preacher (2013) and for parsimony, I removed non-significant interactions after the initial model estimation. I kept the interaction terms of each spatial position and task motivation in the models even if they were non-significant. Further, I kept all main effects in the models, even if they were non-significant.

5.5 | Results

Excepting the subsequent section, I refer to the indirect, direct, and total effects of the spatial position variables only. The information search and choice models' raw coefficients including standard errors and p values are given in Tables A.5 and A.6, respectively.

5.5.1 | Information search–choice relationship

The results are in line with Study 1's results in that both segments predict choice, with the final information search ($\beta = .557$, $p < .001$) having a greater impact on choice than the initial information search ($\beta = .222$, $p < .001$) with non-overlapping confidence intervals.

5.5.2 | Inferential test for moderated mediation

To access the moderation of the mediation, I computed indices of moderated mediation (Hayes, 2015). Detailed information is given in Table A.7. Task motivation does not moderate any spatial position effects through initial information search, ($p > .1$). In line with my prediction, task motivation moderates the mediation through later information search in both the parallel and the serial mediation model. Specifically, in the serial mediation model the effect product images placed “right” exert on choice through later information search significantly differs between motivational conditions. This is indicated by the index's 95% confidence interval that does not straddle zero. In the parallel mediation model, the effect differs based on a 90% confidence interval.

5.5.3 | Indirect effects

As Figure 3 illustrates, every spatial position excepting the “center-right” position exerts an effect on product choice through information search as is indicated by total indirect effects that differ significantly (95% confidence intervals) from zero ($\beta_{totalindirect-left} = -.039$; $\beta_{totalindirect-centerLeft} = .033$; $\beta_{totalindirectcenter} = .080$; $\beta_{totalindirect-centerRight} = -.003$; $\beta_{totalindirect-right-lowMotivation} = -.089$; $\beta_{totalindirect-right-highMotivation} = -.053$). For information on the confidence intervals, see Table A.8. As Table 2 suggests and as Figure 3 illustrates, primacy dominates for product images placed “center-left,” “center,” and “right,” while recency dominates for product images placed “left.” As speculated, the total indirect effect for product images placed at the “right” edge is closer to zero when motivation is high than when motivation is low. Moreover, as Table 1 shows, the results are congruent with Study 1's results and hence also with the predictions made in the theory section. There are slight differences regarding the total indirect effect of “center-left,” which differs more clearly from zero ($Confidence\ Interval_{Study2} = 95\%$ vs. $Confidence\ Interval_{Study1} = 90\%$) and for the total indirect effect of “center-right,” which does not differ from zero.

5.5.4 | Direct effects

The direct effect for product images placed “center-left” differs by task motivation ($\beta_{centerLeftXtaskMotivation} = -.264$, $p = .016$). Probing the moderation reveals that the direct effect does not differ significantly from zero when motivation is low ($\beta = .056$, $p = .660$). It differs negatively and significantly from zero when motivation is high ($\beta = -.471$, $p = .01$).

For the remaining spatial positions, the interaction with task motivation is non-significant ($\beta_{leftXtaskMotivation} = .075$, $p = .421$; $\beta_{centerXtaskMotivation} = .092$, $p = .421$; $\beta_{centerRightXtaskMotivation} = -.084$, $p = .457$; $\beta_{rightXtaskMotivation} = .181$, $p = .108$). Further, for these spatial positions, a significant direct effect ($\beta_{left} = .568$, $p < .001$;

TABLE 2 Results of moderated serial mediation analysis of Study 2.

Position	Primacy			Recency			Primacy + recency						
	Initial fix	Specific indirect effect through initial information search		Specific indirect effect through initial information search, which causally influences later information search	Specific indirect effect through later information search	Total indirect effect		95% CI					
		Coef.	95% CI			Coef.	95% CI						
Left	Few	0.008	-0.002	0.019	0.003	-0.001	0.006	-0.050	-0.073	-0.029	-0.039	-0.064	-0.015
Left	Avg				0.005	-0.001	0.011				-0.037	-0.063	-0.013
Left	Many				0.009	-0.001	0.022				-0.032	-0.060	-0.006
Center-left	Few	0.030	0.022	0.040	0.010	0.008	0.013	-0.022	-0.039	-0.008	0.018	-0.001	0.036
Center-left	Avg				0.019	0.013	0.026				0.026	0.007	0.045
Center-left	Many				0.033	0.020	0.050				0.041	0.018	0.065
Center	Few	0.032	0.023	0.042	0.011	0.008	0.014	0.025	0.011	0.039	0.067	0.051	0.085
Center	Avg				0.020	0.014	0.027				0.076	0.059	0.095
Center	Many				0.035	0.022	0.052				0.091	0.070	0.115
Center-right	Few	-0.021	-0.030	-0.014	-0.009	-0.012	-0.006	0.032	0.017	0.050	0.003	-0.015	0.022
Center-right	Avg				-0.015	-0.022	-0.010				-0.004	-0.022	0.017
Center-right	Many				-0.026	-0.039	-0.015				-0.014	-0.036	0.008
Right LM	Few	-0.049	-0.065	-0.035	-0.017	-0.021	-0.012	-0.009	-0.039	0.021	-0.075	-0.109	-0.041
Right LM	Avg				-0.030	-0.042	-0.021				-0.088	-0.125	-0.053
Right LM	Many				-0.054	-0.081	-0.034				-0.112	-0.155	-0.072
Right HM	Few	-0.049	-0.065	-0.035	-0.017	-0.021	-0.012	0.039	0.012	0.067	-0.027	-0.059	0.005
Right HM	Avg				-0.030	-0.042	-0.021				-0.041	-0.074	-0.006
Right HM	Many				-0.054	-0.081	-0.034				-0.064	-0.105	-0.025

Note: Significant coefficients printed in bold ($p < .05$). "Initial information search" ("Later information search") = first (second) half of total number of fixations per respondent and task. Total indirect effect = sum of all specific indirect effects. "LM" ("HM") = low (high) motivation. "Initial fix" represents the number of fixations per respondent, task, and product in the first half of the information process. "Avg" = average within respondents mean value per respondent, task, and product, that is, 4.2 fixations. Due to the mean centering, the value used for computation is 0. "Few" ("Many") = the average 16th (84th) percentile of the mean centered values, that is, -3.71 (3.52).

$\beta_{center} = -.238, p = .041$; $\beta_{centerRight} = -.433, p < .001$; $\beta_{right} = .311, p = .007$), opposite in sign to a corresponding significant total indirect effect, is prevalent.

5.5.5 | Total effects

Between the two motivational conditions, the total effect of products placed “center-left” ($\beta_{centerLeftXtaskMotivation} = -.268, p = .002$) and “right” ($\beta_{RightXtaskMotivation} = .225, p = .045$) differs, while for the other spatial positions, it does not ($\beta_{LeftXtaskMotivation} = -.063, p = .592$; $\beta_{CenterXtaskMotivation} = .050, p = .623$; $\beta_{CenterRightXtaskMotivation} = .056, p = .454$).

As Figure 3 illustrates, the negative total indirect effect for product images placed “right” when task motivation is low translates into a negative and significant total effect ($\beta = -.403, p = .032$). In contrast, due to a direct effect opposite in sign and similar in magnitude, the negative total indirect effect of product images placed “right” does not translate into a total negative effect when motivation is high ($\beta = .047, p = .691$).

The positive total indirect effect for products placed “center-left” when motivation is low translates into a positive and significant total effect ($\beta = .278, p < .022$). In turn, due to a direct effect opposite in sign and greater in magnitude, the positive total indirect effect when motivation is high does not translate into a positive total effect ($\beta = -.258, p < .024$).

For the remaining spatial positions, total indirect and direct effect offset each other as the total effect is non-significant ($\beta_{left} = .04, p = .735$; $\beta_{center} = .092, p = .367$, $\beta_{centerRight} = .036, p = .651$). Therefore, the mediating role of information search for product images placed at these positions is limited.

In computing importance weights from individual part-worth utilities and averaging these weights for each motivational group, I could show that for motivated participants among the 10 possible ranks in preference space, spatial position ranks ninth, while for less motivated participants, spatial position ranks eighth.

5.6 | Discussion

In both studies, spatial position exerts an effect on choice through information search, and the causal mechanisms, that is, primacy and recency, found in Study 1 are congruent with the causal mechanisms in Study 2.

Specifically, in both studies, participants were less likely to choose product images placed “right” since these product images were inferior in making eye contact. Further, in both studies, center positions, that is, in Study 1 the “center” and in Study 2 “center-left,” increased choice likelihood as product images placed at these positions were superior in making eye contact. Across both studies, primacy was consistently the dominant mechanism for these spatial positions. Thus, the emerging picture shows that information unrelated to participants' underlying values influences multi-attribute choice due to primacy rather than recency.

As Study 2 reveals for participants with a high task motivation, the significant total indirect effect associated with product images placed “center-left” and at the “right” edge do not translate into a total effect on choice, while for participants with low task motivation, it does. Recalling the dominant mechanism for these spatial positions, the results suggest that increasing task motivation decreases primacy. Indeed, when motivation is high, direct effects offset each spatial position's indirect effect. This suggests that spatial position effects on choice through information search for motivated participants are minimal.

6 | ROBUSTNESS ASSESSMENT

I performed several robustness checks that confirm the stability of the results.

- First, I used different information search metrics. Specifically, I used fixation duration as information search metric and divided the viewing process based on that metric.
- Second, I used fixation count as information search metric while creating the segments with the fixation duration metric.
- Third, I specified information search models that control for participants' heterogeneity. More precisely, I estimated fixed effects negative binomial models with clustered robust standard errors.
- Fourth, where appropriate, I used the model's raw coefficients for computing indirect effects and for computing the indices of moderated mediation instead of using the first partial derivative framework.
- Fifth, instead of using 100 ms to determine a fixation, I used a different cut-off, that is, 67 ms.

In each of the five checks, the results are similar to the results outlined in the previous sections, and I can draw the same conclusions.

7 | GENERAL DISCUSSION

I used a choice-based conjoint analysis in combination with eye tracking to analyze spatial position effects in the light of primacy and recency during simulated in-store decision-making. I analyzed the effects across two experiments that both used quasi-realistic product designs to improve external validity and generalizability.

The order effect I observe is consistent with a large body of research in experimental psychology, behavioral economics, and marketing that acknowledges that decision-makers' judgments and choices can be manipulated by normatively irrelevant decision contexts or factors (Ariely et al., 2003; Atalay et al., 2012; Levav et al., 2010; Payne et al., 1993; Reutskaja et al., 2011; Tversky & Kahneman, 1974). However, it might be possible to explain spatial position effect from a personal relevance, and hence, purely goal-

driven point of view, albeit under implausible assumptions. Participants can hold a priori shelf placement beliefs about certain spatial positions, such as that products in the center are the best deal or that products to the right have better quality (Valenzuela & Raghuram, 2009; Valenzuela & Raghuram, 2015). In both experiments, the participants chose between product images with multiple features that were shuffled across choice tasks. The shuffling was obvious to participants who looked at the five products images in the choice task. Additionally, from the second choice task, participants were aware that the randomization process was ongoing. Therefore, spatial position effects on choice were more likely not related to participants' underlying values. This view on spatial position effects during repeated conjoint choices also matches previous research (Meißner et al., 2016). Recalling that attribute importance for spatial position compared to the other attributes is rather low, it seems reasonable to conclude that spatial position does bias multi-attribute repeated product choice through initial information search, but only a little.

The fact that spatial position does bias choice through initial information search might explain why center effects on choice slightly differed across the two studies. In Study 1, a fixation cross ensured that participants started their search for product information in the "center," while in Study 2, they could choose freely where to look at initially. Hence, consumers could naturally shift their very first fixations slightly to the left in a setting with five product images arranged horizontally, which in turn influence choice. Put differently, in Study 1, center effects could, to some extent, be artificially stimulated as, for example, in Reutskaja et al. (2011), while in Study 2, the center effect occurred more naturally. This is, however, speculative and needs further research, for example, by manipulating the location of the initial fixation cross between individuals.

Further, the finding that for participants with low (high) task motivation, primacy effects are more (less) prevalent, extends research from other domains (Petty et al., 2001) to a multi-attribute product choice context. Importantly, this study's findings have been generated through a process-tracing approach that provides a fine-grained view on the cognitive processes underlying consumer decision-making (Schulte-Mecklenbeck et al., 2017; Zuschke, 2020a). Future researchers can examine other factors that affect the level of information elaboration, such as choice overload (Reutskaja et al., 2018).

The results extend previous research (Reutskaja et al., 2011) by showing that in a multi-attribute setting primacy rather than recency biases product choice. Accordingly, the results provide evidence that for information unrelated to participants' underlying values, the causal influence of attention on choice generalizes to more complex decisions; however, due to the low importance of spatial position, the impact is limited. Relatedly, an open question remains as to whether and how the causal influence of attention on choice applies to information about products that are of personal relevance. Indeed, there is some evidence that for this type of information, the causal nature unfolds during later information search, thus recency (Bhatnagar & Orquin, 2022). However, more research is clearly needed.

In line with previous research (Chandon et al., 2009), most total indirect effects are offset by direct effects. As Zhao et al. (2010)

pointed out, this indicates that an important mediator is omitted. One such mediator could be peripheral vision (Perkovic et al., 2022; Wästlund et al., 2018). Future research could design experiments where peripheral vision is controlled for and could use the methodological approach elaborated on in this research. A possibility to identify other mediators would be to use retrospective verbal protocols (Schulte-Mecklenbeck et al., 2017; Zuschke, 2020a) in addition to eye tracking.

Although many disciplines use mediation analysis to make causal claims, it has also faced some criticism, mainly due to being improperly used (Kline, 2015; Thoemmes, 2015; Vancouver & Carlson, 2015). To minimize these concerns, I used standard errors that are robust to some kind of misspecification, eye tracking to unobtrusively measure the mediator, and discrete choice (an approach that more realistically resembles decision-making in real life) to measure the outcome. This mediator–outcome measurement additionally reduces common methods bias. Further, I replicated the findings of one experiment in another experiment, I explained why a serial mediation model with information search as mediator and choice as outcome is the most plausible model, and I used a manipulated moderator based on theory.

The claim that information unrelated to consumers' underlying values bias choice due to primacy rather than recency (when task motivation is low) rests on the argument that both the total indirect effect and the total effect significantly differ from zero in the same direction. However, the practice of significance testing has been criticized (Kline, 2015). To circumvent such dichotomous statements, the percentage mediated could be calculated in addition (Pieters, 2017). However, a competitive mediation pattern, the non-linear relationships, and the multilevel data prevent calculation of the percentage mediated. As several authors recommended, I report the models' coefficients' exact *p* values as minimal solution for the problem (Gigerenzer, 2018; Pieters, 2017). Additionally, the size of the total effects of the spatial positions that are affected by recency, that is, "left" and "center-right," are rather small in comparison with the effects that differ significantly from zero and that are affected by primacy, which suggests a minor influence of recency. Future research could back-up mediation analysis with computational modeling approaches to corroborate such statements (Gluth et al., 2020; Reutskaja et al., 2011).

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the author upon reasonable request.

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REFERENCES

- Ariely, D., Loewenstein, G., & Prelec, D. (2003). "Coherent arbitrariness": Stable demand curves without stable preferences. *The Quarterly Journal of Economics*, 118(1), 73–106. <https://doi.org/10.1162/00335530360535153>
- Atalay, A. S., Bodur, H. O., & Rasolofoarison, D. (2012). Shining in the center: Central gaze cascade effect on product choice. *Journal of Consumer Research*, 39(4), 848–866. <https://doi.org/10.1086/665984>
- Bagchi, R., & Davis, D. F. (2012). \$29 for 70 items or 70 items for \$29? How presentation order affects package perceptions. *Journal of Consumer Research*, 39(1), 62–73. <https://doi.org/10.1086/661893>
- Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), 1173–1182. <https://doi.org/10.1037/0022-3514.51.6.1173>
- Bettman, J. R., Luce, M. F., & Payne, J. W. (1998). Constructive consumer choice processes. *Journal of Consumer Research*, 25(3), 187–217. <https://doi.org/10.1086/209535>
- Bhatnagar, R., & Orquin, J. L. (2022). A meta-analysis on the effect of visual attention on choice. *Journal of Experimental Psychology: General*, 151, 2265–2283. <https://doi.org/10.1037/xge0001204>
- Bialkova, S., Grunert, K. G., Juhl, H. J., Wasowicz-Kirylo, G., Stysko-Kunkowska, M., & van Trijp, H. C. M. (2014). Attention mediates the effect of nutrition label information on consumers' choice. Evidence from a choice experiment involving eye-tracking. *Appetite*, 76, 66–75. <https://doi.org/10.1016/j.appet.2013.11.021>
- Bialkova, S., & van Trijp, H. (2010). What determines consumer attention to nutrition labels? *Food Quality and Preference*, 21(8), 1042–1051. <https://doi.org/10.1016/j.foodqual.2010.07.001>
- Burgess, L., & Street, D. J. (2003). Optimal designs for 2^k choice experiments. *Communications in Statistics - Theory and Methods*, 32(11), 2185–2206. <https://doi.org/10.1081/STA-120024475>
- Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. *Journal of Personality and Social Psychology*, 42(1), 116–131. <https://doi.org/10.1037/0022-3514.42.1.116>
- Cameron, A. C., & Trivedi, P. K. (2005). *Microeconomics: Methods and applications* (1. publ). Cambridge University Press. <https://doi.org/10.1017/CBO9780511811241>
- Carlson, K. A., Meloy, M. G., & Russo, J. E. (2006). Leader-driven primacy: Using attribute order to affect consumer choice. *Journal of Consumer Research*, 32(4), 513–518. <https://doi.org/10.1086/500481>
- Cattin, P., & Wittink, D. R. (1982). Commercial use of conjoint analysis: A survey. *Journal of Marketing*, 46(3), 44–53. <https://doi.org/10.1177/00222498204600308>
- Cavanagh, J. F., Wiecki, T. V., Kochar, A., & Frank, M. J. (2014). Eye tracking and pupillometry are indicators of dissociable latent decision processes. *Journal of Experimental Psychology: General*, 143(4), 1476–1488. <https://doi.org/10.1037/a0035813>
- Celsi, R. L., & Olson, J. C. (1988). The role of involvement in attention and comprehension processes. *Journal of Consumer Research*, 15(2), 210. <https://doi.org/10.1086/209158>
- Chandon, P., Hutchinson, J. W., Bradlow, E. T., & Young, S. H. (2009). Does in-store marketing work?: Effects of the number and position of shelf facings on brand attention and evaluation at the point of purchase. *Journal of Marketing*, 73(6), 1–17. <https://doi.org/10.1509/jmkg.73.6.1>
- Christenfeld, N. (1995). Choices from identical options. *Psychological Science*, 6(1), 50–55. <https://doi.org/10.1111/j.1467-9280.1995.tb00304.x>
- Ding, M. (2007). An incentive-aligned mechanism for conjoint analysis. *Journal of Marketing Research*, 44(2), 214–223. <https://doi.org/10.1509/jmkr.44.2.214>
- Ding, M., Grewal, R., & Liechty, J. (2005). Incentive-aligned conjoint analysis. *Journal of Marketing Research*, 42(1), 67–82. <https://doi.org/10.1509/jmkr.42.1.67.56890>
- Dong, S., Ding, M., & Huber, J. (2010). A simple mechanism to incentive-align conjoint experiments. *International Journal of Research in Marketing*, 27(1), 25–32. <https://doi.org/10.1016/j.ijresmar.2009.09.004>
- Drèze, X., Hoch, S. J., & Purk, M. E. (1994). Shelf management and space elasticity. *Journal of Retailing*, 70(4), 301–326. [https://doi.org/10.1016/0022-4359\(94\)90002-7](https://doi.org/10.1016/0022-4359(94)90002-7)
- Edwards, J. R., & Lambert, L. S. (2007). Methods for integrating moderation and mediation: A general analytical framework using moderated path analysis. *Psychological Methods*, 12(1), 1–22. <https://doi.org/10.1037/1082-989X.12.1.1>
- Ein-Gar, D., Shiv, B., & Tormala, Z. L. (2012). When blemishing leads to blossoming: The positive effect of negative information. *Journal of Consumer Research*, 38(5), 846–859. <https://doi.org/10.1086/660807>
- Foulsham, T., Frost, E., & Sage, L. (2018). Stable individual differences predict eye movements to the left, but not handedness or line bisection. *Vision Research*, 144, 38–46. <https://doi.org/10.1016/j.visres.2018.02.002>
- Foulsham, T., Gray, A., Nasiopoulos, E., & Kingstone, A. (2013). Leftward biases in picture scanning and line bisection: A gaze-contingent window study. *Vision Research*, 78, 14–25. <https://doi.org/10.1016/j.visres.2012.12.001>
- Geldhof, G. J., Anthony, K. P., Selig, J. P., & Mendez-Luck, C. A. (2018). Accommodating binary and count variables in mediation. *International Journal of Behavioral Development*, 42(2), 300–308. <https://doi.org/10.1177/0165025417727876>
- Gigerenzer, G. (2018). Statistical rituals: The replication delusion and how we got there. *Advances in Methods and Practices in Psychological Science*, 1(2), 198–218. <https://doi.org/10.1177/2515245918771329>
- Gluth, S., Kern, N., Kortmann, M., & Vitali, C. L. (2020). Value-based attention but not divisive normalization influences decisions with multiple alternatives. *Nature Human Behaviour*, 4(6), 634–645. <https://doi.org/10.1038/s41562-020-0822-0>
- Gluth, S., Spektor, M. S., & Rieskamp, J. (2018). Value-based attentional capture affects multi-alternative decision making. *eLife*, 7, e39659.
- Hartmann, J., Heitmann, M., Schamp, C., & Netzer, O. (2021). The power of brand selfies. *Journal of Marketing Research*, 58(6), 1159–1177. <https://doi.org/10.1177/00222437211037258>
- Haugtvedt, C. P., & Wegener, D. T. (1994). Message order effects in persuasion: An attitude strength perspective. *Journal of Consumer Research*, 21(1), 205. <https://doi.org/10.1086/209393>
- Hayes, A. F. (2015). An index and test of linear moderated mediation. *Multivariate Behavioral Research*, 50(1), 1–22. <https://doi.org/10.1080/00273171.2014.962683>
- Hayes, A. F., & Preacher, K. J. (2010). Quantifying and testing indirect effects in simple mediation models when the constituent paths are nonlinear. *Multivariate Behavioral Research*, 45(4), 627–660. <https://doi.org/10.1080/00273171.2010.498290>
- Hayes, A. F., & Preacher, K. J. (2013). Conditional process modeling: Using structural equation modeling to examine contingent causal processes. In G. R. Hancock & R. O. Mueller (Eds.), *Quantitative methods in education and the behavioral sciences. Structural equation modeling. A second course* (pp. 219–266). Information Age Publishing Inc.
- Hayes, A. F., & Rockwood, N. J. (2020). Conditional process analysis: Concepts, computation, and advances in the modeling of the contingencies of mechanisms. *American Behavioral Scientist*, 64(1), 19–54. <https://doi.org/10.1177/0002764219859633>

- Hogarth, R. M., & Einhorn, H. J. (1992). Order effects in belief updating: The belief-adjustment model. *Cognitive Psychology*, 24(1), 1–55. [https://doi.org/10.1016/0010-0285\(92\)90002-J](https://doi.org/10.1016/0010-0285(92)90002-J)
- Hole, A. R. (2007). Fitting mixed logit models by using maximum simulated likelihood. *Stata Journal*, 7, 388–401. <https://doi.org/10.1177/1536867X0700700306>
- Johnson, E. J., Payne, J. W., & Bettman, J. R. (1988). Information displays and preference reversals. *Organizational Behavior and Human Decision Processes*, 42(1), 1–21. [https://doi.org/10.1016/0749-5978\(88\)90017-9](https://doi.org/10.1016/0749-5978(88)90017-9)
- Kliene, R. B. (2015). The mediation myth. *Basic and Applied Social Psychology*, 37(4), 202–213. <https://doi.org/10.1080/01973533.2015.1049349>
- Krajbich, I., Armel, C., & Rangel, A. (2010). Visual fixations and the computation and comparison of value in simple choice. *Nature Neuroscience*, 13(10), 1292–1298. <https://doi.org/10.1038/nn.2635>
- Krajbich, I., & Rangel, A. (2011). Multialternative drift-diffusion model predicts the relationship between visual fixations and choice in value-based decisions. *Proceedings of the National Academy of Sciences of the United States of America*, 108(33), 13852–13857. <https://doi.org/10.1073/pnas.1101328108>
- Kreplin, U., Thoma, V., & Rodway, P. (2014). Looking behaviour and preference for artworks: The role of emotional valence and location. *Acta Psychologica*, 152, 100–108. <https://doi.org/10.1016/j.actpsy.2014.08.003>
- Krull, J. L., & MacKinnon, D. P. (1999). Multilevel mediation modeling in group-based intervention studies. *Evaluation Review*, 23(4), 418–444. <https://doi.org/10.1177/0193841X9902300404>
- Lancsar, E., Louviere, J., & Flynn, T. (2007). Several methods to investigate relative attribute impact in stated preference experiments. *Social Science & Medicine* (1982), 64(8), 1738–1753. <https://doi.org/10.1016/j.socscimed.2006.12.007>
- Levav, J., Heitmann, M., Herrmann, A., & Iyengar, S. S. (2010). Order in product customization decisions: Evidence from field experiments. *Journal of Political Economy*, 118(2), 274–299. <https://doi.org/10.1086/652463>
- Liechty, J., Pieters, R., & Wedel, M. (2003). Global and local covert visual attention: Evidence from a Bayesian hidden Markov model. *Psychometrika*, 68(4), 519–541. <https://doi.org/10.1007/BF02295608>
- MacKinnon, D. P., Fairchild, A. J., & Fritz, M. S. (2007). Mediation analysis. *Annual Review of Psychology*, 58, 593–614. <https://doi.org/10.1146/annurev.psych.58.110405.085542>
- McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, 3(4), 303–328. [https://doi.org/10.1016/0047-2727\(74\)90003-6](https://doi.org/10.1016/0047-2727(74)90003-6)
- McFadden, D., & Train, K. (2000). Mixed MNL models for discrete response. *Journal of Applied Econometrics*, 15(5), 447–470. [https://doi.org/10.1002/1099-1255\(200009/10\)15:5<447::AID-JAE570>3.0.CO;2-1](https://doi.org/10.1002/1099-1255(200009/10)15:5<447::AID-JAE570>3.0.CO;2-1)
- Meißner, M., Musalem, A., & Huber, J. (2016). Eye tracking reveals processes that enable conjoint choices to become increasingly efficient with practice. *Journal of Marketing Research*, 53(1), 1–17. <https://doi.org/10.1509/jmr.13.0467>
- Meißner, M., Oppewal, H., & Huber, J. (2019). Surprising adaptivity to set size changes in multi-attribute repeated choice tasks. *Journal of Business Research*, 111, 163–175.
- Milosavljevic, M., Navalpakkam, V., Koch, C., & Rangel, A. (2012). Relative visual saliency differences induce sizable bias in consumer choice. *Journal of Consumer Psychology*, 22(1), 67–74. <https://doi.org/10.1016/j.jcps.2011.10.002>
- Mormann, M., & Russo, J. E. (2021). Does attention increase the value of choice alternatives? *Trends in Cognitive Sciences*, 25(4), 305–315. <https://doi.org/10.1016/j.tics.2021.01.004>
- Nikolova, H. D., & Inman, J. J. (2015). Healthy choice: The effect of simplified point-of-sale nutritional information on consumer food choice behavior. *Journal of Marketing Research*, 52(6), 817–835. <https://doi.org/10.1509/jmr.13.0270>
- Orquin, J. L., & Holmqvist, K. (2018). Threats to the validity of eye-movement research in psychology. *Behavior Research Methods*, 50(4), 1645–1656. <https://doi.org/10.3758/s13428-017-0998-z>
- Orquin, J. L., Lahm, E. S., & Stojić, H. (2021). The visual environment and attention in decision making. *Psychological Bulletin*, 147(6), 597–617. <https://doi.org/10.1037/bul0000328>
- Orquin, J. L., & Mueller Loose, S. (2013). Attention and choice: A review on eye movements in decision making. *Acta Psychologica*, 144(1), 190–206. <https://doi.org/10.1016/j.actpsy.2013.06.003>
- Ossandón, J. P., Onat, S., & König, P. (2014). Spatial biases in viewing behavior. *Journal of Vision*, 14(2), 20. <https://doi.org/10.1167/14.2.20>
- Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker*. Cambridge University Press. <https://doi.org/10.1017/CBO9781139173933>
- Perkovic, S., Schoemann, M., Lagerkvist, C.-J., & Orquin, J. L. (2022). Covert attention leads to fast and accurate decision-making. *Journal of Experimental Psychology: Applied*. <https://doi.org/10.1037/xap0000425>
- Petty, R. E., & Cacioppo, J. T. (1986). *Communication and persuasion: Central and peripheral routes to attitude change*. Springer Series in Social Psychology. Springer New York. <https://doi.org/10.1007/978-1-4612-4964-1>
- Petty, R. E., Tormala, Z. L., Hawkins, C., & Wegener, D. T. (2001). Motivation to think and order effects in persuasion: The moderating role of chunking. *Personality and Social Psychology Bulletin*, 27(3), 332–344. <https://doi.org/10.1177/0146167201273007>
- Pieters, R. (2017). Meaningful mediation analysis: Plausible causal inference and informative communication. *Journal of Consumer Research*, 44(3), 692–716. <https://doi.org/10.1093/jcr/ucx081>
- Pieters, R., & Warlop, L. (1999). Visual attention during brand choice: The impact of time pressure and task motivation. *International Journal of Research in Marketing*, 16(1), 1–16. [https://doi.org/10.1016/S0167-8116\(98\)00022-6](https://doi.org/10.1016/S0167-8116(98)00022-6)
- Pieters, R., & Wedel, M. (2007). Goal control of attention to advertising: The Yarbus implication. *Journal of Consumer Research*, 34(2), 224–233. <https://doi.org/10.1086/519150>
- Pinnel, J., & Englert, S. (1997). The number of choice alternatives in discrete choice modeling. In *Proceedings of the Sawtooth Software Conference* (pp. 121–153). CiteSeer.
- Preacher, K. J., Rucker, D. D., & Hayes, A. F. (2007). Addressing moderated mediation hypotheses: Theory, methods, and prescriptions. *Multivariate Behavioral Research*, 42(1), 185–227. <https://doi.org/10.1080/00273170701341316>
- Preacher, K. J., & Selig, J. P. (2012). Advantages of Monte Carlo confidence intervals for indirect effects. *Communication Methods and Measures*, 6(2), 77–98. <https://doi.org/10.1080/19312458.2012.679848>
- Reutskaja, E., Lindner, A., Nagel, R., Andersen, R. A., & Camerer, C. F. (2018). Choice overload reduces neural signatures of choice set value in dorsal striatum and anterior cingulate cortex. *Nature Human Behaviour*, 2(12), 925–935. <https://doi.org/10.1038/s41562-018-0440-2>
- Reutskaja, E., Nagel, R., Camerer, C. F., & Rangel, A. (2011). Search dynamics in consumer choice under time pressure: An eye-tracking study. *American Economic Review*, 101(2), 900–926. <https://doi.org/10.1257/aer.101.2.900>
- Revelt, D., & Train, K. (1998). Mixed logit with repeated choices: Households' choices of appliance efficiency level. *Review of Economics and Statistics*, 80(4), 647–657. <https://doi.org/10.1162/003465398557735>
- Russo, J., Medvec, V. H., & Meloy, M. G. (1996). The distortion of information during decisions. *Organizational Behavior and Human Decision Processes*, 66(1), 102–110. <https://doi.org/10.1006/obhd.1996.0041>
- Russo, J. E., Carlson, K. A., & Meloy, M. G. (2006). Choosing an inferior alternative. *Psychological Science*, 17(10), 899–904. <https://doi.org/10.1111/j.1467-9280.2006.01800.x>

- Russo, J. E., & Leclerc, F. (1994). An eye-fixation analysis of choice processes for consumer nondurables. *Journal of Consumer Research*, 21(2), 274. <https://doi.org/10.1086/209397>
- Ryan, M., Krucien, N., & Hermens, F. (2018). The eyes have it: Using eye tracking to inform information processing strategies in multi-attributes choices. *Health Economics*, 27(4), 709–721. <https://doi.org/10.1002/hec.3626>
- Schulte-Mecklenbeck, M., Johnson, J. G., Böckenholt, U., Goldstein, D. G., Russo, J. E., Sullivan, N. J., & Willemsen, M. C. (2017). Process-tracing methods in decision making: On growing up in the 70s. *Current Directions in Psychological Science*, 26(5), 442–450. <https://doi.org/10.1177/0963721417708229>
- Shi, S. W., Wedel, M., & Pieters, F. G. M. (2013). Information acquisition during online decision making: A model-based exploration using eye-tracking data. *Management Science*, 59(5), 1009–1026. <https://doi.org/10.1287/mnsc.1120.1625>
- Shimojo, S., Simion, C., Shimojo, E., & Scheier, C. (2003). Gaze bias both reflects and influences preference. *Nature Neuroscience*, 6(12), 1317–1322. <https://doi.org/10.1038/nn1150>
- Simon, H. A. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, 69(1), 99–118. <https://doi.org/10.2307/1884852>
- Stewart, N., Gächter, S., Noguchi, T., & Mullett, T. L. (2016). Eye movements in strategic choice. *Journal of Behavioral Decision Making*, 29(2–3), 137–156. <https://doi.org/10.1002/bdm.1901>
- Stolzenberg, R. M. (1980). The measurement and decomposition of causal effects in nonlinear and nonadditive models. *Sociological Methodology*, 11, 459–488. <https://doi.org/10.2307/270872>
- Stüttgen, P., Boatwright, P., & Monroe, R. T. (2012). A satisficing choice model. *Marketing Science*, 31(6), 878–899. <https://doi.org/10.1287/mksc.1120.0732>
- Swait, J., & Adamowicz, W. (2001). The influence of task complexity on consumer choice: A latent class model of decision strategy switching. *Journal of Consumer Research*, 28(1), 135–148. <https://doi.org/10.1086/321952>
- Tatler, B. W. (2007). The central fixation bias in scene viewing: Selecting an optimal viewing position independently of motor biases and image feature distributions. *Journal of Vision*, 7(14), 4. <https://doi.org/10.1167/7.14.4>
- Thoemmes, F. (2015). Reversing arrows in mediation models does not distinguish plausible models. *Basic and Applied Social Psychology*, 37(4), 226–234. <https://doi.org/10.1080/01973533.2015.1049351>
- Toubia, O., de Jong, M. G., Stieger, D., & Füller, J. (2012). Measuring consumer preferences using conjoint poker. *Marketing Science*, 31(1), 138–156. <https://doi.org/10.1287/mksc.1110.0672>
- Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science (New York, N.Y.)*, 185(4157), 1124–1131. <https://doi.org/10.1126/science.185.4157.1124>
- Valenzuela, A., & Raghurir, P. (2009). Position-based beliefs: The center-stage effect. *Journal of Consumer Psychology*, 19(2), 185–196. <https://doi.org/10.1016/j.jcps.2009.02.011>
- Valenzuela, A., & Raghurir, P. (2015). Are consumers aware of top-bottom but not of left-right inferences? Implications for shelf space positions. *Journal of Experimental Psychology: Applied*, 21(3), 224–241. <https://doi.org/10.1037/xap0000055>
- van der Lans, R., Pieters, R., & Wedel, M. (2008a). Eye-movement analysis of search effectiveness. *Journal of the American Statistical Association*, 103(482), 452–461. <https://doi.org/10.1198/016214507000000437>
- van der Lans, R., Pieters, R., & Wedel, M. (2008b). Research note—Competitive brand salience. *Marketing Science*, 27(5), 922–931. <https://doi.org/10.1287/mksc.1070.0327>
- van Herpen, E., & van Trijp, H. C. (2011). Front-of-pack nutrition labels. Their effect on attention and choices when consumers have varying goals and time constraints. *Appetite*, 57(1), 148–160. <https://doi.org/10.1016/j.appet.2011.04.011>
- van Nierop, E., Fok, D., & Franses, P. H. (2008). Interaction between shelf layout and marketing effectiveness and its impact on optimizing shelf arrangements. *Marketing Science*, 27(6), 1065–1082. <https://doi.org/10.1287/mksc.1080.0365>
- Vancouver, J. B., & Carlson, B. W. (2015). All things in moderation, including tests of mediation (at least some of the time). *Organizational Research Methods*, 18(1), 70–91. <https://doi.org/10.1177/1094428114553059>
- Vuorre, M., & Bolger, N. (2018). Within-subject mediation analysis for experimental data in cognitive psychology and neuroscience. *Behavior Research Methods*, 50(5), 2125–2143. <https://doi.org/10.3758/s13428-017-0980-9>
- Wästlund, E., Otterbring, T., Gustafsson, A., & Shams, P. (2015). Heuristics and resource depletion: Eye-tracking customers' in situ gaze behavior in the field. *Journal of Business Research*, 68(1), 95–101. <https://doi.org/10.1016/j.jbusres.2014.05.001>
- Wästlund, E., Shams, P., & Otterbring, T. (2018). Unsold is unseen ... or is it? Examining the role of peripheral vision in the consumer choice process using eye-tracking methodology. *Appetite*, 120, 49–56. <https://doi.org/10.1016/j.appet.2017.08.024>
- Webster, D. M., Richter, L., & Kruglanski, A. W. (1996). On leaping to conclusions when feeling tired: Mental fatigue effects on impression primacy. *Journal of Experimental Social Psychology*, 32(2), 181–195. <https://doi.org/10.1006/jesp.1996.0009>
- Wedel, M., Pieters, R., & van der Lans, R. (2022). Modeling eye movements during decision making: A review. *Psychometrika*. <https://doi.org/10.1007/s11336-022-09876-4>
- Willemsen, M. C., Böckenholt, U., & Johnson, E. J. (2011). Choice by value encoding and value construction: Processes of loss aversion. *Journal of Experimental Psychology: General*, 140(3), 303–324. <https://doi.org/10.1037/a0023493>
- Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.
- Zhang, Z., Zyphur, M. J., & Preacher, K. J. (2009). Testing multilevel mediation using hierarchical linear models. *Organizational Research Methods*, 12(4), 695–719. <https://doi.org/10.1177/1094428108327450>
- Zhao, X., Lynch, J. G., & Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, 37(2), 197–206. <https://doi.org/10.1086/651257>
- Zuschke, N. (2020a). An analysis of process-tracing research on consumer decision-making. *Journal of Business Research*, 111, 305–320. <https://doi.org/10.1016/j.jbusres.2019.01.028>
- Zuschke, N. (2020b). The impact of task complexity and task motivation on in-store marketing effectiveness: An eye tracking analysis. *Journal of Business Research*, 116, 337–350. <https://doi.org/10.1016/j.jbusres.2020.05.009>

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APPENDIX A

To compute indirect effects, I used the models' population-level estimates (Vuorre & Bolger, 2018). As Hayes and Preacher (2010) suggested, I set all but the focal antecedent to their sample means, that is, to 0. Moreover, to enhance interpretability, I re-arranged the equation by taking the antilog on both sides of the equation. The prediction equation in (4) therefore reduces to

$$\hat{M} = e^{a_0 + a * focalAntecedent}, \tag{A1}$$

where

- *focalAntecedent* = depending on the specific indirect effect that is calculated an observable variable indicating the spatial position of interest or an observable variable indicating initial information search when used as predictor for later information search.
- *a* = the corresponding coefficient that is unobserved.

Following procedures of Hayes and Preacher (2010) and Geldhof et al. (2018), I first derived the first partial derivative of \hat{M} with respect to the focal antecedent, that is,

$$\frac{\hat{M}}{\partial focalAntecedent} = a * e^{a_0 + a * focalAntecedent}. \tag{A2}$$

Next, I derived the first partial derivative of the choice model's probability function. More precisely, I derived the marginal response of the probability of choosing alternative *j* when information search increases for the same alternative *j* and is unchanged for the other alternatives (Cameron & Trivedi, 2005, p. 580; Wooldridge, 2010, p. 524).

$$\frac{\partial p_j}{\partial focalMediator} = p_j(1 - p_j) * b, \tag{A3}$$

where

- *focalMediator* = depending on the indirect effect calculated, an observable variable indicating initial information search, later information search, respectively.
- *b* = the choice model's corresponding raw coefficient.

I follow recommendations of Hayes and Preacher (2010) and compute the indirect effect for the only change in the spatial position variable that is meaningful, that is, from zero (the mean). As pointed out by Geldhof et al. (2018), the indirect effects are conditional on the focal antecedent and the corresponding value of \hat{M} as introduced in (A1) when calculating *p_j* in (A3). In the case of the parallel indirect effects, the marginal response of the probability of choosing alternative *j* calculates 0.2 * 0.8 * *b* while for the serial mediation *p_j* varies with the actual level of initial information search.

As in mediation analysis with linear relationships, multiplying the information search models' first partial derivative and the choice model's first partial derivative yields indirect effects.

TABLE A.1 Multilevel negative binomial information search models of Study 1.

Independent variables	1st half of information search process Model 1a a1 path DV: Fixations per product			2nd half of information search process Model 1b: Parallel mediation a2 path DV: Fixations per product			2nd half of information search process Model 1c: Serial mediation a2, and d paths DV: Fixations per product		
	Coef.	Std. Err.	p value	Coef.	Std. Err.	p value	Coef.	Std. Err.	p value
Position									
Left	0.025	0.0315	.422	-0.223	0.0274***	<.001	-0.213	0.0291***	<.001
Center-left	0.182	0.0236***	<.001	-0.022	0.0278	.439	-0.071	0.0277**	.010
Center	0.433	0.0229***	<.001	0.090	0.0250***	<.001	-0.027	0.0263	.299
Center-right	-0.113	0.0225***	<.001	0.163	0.0229***	<.001	0.190	0.0234***	<.001
Right	-0.527	0.0399***	<.001	-0.008	0.0333	.809	0.121	0.0338***	<.001
(Serial) Mediator									
Initial information search							0.110	0.0076***	<.001
Task experience									
2nd quarter	0.025	0.0180	.171	0.038	0.0196*	.053	0.025	0.0155	.109
3rd quarter	-0.062	0.0192***	.001	-0.105	0.0211***	<.001	-0.082	0.0165***	<.001
4th quarter	-0.138	0.0208***	<.001	-0.132	0.0225***	<.001	-0.090	0.0185***	<.001
Product attributes									
Number of birds	-0.042	0.0104***	<.001	-0.058	0.0148***	<.001	-0.043	0.0146***	.003

TABLE A.1 (Continued)

Independent variables	1st half of information search process Model 1a a1 path DV: Fixations per product			2nd half of information search process Model 1b: Parallel mediation a2 path DV: Fixations per product			2nd half of information search process Model 1c: Serial mediation a2, and d paths DV: Fixations per product		
	Coef.	Std. Err.	p value	Coef.	Std. Err.	p value	Coef.	Std. Err.	p value
Key ingredients	0.027	0.0112**	.016	0.140	0.0198***	<.001	0.130	0.0186***	<.001
Bird color	0.034	0.0109***	.002	0.100	0.0171***	<.001	0.092	0.0162***	<.001
Key ingredients' color	-0.027	0.0102***	.009	0.012	0.0127	.330	0.020	0.0128	.111
Window	0.065	0.0123***	<.001	0.164	0.0222***	<.001	0.142	0.0202***	<.001
Size	0.209	0.0218***	<.001	0.262	0.0318***	<.001	0.208	0.0281***	<.001
Brand	0.010	0.0082	.243	0.016	0.0110	.154	0.013	0.0107	.241
Package color	-0.019	0.0148	.210	-0.045	0.0211**	.032	-0.042	0.0184**	.022
Appeal	0.043	0.0094***	<.001	0.035	0.0158**	.026	0.017	0.0147	.237
Constant	0.689	0.0443***	<.001	0.602	0.0406***	<.001	0.583	0.0407***	<.001
Upper-level variance									
Participant	0.217	0.030***	<.001	0.181	0.026***	<.001	0.177	0.025***	<.001
Number of birds	Specified as fixed			Specified as fixed			Specified as fixed		
Key ingredients	Specified as fixed			0.006	0.006***	<.001	0.022	0.005***	<.001
Bird color	Specified as fixed			0.013	0.005***	.005	0.012	0.004***	.006
Key ingredients' color	Specified as fixed			Specified as fixed			Specified as fixed		
Window	0.004	0.002*	.078	0.039	0.008***	<.001	0.030	0.007***	<.001
Size	0.042	0.007***	<.001	0.102	0.016***	<.001	0.076***	0.013***	<.001
Brand	Specified as fixed			Specified as fixed			Specified as fixed		
Package color	0.042	0.007***	<.001	0.029	0.007***	<.001	0.018	0.005***	<.001
Appeal	Specified as fixed			0.009	0.004**	.029	0.007**	0.004**	.047
Negative binomial	0.652			1.205			1.038		
Goodness of fit									
-2Log likelihood	28,132			31,874			31,154		
BIC	28,169			31,939			31,218		

Note: All standard errors are robust. The different paths are illustrated in Figure 1.

Abbreviation: DV, dependent variable.

* $p < .1$, ** $p < .05$, and *** $p < .01$.

TABLE A.2 Mixed logit choice models of Study 1.

Independent variables	Without information search Model 2a: c path (total effect) DV: Product choice			With information search Model 2b: c' (direct effect), b1, and b2 paths DV: Product choice		
	Coef.	Std. Err.	p value	Coef.	Std. Err.	p value
Position						
Left	−0.090	0.075	.229	0.481	0.093***	<.001
Center-left	0.109	0.067	.106	−0.001	0.084	.994
Center	0.240	0.061***	<.001	−0.135	0.082*	.099
Center-right	0.062	0.062	.314	−0.292	0.084***	.001
Right	−0.320	0.074***	<.001	−0.053	0.105	.611
Mediators						
Initial information search				0.281	0.045***	<.001
Later information search				0.716	0.054***	<.001
Product attributes						
Number of birds	−0.283	0.068***	<.001	−0.183	0.063***	.004
Key ingredients	0.533	0.070***	<.001	0.294	0.064***	<.001
Bird color	0.375	0.074***	<.001	0.279	0.071***	<.001
Key ingredients' color	0.064	0.042	.128	0.086	0.042**	.039
Window	0.512	0.096***	<.001	0.295	0.065***	<.001
Size	0.455	0.110***	<.001	0.072	0.084	.388
Brand	0.018	0.034	.589	0.007	0.036	.844
Package color	−0.224	0.084***	.007	−0.105	0.059*	.076
Appeal	0.123	0.070*	.081	0.031	0.075	.678
Upper-level standard deviations						
NumBirds	0.479	0.068***	<.001	0.470	0.064***	<.001
KeyIngred	0.798	0.090***	<.001	0.463	0.072***	<.001
BirdColor	0.646	0.088***	<.001	0.507	0.085***	<.001
KeyIngredCol	0.220	0.052***	<.001	Specified as fixed		
ProductView	0.635	0.081***	<.001	0.514	0.090***	<.001
Size	1.029	0.148***	<.001	0.692	0.128***	<.001
Brand	0.136	0.079*	.083	Specified as fixed		
PacColor	0.597	0.088***	<.001	0.500	0.092***	<.001
Appeal	0.561	0.086***	<.001	0.538	0.103***	<.001
Goodness of fit						
−2Log likelihood	4682			2859		
BIC	4884			3061		
Pseudo R	.26			.55		

Note: All standard errors are robust. “Initial information search” (“Later information search”) = first (second) half of total number of fixations per respondent and task. Model estimated with 700 halton draws and a burn in of 250. The different paths are illustrated in Figure 1.

Abbreviation: DV, dependent variable (0 = no choice; 1 = choice).

* $p < .1$, ** $p < .05$, and *** $p < .01$.

TABLE A.3 Results of parallel mediation analysis of Study 1.

Position	Specific indirect effect through initial information search			Specific indirect effect through later information search			Total indirect effect		
	Coef.	95% CI		Coef.	95% CI		Coef.	95% CI	
Left	0.002	-0.003	0.008	-0.047	-0.061	-0.034	-0.045	-0.060	-0.030
Center-left	0.016	0.010	0.024	-0.005	-0.016	0.007	0.012*	0.001	0.023
Center	0.039	0.026	0.052	0.019	0.008	0.030	0.058	0.041	0.075
Center-right	-0.010	-0.016	-0.005	0.034	0.024	0.046	0.024	0.012	0.037
Right	-0.047	-0.065	-0.031	-0.002	-0.016	0.012	-0.049	-0.071	-0.028

Note: Significant coefficients printed in bold ($p < .05$). "Initial information search" ("Later information search") = first (second) half of total number of fixations per respondent and task. Total indirect effect = sum of all specific indirect effects.

*Significance based on 90% confidence interval.

TABLE A.4 Results of serial mediation analysis of Study 1.

Position	Primacy			Recency			Primacy and recency					
	Initial fix	Specific indirect effect through <i>initial</i> information search		Initial fix	Specific indirect effect through <i>initial</i> information search, which <i>causally</i> influences <i>later</i> information search		Initial fix	Specific indirect effect through <i>later</i> information search				
		Coef.	95% CI		Coef.	95% CI		Coef.	95% CI	Coef.	95% CI	
Left	Few	0.002	-0.003	0.008	0.001	-0.001	0.003	-0.044	-0.031	-0.041	-0.056	-0.026
Left	Avg				0.001	-0.002	0.004			-0.040	-0.056	-0.026
Left	Many				0.002	-0.003	0.006			-0.040	-0.056	-0.025
Center-left	Few	0.016	0.010	0.024	0.005	0.004	0.007	-0.015	-0.003	0.007	-0.007	0.021
Center-left	Avg				0.008	0.006	0.011			0.010	-0.004	0.024
Center-left	Many				0.013	0.008	0.018			0.014	0.001	0.029
Center	Few	0.039	0.026	0.052	0.013	0.010	0.016	-0.006	0.005	0.046	0.029	0.064
Center	Avg				0.020	0.015	0.025			0.053	0.035	0.071
Center	Many				0.030	0.022	0.040			0.064	0.044	0.084
Center-right	Few	-0.010	-0.016	-0.005	-0.004	-0.006	-0.002	0.039	0.028	0.025	0.013	0.038
Center-right	Avg				-0.006	-0.009	-0.003			0.023	0.011	0.037
Center-right	Many				-0.009	-0.014	-0.005			0.020	0.007	0.034
Right	Few	-0.047	-0.065	-0.031	-0.016	-0.019	-0.012	0.025	0.011	-0.038	-0.061	-0.016
Right	Avg				-0.024	-0.031	-0.018			-0.046	-0.069	-0.023
Right	Many				-0.037	-0.050	-0.026			-0.059	-0.084	-0.034

Note: Significant coefficients printed in bold ($p < .05$). "Initial information search" ("Later information search") = first (second) half of total number of fixations per respondent and task. Total indirect effect = sum of all specific indirect effects. "Initial fix" represents the number of fixations per respondent, task, and product in the first half of the information process. "Avg" = within respondents mean value, that is, 2.5 fixations. Due to the mean centering, the value used for computation is 0. "Few" ("Many") = the average 16th (84th) percentile of the mean centered values, that is, -2.2 (2.2).

TABLE A.5 Multilevel negative binomial information search models of Study 2.

Independent variables	1st half of information search process Model 3a a1 path			2nd half of information search process Model 3b: Parallel mediation a2 path			2nd half of information search process Model 3c: Serial mediation a2, and d paths		
	DV: Fixations per product			DV: Fixations per product			DV: Fixations per product		
	Coef.	Std. Err.	p value	Coef.	Std. Err.	p value	Coef.	Std. Err.	p value
Position									
Left	0.068	0.0408*	.098	-0.173	0.0373***	<.001	-0.191	0.0387***	<.001
Center-left	0.248	0.0239***	<.001	0.010	0.0262	.692	-0.085	0.0287***	.003
Center	0.262	0.0236***	<.001	0.175	0.0275***	<.001	0.094	0.0252***	<.001
Center-right	-0.174	0.0252***	<.001	0.067	0.0295**	.023	0.124	0.0296***	<.001
Right	-0.404	0.0372***	<.001	-0.080	0.0363**	.028	0.058	0.0380	.128
(Serial) Mediator									
Initial information search							0.083	0.0082***	<.001
Moderators									
Task motivation	0.171	0.0539***	.001	0.170	0.0562***	.002	0.171	0.0582***	.003
Position * Motivation									
Left * Task motivation	0.039	0.0404	.333	-0.031	0.0372	.408	-0.049	0.0397	.222
Center-left * Task motivation	-0.003	0.0243	.91	-0.037	0.0261	.153	-0.046	0.0296	.118
Center * Task motivation	-0.033	0.0236	.16	-0.025	0.0273	.370	-0.039	0.0256	.131
Center-right * Task motivation	-0.008	0.0250	.75	0.027	0.0296	.354	0.043	0.0318	.177
Right * Task motivation	0.005	0.0374	.90	0.065	0.0358*	.069	0.090	0.0404**	.025
Probing of significant moderations									
Right when motivation is low				-0.145	0.0591***	.014	-0.033	0.0586	.578
Right when motivation is high				-0.014	0.0414	.730	0.148	0.0522***	.004
Task experience									
2nd quarter	0.007	0.0251	.775	-0.006	0.0281	.829	0.005	0.0203	.816
3rd quarter	-0.171	0.0274***	<.001	-0.181	0.0293***	<.001	-0.100	0.0210***	<.001
4th quarter	-0.305	0.0293***	<.001	-0.319	0.0333***	<.001	-0.206	0.0272***	<.001
Product attributes									
Origin	-0.011	0.0116	.345	0.010	0.0220	.637	0.011	0.0211	.608
KeyVisual	0.058	0.0149***	<.001	0.092	0.0268***	<.001	0.077	0.0247***	.002
Saliency	0.074	0.0178***	<.001	0.146	0.0251***	<.001	0.122	0.0213***	<.001
Milk	0.001	0.0124	.935	0.007	0.0169	.675	0.009	0.0170	.616
Behavior	-0.002	0.0138	.888	0.017	0.0185	.357	0.019	0.0190	.329
Color	0.037	0.0147**	.012	0.039	0.0220*	.074	0.028	0.0210	.183
Size	0.141	0.0184***	<.001	0.173	0.0311***	<.001	0.126	0.0279***	<.001
Type	0.031	0.0176*	.079	0.031	0.0373	.406	0.023	0.0327	.486
Cocoa	0.029	0.0143**	.042	0.091	0.0261***	<.001	0.080	0.0239***	<.001
Constant	1.232	0.0542***	<.001	1.116	0.0566***	<.001	1.077	0.0593***	<.001
Upper-level variance									
Participant	0.214	0.038***	<.001	0.227	0.041***	<.001	0.244	0.044***	<.001
Origin	Specified as fixed			0.014	0.006**	.018	0.013	0.006**	.017
KeyVisual	Specified as fixed			0.032	0.009***	<.001	0.027	0.008***	<.001
Saliency	0.010	0.004***	.009	0.026	0.008***	.001	0.015	0.006**	.014
Milk	Specified as fixed			Specified as fixed			Specified as fixed		
Behavior	Specified as fixed			Specified as fixed			Specified as fixed		
Color	Specified as fixed			0.014	0.006**	.021	0.013	0.006**	.024

(Continues)

TABLE A.5 (Continued)

Independent variables	1st half of information search process Model 3a a1 path			2nd half of information search process Model 3b: Parallel mediation a2 path			2nd half of information search process Model 3c: Serial mediation a2, and d paths		
	DV: Fixations per product			DV: Fixations per product			DV: Fixations per product		
	Coef.	Std. Err.	p value	Coef.	Std. Err.	p value	Coef.	Std. Err.	p value
Size	0.012	0.004***	.007	0.051	0.012***	<.001	0.039	0.010***	<.001
Type	0.010	0.004**	.013	0.085	0.018***	<.001	0.062	0.014***	<.001
Cocoa	Specified as fixed			0.030	0.009***	<.001	0.023	0.007***	.001
Negative binomial	0.826			1.485			1.311		
Goodness of fit									
-2Log likelihood	17,542			20,157			19,555		
BIC	17,577			20,211			19,624		

Note: All standard errors are robust. Task motivation mean = -0.04. The different paths are illustrated in Figure 1.

Abbreviation: DV, dependent variable.

*p < .1, **p < .05, and ***p < .01.

TABLE A.6 Mixed logit choice models of Study 2.

Independent variables	Without information search Model 4a: c path (total effect) DV: Product choice			With information search Model 4b: c' (direct effect), b1, and b2 paths DV: Product choice		
	Coef.	Std. Err.	p value	Coef.	Std. Err.	p value
Position						
Left	0.040	0.117	.735	0.568	0.086***	<.001
Center-left	0.010	0.081	.901	-0.207	0.114*	.068
Center	0.092	0.102	.367	-0.238	0.116**	.041
Center-right	0.036	0.080	.651	-0.433	0.114***	<.001
Right	-0.178	0.109	.103	0.311	0.115***	.007
Mediators						
Initial information search				0.222	0.025***	<.001
Later information search				0.557	0.045***	<.001
Position * Motivation						
Left * Task motivation	-0.063	0.117	.592	0.075	0.093	.421
Center-left * Task motivation	-0.268	0.086***	.002	-0.264	0.109**	.016
Center * Task motivation	0.050	0.101	.623	0.092	0.115	.421
Center-right * Task motivation	0.056	0.075	.454	-0.084	0.114	.457
Right * Task motivation	0.225	0.112**	.045	0.181	0.113	.108
Probing of significant moderations						
Center-left when motivation is high	-0.258	0.114**	.024	-0.471	0.182**	.010
Right when motivation is high	0.047	0.118	.691	N/A		
Center-left when motivation is low	0.278	0.121**	.022	0.056	0.128	.660
Right when motivation is low	-0.403	0.187**	.032	N/A		
Product attributes						
Origin	0.060	0.271	.824	-0.067	0.077	.380
KeyVisual	0.365	0.186*	.051	0.128	0.062**	.038
Saliency	0.489	0.117***	<.001	0.315	0.080***	<.001
Milk	0.120	0.062*	.052	0.186	0.048***	<.001

TABLE A.6 (Continued)

Independent variables	Without information search Model 4a: c path (total effect) DV: Product choice			With information search Model 4b: c' (direct effect), b1, and b2 paths DV: Product choice		
	Coef.	Std. Err.	p value	Coef.	Std. Err.	p value
Behavior	0.012	0.073	.868	−0.010	0.052	.856
Color	0.170	0.162	.292	0.098	0.062	.113
Size	0.539	0.131***	<.001	0.068	0.066	.301
Type	0.008	0.092	.929	−0.090	0.086	.293
Cocoa	0.384	0.166**	.020	0.083	0.057	.146
Product attributes * Moderator						
Task motivation * Cocoa				−0.118	0.057**	.037
Upper-level standard deviations						
Origin	0.876	0.230***	<.001	0.414	0.150***	.006
KeyVisual	0.619	0.166***	<.001	Specified as fixed		
Saliency	0.704	0.098***	<.001	0.399	0.093***	<.001
Milk	0.294	0.063***	<.001	Specified as fixed		
Behavior	0.387	0.133***	.004	Specified as fixed		
Color	0.609	0.146***	<.001	0.221	0.137*	.121
Size	0.973	0.164***	<.001	0.201	0.120	.113
Type	1.287	0.153***	<.001	0.493	0.143***	.001
Cocoa	0.832	0.193***	<.001	Specified as fixed		
Goodness of fit						
−2Log likelihood	2850			1355		
BIC	3077			1573		
Pseudo R	.28			.66		

Note: All standard errors are robust. Task motivation = high task motivation. “Initial information search” (“Later information search”) = first (second) half of total number of fixations per respondent and task. N/A = not applicable as the moderation is non-significant ($p > 0.1$). Model estimated with 2500 halton draws and a burn in of 500. The different paths are illustrated in Figure 1.

Abbreviation: DV, dependent variable (0 = no choice; 1 = choice).

* $p < .10$, ** $p < .05$, and *** $p < .01$.

TABLE A.7 Indices of moderated mediation of Study 2.

Index of moderated mediation	Initial information search			Later information search (parallel mediation model)			Later information search (serial mediation model)		
	Coef.	95% CI		Coef.	95% CI		Coef.	95% CI	
Left * motivation * information search	0.005	−0.005	0.015	−0.008	−0.028	0.012	−0.013	−0.034	0.007
Center-left * motivation * information search	0.001	−0.006	0.005	0.001	−0.024	0.004	−0.012	−0.028	0.003
Center * motivation * information search	−0.004	−0.010	0.002	−0.007	−0.021	0.008	−0.010	−0.024	0.003
Center-right * motivation * information search	−0.001	−0.007	0.005	0.007	−0.008	0.024	0.011	−0.005	0.028
Right * motivation * information search	0.001	−0.008	0.010	0.018*	0.002	0.034	0.024	0.003	0.046

Note: Significant coefficients printed in bold ($p < .05$). “Initial information search” (“Later information search”) = first (second) half of total number of fixations per respondent and task. Motivation = high motivation.

*Significance based on 90% confidence interval.

TABLE A.8 Results of moderated parallel mediation analysis of Study 2.

Position	Specific indirect effect through initial information search			Specific indirect effect through later information search			Total indirect effect		
	Coef.	95% CI		Coef.	95% CI		Coef.	95% CI	
Left	0.008	−0.002	0.019	−0.047	−0.070	−0.026	−0.039	−0.064	−0.016
Center-left	0.030	0.022	0.040	0.003	−0.011	0.017	0.033	0.017	0.050
Center	0.032	0.023	0.042	0.048	0.031	0.066	0.080	0.061	0.100
Center-right	−0.021	−0.030	−0.014	0.018	0.002	0.035	−0.003	−0.021	0.015
Right LM	−0.049	−0.065	−0.035	−0.039	−0.073	−0.007	−0.089	−0.125	−0.054
Right HM				−0.004	−0.026	0.018	−0.053	−0.081	−0.027

Note: Significant coefficients printed in bold ($p < .05$). Initial information search = first half of total number of fixations per respondent and task. Later information search = second half of total number of fixations per respondent and task. Total indirect effect = sum of all specific indirect effects. “LM” (“HM”) = low (high) motivation.

AUTHOR BIOGRAPHY

Nick Zuschke studies consumer decision-making. He uses theories, tools, and methods from marketing, psychology,

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