Journal of Business Research 116 (2020) 337–350

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

The impact of task complexity and task motivation on in-store marketing effectiveness: An eye tracking analysis

Nick Zuschke

University of Hamburg, Chair of Marketing and Innovation, Von-Melle-Park 5, 20146 Hamburg, Germany

ARTICLE INFO

Keywords:
Eye tracking
Choice-based conjoint
In-store marketing
Size
Saliency
Consumer decision-making

ABSTRACT

A great deal of consumers' purchasing decisions at the grocery store are made in rather unplanned ways. This offers businesses the opportunity to influence consumers through in-store marketing activities. However, in real-life shopping consumers typically experience many sensory stimuli that could potentially affect their behavior, making it critically important for marketers to understand the mechanisms that lead to product choice. Results of a choice-based conjoint experiment combined with eye tracking show that as the number of products to choose from (task complexity) increases, motivated participants search more for products with superior attention-drawing properties, and increase their liking of such products, i.e., large products and more salient products, and consequently are more likely to choose these products. For less motivated participants this mechanism is limited to large products. Further, for less motivated participants looking at a product influences the decision, in part beyond consciously liking it.

1. Introduction

Consumers frequently buy products commonly referred to as fast-moving consumer goods (FMCG), such as soap, shampoo, or chocolate bars. These kinds of products are often purchased at the grocery store, where many choices are made in rather unplanned ways (Inman, Winer, & Ferraro, 2009). This provides opportunities for both manufacturers and retailers to intervene and influence such purchase decisions through in-store marketing activities. Several activities, such as varying a product's position on the shelf (Christenfeld, 1995), its number of shelf facings (Eisend, 2014), or its visual conspicuity (Milosavljevic, Navalpakkam, Koch, & Rangel, 2012), have proven to be successful in influencing consumers' choices. These findings have compelling implications for business and justify in-store marketing expenditure. However, in real-life shopping consumers typically experience many sensory stimuli that could potentially affect their behavior, making it critically important for marketers to understand the mechanisms that lead to product choice.

One stream of research proposes that consumers' shopping behavior, and hence the choices they make, depends on the mental resources they are willing to invest in the purchasing decision (Inman et al., 2009; Sciandra, Inman, & Stephen, 2019). Indeed, the idea of a rational decision maker with unlimited cognitive resources that searches for all available information has already been questioned decades ago (Simon, 1955). Studies that analyzed the cognitive processes underlying consumers' choices have demonstrated that in many situations decision makers tend to simplify their information search behavior and information processing, which implies that preferences are often constructed, rather than merely revealed (Bettman, Luce, & Payne, 1998; Payne, Bettman, & Johnson, 1993; Zuschke, 2020). Hence, consumers' information search behavior is one of the determinants of the success of in-store marketing activities. Consequently, it is essential to consider factors that influence consumers' information search activities.

A line of research that has extensively analyzed consumers' information search activities in relation to product choice is visual attention research on consumer decision-making. Research in this stream has consistently demonstrated that consumers search for information that is related to products' physical attention-drawing properties. This is especially true of purchase decisions in which products are manipulated regarding their visual saliency, size, and position on the shelf, which constitute typical in-store marketing activities (Atalay, Bodur, & Rasolofoarison, 2012; Chandon, Hutchinson, Bradlow, & Young, 2009; Milosavljevic et al., 2012; Orquin, Bagger, Lahm, Grunert, & Scholderer, 2020; Peschel, Orquin, & Mueller Loose, 2019; Reutskaja, Nagel, Camerer, & Rangel, 2011). In visual attention research on consumer decision-making, these in-store activities are often referred to as bottom-up factors, and the eye movements caused by these factors are referred to as bottom-up control of visual attention. In contrast, factors that influence consumers' goals are referred to as top-down factors, and eye movements caused by these factors are referred to as top-down

E-mail address: nick.zuschke@uni-hamburg.de.

https://doi.org/10.1016/j.jbusres.2020.05.009
Received 24 April 2019; Received in revised form 3 May 2020; Accepted 4 May 2020

control of visual attention (Orquin & Mueller Loose, 2013). For example, research has regularly demonstrated that consumers' search for information differs depending on their task motivation (Bialkova et al., 2014; Celsi & Olson, 1988; Pieters & Warlop, 1999; Van Herpen & van Trijp, 2011; Visschers, Hess, & Siegrist, 2010). A third category that involves both bottom-up and top-down factors can be classified as the intersection between attention and working memory resources. Factors that impose changes in working memory demands, such as task complexity, are referred to as working memory factors (Orquin & Mueller Loose, 2013). In fact, task complexity has consistently been found to influence the information search behavior of a person making a decision (Horstmann, Ahlgrimm, & Glöckner, 2009; Lohse & Johnson, 1996; Meißner, Oppewal, & Huber, 2020; Payne, 1976; Reutskaja et al., 2011)

There is growing evidence that working memory demands and their impact on information search behavior and information processing play an important role during in-store shopping (Nikolova & Inman, 2015; Sciandra et al., 2019), and particularly in the effectiveness of in-store marketing activities (Zuschke, 2020). However, studies that have found that in-store marketing activities impact consumers' information search behavior and their choices are limited to simple choices of quasi-realistic products (Atalay et al., 2012; Chandon et al., 2009; Milosavljevic et al., 2012; Reutskaja et al., 2011). Meißner, Musalem, and Huber (2016), e.g., used a multi-attribute choice task with largely textual product information and found very limited evidence for the influence of in-store marketing activities, i.e., the effect of a product's position on product choice was minimal. However, they did not analyze the influence of working memory demands on position effects. Moreover, large-scale studies that discussed shopping behavior from a working memory angle could not directly observe consumers' information search and hence information processing behavior (Elshiewy & Boztug, 2018; Nikolova & Inman, 2015; Sciandra et al., 2019); however, different information search activities could possibly produce the same outcome (Glöckner & Herbold, 2011; Schulte-Mecklenbeck et al., 2017).

Thus, in order to improve our understanding of how in-store marketing activities impact product choice, we need an approach that systematically manipulates consumers' information search activities and directly observes the cognitive processes underlying their purchase decisions. To the best of my knowledge, this approach is not covered in the literature yet. The current study addresses this gap by manipulating top-down control, i.e., task motivation; working memory demands, i.e., information complexity; and bottom-up factors, i.e., size and saliency. Also, it analyzes these factors' influence on information searching and product choice.

This paper belongs to a research stream that uses choice-based conjoint (CBC) analysis in combination with eye tracking methodology (Meißner et al., 2016, 2020; Toubia, de Jong, Stieger, & Füller, 2012; Yang, Toubia, & de Jong, 2015) to shed light on the cognitive processes underlying consumer decision-making. Specifically, I analyze data to determine the likelihood that consumers will choose large products and salient products in a multi-attribute choice context. In addition to product choice, I measure how much information searching, in terms of the number of fixations devoted to a product, takes place. I combine both measures in a multilevel (moderated) moderated mediation analysis. Importantly, to improve external validity and generalizability, this study uses quasi-naturalistic products and analyzes more than one product characteristic, since previous research suggests that visual attention mediates the effect of product characteristics on product choice in different ways (Chandon et al., 2009; Peschel et al., 2019). In order to disentangle bottom-up and top-down control of visual attention, I additionally use liking ratings (Atalay et al., 2012).

One study similar to the current one is the seminal article of Pieters and Warlop (1999). They experimentally varied top-down control and working memory demands while bottom-up factors were explored but not manipulated. They found that depending on task motivation and task complexity, participants more frequently searched for a product's brand name, pictorial, or ingredient information. Moreover, they showed that looking at a product was a reliable predictor of product choice. However, due to how their study was designed, they could not analyze how bottom-up properties relate to product choice. Hence, they could not establish a formal relationship between bottom-up factors, information search and product choice by means of a mediation analysis. Consequently, they also could not analyze how this mediation process was moderated by top-down and working memory processes. These limitations are addressed in this study.

2. Theory and hypotheses

Early process tracing research used attention to information as a proxy for information acquisition, while information acquisition, in turn, was used to infer information processing. The assumption is that less information acquisition correlates with less investment of mental effort and hence implies simplified information processing (Payne, Bettman, & Johnson, 1988). Eye tracking research on decision-making used visual attention, more specifically fixations, to determine information acquisition and to infer information processing (Russo & Leclerc, 1994). However, the underlying assumption that fixated information is processed in the mind (Just & Carpenter, 1980) has been criticized (Anderson, Bothell, & Douglass, 2004) and, as Orquin and Holmqvist (2018) pointed out, has to be proven rather than assumed. Therefore, I use the more neutral term "amount of information search" (Meißner et al., 2020), and measure the number of fixations a product receives. Due to the complementary use of data on actual choices, I am able to reveal whether searched-for information was also processed and considered for choice (Kwak, Payne, Cohen, & Huettel, 2015).

2.1. In-store marketing activities

2.1.1. Visual saliency improvements

Visual saliency refers to a stimulus's conspicuity in a visual scene. Visual conspicuity typically covers perceptual features such as color, contrast, or edge orientation. Computational models have been developed that calculate topographical saliency maps, indicating the visual conspicuity of a region in a given visual scene. Moreover, based on visual conspicuity, computational models predict the regions at which people will look (Itti & Koch, 2001).

Although it has been proposed that saliency does not influence decision-making (Tatler, Hayhoe, Land, & Ballard, 2011), there is evidence from advertising research (Lohse, 1997), product choice research (Milosavljevic et al., 2012), and nutrition label research (Bialkova et al., 2014; Enax, Krajbich, & Weber, 2016; Jones & Richardson, 2007; Peschel et al., 2019; Van Herpen & van Trijp, 2011) that, to some extent, saliency can influence decision-making. Indeed, consumer neuroscience (Hare, Camerer, & Rangel, 2009; Hare, Malmaud, & Rangel, 2011) and large-scale studies (Elshiewy & Boztug, 2018; Nikolova & Inman, 2015) have provided evidence that attention to certain information can increase its mental representation. Importantly, research on nutrition labels provides evidence that visual attention mediates the effect of saliency on consumers' responses (Bialkova et al., 2014; Peschel et al., 2019).

Manipulation of saliency often modifies the contrast or brightness of an entire product (Milosavljevic et al., 2012) or of a single product feature (Orquin et al., 2020), resulting in a transparency effect. Research on design characteristics shows that transparency of an object, and hence the contrast of an object, is associated with the aesthetics of a product, which determine its perceived harmony (Orth & Malkewitz, 2008). Harmony, in turn, was found to influence attention to and liking of a product (Kumar & Garg, 2010). Relatedly, consumer neuroscience provides evidence that aesthetic packages generate some reward value and therefore are preferred over less aesthetic products (Reimann, Zaichkowsky, Neuhaus, Bender, & Weber, 2010; Stoll, Baecke, & Kenning, 2008). Thus, lowering the brightness of distractor products or features ensures that the target product shows superior visual conspicuity. However, lowering the brightness also lowers the product's attractiveness, even if no other product characteristics change. Thus, consumers more frequently look at the salient product due to consciously disliking the non-salient product.

Taken together, various studies suggest that saliency as bottom-up manipulation affects both bottom-up control of visual attention due to showing superior visual conspicuity and top-down control of visual attention due to looking more attractive than non-salient products manipulated with a transparency effect. Moreover, as outlined above, there is evidence that salient information acquired due to both bottom-up and top-down control of visual attention influences the information consumers process mentally during decision-making. Consequently, I expect consumers to focus more on salient products, which in turn reflects how consumers weight this feature in the decision-making process. This in turn leads to a choice advantage for salient products, leading to the following hypotheses:

- **H1a**: Consumers' amount of information search per product is greater when the product is salient, than when it is not salient.
- **H1b**: Consumers are more likely to choose products that are more salient.
- **H1c**: The amount of information search per product mediates consumers' preference for more salient products.

2.1.2. Size increments

In an extensive literature review, Peschel and Orquin (2013) showed that visual attention research on surface size mainly focuses on advertising research. In advertising research, findings suggest that larger ads receive more visual attention (Pieters & Wedel, 2004, 2007; Rosbergen, Pieters, & Wedel, 1997; Wedel & Pieters, 2000) and that visual attention influences consumers' performance on certain advertising metrics (Janiszewski, 1998; Rosbergen et al., 1997). J. Zhang, Wedel, and Pieters (2009) extended these results by showing that larger advertisements lead to more sales. More importantly, they showed that the amount of visual attention given to advertisements in the lab fully mediated the positive effect of advertisements' size on actual product sales.

In research on product choice, research on size effects typically focuses on the amount of retail shelf space dedicated to a brand or brand category and its effect on sales (Campo & Gijsbrechts, 2005; Eisend, 2014). Chandon et al. (2009) extended the results on size effects, i.e., shelf space increments stimulate sales, and found that size effects on brand choice were fully mediated by visual attention. Moreover, there is evidence that this mechanism generalizes to size increments of single product attributes (Bialkova & van Trijp, 2010; Peschel et al., 2019).

A topic connected to a product's size is food consumption quantity. Larger packages (Wansink, 1996) and larger portions (Zlatevska, Dubelaar, & Holden, 2014) were found to increase food consumption quantity.

Taken together, the studies suggest that size as bottom-up manipulation affects bottom-up control of visual attention, resulting in more information searching. Further, there is evidence that consumers mentally process that information and put more weight on it in the decision-making process. Although extant studies on consumption behavior have not analyzed product choice in a typical retail environment, it seems reasonable that consumers' preference for larger portion sizes translates into preference for products offering more content. Therefore, larger packages and thus larger portion sizes trigger top-down processes. Consequently, I expect consumers to focus more on large products, which in turn reflects how consumers weight this attribute in the decision-making process, leading to the following hypotheses:

- **H2a**: Consumers' amount of information search per product is greater when the product is large, than when it is small.
- **H2b**: Consumers are more likely to choose products that are large.
- **H2c**: The amount of information search per product mediates consumers' preference for large products.

2.2. The influence of task complexity and task motivation on adaptivity

Using a choice task where consumers had to decide on renting an apartment, Payne (1976) presented information to participants in an alternative-attribute matrix and experimentally varied the number of alternatives and attributes. The results showed that increasing both the number of alternatives and the number of attributes stimulated respondents to ignore certain information. Numerous studies have confirmed and replicated these early results (Bettman et al., 1998; Ford, Schmitt, Schechtman, Hults, & Doherty, 1989; Payne et al., 1993).

Studies using eye-tracking methodology extended results by showing that, in total, consumers use more fixations as complexity increases (Horstmann et al., 2009; Lohse, 1997; Meißner et al., 2020). Moreover, there is evidence that results generalize to consumer environments where information is not presented in an alternative-attribute matrix (Orquin et al., 2020; Reutskaja et al., 2011). Therefore, I expect that consumers who choose between five instead of three products show a higher number of total fixations. However, the set size increment is greater than the ability to fixate the same amount of information per alternative, leading to the following hypothesis:

- **H3:** Consumers' amount of information search per product is lower for consumers in the high–task complexity condition than for consumers in the low–task complexity condition.

Using reaction time analysis and verbal protocols, Celsi and Olson (1988) analyzed consumers' attention to and comprehension of advertisements showing tennis products. They found that consumers with low task motivation acquired a relatively low amount of information. Relatedly, during conjoint choices, motivated consumers were found to fixate on up to 20% more information than less motivated consumers (Toubia et al., 2012). Therefore, I hypothesize:

- **H4:** The amount of information search per product is higher for consumers in the high–task motivation condition than for consumers in the low–task motivation condition.

2.3. Adaptivity as a moderator for in-store marketing effectiveness

2.3.1. Task complexity

Studies using a choice based conjoint design provided evidence that consumers who were coping with working memory demands utilized less product information (Swait & Adamowicz, 2001), and fixated less often on a choice option (Meißner et al., 2020). Additionally, Toubia et al. (2012) provided evidence that the amount of fixated information relates to the information consumers processed and considered in conjoint choices. Similarly, Pieters and Warlop (1999) revealed that, independent of task motivation, increased working memory demands stimulated consumers to focus more on cognitively less taxing product attributes.

Research on simple choices has shown that in-store characteristics, i.e., the position and the saliency of a product, stimulated choice likelihood as working memory demands increased (Milosavljevic et al., 2012; Reutskaja et al., 2011) or when working memory demands were high (Atalay et al., 2012). Moreover, these studies provide evidence that visual attention actively influenced the decision (Orquin & Mueller Loose, 2013; Zuschke, 2020).

Taken together, the results mentioned above suggest that increasing working memory demands stimulate consumers to simplify information processing. This simplified processing in turn can hinder consumers' search for more relevant information that has inferior attention-drawing properties (Orquin & Mueller Loose, 2013), since consumers trade off between maximizing accuracy and minimizing effort (Payne et al., 1993). However, a moderated mediation analysis that could confirm the moderating role of task complexity on the effects of in-store characteristics through visual attention on product choice is missing. Consequently, I expect consumers to fixate more often on salient products and large products as complexity increases. In turn, this higher amount of information searching reflects how consumers weight these characteristics in the decision-making process, which translates into large products and salient products being more likely to be chosen. In sum, this leads to the following hypotheses:

H5: The effect of saliency on product choice through information search increases as task complexity increases.

H6: The effect of large size on product choice through information search increases as task complexity increases.

2.3.2. Task motivation

Research on task motivation and (visual) attention has revealed that consumers with high task motivation invest more mental effort to grasp the information and focus more on relevant information (Celsi & Olson, 1988; Pieters & Warlop, 1999). Similarly, research on nutrition label design has revealed that consumers with a health motivation fixated more frequently and/or longer on health-related information (Bialkova et al., 2014; Bialkova & van Trijp, 2010; Van Herpen & van Trijp, 2011; Visschers et al., 2010). Relatedly, several studies found that the weight consumers give to product attributes during the decision-making process differed depending on whether or not they were motivated by incentive alignment (Ding, 2007; Ding, Grewal, & Liechty, 2005; Dong, Ding, & Huber, 2010; Toubia et al., 2012).

In sum, there is evidence that task motivation influences the information consumers fixate on and mentally process when making choices. Recalling that consumers prefer salient and large products due to both bottom-up and top-down factors, consumers with stronger top-down control have greater interest in design and portion size features. Consequently, these consumers can be expected to fixate more frequently on salient products and large products due to higher personal relevance. In turn, bottom-up control of visual attention can be assumed to influence consumers with a lower level of top-down control, since these consumers fixate less frequently on product attributes that may be of personal relevance but show inferior attention-drawing properties. Thus, consumers with weak top-down control will perform more information searching for large products and salient products as well. Predicting whether saliency and size more strongly influence consumers with strong or weak top-down control thus depends on the relative contribution of bottom-up and top-down control. However, as pointed out by Orquin and Lagerkvist (2015), research on this topic has produced ambiguous results (Itti & Koch, 2001; Orquin et al., 2020; Orquin & Lagerkvist, 2015; Tatler et al., 2011). Therefore, instead of predicting the moderating role of task motivation on the effect of bottom-up manipulations on product choice through information search, I rather explore this question.

2.3.3. Combined effects

Similar to the difficulty of predicting whether top-down control interacts with bottom-up control, it is difficult to predict whether working memory demands, i.e., task complexity, and top-down control, i.e., task motivation, interactively influence the effect of saliency and size on product choice through the information search. On the one hand, superior attention-drawing properties can help participants with high task motivation to search more effectively for products carrying these features (Van der Lans, Pieters, & Wedel, 2008) as working memory demands increase. In this case, I would expect the indirect effects of saliency and size to increase more for participants with high task motivation than for participants with low task motivation. On the other hand, superior attention-drawing properties can hinder participants with low task motivation from searching for other, more relevant information as working memory demands increase. In this case, I would expect the effects of saliency and size to increase more for participants with low task motivation.

2.4. Discriminating between bottom-up and top-down control of visual attention

Disentangling bottom-up and top-down control of visual attention requires the use of additional measures, such as consciously articulated inference ratings (Atalay et al., 2012; Valenzuela & Raghubir, 2009). Atalay et al. (2012) found that visual attention to products that were located in the center of a horizontal array mediated consumers' preference for these products, while inference ratings that acted as a parallel mediator did not mediate consumers' preference for products placed in the center. This showed that looking at a product, not the evaluation of a product, determined choice, providing evidence for an active role of visual attention during decision-making. Additionally, learning effects can help to disentangle bottom-up and top-down control. That is, research has consistently found that the influence of bottom-up control of visual attention on product choice decreases as participants become familiar with the presented information (Meißner et al., 2016; Orquin, Bagger, & Mueller Loose, 2013; Orquin, Chrobot, & Grunert, 2018).

Therefore, comparing the indirect effect of saliency and size through information search with the indirect effect of size and saliency through liking ratings that are made after participants have been familiarized with the choice tasks helps to discriminate between bottom-up and top-down control of visual attention. If bottom-up control influences the decision, i.e., if looking at a product to some extent influences the decision beyond liking it, I expect that mediation effects prevalent in the information search analysis will not translate into mediation patterns through liking. Accordingly, if bottom-up control of visual attention is only of minor influence and participants' choices are mainly driven by top-down control of visual attention, I expect the mediation patterns between information search and liking to be the same.

The conceptual model and the hypotheses are depicted in Fig. 1.

3. Method

3.1. Participants and stimuli

Two hundred students at a large European university participated in the experiment. Due to measurement errors and incomplete data, 172 participants remained for analysis. The final number of participants per cell was 37 in high task complexity–high task motivation, 40 in high task complexity–low task motivation, 51 in low task complexity–high task motivation, and 44 in low task complexity–low task motivation. All participants were right-handed, had normal or corrected to normal vision, and were randomly assigned to one of the four conditions. Participants in the low–task complexity condition were paid €5, while participants in the high–task complexity condition were paid €10.

The choice experiment was designed with chocolate bars, a typical everyday consumer product. In order to increase external validity, a quasi-naturalistic product representation was used. The chocolate bars were adapted from ones available in the local market and carried typical product attributes. To avoid brand familiarity effects, the presented chocolate bars carried a fictitious brand name and modified design features. As shown in Table 1, a chocolate bar is characterized by nine product attributes with two features each. The size of a chocolate bar on the screen approximated the typical size of a chocolate bar in the local market.

3.2. Design

The experiment was run as a 2 × 2 (task motivation × task complexity) between-subjects design. In order to manipulate task complexity, I refer to Meißner et al. (2020), who varied set size between two and five alternatives, resulting in 12–30 available pieces of textual

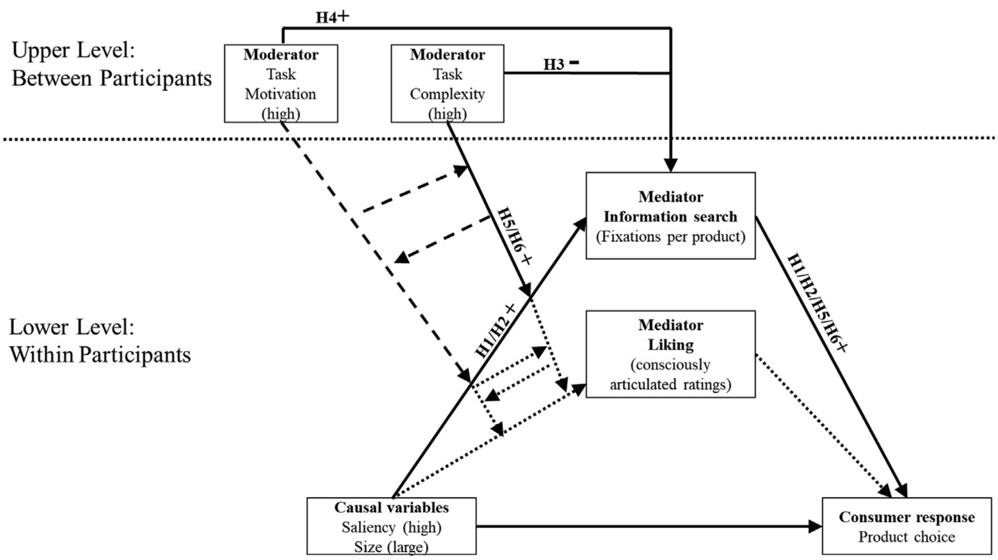

Fig. 1. Conceptual model. Note: Dashed arrows represent effects without specific predictions. "+" and "–" indicate the direction of the hypothesized effects. Dotted arrows represent effects in relation to liking. The crossing of arrows indicates that the moderators are tested for their influence on both "information search" and "liking." Liking effects are used to disentangle bottom-up and top-down control of attention and are not related to a specific hypothesis. For a better overview, the arrows from the moderators to liking, i.e., the equivalents of H3 and H4, are not displayed.

Table 1
Product attributes and features.

Attribute	Features
Saliency	Sharp contrast vs. light contrast
Size	Large package/bar (130 g) vs. small package/bar (100 g)
Origin	Swiss chocolate vs. Ecuadorian chocolate
Key visual	Can vs. drop
Milk	Whole milk vs. alpine milk
Behavior	Melting vs. creamy
Package color	Dark blue vs. light blue
Type	Aerated chocolate vs. plain chocolate
Cocoa	25% vs. 35%

information. Recalling that textual information is cognitively more taxing than pictorial information (Pieters & Warlop, 1999), I provide 27 and 45 pieces of available information, corresponding with three and five alternatives. The number of alternatives is also in line with recommendations about the set size in conjoint choices (Pinnel & Englert, 1997).

In line with previous research (Pieters & Warlop, 1999), I manipulated task motivation by offering an intrinsic and an extrinsic reward. Prior to onset of the first choice task, consumers in the high-task motivation condition read that the study's purpose was to test several products that were about to be introduced in the local market and that their input would be very helpful in developing a product that sold well. Moreover, these participants were promised a product, i.e., a bar of chocolate that best matched their subsequent choices. In contrast, participants in the low–task motivation condition did not receive a reward, and prior to onset of the first choice task, they read that the study was part of the development of a new product test.

I followed the common practice of manipulating saliency by varying the contrast. More specifically, I varied the opacity of the product attributes, "chocolate type" and "key visual." Lowering the opacity of these design elements creates a slight transparency effect, leading to inferior visual conspicuity of the entire product. To ensure that the manipulation was successful, I used a MATLAB implementation (Walther & Koch, 2006) of the feature-based saliency algorithm of Itti, Koch, and Niebur (1998). The algorithm predicts the rank order of locations given visual attention after stimulus onset. Since the visual conspicuity of a product will in part be determined by the relative contrast between products, the algorithm confirmed that in each choice task, salient products were attended to first. Fig. 2 depicts choice task five for both task complexity conditions and shows the rank order predictions.

Size was manipulated by enlarging the overall size of the displayed chocolate by 20%. Additionally, design elements were slightly enlarged, and the font size of the text elements was increased by one point to provide a consistent appearance. To ensure that participants recognized that the larger package went along with more content, a tag containing the content in grams was positioned below the product.

Having nine attributes with two features each results in 512 possible products. This implies more than 100 choice tasks in the high–task complexity conditions. To reduce this number to a manageable size, I followed the design introduced by Burgess and Street (2003, p. 2202) and used only a fraction of the possible products, i.e., 80. Since this design is 100% efficient, each feature occurred with equal frequency, i.e., 40 times; attributes were orthogonal, i.e., independent of each other; and each feature repeated itself with minimum frequency, such that, for example, participants could choose between three large and two small products and vice versa. For the participants in the low–task complexity condition, I used the same design, reducing the number of displayed products to three. More specifically, I removed the alternatives displayed at the edges. This implies that each feature in the low–task complexity condition occurred with equal frequency, i.e., 40 times; attributes were orthogonal; and each feature repeated itself with minimum frequency, such that, for example, participants could choose between two large and one small product and vice versa. Importantly, this procedure allows comparisons between the conditions. In all conditions, participants had to answer 16 choice tasks. To prevent any order effects, the order of the choice tasks was randomized for each participant. I used effect coding (-1;1), such that the mean of each lower-level predictor, including interactions with upper-level variables, equaled zero within a participant.

3.3. Procedure and measures

Each participant was seated in front of a 24-inch screen with a resolution of 1920 × 1200 pixels, approximately 70 cm away from it, and each was informed that their eye movements were monitored. A Tobii X60 eye tracker was mounted below the screen and tracked eye movements unobtrusively using infrared cameras with a sampling rate of 60 Hz. Prior to each recording, participants had to follow a moving dot to calibrate the eye tracker. The software Tobii Studio was used to present the stimuli. Before the actual experiment started, participants completed warmup trials to familiarize themselves with the choice buttons (the 1–5 keys on the keyboard) and the product presentations. Fixations were classified by Tobii studio with a velocity threshold algorithm (I-VT). Since consumers can be expected to gather information

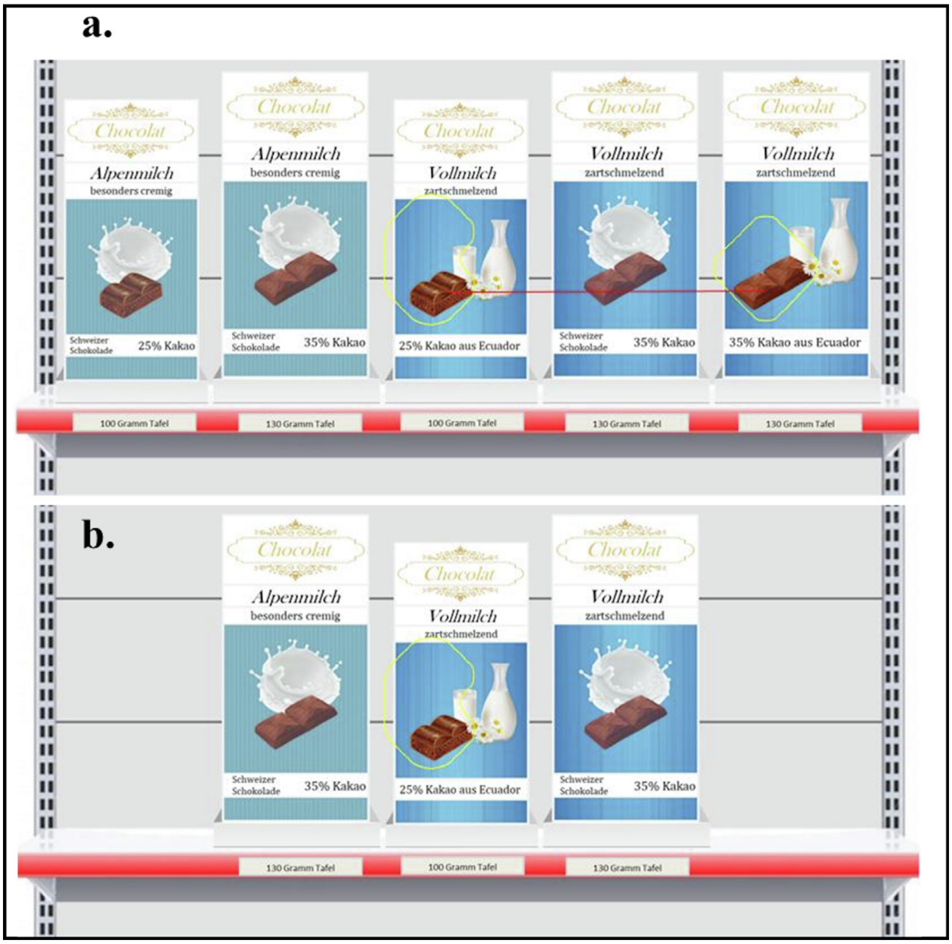

Fig. 2. Example of choice task number five. Note: a = choice task number five in the high–task complexity condition, b = choice task number five in the low-complexity condition. In b, the opacity of the chocolate type picture (plain piece) and the key visual picture (drop) of the left and right chocolate bars was lowered. This leads to a slight transparency effect for these products and makes their attention-drawing properties inferior. The yellow circle represents the area where decision-makers will look first according to the saliency algorithm. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

through peripheral vision (Wästlund et al., 2018), areas of interest were drawn on the product level instead of on the attribute level. More specifically, one area of interest comprised the entire chocolate bar, the corresponding presentation box, and the tag with the textual size information. I did not use a fixation cross prior to stimulus onset.

After completing all choice tasks, participants were surveyed. They first answered questions about task motivation, followed by questions about product realism and inferences. Task motivation was assessed by three items from the involvement scale of Laurent and Kapferer (1985). The items read: "When choosing a chocolate bar, it is not a big deal if you make a mistake," "Choosing the wrong chocolate bar is annoying," and "If my decisions turn out to be wrong, I would feel bad about it." The answers were rated on a 7-point scale ranging from "completely disagree" (1) to "completely agree" (7). These items were averaged into a single variable (Cronbach's alpha = 0.72). To ensure that products were perceived to be quasi-realistic, participants rated their answers to the statements "The chocolate bars look real" and "I could face those chocolate bars in a store, too" on the 7-point scale mentioned above. Both items showed significant correlation ($r = 0.503$ $p < 0.01$). Therefore, they were averaged (Cronbach's alpha = 0.67). Participants then completed all 16 choice tasks again. The order of choice tasks was randomized and hence differed from the first choice experiment. However, this time they were required to rate each product on a liking scale. The item read: "Please answer the following statement. I like the product." The answers were rated on a 9-point scale ranging from not at all (1) to extremely (9). To sustain participants' attention, they performed a filler task after rating four choice tasks. After completing all choice tasks, participants answered additional questions which were beyond the scope of the current paper and therefore will not be discussed in more detail.

3.4. Mediation analysis

Four steps and three linear regression analyses are needed to test for mediation (Preacher, Rucker, & Hayes, 2007); these analyses were extended to binary and count variables (Geldhof, Anthony, Selig, & Mendez-Luck, 2018), reformulated for multilevel settings (Krull & MacKinnon, 2001; Z. Zhang, Zyphur, & Preacher, 2009), and applied in discrete choice settings (Liu, Finkelstein, Kruk, & Rosenthal, 2018). Therefore, verifying hypotheses H1 and H2 required (A) a relationship between the independent variables' size/saliency and the outcome variable product choice (test for *c* paths), (B) a relationship between saliency/size and information search/liking (a paths), and (C) the mediator information search/liking (*b* paths) to predict product choice, when product choice is regressed on saliency, size, information search, and liking. With the same regression as in (C), (D) showed whether the effect of saliency and size was partially, fully, or not mediated by information search and liking (*c'* paths). To probe the indirect effect, i.e., by testing the significance of the *ab* paths, I derived 95% confidence intervals using 100,000 Monte Carlo simulations (Geldhof et al., 2018; Preacher & Selig, 2012).

3.5. (Moderated) moderated mediation analysis

Testing for hypotheses H5 and H6 and the additional research questions required an extension of the mediation analysis as described above. Since I assume that the magnitude of the indirect effect of saliency and size on product choice depends on task complexity and task motivation, a moderated mediation was needed (Preacher et al., 2007). Moderated mediation needs the same four steps as outlined above but requires the inclusion of the moderator variables and interaction terms between the moderators and the causal variables. Moderated mediation implies that task complexity and task motivation additively moderate the effect of saliency and size through the mediators on product choice. Thus, the influence of one moderator on the causal variables is fixed to be independent of the second moderator. However, it is also possible that task complexity and task motivation interactively influence the indirect effects of saliency and size. Testing for these interactions requires a moderated moderated mediation analysis (Hayes, 2018).

3.6. Model specifications

The 95 participants in the low–task complexity condition completed 16 choice tasks containing three product alternatives, resulting in 4560 observations. The 77 participants in the high–task complexity condition completed 16 choice sets containing five product alternatives, resulting in 6160 observations. Thus, the final dataset consisted of 10,720 observations. Due to the repeated measure design of the study, I estimated multilevel models to account for dependency and the hierarchical structure in the data.

3.6.1. Information search and liking

I operationalized "information search" as the number of fixations a product receives. The number of fixations is a count variable, which suggests a Poisson model, or in case of over-dispersion, a negative binomial regression model (NBRM). Since the variance in the data was larger than the mean, I chose an NBRM with random individual intercepts. The mediation analysis model has the form

$$\mathrm{M}_{inf_{njk}}\ NegativeBinomial(\lambda_{njk}), \tag{1}$$

with

$$\ln\lambda_{njk} = \alpha_n + a_0 + a_{att1}X_{att\,njk} + a_{exp_1}X_{exp_{nj}} + a_2W_n + a_3Z_n + a_6W_nZ_n \tag{2}$$

where $\mathrm{M}_{inf_{njk}}$represents the observed number of fixations for participant n in choice task j on alternative k, following a negative binomial distribution governed by the parameter λ_{njk}. In turn, this parameter was modeled using a log link function characterized as follows:

- α_n = participant random effects
- a_0 = constant term (grand mean)
- $X_{att\,njk}$ = a vector of product attributes (independent variables) for participant n in choice task j for alternative k
- a_{att_1} = the corresponding vector of coefficients for $X_{att\,njk}$
- W_n = a variable indicating the complexity condition for participant n
- a_2 = the corresponding coefficient for w_n
- Z_n = a variable indicating the motivation condition for participant n
- a_3 = the corresponding coefficient for z_n
- W_nZ_n = interaction term between complexity and motivation for participant n
- a_6 = the corresponding vector for W_nZ_n

As pointed out by Orquin et al. (2020), previous research has shown that repeated measure designs facilitate top-down control of visual attention, since consumers become more efficient with practice, i.e., they focus more on information of personal relevance as the task progresses (Meißner et al., 2016, 2020). Consequently, the influence on bottom-up control of visual attention diminishes as the task progresses (Orquin et al., 2013). In order to control for systematic variance across choice tasks from the same subject due to the repeated measurement design, I used

- $X_{exp_{nj}}$ = a vector of binary variables indicating whether participant n completed choice task j in the first, second, third, or fourth quarter of the choice experiment
- a_{exp_1} = The corresponding vector of coefficients for $X_{exp_{nj}}$

The (moderated) moderated mediation model extends the model in (2) and has the following form:

$$\ln\lambda_{njk} = \alpha_n + a_0 + a_{att1}X_{att\,njk} + a_{exp_1}X_{exp_{nj}} + a_2W_n + a_3Z_n + a_6W_nZ_n + a_4X_{njk}W + a_5X_{njk}Z_n + a_7X_{njk}W_nZ_n \tag{3}$$

where

- $X_{njk}W_n$ = a vector of interaction terms between product attributes of alternative k and complexity for participant n in choice task j
- a_5 = the corresponding vector of coefficients for $X_{njk}W_n$
- $X_{njk}Z_n$ = a vector of interaction terms between product attributes of alternative k and motivation for participant n in choice task j
- a_5 = the corresponding vector of coefficients for $X_{njk}Z_n$
- $X_{njk}W_nZ_n$ = a vector of interaction terms between product attributes of alternative k and the complexity and motivation for participant n in choice task j
- a_7 = the corresponding vector of coefficients for $X_{njk}W_nZ_n$

For the liking measurement, I used a linear mixed model (LMM) with an identity link function. The mediation model has the following form:

$$\mathrm{M}_{lik_{njk}} = \alpha_n + a_0 + a_{att1}X_{att\,njk} + a_2W_n + a_3Z_n + a_6W_nZ_n \tag{4}$$

where $\mathrm{M}_{lik_{njk}}$represents liking ratings for participant n in choice task j for alternative k.

The (moderated) moderated mediation model extends the model in (4) and has the following form:

$$\mathrm{M}_{lik_{njk}} = \alpha_n + a_0 + a_{att1}X_{att\,njk} + a_2W_n + a_3Z_n + a_6W_nZ_n + a_4X_{njk}W + a_5X_{njk}Z_n + a_7X_{njk}W_nZ_n \tag{5}$$

3.6.2. Model selection

For both the information search models and the liking models, I considered models that included all main effects and all interactions. In order to present parsimonious models, I reduced each model by restricting the analysis to interaction effects that in either the information search models or the liking models were significant or relevant to testing the hypotheses. If an interaction was significant, the main effects were kept in the model, even when they were insignificant. The models with all main effects and interactions and the reduced models yielded consistent results. Thus, I only report results on the reduced models. I estimated the models with Stata version 15 using the command *meglm.* All standard errors are robust and calculated with a sandwich estimator of variance using the option *vce(robust).*

3.6.3. Product choice

Since participants can only choose one product in a specific position per choice set, I modeled the binary outcome variable "product choice" by means of a mixed logit (ML) model. The ML model is a generalization of the multinomial logit (MNL) model (McFadden, 1973), since it allows for capturing random taste and does not require an independence of irrelevant alternatives assumption (IIA) (McFadden & Train, 2000; Revelt & Train, 1998). The ML model is based on random utility theory. It assumes that a (stochastic) utility U of a participant n for alternative k in choice set j consists of a deterministic part c_nX_{njk} and an unobserved random error component $\in_{njk}$ and has the form

$$U_{base\,njk} = c_nX_{njk} + \in_{njk} \tag{6}$$

where

- X_{njk} = a vector of product attributes (observed variables) for participant n in choice task j and alternative k

- c_n = the corresponding vector of coefficients for x_{njk} that is unobserved for each participant
- $\in_{njk}$ = unobserved random error term that follows a Gumbel distribution and that is independent of c_n and X_{njk}

The model that establishes a relationship between the mediator and the outcome variable "product choice" has the form

$$U_{med\,njk} = c'_n X_{njk} + b_{inf_n} M_{inf\,njk} + b_{lik_n} M_{lik\,njk} + \in_{njk} \tag{7}$$

where

- c'_n = a vector of coefficients for X_{njk} that is unobserved for each participant (direct effect)
- $M_{inf\,njk}$ = the independent (observed) variable "information search" for participant n in choice task j and alternative k
- b_{inf_n} = the corresponding coefficient for $M_{inf\,njk}$ that is unobserved for each participant
- $M_{lik\,njk}$ = the independent (observed) variable "liking" for participant n in choice task j and alternative k
- b_{lik_n} = the corresponding coefficient for $M_{lik\,njk}$ that is unobserved for each participant

I estimated mixed logit models that treat all effects as random effects under the initial assumption that coefficients are independently normally distributed in the population. I estimated the models with Stata version 15 using the user-written program *mixlogit* (Hole, 2007).

4. Results

4.1. Manipulation checks

Subjects in the high–task motivation condition scored significantly higher on the involvement measure than subjects in the low–task motivation condition (m_{low} = 3.4; m_{high} = 4.2, t(170) = -3.992, $p < 0.01$), indicating that task motivation was successfully manipulated. The subjects deemed the products to be naturalistic, since the respective mean of 5.3 differs significantly from the scales' midpoint (t (171) = 8.863, $p < 0.01$).

4.2. Mediation analysis

4.2.1. Search for information and liking of salient and large products

The results of Model A1 in Table 2 show that the amount of information search for salient products and large products positively differs ($p < 0.01$) from the grand mean, i.e., $e^{2.192} = 8.95$ fixations. More specifically, a salient product increases the amount of information search per product by $e^{0.089} - 1$= 9.3%, while a large product increases the amount of information search by $e^{0.113} - 1$= 12%. Thus, hypotheses H1a and H2a can be confirmed. Results of Model B1 in Table 2 show a similar pattern for liking ratings. A salient product increases liking ratings by $\frac{0.253}{6.625} * 100 = 3.8\%$ ($p < 0.01$) while a large product increases liking ratings by $\frac{0.058}{6.625} * 100 = 1.2\%$ ($p < 0.01$).

4.2.2. Choice of salient and large products

Next, I investigated the influence of saliency and size on product choice. As the results of Model U_{base} in Table 3 show, a salient product increases choice likelihood by $e^{0.509} - 1$= 66.4%, while a large product increases choice likelihood by $e^{0.347} - 1$= 41.5% ($p < 0.01$). More specifically, salient products provide greater utility than large products (with non-overlapping confidence intervals). On average, saliency, in fact, is the most important attribute among the entire set of attributes. Thus, hypotheses H1b and H2b can be confirmed.

4.2.3. Impact of searching for information and liking of a product on choice of large and salient products

The next section investigates whether the effects of saliency and size on product choice operate through information search and consciously articulated liking ratings. Put differently, I analyze whether indirect effects are prevalent.

As shown in Table 3 Model U_{med} information search significantly predicts product choice ($p < 0.01$). More specifically, for each fixation on a product, its choice likelihood increases by 51.3%. Moreover, the indirect effects of saliency (*ab* = 0.037; 95%CI[0.027,0.048]) and size (*ab* = 0.047; 95%CI[0.036,0.059]) on product choice through information search are significant, as indicated by 95% confidence intervals that do not straddle zero. Thus, hypotheses H1c and H2c can be confirmed. Liking significantly predicts product choice as well. A one-unit increase in liking rating increases the likelihood of a product being chosen by 106.3%. The indirect effects of saliency (*ab* = 0.183; 95%CI [0.124,0.248]) and size (*ab* = 0.042; 95%CI[0.022,0.064]) on product choice through liking are significant.

Moreover, the results in Table 3 Model U_{med} show that the effect of size on product choice is fully mediated by information search and liking (*c'*=0.001, $p > 0.1$). In fact, when removing the mediator "liking," information search still fully mediates the effect of size on choice. In contrast, saliency shows a positive direct effect on product choice (*c'*=0.154, $p < 0.01$), indicating that the influence through visual attention and liking is limited.

4.3. Search for information and liking of products across task complexity and task motivation

Both task motivation ($p < 0.01$) and task complexity ($p < 0.05$) have a significant effect on the amount of information search. Participants in the high–task motivation condition searched for 16.2% more information. In contrast, participants choosing between five instead of three products, on average, searched for 7.6% less information. The interaction between task motivation and task complexity is not significant ($p > 0.1$). Thus, in line with research on attitude formation and decision-making, task motivation and task complexity operate additively, i.e., less opportunity under higher working memory demands is compensated for by more task motivation and vice versa (Bettman et al., 1998; Payne et al., 1993; Petty & Cacioppo, 1986). This provides substantial support for hypotheses H3 and H4. The results for liking are similar. Task motivation increases liking by 2.7%, and task complexity decreases liking by 3.8%. Thus, on the one hand, participants adapt to task complexity and task motivation by looking more (less) frequently at a product. On the other hand, participants' evaluation of a product under these conditions becomes more (less) positive.

4.4. (Moderated) moderated mediation analysis

The results suggest that participants chose salient and large products, since they looked at these products more frequently and evaluated them more positively. Moreover, task motivation and task complexity influence both consumers' information searching activities and their evaluation of a product. However, it remains unclear whether the changes in evaluation and information search impact the indirect effects in-store marketing activities have on the choice of salient and large products. The next section addresses this issue.

4.4.1. Impact of task complexity and task motivation on the indirect effects of size

The results given in Table 4 and Fig. 3 show that task motivation does not moderate the indirect effect of size on product choice through information search (*ab* = 0.000; 95%CI[-0.009;0.009]) since the index of "partial moderated mediation" (Hayes, 2018), as indicated by a 95% confidence interval that straddles zero, is not significant. However, a significant index of partial moderated mediation provides evidence that

Table 2
Estimates for random effects negative binomial and linear mixed models.

Independent variables	Model A1: Mediation analysis model		Model A2: Mediation analysis model		Model B1: (Moderated) moderated mediation analysis model		Model B2: (Moderated) moderated mediation analysis model	
	Information Search		Liking		Information Search		Liking	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
In-store activity								
Saliency	0.089	0.012***	0.253	0.038***	0.086	0.011***	0.246	0.036***
Size	0.113	0.013***	0.058	0.014***	0.109	0.012***	0.054	0.013***
Working memory								
Task complexity	−0.079	0.036**	−0.252	0.083**	−0.080	0.036**	−0.252	0.083**
Top-down								
Task motivation	0.150	0.035***	0.180	0.083**	0.150	0.036***	0.180	0.083**
Working memory * top-down								
Task complexity * Task motivation	0.027	0.035	−0.049	0.083	0.026	0.036	−0.049	0.083
In-store activity * working memory								
Saliency * complexity					0.019	0.011*	0.062	0.036*
Size * complexity					0.031	0.012**	0.027	0.013**
In-store activity * top-down								
Saliency * motivation					0.001	0.011	0.016	0.036
Size * motivation					0.001	0.012	0.023	0.013*
In-store activity * top-down * working memory								
Saliency * motivation* complexity					0.019	0.011*	0.052	0.036
Size * motivation* complexity					0.004	0.012	0.013	0.013
Task experience								
Second quarter	0.014	0.017			0.014	0.017		
Third quarter	−0.162	0.018***			−0.163	0.018***		
Fourth quarter	−0.308	0.02***			−0.309	0.02***		
Covariates								
Origin	0.014	0.009	0.036	0.039	0.017	0.009*	0.035	0.035
Key visual	0.054	0.011***	0.153	0.036***	0.055	0.011***	0.153	0.036***
Milk	0.006	0.008	0.047	0.014***	0.006	0.008	0.047	0.014***
Behavior	0.003	0.009	0.000	0.012	0.003	0.009	0.000	0.012
Color	0.046	0.011***	0.131	0.032***	0.048	0.01***	0.141	0.031***
Type	0.021	0.016	−0.070	0.053	0.021	0.016	−0.070	0.053
Cocoa	0.052	0.011***	0.220	0.029***	0.052	0.012***	0.220	0.029***
Covariates * moderators								
Color * complexity					−0.007	0.01	−0.063	0.032**
Origin * complexity					−0.018	0.009**	−0.019	0.035
Color * motivation					−0.019	0.011*	−0.065	0.031**
Origin * motivation					0.007	0.009	−0.046	0.035
Origin * motivation * complexity					−0.003	0.009	−0.077	0.035**
Constant	2.192	0.036***	6.625	0.083***	2.191	0.036***	6.625	0.083***
Upper level variance								
Participant	0.198	0.027**	1.105	0.096**	0.198	0.027**	1.106	0.095**
Residual			2.193	0.175**			2.167	0.169**
Goodness of fit								
Log likelihood	−34327		−19715		−34306		−19653	
AIC	68690		39461		68671		39357	

Note: "Saliency" = high saliency, "size" = large size, "origin" = Swiss chocolate, "key visual" = can, "milk" = alpine milk, "behavior" = melting, "color" = dark blue, "type" = aerated chocolate, "cocoa" = 35%, "complexity" = high complexity, "motivation" = high motivation. Percentage changes in fixations can be derived by $e^{rawcoefficient}$-1. Percentage changes in liking ratings can be derived by $\frac{rawcoefficient}{constant} * 100$. P-values are based on robust standard errors. ***p < 0.01, **p < 0.05, *p < 0.1.

task complexity (*ab* = 0.013; 95%CI[0.003;0.023]) does moderate the indirect effect of size on product choice through information search. Thus, the results support hypotheses H6. There is no evidence that task complexity and task motivation interactively influence the indirect effect of size, as indicated by a non-significant index of moderated moderated mediation (*ab* = 0.002; 95%CI[-0.008;0.011]).

The results for moderation effects on the indirect effect of size through liking have both similarities and differences. Similar to the mediation by information search, task complexity moderates the indirect effect of size (*ab* = 0.020; 95%CI[0.001;0.039]). In contrast to the mediation through information search, a significant index of partial moderated mediation (*ab* = 0.017; 90%CI[0.001;0.033]), as indicated by a 90% confidence interval that does not straddle zero, shows that task motivation moderates the indirect effect of size through liking.

Thus, on the one hand, as complexity increases, participants search more for large products and evaluate large products more positively, which in both cases carries through to product choice.

On the other hand, motivated and less motivated participants differ in their indirect effect of size through liking but not in their indirect effect of size through information search.

4.4.2. *Impact of task complexity and task motivation on the indirect effects of saliency*

A significant index of moderated moderated mediation (*ab* = 0.008;

Table 3
Estimates for mixed logit models.

	Model U_{base}		Model U_{med}	
	C path		C'/b path	
	Coef.	Std. Err.	Coef.	Std. Err.
In-store activity				
Saliency	0.509	0.054***	0.154	0.047***
Size	0.347	0.053***	0.001	0.048
Covariates				
Origin	0.053	0.051	0.005	0.050
Key visual	0.315	0.053***	0.058	0.042
Milk	0.074	0.035**	0.089	0.040**
Behavior	0.044	0.041	0.049	0.043
Color	0.284	0.054***	0.174	0.049***
Type	−0.050	0.073	0.047	0.045
Cocoa	0.440	0.068***	0.050	0.043
Mediators				
Liking			0.724	0.062***
Information search			0.414	0.022***
Upper level standard deviations				
Saliency	0.649	0.051***	0.264	0.072***
Size	0.633	0.051***	0.285	0.068***
Origin	0.621	0.051***	0.351	0.066***
Key visual	0.614	0.06***	0.010	0.113
Milk	0.298	0.045***	0.125	0.109
Behavior	0.429	0.041***	0.245	0.071***
Color	0.764	0.057***	0.363	0.064***
Type	1.091	0.082***	0.234	0.700***
Cocoa	0.688	0.07***	0.151	0.098
Information search			0.160	0.016***
Liking			0.437	0.067***
Information criteria				
Log likelihood	−2744		−1425	
AIC	5523		2895	
Pseudo R	0.25		0.61	

Note: Model U_{base} represents estimates of the mixed logit model for product choice without the mediators being included. U_{med} represents estimates of the mixed logit model for product choice with the mediators being included. "Saliency" = high saliency, "size" = large size, "origin" = Swiss chocolate, "key visual" = can, "milk" = alpine milk, "behavior" = melting, "color" = dark blue, "type" = aerated chocolate, "cocoa" = 35% ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

90%CI[0.0004;0.015]) shows that task complexity and task motivation interactively influence the indirect effect of saliency through information search. Probing this moderation of moderated mediation reveals (see Table 4 "conditional moderated mediation" for a summary of the coefficients and Fig. 3 for a graphical representation) that the indirect effect of saliency does not significantly differ between participants with high task motivation and participants with low task motivation in either the low–task complexity condition (*ab* = -0.007; 95%CI[-0.020;0.005]) or the high–task complexity condition (*ab* = 0.008; 95%CI [-0.004;0.021]). However, task complexity moderates the effect of saliency on product choice through information search when task motivation is high (*ab* = 0.016; 95%CI[0.003;0.029]), but it does not moderate the indirect effect of saliency when task motivation is low (*ab* = 0.000; 95%CI[-0.013;0.013]). Thus, hypothesis H5 is supported for participants with a high task motivation.

Contrastively, a non-significant index of moderated moderated mediation (*ab* = 0.012; 95%CI[-0.040;0.063]) shows that task complexity and task motivation do not interactively influence the indirect effect of saliency through liking. However, a significant index of partial moderated mediation (*ab* = 0.045; 90%CI[0.002;0.089]) reveals that task complexity moderates the indirect effect of saliency through liking for both motivated and less motivated participants. Moreover, all *ab* paths differ significantly from zero (see Table 4 "*ab* path for saliency"), suggesting that participants in both task motivation conditions consistently consider saliency to be of personal relevance.

In sum, as complexity increases, only motivated participants search more for salient products, which carries through to product choice. In contrast, as complexity increases, both motivated and less motivated participants evaluate salient products more positively, which carries through to product choice.

5. Discussion

In a simulated shelf experiment, participants chose between quasi-realistic chocolate bars carrying attributes typical of this product category. I used CBC analysis in combination with eye tracking and liking ratings to analyze the impact of popular in-store marketing activities, i.e., modifications of the visual saliency and the size of a product, on consumers' information search behavior, consumers' liking of a product, and consumers' choices. At the same time, I controlled for top-down factors, such as task motivation, and for working memory processes, such as task complexity.

5.1. Adaptation to task complexity and task motivation

To analyze the impact of the different factors on information search, I used multilevel regression analysis with the fixation count as the dependent variable. To disentangle bottom-up and top-down control of visual attention, I additionally analyzed the impact of the different factors on liking by means of multilevel regression analysis with consciously articulated liking ratings as the dependent variable. When not differentiating between different kinds of products, thus considering consumer decision-making in relation to looking at a product in general, the results confirm that decision makers adapt to increasing task complexity by reducing the amount of information search per product (Ford et al., 1989; Lohse, 1997; Meißner et al., 2020; Payne, 1976; Reutskaja et al., 2011). They also adapt to increasing task motivation by increasing the amount of information search per product (Celsi & Olson, 1988; Toubia et al., 2012). These results provide robust evidence that consumers adapt their information search behavior across various contexts. The effects of task motivation and task complexity are similar for consciously articulated liking ratings. Put differently, looking less frequently at a product is paralleled by less liking of the product, and looking more frequently at a product is paralleled by more liking of the product. Importantly, products were identical between conditions. Thus, there is evidence that looking at and liking an item are tightly coupled in this study.

5.2. In-store marketing effectiveness

To analyze the impact of in-store marketing activities, i.e., improvements in the visual saliency and increments in the size of a product, on product choice, I rely on random utility theory and a mixed model approach. The results show that both a salient product and a large product increase choice likelihood. A multilevel mediation analysis reveals that the amount of information search per product and liking of a product fully mediate the positive effect of size on product choice. Indeed, information search, when specified as a single mediator, fully mediates the effect of size on product choice. This shows that findings from research on feature advertisements (Z. Zhang et al., 2009) and on shelf facings (Chandon et al., 2009) generalize to the size of a product in a multi-attribute quasi-realistic choice context. In contrast, the effect of saliency is partially mediated, which suggests that saliency triggers aspects of the decision-making process that do not necessarily translate into visual attention to and conscious liking of a product, such as emotions (Loewenstein, 2000). Another explanation would be that eye tracking does not capture the visual attention process entirely, i.e., participants also acquire information through peripheral vision (Wästlund et al., 2018). However, although participants can easily identify the size of the product through peripheral vision, the effect of size is fully mediated by visual attention. Moreover, information

Table 4
Indices of partial moderated mediation, moderated moderated mediation, and indirect effects.

		Coef.	95% CI Lower Limit	95% CI Upper Limit	Coef.	95% CI Lower Limit	95% CI Upper Limit
		Information search			Liking		
Indices of partial moderated mediation							
In-store activity * working memory							
Saliency × complexity		**0.008***	0.0004	0.015	**0.045***	0.002	0.089
Size × complexity		**0.013**	0.003	0.023	**0.020**	0.001	0.039
In-store activity * top-down							
Saliency × motivation		0.000	−0.009	0.009	0.012	−0.040	0.063
Size × motivation		0.000	−0.009	0.010	**0.017***	0.001	0.033
Indices of moderated moderated mediation							
In-store activity * working memory * top-down							
Saliency × complexity × motivation		**0.008***	0.0004	0.015	0.012	−0.040	0.063
Size × complexity × motivation		0.002	−0.008	0.011	0.009	−0.009	0.028
ab paths for saliency							
High complexity | high motivation		**0.052**	0.033	0.071	**0.235**	0.142	0.336
Low complexity | high motivation		**0.020**	0.002	0.039	**0.145**	0.055	0.240
High complexity | low motivation		**0.035**	0.017	0.054	**0.211**	0.120	0.311
Low complexity | low motivation		**0.035**	0.017	0.053	**0.122**	0.032	0.215
ab paths for size							
High complexity | high motivation		**0.058**	0.041	0.077	**0.075**	0.042	0.111
Low complexity | high motivation		**0.033**	0.016	0.050	**0.036**	0.004	0.070
High complexity | low motivation		**0.058**	0.040	0.076	**0.042**	0.010	0.076
Low complexity | low motivation		**0.033**	0.015	0.049	0.003	−0.029	0.035
Conditional moderated mediation							
Saliency							
By complexity	High motivation	**0.016**	0.003	0.029			
	Low motivation	0.000	−0.013	0.013			
By motivation	High complexity	0.008	−0.004	0.021			
	Low complexity	−0.007	−0.020	0.005			

Significant values are printed in bold. *Significance based on 90% confidence intervals.

acquired through peripheral vision to some extent can be captured by the mediator liking. Therefore, peripheral vision seems less likely as an explanation.

5.3. Adaptivity and in-store marketing effectiveness

A multilevel (moderated) moderated mediation analysis analyzes the impact of working memory processes, i.e., different levels of task complexity, and the impact of top-down processes, i.e., different levels of task motivation, on the indirect effects in-store marketing activities have on product choice.

The results show that motivated participants choosing among five products searched more for both large products and salient products than motivated participants choosing among three products. Also, they

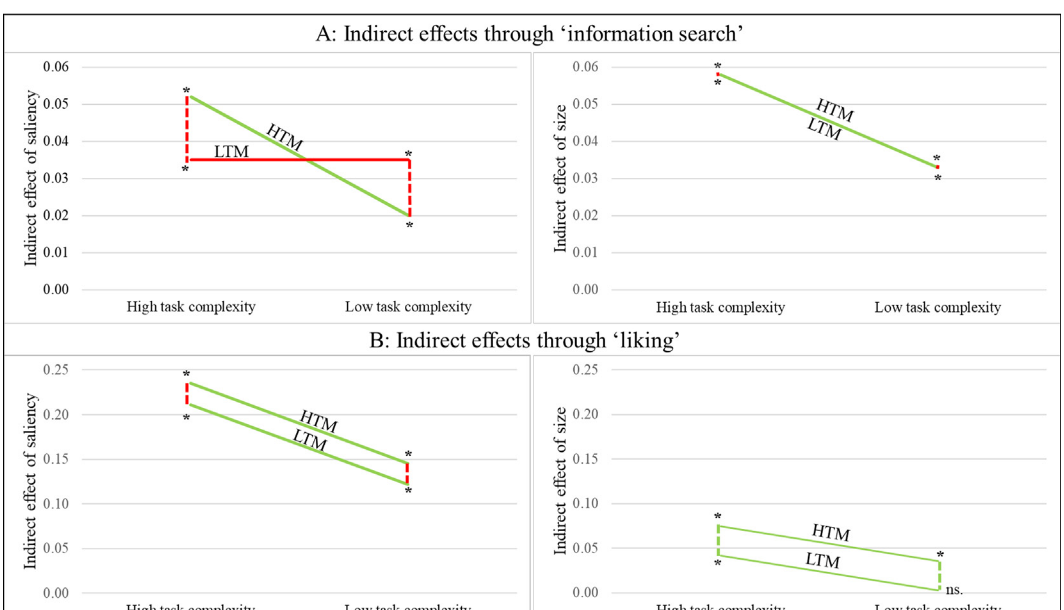

Fig. 3. Indirect effects of size and saliency across task complexity and task motivation. Note: Green (red) lines represent (non–)significant conditional moderated mediation indices for high saliency and information search and (non–)significant partial moderated moderation indices for large size and information search/liking and for high saliency and liking, * = significant coefficient for *ab* path, ns. = non-significant coefficient for *ab* path. LTM = low task motivation, HTM = high task motivation. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

evaluated these products more positively. The effect on information search, as well as the effect on liking, carry through to product choice. Thus, motivated participants increased their search for information and their liking of products with superior attention-drawing properties when the number of products to choose from increased.

Less motivated participants more frequently searched for and increased their liking of large products as complexity increased, too. Moreover, with these participants, both the effect on information search and the effect on liking carry through to product choice. Thus, in the case of large products, less motivated participants also increased their search for information and their liking of products with superior attention-drawing properties when the number of products to choose from increased.

Similar to motivated participants less motivated ones evaluated salient products more positively as complexity increased, leading to an indirect effect of saliency on product choice; however, as complexity increased they did not look for salient products more frequently. Consequently, there was no indirect effect of saliency through information search. Hence, when completing the choice experiment for the first time, less motivated participants did not search for salient products more frequently as complexity increased, although when completing the choice tasks for the second time, they evaluated salient products more positively as complexity increased. This suggests that when learning effects were less prevalent and responses were not consciously articulated, less motivated participants simplified their information processing in that the attention drawing properties and the attractiveness of salient products were not sufficient to compete against the attention-drawing properties and attractiveness of large products. This corroborates previous research which demonstrated that the influence of saliency on visual attention and decision-making is limited when additional bottom-up factors such as size manipulations are prevalent (Peschel et al., 2019). Further, less motivated participants and motivated participants did not differ in the indirect effect of size through information search, while the indirect effect of size through liking was smaller for less motivated ones.

Additionally, for both motivated and less motivated participants, the effect of visual saliency was connected to top-down control of visual attention, i.e., participants consistently evaluated salient products more positively. This suggests that saliency itself, as manipulated by varying the contrast of certain elements, can trigger top-down processes. This fact has largely been ignored in saliency effects analyses and should be considered in future research. Indeed, Husić-Mehmedović, Omeragić, Batagelj, and Kolar (2017) found that salient products received more fixations, but they scored (below) average on recall and likeability. Thus, businesses have to manipulate saliency with caution, since minor changes in a product's appearance can influence how consumers evaluate it.

6. Conclusion and implications

The picture that emerges is that typical in-store marketing activities, such as improving the visual saliency and incrementing the size of a product, can effectively stimulate product choice. These activities are effective, since in this study, enlarging a product and improving a product's visual saliency stimulated consumers to look more frequently at these products and to increase their liking of these products. These effects, in turn, increase the likelihood of choosing large products and more salient products. Moreover, when the choice environment becomes more complex, i.e., the number of products to choose from increases, and hence working memory demands increase, consumers more frequently choose large products and salient products. They do so since they search more for and increase their liking of products with superior attention-drawing properties. Together with the finding that looking more (less) at a product is paralleled by more (less) liking of the product, this study provides evidence that the close link between looking at a product and preference construction, as documented by previous research (Armel, Beaumel, & Rangel, 2008; Krajbich, Armel, & Rangel, 2010; Krajbich & Rangel, 2011), also applies to a multi-attribute choice context with quasi-realistic products. Additionally, the differences between motivated and less motivated participants in both the number of successful in-store marketing activities and in the indirect effects through information search and liking, suggest that for less motivated participants looking at a product influences the decision, in part beyond consciously liking it (Orquin & Mueller Loose, 2013; Orquin, Perkovic, & Grunert, 2018).

Recalling that a great portion of decisions are made in-store, this study provides further justification for in-store marketing expenditure. Importantly, this study shows that the effectiveness of typical in-store marketing activities increases as working memory demands increase. From a managerial perspective, this finding offers opportunities to direct consumers' decisions more effectively. Managers could use these activities in situations where consumers, on average, can be expected to have fewer mental resources available, for example, when they approach the checkout area and have depleted resources after shopping for several products (Wästlund, Otterbring, Gustafsson, & Shams, 2015). As Chandon et al. (2009) pointed out, the impact of in-store-marketing activities on product choice generally, is small compared to that of out-of-store activities. However, the in-store-marketing activities identified in this study, can create a competitive advantage at the point of purchase, which builds up over time and ultimately contributes to out-of-store factors.

7. Future research and limitations

Since I used learning effects to disentangle bottom-up and top-down control of attention, the display format provided some external orientation cues, in that attributes appeared in the same order and roughly on the same row. Additionally, alternatives were always displayed in the same position. This might have caused the influence of bottom-up control to be underrepresented (Orquin et al., 2018). Moreover, to decrease complexity, only one type of product was used in the study. Future research could address these limitations by using quasi-naturalistic products and a design that varies the position of the alternatives, decreases the number of product attributes so that fewer tasks are necessary to preserve statistical efficiency, and uses different product categories and product types. Shuffling of choice sets across different product types and categories should further decrease learning effects and hence increase external validity. These improvements, however, come at the cost of difficulties in disentangling bottom-up and top-down control with the help of learning effects. Therefore, when using a CBC design with quasi-naturalistic products and mainly unpredictable object locations, it is advisable to use a different approach for disentangling bottom-up and top-down control. One solution, for example, could be to explicitly tell participants that large products do not carry more content and that they are only displayed in different sizes to mimic a realistic in-store representation, thus modifying the decision value of an object via task instructions (Orquin & Lagerkvist, 2015; Pieters & Wedel, 2007). If any size effects then become prevalent, they can be attributed to bottom-up control of visual attention. This approach, however, cannot reveal whether consumers become more effective in searching for information of personal relevance.

Another limitation of this study is that price is not included as an attribute. On the one hand, this was done to focus on the causal mechanisms, which is typical in visual attention research on consumer decision-making (Atalay et al., 2012; Krajbich et al., 2010; Milosavljevic et al., 2012; Reutskaja et al., 2011). On the other hand, this decision was intended to avoid any interaction between large products and less expensive products. Therefore, future research could use the task instruction approach mentioned above to test whether the mechanism identified in this study generalizes to a setup where price is included. Relatedly, participants in the low–task motivation condition were not incentive-aligned. Although not uncommon in CBC studies

(Meißner et al., 2016, 2020), this could to some extent have induced participants in the low–task motivation condition to make choices according to their attention. Future research could address this limitation by making both motivational stages incentive-aligned.

Funding

This work was supported (data collection cost) by the Graduate School of the faculty of Business, Economics and Social Sciences of the University of Hamburg.

Acknowledgement

I thank the staff of the research lab (Olaf Bock, Lukas Lapschieß, and Ziad Zorgati) of the faculty of Business, Economics and Social Sciences of the University of Hamburg for their support in collecting data.

References

Anderson, J. R., Bothell, D., & Douglass, S. (2004). Eye movements do not reflect retrieval processes: Limits of the eye-mind hypothesis. *Psychological Science, 15*(4), 225–231. https://doi.org/10.1111/j.0956-7976.2004.00656.x.

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

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.

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.

Bialkova, S., Grunert, K. G., Juhl, H. J., Wasowicz-Kirylo, G., Stysko-Kunkowska, M., & van Trijp, Hans 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.

Campo, K., & Gijsbrechts, E. (2005). Retail assortment, shelf and stockout management: Issues, interplay and future challenges. *Applied Stochastic Models in Business and Industry, 21*(4–5), 383–392. https://doi.org/10.1002/asmb.574.

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.

Eisend, M. (2014). Shelf space elasticity: A meta-analysis. *Journal of Retailing, 90*(2), 168–181. https://doi.org/10.1016/j.jretai.2013.03.003.

Elshiewy, O., & Boztug, Y. (2018). When Back of Pack Meets Front of Pack: How Salient and Simplified Nutrition Labels Affect Food Sales in Supermarkets. *Journal of Public Policy & Marketing, 37*(1), 55–67. https://doi.org/10.1509/jppm.16.100.

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

Ford, J. K., Schmitt, N., Schechtman, S. L., Hults, B. M., & Doherty, M. L. (1989). Process tracing methods: Contributions, problems, and neglected research questions. *Organizational Behavior and Human Decision Processes, 43*(1), 75–117. https://doi.org/10.1016/0749-5978(89)90059-9.

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.

Glöckner, A., & Herbold, A.-K. (2011). An eye-tracking study on information processing in risky decisions: Evidence for compensatory strategies based on automatic processes. *Journal of Behavioral Decision Making, 24*(1), 71–98. https://doi.org/10.1002/bdm.684.

Hare, T. A., Camerer, C. F., & Rangel, A. (2009). Self-control in decision-making involves modulation of the vmPFC valuation system. *Science (New York, N.Y.), 324*(5927), 646–648. https://doi.org/10.1126/Science.1168450.

Hare, T. A., Malmaud, J., & Rangel, A. (2011). Focusing attention on the health aspects of foods changes value signals in vmPFC and improves dietary choice. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience, 31*(30), 11077–11087. https://doi.org/10.1523/JNEUROSCI.6383-10.2011.

Hayes, A. F. (2018). Partial, conditional, and moderated moderated mediation: Quantification, inference, and interpretation. *Communication Monographs, 85*(1), 4–40. https://doi.org/10.1080/03637751.2017.1352100.

Hole, A. R. (2007). Fitting mixed logit models by using maximum simulated likelihood. *Stata Journal. (Volume, 7)*, 388–401.

Horstmann, N., Ahlgrimm, A., & Glöckner, A. (2009). How Distinct are Intuition and Deliberation?: An Eye-Tracking Analysis of Instruction-Induced Decision Modes. SSRN Electronic Journal. Advance online publication. https://doi.org/10.2139/ssrn.1393729.

Husić-Mehmedović, M., Omeragić, I., Batagelj, Z., & Kolar, T. (2017). Seeing is not necessarily liking: Advancing research on package design with eye-tracking. *Journal of Business Research, 80*, 145–154. https://doi.org/10.1016/j.jbusres.2017.04.019.

Inman, J. J., Winer, R. S., & Ferraro, R. (2009). The Interplay among Category Characteristics, Customer Characteristics, and Customer Activities on in-Store Decision Making. *Journal of Marketing, 73*(5), 19–29. https://doi.org/10.1509/jmkg.73.5.19.

Itti, L., & Koch, C. (2001). Computational modelling of visual attention. *Nature Reviews. Neuroscience, 2*(3), 194–203. https://doi.org/10.1038/35058500.

Itti, L., Koch, C., & Niebur, E. (1998). A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence, 20*(11), 1254–1259. https://doi.org/10.1109/34.730558.

Janiszewski, C. (1998). The Influence of Display Characteristics on Visual Exploratory Search Behavior. *Journal of Consumer Research, 25*(3), 290–301. https://doi.org/10.1086/209540.

Jones, G., & Richardson, M. (2007). An objective examination of consumer perception of nutrition information based on healthiness ratings and eye movements. *Public Health Nutrition, 10*(03), https://doi.org/10.1017/S1368980007258513.

Just, M. A., & Carpenter, P. A. (1980). A theory of reading: From eye fixations to comprehension. *Psychological Review, 87*(4), 329–354. https://doi.org/10.1037/0033-295X.87.4.329.

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.

Krull, J. L., & MacKinnon, D. P. (2001). Multilevel Modeling of Individual and Group Level Mediated Effects. *Multivariate Behavioral Research, 36*(2), 249–277. https://doi.org/10.1207/S15327906MBR3602_06.

Kumar, M., & Garg, N. (2010). Aesthetic principles and cognitive emotion appraisals: How much of the beauty lies in the eye of the beholder? *Journal of Consumer Psychology, 20*(4), 485–494. https://doi.org/10.1016/j.jcps.2010.06.015.

Kwak, Y., Payne, J. W., Cohen, A. L., & Huettel, S. A. (2015). The Rational Adolescent: Strategic Information Processing during Decision Making Revealed by Eye Tracking. *Cognitive Development, 36*, 20–30. https://doi.org/10.1016/j.cogdev.2015.08.001.

Laurent, G., & Kapferer, J.-N. (1985). Measuring Consumer Involvement Profiles. *Journal of Marketing Research, 22*(1), 41. https://doi.org/10.2307/3151549.

Liu, N., Finkelstein, S. R., Kruk, M. E., & Rosenthal, D. (2018). When Waiting to See a Doctor Is Less Irritating: Understanding Patient Preferences and Choice Behavior in Appointment Scheduling. *Management Science, 64*(5), 1975–1996. https://doi.org/10.1287/mnsc.2016.2704.

Loewenstein, G. (2000). Emotions in Economic Theory and Economic Behavior. *American Economic Review, 90*(2), 426–432. https://doi.org/10.1257/aer.90.2.426.

Lohse, G. L. (1997). Consumer Eye Movement Patterns on Yellow Pages Advertising. *Journal of Advertising, 26*(1), 61–73. https://doi.org/10.1080/00913367.1997.10673518.

Lohse, G. L., & Johnson, E. J. (1996). A Comparison of Two Process Tracing Methods for Choice Tasks. *Organizational Behavior and Human Decision Processes, 68*(1), 28–43. https://doi.org/10.1006/obhd.1996.0087.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In P. Zarembka (Ed.). *Economic theory and mathematical economics. Frontiers in econometrics* (pp. 105–142). New York: Academic Press.

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.

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. (2020). Surprising adaptivity to set size changes in multi-attribute repeated choice tasks. *Journal of Business Research, 111*, 163–175. https://doi.org/10.1016/j.jbusres.2019.01.008.

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.

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., Bagger, M. P., Lahm, E. S., Grunert, K. G., & Scholderer, J. (2020). The visual ecology of product packaging and its effects on consumer attention. *Journal of Business Research, 111*, 187–195. https://doi.org/10.1016/j.jbusres.2019.01.043.

Orquin, J. L., Bagger, M. P., & Mueller Loose, S. (2013). Learning affects top down and bottom up modulation of eye movements in decision making. *Judgment and Decision Making, Vol. 8*, 700–716.
Orquin, J. L., Chrobot, N., & Grunert, K. G. (2018). Guiding Decision Makers' Eye Movements with (Un)Predictable Object Locations. *Journal of Behavioral Decision Making, 31*(3), 341–354. https://doi.org/10.1002/bdm.2060.
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., & Lagerkvist, C. J. (2015). Effects of salience are both short- and long-lived. *Acta Psychologica, 160*, 69–76. https://doi.org/10.1016/j.actpsy.2015.07.001.
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.
Orquin, J. L., Perkovic, S., & Grunert, K. G. (2018). Visual Biases in Decision Making. *Applied Economic Perspectives and Policy, 118*(1), 73. https://doi.org/10.1093/aepp/ppy020.
Orth, U. R., & Malkewitz, K. (2008). Holistic Package Design and Consumer Brand Impressions. *Journal of Marketing, 72*(3), 64–81. https://doi.org/10.1509/jmkg.72.3.64.
Payne, J. W. (1976). Task complexity and contingent processing in decision making: An information search and protocol analysis. *Organizational Behavior and Human Performance, 16*(2), 366–387. https://doi.org/10.1016/0030-5073(76)90022-2.
Payne, J. W., Bettman, J. R., & Johnson, E. J. (1988). Adaptive strategy selection in decision making. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14*(3), 534–552. https://doi.org/10.1037//0278-7393.14.3.534.
Payne, J. W., Bettman, J. R., & Johnson, E. J. (1993). *The adaptive decision maker.* Cambridge: Cambridge Univ. Press.
Peschel, A. O., & Orquin, J. L. (2013). A review of the findings and theories on surface size effects on visual attention. *Frontiers in Psychology, 4*, 902. https://doi.org/10.3389/fpsyg.2013.00902.
Peschel, A. O., Orquin, J. L., & Mueller Loose, S. (2019). Increasing consumers' attention capture and food choice through bottom-up effects. *Appetite, 132*, 1–7. https://doi.org/10.1016/j.appet.2018.09.015.
Petty, R. E., & Cacioppo, J. T. (1986). The Elaboration Likelihood Model of Persuasion. In Advances in Experimental Social Psychology (Vol. 19, pp. 123–205). Elsevier. https://doi.org/10.1016/S0065-2601(08)60214-2.
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.
Pieters, R., & Wedel, M. (2004). Attention capture and transfer in advertising: Brand, pictorial, and text-size effects. *Journal of Marketing, 68*(2), 36–50. https://doi.org/10.1509/jmkg.68.2.36.27794.
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. *Proceedings of the Sawtooth Software Conference* (pp. 121–153). .
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.
Reimann, M., Zaichkowsky, J., Neuhaus, C., Bender, T., & Weber, B. (2010). Aesthetic package design: A behavioral, neural, and psychological investigation. *Journal of Consumer Psychology, 20*(4), 431–441. https://doi.org/10.1016/j.jcps.2010.06.009.
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.
Rosbergen, E., Pieters, R., & Wedel, M. (1997). Visual Attention to Advertising: A Segment-Level Analysis. *Journal of Consumer Research, 24*(3), 305–314. https://doi.org/10.1086/209512.
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.
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.
Sciandra, M. R., Inman, J. J., & Stephen, A. T. (2019). Smart phones, bad calls? The influence of consumer mobile phone use, distraction, and phone dependence on adherence to shopping plans. *Journal of the Academy of Marketing Science, 47*(4), 574–594. https://doi.org/10.1007/s11747-019-00647-9.
Simon, H. A. (1955). A Behavioral Model of Rational Choice. *The Quarterly Journal of Economics, 69*(1), 99. https://doi.org/10.2307/1884852.
Stoll, M., Baecke, S., & Kenning, P. (2008). What they see is what they get? An fMRI-study on neural correlates of attractive packaging. *Journal of Consumer Behaviour, 7*(4–5), 342–359. https://doi.org/10.1002/cb.256.
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., Hayhoe, M. M., Land, M. F., & Ballard, D. H. (2011). Eye guidance in natural vision: Reinterpreting salience. *Journal of Vision, 11*(5), 5. https://doi.org/10.1167/11.5.5.
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.
Valenzuela, A., & Raghubir, 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.
Van der Lans, R., Pieters, R., & Wedel, M. (2008). 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. M. (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.
Visschers, V., Hess, R., & Siegrist, M. (2010). Health motivation and product design determine consumers' visual attention to nutrition information on food products. *Public Health Nutrition, 13*(7), 1099–1106. https://doi.org/10.1017/S1368980009993235.
Walther, D., & Koch, C. (2006). Modeling attention to salient proto-objects. *Neural Networks : The Official Journal of the International Neural Network Society, 19*(9), 1395–1407. https://doi.org/10.1016/j.neunet.2006.10.001.
Wansink, B. (1996). Can Package Size Accelerate Usage Volume? *Journal of Marketing, 60*(3), 1. https://doi.org/10.2307/1251838.
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.
Wedel, M., & Pieters, R. (2000). Eye Fixations on Advertisements and Memory for Brands: A Model and Findings. *Marketing Science, 19*(4), 297–312. https://doi.org/10.1287/mksc.19.4.297.11794.
Yang, L., Toubia, O., & de Jong, M. G. (2015). A Bounded Rationality Model of Information Search and Choice in Preference Measurement. *Journal of Marketing Research, 52*(2), 166–183. https://doi.org/10.1509/jmr.13.0288.
Zhang, J., Wedel, M., & Pieters, R. (2009). Sales Effects of Attention to Feature Advertisements: A Bayesian Mediation Analysis. *Journal of Marketing Research, 46*(5), 669–681. https://doi.org/10.1509/jmkr.46.5.669.
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.
Zlatevska, N., Dubelaar, C., & Holden, S. S. (2014). Sizing up the Effect of Portion Size on Consumption: A Meta-Analytic Review. *Journal of Marketing, 78*(3), 140–154. https://doi.org/10.1509/jm.12.0303.
Zuschke, N. (2020). 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.

Nick Zuschke holds a PhD in marketing. His main research interests are (i) in the area of consumers' cognitive processes during decision-making, and (ii) in methodological approaches that enrich discrete choice experiments with decision process measures, such as those using eye tracking.