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Examining consumers' decision-making by means of eye tracking in lab and field settings

PhD dissertation

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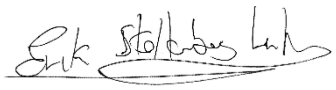

Erik Stoltenberg Lahm

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Executive Summary

In recent years, behavioral scientists, as well as policy makers have shown increasing interest in choice architecture. However, if policy makers want decision-makers to act, they need to capture their attention. An understanding of how to capture their attention would benefit many stakeholders and lead to more effective policy making. Through a series of experiments, this thesis investigates the factors which capture the decision-makers' visual attention and how this influences their decision-making.

Paper I meta-analyzed empirical studies on the eye movements in decision-making and provided a quantitative overview of the factors driving them in the same. We found that seemingly arbitrary properties of the visual environment, such as the, size, salience, or positioning of information, influences the information that we attend to, thus biasing our intake of information. This is a unique finding that calls into question several assumptions about how decision-makers search for and integrate information in their visual environment. The magnitude of the effect of our visual environment is quite substantial and cannot be ignored while designing visual information.

Paper II investigated how these visual properties emerge in our everyday environment and found that these work as a barrier for the successful integration of relevant information. Second, we tested the robustness of these properties against the consumers' health motivations and found that irrespective of the motivation, the environmental properties are capable of capturing visual attention, and this has a direct influence on the consumers' choice.

Paper III extended the toolbox of visual properties by introducing a new structure to the visual environment, namely the perceptual grouping of relevant information, and discovered that this phenomenon can lead consumers to attend grouped information with a higher likelihood.

Paper IV concludes the thesis by showing how the perceptual order in which consumers intake information is essential in how and what they end up choosing. This effect was tested in both a laboratory experiment and replicated in a traditional supermarket.

This thesis makes the following conclusions; while it is true that consumers preferentially attend to options that align with their goals, preferences, or habits, environmental features play a role in determining which information is attended, and more importantly, what goes unnoticed and therefore will not be taken into consideration while the consumers are making decisions.

Danish Summary

Inden for de senere år har forskere såvel som politiske beslutningstagere udvist en stigende interesse for adfærdsdesign. Såfremt politiske beslutningstagere ønsker, at befolkningen skal forandre sig, er de nødt til at fange deres opmærksomhed. En bedre forståelse for, hvordan man fanger individers opmærksomhed, vil komme mange interessenter til gavn og leder til mere effektive politiske interventioner. Gennem en række eksperimenter undersøger denne afhandling, hvilke faktorer der påvirker individers visuelle opmærksomhed, og hvordan dette påvirker deres beslutningsproces.

Den første artikel metaanalyserer empiriske studier omhandlende øjenbevægelser i beslutningstagning og giver et kvantitativt overblik over, hvilke faktorer der har effekt på beslutningstagning. Vi fandt, at tilsyneladende vilkårlige egenskaber i det visuelle miljø som f.eks. størrelse, saliens eller position af information påvirker, hvilken information der bliver kigget på. Derigennem skaber det et bias for vores informationsindtagning. Det er et unikt resultat, der sætter spørgsmålstegn ved de nuværende forudsætninger om, hvordan beslutningstagere søger og integrerer information i deres visuelle miljø. Vigtigheden af vores visuelle miljøs indvirkning på vores opmærksomhed kan ikke ignoreres, hvis vi ønsker succesfuld integrering af visuel information.

Den anden artikel undersøger, hvordan disse visuelle egenskaber opstår i vores hverdagssituationer og fandt, at måden, hvorpå vores visuelle miljø er struktureret, fungerer som en barriere for at se og integrere relevant information. Derudover testede vi, hvor robust denne effekt var over for forbrugernes mål og præferencer. Vi fandt, at uanset forbrugerens mål så er det visuelle miljø i stand til at fange folks opmærksomhed, og dette har en direkte påvirkning på deres valg.

Den tredje artikel udvider forståelsen fra den første og anden artikel ved at introducere en ny metode, hvorpå det visuelle miljø kan fange folks opmærksomhed. Ved brug af perceptuel gruppering

af relevant information fandt vi, at dette kan lede folks opmærksomhed til den grupperede information med en større sandsynlighed, end havde det ikke været grupperet.

Den fjerde artikel afslutter denne afhandling ved at påvise, hvordan rækkefølgen af informationsindtagning påvirker forbrugerens endelige valg. Denne effekt blev testet både i et laboratorieeksperiment, og senere replikkerede vi effekten i et supermarked.

Denne afhandling konkluderer følgende; mens det er sandt, at forbrugerne kigger på ting, der er i overensstemmelse med deres mål, præferencer eller vaner, har vores visuelle miljø en afgørende betydning for, hvilken information der ultimativt bliver kigget på. Det vigtigste er imidlertid, hvad der går uset hen, da dette af naturlige årsager ikke vil blive taget i betragtning, når vi foretager vores valg.

Contents

1

Introduction

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It turns out that the environmental effects on behavior are a lot stronger than most people expect.

Daniel Kahneman

Most of the decisions we make as citizens and consumers take place in a visual world. If we think of our latest Google search or trip to the supermarket, we use our eyes to inspect the search results or the available products. Most of our decisions are based on visual information. This means that how we search and integrate visual information plays a crucial role in our buying decisions. Visual decision-making is a special kind of task in which information is valued differently in every case due to variations in the visual environment (Gold & Stocker, 2017). Naturally, this mitigates how consumers receive information. For instance, policy-makers normally assume that if consumers are provided will all relevant information before making a decision, they will make informed choices (John, 2018). However, as mentioned above, this is often not sufficient, unless the policy-makers have carefully considered how consumers integrate visual information in the exact context in which a decision is made. Otherwise, there is a risk that the information goes unnoticed. Understanding the processes of visual decision-making is, therefore, paramount to ensure that information is used by consumers. In recent years, policy-makers have shifted their focus from seeking to inform the public to influencing them using choice architecture, more universally known as nudging (Thaler & Sunstein, 2008). Nudging is a choice manipulation that guides the decision-makers’ behavior in a predictable manner and yet, maintains their freedom of choice. However, there are some barriers to successful nudges. Consider how, in 2008, the city of New York became the first city to enact mandatory calorie labeling legislation in fast-food restaurants, a public health strategy intended to steer consumers away from unhealthy food consumption. Against the policy-makers’ expectations, no favorable differences in the calorie intake were observed as a result of the labeling. However, those consumers who noticed the calorie labels consumed fast food to a lesser extent less than those who did not notice the labels (Vadiveloo, Dixon, & Elbel, 2011). The Scandinavian countries have introduced similar interventions in an attempt to nudge consumers toward healthier eating by labeling the healthier alternatives within a product category (Ministry of Environment and Food of Denmark, 2018). Most findings show that consumers do not use all the information as they rely on other decision cues (Orquin, Chrobot, & Grunert, 2018). However, as the research in this dissertation showcases, if consumers attend to the labeling, it might work to change their choice (Paper 2).

Not only is our visual attention important for making good decisions, so too is the environmental structure, which can play a crucial role in our decision-making. Instead of informing people with labels, choice architects have been changing our environment for a while. For instance, Freedman and Brochado (2010) changed the portion sizes in a college canteen and found it to reduce food consumption. Similarly, Ensaff et al. (2015) changed the layout of a canteen and found that people ate fewer calories when calorie-dense food was not kept in a clear view. In Denmark, the largest retail store has reduced its sales of tobacco by removing it from the shelf (*"20 millioner færre solgte cigaretter i Netto, føtex og Bilka"*, 2019). Similar effects have been found in restaurant menus where customers were presented with alternative versions of a menu in which the healthy food was presented at the top, the middle, or the bottom of the menu card (Dayan & Bar-Hillel, 2011). The study found that customers were more likely to choose food options at the top of the menu. This branch of attention mechanisms can be described as a bottom-up process or an environmental order effect (for an elaboration, see section below). The idea that behavior could be influenced without informing people first is not new. It has been a core focus of psychological and behavioral sciences over decades Broers, De Breucker, Van den Broucke, & Luminet, 2017; Thaler & Sunstein, 2008; Tversky & Kahneman, 1973). However, the former cases illustrate the importance of understanding the attention process since it is fair to say that a better understanding of the consumers' visual attention would have increased the success of the policy intervention. Put differently, for nudging to be effective, the policy-makers depend on people paying attention to certain aspects of the environment. Therefore, despite its intuitive appeal, the processes behind visual decision-making are poorly understood, and as the above cases illustrate, it can sometimes work as a direct hindrance to the effectiveness of consumer policies. This is why a deeper understanding of visual decision-making is fundamental for effective consumer policies. However, many other areas, such as marketing, financial, or medical decision-making, may also benefit from this approach.

The four papers in this dissertation are driven by the desire to understand better:

What drives visual attention in decision-making?

In particular, the papers are motivated by how visual properties capture our attention. This is done by integrating vision and decision research in an attempt to bridge the understanding of what and when attention affects choices. To address this overarching question, the first paper of the present dissertation meta-analyzed empirical evidence of the role of visual attention in the decision-making literature. It provides guidance on what has been learned so far, reviewed factors that guide visual attention, and quantitatively synthesized their relative importance.

One of the major contributions from the meta-analysis is the discovery of the importance of our visual environment in guiding attention. A finding calls into question several assumptions about how decision-makers search for and integrate information in their visual environment. Thus, the second paper deals with the environmental factors of our visual environment and how these can act as potential barriers for the integration of visual stimulus. We showed that enhancing the visual conspicuity of nutritional labels increased the likelihood that consumers attended this information, and used this in their decision-making. Therefore, we concluded the paper with concreate recommendations for policy-makers to enhance visual attention.

In the third paper, I wanted to extend the knowledge from paper II. However, in the places where the recommendations from the second paper rely on a paternalistic view, that is, in order for the recommendations to be successful, product designers are forced to give up space from their brand-related attributes in favor of nutritional and credence information. Therefore, I wanted to address barriers in the environment alternatively, to investigate whether a less dramatic change of the micro-environment, that is, product packaging, could bypass the barriers to the successful integration of information. By means of gestalt properties, I investigated whether perceptual grouping of nutritional labels could bypass the environmental barriers found in the second paper. This paper contributes with a new application of gestalt principals on product packaging and can be used to close the gap in interest, where both product designers and policy-makers can benefit from the perceptual grouping of nutritional information.

While the first three papers focus mainly on factors that influence visual attention, the fourth paper investigates the downstream effect of visual attention on choice. More specifically, it was investigated how the perceptual order of integrating visual information impacts the decision-makers' choice. The order effect has been shown numerous times to have a downstream effect on choice (Bar-Hillel, 2015). More specifically, I was interested in understanding this phenomenon in consumer decision-making by understanding consumers' search behavior and how this influences the perceptual order of information integration in simultaneously presented visual environments free of mere position effects, that is, the position in which information occurs is uncorrelated with its decision value. In both a controlled laboratory experiment and a supermarket, the perceptual order had an influence on the consumers' choice, where products seen first were more likely to be chosen.

In what follows, I first introduce the basics of attention and how to measure it. Second, I briefly discuss the history of the role of eye movements in the decision-making literature, and this introduction is rounded of by summarizing the known factors influencing visual attention. I conclude with the overall contribution and an overview of the four scientific papers included in this dissertation.

How to measure attention

Many methods have been proposed to measure attention in decision-making, all under the umbrella term *process tracing*. The overarching goal of process tracing is to understand the cognitive process underlying decision-making. *"It offers a window onto the cognitive processes that result in a preference or an inference"* (Schulte-Mecklenbeck, Sohn, de Bellis, Martin, & Hertwig, 2013, p. 243; see also Schulte-Mecklenbeck et al., 2011). Some methods of process tracing are indirect, inferring attention through a person's behavior, while others more directly measure what people process at a given time, such as eye tracking and neurological processes (Schulte-Mecklenbeck et al., 2013). This dissertation relies on eye tracking as a measure of attention. However, before applying the eye-tracking methodology, it is important to understand how the eye movement process works. This section, therefore, works as a review of the basic understanding of eye movements. First, it is important to understand that even though we experience our visual environment as a whole and clear picture, we experience high visual acuity only within a limited part of our visual field at about a 2-degree visual angle (equivalent to the size of your thumbnail if you outstretch your arm). This part of high acuity is called our fovea, and we are constantly moving our eyes to redirect our fovea to the details of interest in our visual space (Henderson, 2003). Second, it is important to understand that our visual system consists of two main mechanisms. To maintain high acuity in the fovea, our eyes need to be positioned in a relatively still manner on the object of interest, which has to be in the fovea for about 200–500 msec. This is known as a fixation, that is, periods of high visual acuity. To fixate another object, we need to reposition our eyes toward that object. This is done by moving our eyes swiftly over the visual environment. This type of eye movement is known as saccades and lasts for approximately 40 msec. During saccades, there is little if any visual processing of the environment (Duchowski, 2007). This is where eye-tracking analysis becomes interesting. Even though eye tracking is subject to a methodological hype (Orquin & Holmqvist, 2018), the technic is not new. Eye tracking can be dated back to as far as the late 1800s, where Louis Émile Javal manually observed individuals' eye movements while reading a text (Huey, 1908). The first automated eye tracker was invented at the beginning of the 19th century (Young and Sheena, 1975), where individuals were fitted with a metallic contact lens which used a plaster of paris ring attached directly to the cornea and through mechanical linkages to recording pens, which was likely to have been a rather unpleasant experience for them. Nowadays, eye tracking has become a fairly simple process, while the methodology for the same varies slightly between different types of hardware. It most commonly relies on cornel reflection, where the eye tracker sends out a small infrared light into the eye (Holmqvist et al., 2011). The image captured by the camera is then used to identify the reflection of the light source on the cornea and in the pupil. From there, one can calculate a vector formed by the angle between the cornea and pupil reflections; the direction of the vector can then be used to calculate the fixation direction (Duchowski, 2007). Since we experience high visual acuity only during fixations, measuring the position of the eyes becomes increasingly useful for understanding the attention process. Being able to use eye movements to help identify the nature of the attention process depends on one critical assumption — that the participants' fixation process reflects the attention process. However, this assumption is relatively easy to falsify by empirical evidence. For example, by asking participants to maintain their gaze while performing a peripheral discrimination task, attention is readily dissociated from the gaze direction; in other words, people can voluntarily decouple attention and vision by fixating at one location while attending to stimuli in another location (Posner, Snyder, & Davidson, 1980). Despite this knowledge, most of the work studying eye movements to understand the attention process takes this assumption for granted. A question worth pondering is whether this is due to the fact that researchers in eye tracking are particularly naïve. For instance, there is an alternative case where eye movements are unrelated to visual attention; that is, eye movements occur in completely random ways with respect to the underlying cognitive process.

Why it is true that it is possible to decouple eye movements from attention or, in contrast, shift gaze without also shifting attention is impossible (Deubel & Schneider, 1996). Owing to this and the fact that this decoupling effect is usually rare, most eye-tracking studies in decision-making do not consider this as an issue (Orquin & Holmqvist, 2018). In sum, given the abovementioned, I believe it is fair to conclude that attention and eye movements are co-occurring and thus can be used informatively to infer attention. Concerning visual decision-making, we can apply this knowledge to infer that, if an object receives no fixation, it is unseen and, therefore, unavailable for the decision-maker and will not enter the decision-making phase (as in the case of the New York City labeling scheme). However, this applies only in unfamiliar situations since, in familiar environments, the decision-maker can use his spatial memory to actively ignore specific elements before they are perceived (Orquin et al., 2018).

Understanding the role of vision in decision-making

We begin by coveting what we see every day. … and don't your eyes seek out the things you want?

H. Lecter in *The Silence of the Lambs*

The role of vision is, unsurprisingly, to acquire information about the world around us. For a long period, decision research has held that this is the *only* role of vision. Historically, most decision-making theories posit that the decision-makers acquire all information presented to them, and from here, it follows that our eyes are to passively acquire this information (Orquin & Mueller Loose, 2013). However, decision-makers frequently fail to acquire even relevant information. Take, for instance, the New York City example. Here, only a small piece of information is presented. However, many consumers failed even to attend to it. Even in relatively simple environments, where only two pieces of information are presented, participants in a laboratory study frequently failed to acquire *all* information (Ashby & Rakow, 2014). The neo-classical view on decision-makers would label such a failure to acquire all information as an irrational behavior (Orquin, Bagger, & Mueller Loose, 2013). However, several theories and paradigms have been interested in understanding how the visual environment enters the mind of the decision-maker. To explain the observation of inattention, Herbert Simon (1956) proposed that instead of being irrational, decision-makers were actively choosing to adapt to the visual environment by employing a satisficing heuristic, that is, a strategy exploiting shortcuts in an environment, such as ignoring irrelevant information (Simon, 1956). The satisficing heuristic prescribes that decision-makers search through choice options one at a time until a sufficiently satisfactory option has been identified. The process guarantees a satisfactory choice without the burden of attending to all information. The satisficing heuristic later became part of a wider toolbox of heuristics that decision-makers can apply to any decision problem. The toolbox program, highly advocated by the ABC group led by Gerd Gigerenzer, has placed special emphasis on the relationship between the human mind and the nature of the environment (Gigerenzer & Selten, 2002). In other words, heuristics are a product of learning from the environment and, therefore, often lead to positive outcomes for the decision-maker. Results of computer simulations of heuristics have been found to lead to accurate judgments and even outperform more rigorous models, such as the regression of all information (Gigerenzer et al., 1999). Although bounded rationality and toolbox models, in particular, have taken an important step toward the psychological process models of decision-making, they have maintained the assumption that vision is passively determined by the heuristic (Orquin & Mueller Loose, 2013).

More recently, a new branch of theories has departed; they differ from toolbox models in their assumptions about visual search in decision-making. These evidence accumulation models propose that eye movements play a constructive role in decision-making. The essence of accumulation models is that while consumers attend to an option, they accumulate evidence in favor of that option, and the preference for this option will increase relative to all unattended products. In a nutshell, unattended products accumulate less evidence and hence are less likely to be chosen by the consumer (Krajbich, Armel & Rangel, 2010). This view is corroborated by a range of studies demonstrating that directly manipulating attention in favor of an option increases the likelihood of choosing that option (Armel, Beaumel, & Rangel, 2008; Krajbich, Armel, & Rangel, 2010; Shimojo et al., 2003). In the most recent advances of evidence accumulation models, the visual environment has been considered so that visually prominent options that are more likely to attract attention are also more likely to be chosen (Towal, Mormann, & Koch, 2013). For example, in a study by Milosavljevic and colleagues (2012), they manipulated the relative visual salience of choice options and found visual saliency to influence choices more than preferences. Moreover, this bias increased with a cognitive load, that is, when the decision-maker was faced with too much information or was under time pressure. This effect became particularly strong when participants did not have strong preferences for any of the options (Milosavljevic, Navalpakkam, Koch, & Rangel, 2012). The development of evidence accumulation models has led to a heightened appreciation of the role of vision in decision-making, and the models have become even more sophisticated in describing the perceptual process. Given the compelling evidence suggesting that eye movements influence the decision process (Ghaffari & Fiedler, 2018, Pärnamets et al., 2015; Reeck et al., 2017; Shimojo et al., 2003), it is not surprising that researchers strive to understand eye movements in decision-making better.

Factors known to influence visual attention

The main drivers of visual attention are more thoroughly discussed in Paper 1, where I reviewed and meta-analyzed the main drivers of visual attention and synthesized the effect size thereof. The scope of this section is to provide the reader with an overall understanding of the two main drivers of visual attention. Considerable evidence has been gathered to indicate individual factors guiding visual attention. In vision research, these factors are often referred to as top-down and bottom-up control of attention, occasionally referred to as endogenous and exogenous attention. The former refers to the influence of goals, task instructions, and motivation in driving attention (also defined as goal-driven attention), whereas the latter refers to the influence of the environment in attention capturing, also defined as stimulus-driven attention (Corbetta & Shulman, 2002). It is important to think of visual attention as consisting of both processes; however, much of the literature has been concentrated around top-down attention (for reviews see Orquin & Mueller Loose, 2013; Wedel & Pieters, 2008). While traditional theories in decision-making concerned themselves with rational processing of the environment as mentioned in the previous section, the emphasis now is on analyzing the unconscious stimulus-driven response, such as bottom-up control (Karmarkar & Plassmann, 2019). Currently, there is an ongoing debate about the relative contribution of the two processes in different environments.

On the one hand, it has been argued that in natural environments visual attention is purely top-down driven, not acknowledging visually conspicuous properties as bottom-up control to influence attention (Tatler, Hayhoe, Land, & Ballard, 2011; Theeuwes, 2010). On the other hand, both in the laboratory and in real-world supermarkets, there is evidence suggesting that bottom-up control plays an active role in capturing the consumers' attention (Enax & Krajbich, 2016; Gidlöf, Anikin, Lingonblad, & Wallin, 2017; Milosavljevic et al., 2012). Hitherto, bottom-up and top-down controls have mainly been investigated separately; however, few attempts have been made to understand the relative contribution of the two processes in decision-making. Among the scarce literature that has examined both these aspects simultaneously, they suggest that top-down control exerts a larger influence than bottom-up control (Orquin & Lagerkvist, 2015; Orquin, Bagger, & Loose, 2013). Needless to say, it still remains an unsolved question as to what extent we can attribute each control to influence decision-makers' attention and how much weight should be given to each control. This is an important question for the decision-making literature since a better understanding of the relative contribution of top-down and bottom-up control will benefit models of decision-making substantially.

I will round this section off with two examples, which I believe clarify the importance of understanding visual attention.

As an example, imagine yourself in a situation where you are craving for a snack after a rough day, and decide to visit a fast-food joint like McDonald's. When entering the restaurant, one is well aware that this is not a restaurant where healthy food is available. However, when a person orders the burger, he/she so badly craved for the entire day, he/she is faced with a calorie label, and it is red and screams high on calories. Even after having seen it, however, it is unlikely that the person changes their mind and decides to order a bag of carrots. Therefore, even though the label communicates its value, it is ignored, and visual manipulation failed to change the decision because there was a strong preference for that burger. In line with much of the research that has been presented here, to be influencing consumers effectively through visual manipulation, one must not hold strong preferences.

As another example, the amount of small personal loans issued has increased by roughly 270% between 2015 and 2018 in Denmark (Vild vækst i kviklån). Thinking of the economic irrationality of taking such a loan and the medias covered hereof, it is a remarkable increase. A question to be pondered is whether this is because people are unaware of the consequences (extreme annual costs as a percentage (ACP)) of these loans. To some extent, this is true. However, the visual presentation also plays a crucial role. When these loans normally are advertised, they use emotional stimuli with pictures and texts evoking the ease of processing and the joy of extra cash. However, such advertising is also under regulation by law (Bekendtgørelse af lov om kreditaftaler, 2014). For instance, lenders are obligated to state “clearly” the ACP. However, how “clearly” is defined is open to debate because, for most of this advertising of small personal loans, the ACP is hidden at the bottom among other texts. A recent study by Leboeuf, Choplin, and Stark (2016) found a negative correlation between participants' likelihood to accept a loan and a fixation on ACP. This study clearly indicates that visual attention is an important attribute required to prevent predatory lending, since it seems that when individuals are attending (have fixated) the ACP they realize the economic consequences of the loan in front of them, and creditors are aware of this, since they clearly want to prevent individuals from viewing it, by hiding it.

These two examples illustrate, to some extent, the context-specific elements of visual decision-making. In the fast-food example, the nutritional label was successful for the consumer, but the context was wrong, as one has already decided and holds a strong contextual preference for the burger, and visual attention could not change anything. However, in our second example, visual attention becomes pivotal for the integration of information and choice, since increasing the likelihood of individuals noticing the economic consequences of their action decreased the likelihood of them acting.

Overview of Scientific Papers

This chapter contains an overview of the four scientific papers included in this dissertation. The main results and contribution of each paper are summarized. The papers are organized thematically but not chronologically. Together, they present a picture of the role of eye movements in decision-making and how we can use these insights to guide attention. The papers can be read as they are presented or in any given order of the reader’s choice.

Table 1. Overview of scientific papers included in the dissertation.

Paper	Title	Data/participants	Study design	Main findings	Status
I	A Meta-Analysis of Eye Movements in Decision-Making	Final sample of 54 research articles	Psychometric meta-analysis	While top-down control explains most of decision-makers' visual attention, bottom-up features such as; surface size, set size, positioning, and salience explain an unexpectedly large role.	Under preparation for submission to Psychological Bulletin
II	The Visual Ecology of Product Packaging	Study 1: *N* = 91 completing 120 trials	Study 1: In the first part of Study 1, we analyze the environmental structures of 159 product packages to assess their visual ecology. The second part of Study 1 was a controlled lab experiment. The study used an incomplete randomized block design with 24 versions with 5 choice sets in each resulting in 120 trials.	Study 1 shows that the visual ecology of product packaging has a predictable structure. Packaging elements central to the brand positioning such as the logo, brand, and picture are consistently more salient, larger, and more centrally positioned than packaging elements that relate to socially desirable credence characteristics such as health and sustainability. We also show that this ecological structure plays a large role in determining consumer attention. All three bottom-up factors—salience, size, and distance to center—influence the probability of consumers fixating a product packaging element.	Published in Journal of Business Research

		Study 2: $N = 72$ completing 140 trials	Study 2: Controlled lab experiment utilizing a two-alternative choice experiment with a full factorial mixed within between-subjects design manipulating health motivation between-subjects factor and bottom-up factors as with-in. All were presented twice, resulting in 140 trials.	We find that all bottom-up factors, including set size, influence fixation likelihood. Regarding top-down factors, we find no effect of a health goal or health priming on fixation likelihood, either as main or interaction effects with bottom-up factors.	
III	Perceptual Grouping can Increase Consumers Attention	Study 1: field study with 419 FMCG products	Field study in three of the largest retail stores in Denmark counting the prevalence of perceptual grouping on product packages.	Grouping nutritional labels closely can lead to increases in visual attention.	Under review in Food Quality and Preference
		Study 2: $N = 18$ completing 64 trials	Controlled lab experiment with a fractional factorial within-subjects design manipulating label grouping and position.	Study 2 revealed that perceptual grouping could influence consumers' eye movements if they are directed toward one element of the group. That is, if participants fixated the target label, they were more likely to fixate the grouped label in the grouped condition.	
		Study 3: $N = 32$ completing 128 trials	Controlled lab with a full factorial within-subjects design	In Study 3, when participants were under time pressure, this effect disappeared.	

			manipulating label grouping and position.		
IV	The Effect of Fixation Order on Choice	Study 1: *N* = 32 completing 90 trials	Controlled lab experiment within-subjects design manipulating the set size.	Study 1 shows how the perceptual order can influence consumer choices as a primacy effect, where products seen first are more likely to be chosen compared to products seen later. However, this effect arises merely as a function of how consumers search for information. As set sizes become large, participants are more likely to ignore a growing percentage of products. We computed the probability of choice given fixation order across set size and found a primacy effect on consumers' choice for large set sizes, but no effect for the smallest set sizes.	Working paper
		Study 2: *N* = 56	Quasi-experimental field study using three different product categories in a supermarket.	In Study 2, we replicated the order effect in natural environments more precisely in a supermarket.	

Paper I - A Meta-Analysis of Eye Movements in Decision-Making

Purpose: The purpose of the first paper in this dissertation is to understand the role of eye movements in decision-making. Here, under review, the visual factors which are known to influence visual attention and to aid in understanding the magnitude of the effect of these factors has been discussed

Methodology/procedure: The paper meta-analyzes 58 empirical studies on eye movements in decision-making and provides a quantitative overview of the factors driving eye movements in decision-making. To perform our analysis, we have developed procedures for how to handle issues related to multiple AOIs, multiple metrics, and eye-tracker validity. The procedure for handling eye-tracker validity showed that eye trackers with poorer accuracy in general lead to smaller effect sizes.

Results and conclusion: The results show that internal top-down factors, such as task instruction, preferential viewing, and choice bias, explain the larger part of eye-movement control as predicted by several decision theories. Moreover, external bottom-up factors, such as surface size, position, salience, and set size, play an unexpectedly large role considering that most models assume no role for these factors.

Implications: Our meta-analysis is, to the best of our knowledge, the first to quantitatively summarize findings on top-down and bottom-up control of eye movements in any discipline, including vision science. Naturally, other disciplines may want to take stock of these findings and will have to evaluate the generalizability of the findings to their respective discipline.

Our findings question several assumptions about how decision-makers search for and integrate information. A question to be raised here is why future models in decision-making should incorporate this knowledge to understand and predict the decision-makers’ attention better. Policy-makers and other stakeholders should recognize the importance of the visual environment while developing interventions for enhanced decisions.

Paper II - The Visual Ecology of Product Packaging

Purpose: The purpose of this paper is to explore the concept of visual ecology in consumer research. It aims to answer the research question, which features the consumers' response to the visual environment and what is the structure and distribution of these features. This question is addressed in the context of product packaging.

Methodology/procedure: Study 1 was split into two parts. In the first part of Study 1, we analyzed the environmental structures of 159 product packages to assess their visual ecology. The second part of Study 1 was a controlled lab experiment. The study used an incomplete randomized block design with 24 versions with five choice sets in each, resulting in 120 trials. Study 2 utilized full factorial mixtures within-between subjects design, manipulating health motivation (control, health goal, and health priming) as a between-subjects factor, and target label salience (high, low), target label surface size (small, large), and target label distance to center (ranging from 463 to 208 pixels) as within-subjects factors.

Results and conclusion: Analyzing images of 158 consumer products, we find that within each product, packaging elements have highly predictable visual features. Packaging elements that are closely related to the brand are generally more visually conspicuous, while elements related to credence characteristics such as sustainability and nutrition, which are not necessarily part of the brand positioning but have been added because such information is regarded as socially desirable, are less conspicuous in terms of color, size, and position. We show that these differences influence the consumer attention to specific packaging elements. In the second study, we address some of the limiting conditions of the first study and show that the visual ecology of consumers exerts a strong influence on attention independently of consumer goals. We conclude with predictions of how a change in the conspicuity of packaging elements, due to brand repositioning or policy intervention, might influence consumer attention.

Implications: Understanding the visual environment of consumers can help policy-makers and marketers alike to understand why consumers regularly ignore nutritional information. It would benefit consumers to design interventions that overcome the environmental barriers for successful integration by, for instance, increasing the visual conspicuity of important information.

Paper III - Perceptual Grouping

Purpose: The paper aims to investigate whether a less dramatic change of the micro-environment, that is, product packaging, could bypass the barriers for the successful integration of information. Using gestalt properties, I investigated whether perceptually grouping of nutritional labels could bypass the environmental barriers. Thus, this paper examines the effect of the perceptual grouping of nutritional labels in guiding the consumers' attention.

Methodology/procedure: Study 1 is a field study investigating the prevalence of nutritional label grouping in three different supermarkets in Denmark. Studies 2 and 3 are laboratory experiments utilizing a within-subjects design, manipulating the perceptual grouping of nutritional labels in the context of product packaging. The participants were instructed to perform a preferential choice task in both studies.

Results and conclusion: The paper examines whether the perceptual grouping of nutritional labels can guide the consumers' attention. This phenomenon is tested in three individual studies. In Study 1, the hypothesis was tested by analyzing the prevalence of perceptual grouping in 419 product packages. A prevalence of perceptually grouped nutritional labels was observed when the product characteristics allowed it to. Furthermore, a predicable positional structure was observed, in which groupings appeared at specific positions of the package. In Studies 2 and 3, the hypothesis was tested experimentally, manipulating the grouping of nutritional labels on product packaging. To test the phenomenon of perceptual grouping, two experimental studies manipulating the grouping of nutritional labels on the product packaging were conducted. Study 2 revealed that perceptual grouping could influence the consumers' eye movements if they are directed toward one element of the group. In Study 3, when participants were under time pressure, this effect disappeared. While the effect of perceptual grouping is inconclusive at this point, our findings point toward a direction in which purely perceptual manipulation can guide the consumers' attention. This paper provides some interesting aspects for future research in the area of perceptual manipulation.

Implications: This paper contributes with a new application of gestalt principals on product packaging and can be used to close the gap of interest, where both product designers and policy-makers can benefit from the perceptual grouping of nutritional information. Without compromising brand-related elements, product designs and marketers alike can utilize grouping of nutritional labels to increase the likelihood that consumers notice the information. As a potential benefit, it could decrease the visual clutter and simplify the design further since grouped information requires less space than two separately positioned labels.

Paper IV - The Effect of Fixation Order on Choice

Purpose: The purpose of this paper is to understand the influence of the consumers' order of integrating the perceptual stimuli in their choice behavior.

Methodology/procedure: Study 1 was a laboratory experiment utilizing a with-in study design manipulating the number of available products and their positioning. Study 2 was a quasi-experiment in a supermarket. The participants were instructed to perform a preferential choice task in both studies.

Results and conclusion: We show how the perceptual order can influence consumer choices as a primacy effect, where products seen first are more likely to be chosen compared to the products seen later. However, this effect arises merely as a function of how consumers search for information. As set sizes become large, participants are more likely to ignore a growing percentage of products. We computed the probability of choice, given fixation order across set sizes, and found a primacy effect on the consumers' choice for large set sizes, with no effect for the smallest set sizes. Our findings suggest that the importance of perceptual order arises as consumers truncate their search as a response to the increasing information load.

Implications: These findings have interesting implications for policy-makers and marketers alike, understanding how the perceptual order influences the decision-makers' choices is pivotal for successful integration. If they wish to influence decision-making, they need to ensure that their key message is perceived early in the decision phase, failing which, there is a risk of being uninfluential.

Discussion and conclusion

This study aimed to gain a richer understanding of the role of visual attention in decision-making and how we can use this knowledge to attract the decision-makers' attention. The four scientific papers constituting this dissertation aimed to answer this question through the integration of state-of-the-art methodologies from vision and decision research under the different contexts of decision-making.

In **Paper I,** we meta-analyzed the empirical evidence on visual attention in decision-making. Our results show that the internal top-down factors such as task instruction, preferential viewing, and choice bias explain the larger part of eye-movement control as predicted by several decision theories. More interestingly, contrary to most model assumptions, we show that the external bottom-up factors, such as surface size, position, salience, and set size play an unexpectedly large role in capturing attention, considering that most models assume no role for these factors.

In **Paper II,** we tested the influence of the visual environment on the consumers' likelihood of successful integration of nutritional information. We found that how the microenvironment (product packaging) is structured serves as a barrier for consumers to attend to nutritional information. Since the structure of product packaging prioritizes brand-related packaging elements in terms of their visual conspicuity, while elements related to credence characteristics such as nutrition are visually inconspicuous. Furthermore, we showed that if we rearrange and prioritize nutritional information to become visually conspicuous, it increases the likelihood that consumers attended and used this information in their decision-making process. Finally, and quite interestingly, we found that these bottom-up features were robust against any manipulation of the top-down control. This opens up the question about when bottom-up and top-down controls have a stronger effect on attention. At the same time, we found that relevant and fixated information has the greatest influence on choice.

In **Paper III,** I wanted to expand the knowledge obtained from **Paper II,** especially if we can guide the decision-makers' attention to information without imposing any strict regulations to the original environmental structure. I did so by implanting principals from vision research, namely the gestalt principle to influence the likelihood that decision-makers successfully integrate nutritional information. By perceptually grouping nutritional information, I found a conditional effect on the likelihood that decision-makers attended to nutritional information; that is, if the decision-maker sees one object, the likelihood that she will fixate another object is higher when this is presented in proximity compared to when the same object is presented visually distant. The paper gives an interesting application for policy-makers, as I found a conditional effect on the fixation likelihood for grouped information. If policy-makers wish to introduce a new nutritional label, they can advantageously position the label near an already established and well-used label such as the organic label. This will increase the chances that decision-makers attend the label, and thus integrate it into their decision-making process.

In **Paper IV,** we investigated how the perceptual order of integrating visual information impacts the decision-makers' choice. The order effect has been shown numerous times to have a down-stream effect on choice (Bar-Hillel, 2015), but this has mostly been done in sequential pretentions or by experimentally manipulating the order of presentation. We were interested in whether this effect could be generalized to simultaneously presented information such as a supermarket shelf. We found a strong effect of order on the consumers' choice where objects seen first were more likely to be chosen. This effect unfolded in a controlled laboratory experiment where we randomized the positioning of alternatives so there was no correlation between the position and value. We replicated this finding in a supermarket, where the shelf position is known to be correlated with value. Two questions to be raised here address why we observe such an effect of visual search and whether it is because the consumers are particularly good at finding early in their decision search the options they prefer. The answer to the latter is a no. Regarding the former, we found that this effect arises as an effect of the consumers' response to the increasing information load they encounter in their decision process. They adapt to this by truncating their visual search. Hence, they are ignoring available information. It would be interesting to incorporate knowledge from visual properties such as bottom-up factors to affect the consumers' first fixation to test the boundary conditions of the order effect. To test the downstream effect, future research should strive to increase the knowledge of the order effect by testing the boundary conditions and the context effect by, for instance, incorporating knowledge from visual properties such as bottom-up factors to affect consumers' first fixation.

At a general level, the findings of this dissertation are useful for policy-makers and marketers who wish to influence decision-making alike, either by making individuals take certain information into account or by favoring certain choice alternatives above others. Since the way the information is presented will lead to differing integration of this information, I show that environmental factors that are visually conspicuous and often unrelated to our goal or preferences which influence what and when information is integrated, which potentially could lead to a bias in the information intake. Understanding how visual decision-making works is especially paramount for the new era of policy making that relies on behavioral changes or nudging since a better integration of this knowledge can help policy-makers overcome potential visual biases when individuals are to behave in a certain way. Policy-makers can, for instance, integrate this knowledge through regulations concerning the size and positioning of the most relevant information, such as nutritional information. Alternatively, they could ensure that the environment is not hostile, thereby increasing the likelihood that consumers integrate information in their decision-making process. While some policies actively deal with visual decision-making, such as the EU regulation 1169/2011 on the minimum visibility of nutrition labels (European Parliament, 2011), such paternalistic approaches may not be sufficiently effective. Instead, policy-makers could use the knowledge of visual decision-making in relation to regulations to influence the public behavior by actively changing the environment in which individuals are making decisions, such as changing the order of restaurant menus in a way that healthier alternatives come first to increase the likelihood that individuals choose more healthful products. On a theoretical level, this dissertation contributes to a greater knowledge of eye movements in decision-making, especially the importance of the visual environment. Future models of decision-making could benefit from integrating the knowledge of bottom-up control for a richer understanding of the consumers' decision-making process.

Limitations and future research

A potential limitation of the current work is that it relies on eye movements as a measure of attention, and as discussed earlier, this is an oversimplification. It simply cannot be ruled out that consumers are fixated on something while their minds are elsewhere. A good analogy to describe this can be a person's days as a student when he/she was watching the lecturer walking back and forth while thinking of the Friday bar instead. I am sure that this scenario or a similar one has occurred to you at least once. All of this implies that what I measure in my work is where people look, and not what people think. For the latter, other more sophisticated methods such as FMRI can be used to detect brain activity (Schulte-Mecklenbeck et al., 2011), which per se does not inform us about what people are thinking, but that they react to something. Whether that is internally or externally driven is hard to conclude on as well.

This being the case, I believe that eye tracking has something valuable to offer, while the inference of fixations is equal to attention may be a too hard assumption, in the other case, no fixation infers no attention, and seems more plausible (see Wästlund, Shams, and Otterbring, 2018, for an opposing view).

While the sample sizes of each experiment may at first glance seem low, the number of trials each participant performs is large. Furthermore, to minimize the likelihood that any of the experiments would be underpowered for the detection of a medium-sized effect, power analyses were conducted to determine the sample size and trial size as recommended by Simmons, Nelson, and Simonsohn (2011).

In designing studies, there will be a trade-off between the internal, external, or ecological validity of the methodology, which is why I believe it was particularly important to ensure a high internal validity to establish a better understanding of visual decision-making. To quote Campbell, “If one is in a situation where either internal validity or representativeness [external validity] must be sacrificed, which should it be? The answer is clear. Internal validity is the prior and indispensable consideration.” (Campbell, 1957, p. 310). Future research should test the ecological validity of these findings to generalize this to the real world. The question is whether results obtained in the laboratory generalize to more naturalistic settings, because, if we want to improve individuals’ decision-making, it is the natural environment decisions matter most. I believe that, before you try to generalize, you need to understand the true psychological mechanism, which can be performed only in environments with high internal validity. Only after that can we test the effect in natural environments to conclude the generalizability. This is a classic example of the trade-off between internal and external validity. As an infant, one needs to crawl before he/she can walk; the same holds with psychological research. Moreover, this dissertation never held generalizability as a top priority; rather, the primary purpose was to establish causality, which explains the experimental approach utilized in each empirical investigation.

Most of the work in this dissertation has shown the factors that influence visual attention. I have not, however, tested the context effect of these factors or the direct causality on choice. In Paper II, we found a downstream effect on choice from bottom-up factors, and in paper IV, we found that the relative order in which individuals’ intake information indirectly influences their choices. Where this dissertation has provided unique insights into which factors can attract visual attention, future research should test the boundary conditions of these effects, and if any, test the context effects.

Future models in decision-making should also incorporate the findings from this dissertation to enhance the predictability of choice models. Furthermore, it will be interesting in the future to test the boundary conditions for bottom-up and top-down control of attention, since this dissertation has not tested specific moderations or mediations of these effects. This is particularly interesting for policy-makers to see when visual disruption influences individuals' choices and when it does not. This will provide policy-makers with a broader knowledge of which tool to use from their visual toolbox.

Concluding remark

In four scientific papers, I have shown the important role of our visual environment and how this influences our attention and choices. I found that the environment can act as a barrier to the successful integration of information. While it is true that consumers preferentially attend to options that are in alignment with their goals, preferences, or habits, environmental features play a role in determining which information is attended and, more importantly, what goes unnoticed and, therefore, will not be taken into consideration when consumers are making a decision. Seemingly arbitrary properties of the visual environment, such as the color, size, saliency, or position, influence the likelihood of information to be fixated, which turns out to have a downstream effect on choice. Therefore, it is utterly important to investigate the decision-makers' visual attention.

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2

A Meta-Analysis of Eye Movements in Decision-Making

Under preparation for submission to Psychological Bulletin

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Abstract

As decision-makers, we rely on our eyes for gathering information on a vast number of tasks every day. A growing body of research attempts to understand the drivers of eye movements in decision-making and, hence, how decision-makers gather visual information. Different models have been proposed, assuming that eye movements are either driven by internal, so-called top-down factors, or external, so-called bottom-up factors. We meta-analyze empirical studies on eye movements in decision-making and provide a quantitative overview of the factors driving eye movements. Our findings reveal that the structure of the visual environment is operationalized through the bottom-up factors salience (ρ = .15), surface size (ρ = .39), centrality (ρ = .47), left vs right (ρ = .58), and set size (ρ = .34), has an unexpectedly strong influence on what decision-makers gaze at. The decision-makers gaze more at information that is relevant to their choice, either in terms of task goals (ρ = .50) or subjective preferences (ρ = .51) and gaze more at the eventually chosen option (ρ =.77) regardless of whether the choice is based on preferences or inferences. Our findings call into question many current assumptions about how decision-makers search information and provide a new foundation for future theory development.

Most of the decisions we are performing on a daily basis require visual integration, from navigating the street to reading the newspaper. Likewise, most research on decision-making concerns information that is given, i.e., visually presented. Take, for instance, the case of risky decision-making, where the decision-maker chooses between two gambles. The information in such situations is normally presented visually with respective probabilities and outcomes. Another example is multi-attribute choices in which information is often presented in a matrix-like format with alternatives and attributes in rows and columns. Both these examples rely on the decision-maker to utilize her eyes in order to process the provided information. Naturally, there is only one channel by which visual information can enter the mind of the decision-makers, namely through the eyes. Perhaps because of historical or practical reasons, much JDM research rests on the assumption that decision-makers see everything that is presented to them. However, there is abundant evidence to suggest that decision-makers do not attend all information, even in relatively simple studies where only two pieces of information are presented (Ashby & Rakow, 2014). This failure to attend the information is a serious threat to any model which assumes complete information processing (Van Loo et al., 2015). To make matters worse, it is also clear that decision-makers regularly spend more time attending to some information rather than other information and this attention asymmetry has been shown to influence choice (Ghaffari & Fiedler, 2018; Pärnamets et al. 2015; Reeck, Wall, & Johnson, 2017; Shimojo, Simion, Shimojo, & Scheier, 2003).

While inattention and differential attention may constitute a nuisance in some JDM research, several theories and paradigms have interested themselves about how the visual environment enters the mind of the decision-maker. The work by Herbert Simon on satisficing was one of the earliest theories describing when and why decision-makers ignore decision information (Simon, 1956). The satisficing heuristic prescribes that decision-makers search through choice options one at a time until sufficiently satisfactory options have been identified. The process guarantees a satisfactory choice without the burden of attending to all the information. The satisficing heuristic later became part of a wider toolbox of heuristics that decision-makers can apply to any decision problem. Theories about adaptive decision-making propose that decision-makers adapt to the environment by prioritizing among the available information and attending only to decision-relevant information. This adaptation to the environment is accomplished by applying decision strategies or heuristics that exploit shortcuts in the decision-making process (for reviews, see Gigerenzer & Gaissmaier, 2011; Payne, Bettman, & Johnson, 1992). While the heuristics, e.g., take-the-best, elimination-by-aspect, or lexicographic rules differ in their selection process, they make similar assumptions about visual search, and, hence, about the role of eye movements. These toolbox models assume that the information search is determined by the search rule expressed in the chosen decision strategy. More recently, a new class of models has been developed that differ from toolbox models in their assumptions about the visual search in decision-making. These evidence accumulation models propose that eye movements play a constructive role in decision-making. The aDDM model assumes, for instance, that the information is sampled sequentially and stochastically and that the decision-maker accumulates evidence in favor of an alternative until a decision threshold is reached. Specifically, decision-makers accumulate evidence for an alternative when they are looking at it (Krajbich, Armel, & Rangel, 2010). Similarly, the gaze cascade model assumes that looking at a choice option increases the preference for that option, but unlike the aDDM, it assumes that eye movements are guided by the value of options, i.e., decision-makers look more at preferred options (Shimojo et al., 2003). Another version of the drift-diffusion models assumes that eye movements are guided by both the value and the visual salience of choice options, i.e., both internal and external factors (Towal, Mormann, & Koch, 2013).

The theoretical diversification suggests a growing interest in more realistic models of visual search in decision-making. Considering the body of evidence that suggests that eye movements influence the decision process (Ghaffari & Fiedler, 2018; Pärnamets et al., 2015; Reeck et al., 2017;

Shimojo et al., 2003), it is not surprising that researchers should wish to understand eye movements in decision-making better. The direct comparisons between the theories described here are still lacking, and it is unclear which of these theories better explain eye movements in decision-making. It is, for instance, possible to imagine that internal factors, such as the decision strategy and the value of the choice options account for all or a larger proportion of variance in eye movements while external visual factors only account for a smaller share of variance (Tatler, Hayhoe, Land, & Ballard, 2011; Wedel & Pieters, 2006). In this paper, we aim to advance our understanding of this topic: by meta-analyzing empirical studies on eye movements in decision-making. The resulting synthesis will serve as a basis for future theory development by quantifying the factors influencing eye movements in decision-making.

Top-down and bottom-up factors

In vision research terminology, eye movements are driven by either top-down or bottom-up controlled processes. The models reviewed above differ in their assumptions about the relative role of these two processes. Top-down control refers to factors such as the decision-makers' goals or motives; for instance, the decision strategy or task, while bottom-up control refers to the influence of the visual environment, for instance, the visual prominence or the location of stimuli. The terms top-down and bottom-up control are used to describe several factors which we review below.

In terms of bottom-up control, a great deal of research in vision science has concentrated on the *visual salience* (for reviews see Borji & Itti, 2012**;** Corbetta & Shulman, 2002). The term visual salience refers to the items that differ from their surroundings in terms of visual conspicuity. Eye movements are attracted to the stimuli that differ from their surroundings if those differences are large enough. Several models of visual salience have been proposed, based on various visual aspects such as color, contrast, or movement (Itti & Koch, 2001). These models draw on the assumption that the visual attention is parallel encoded and that the saliency computes a topographic salience map to guide the attention selection (Itti & Koch, 2000). Salience, as a concept, has been subject to debate in vision science, with some scholars suggesting that there may be no true effect of salience. A growing body of research has examined the influence of salience in decision-making (Orquin & Lagerkvist, 2015; Towal et al., 2013; Lohse, 1997; Milosavljevic, Navalpakkam, Koch, & Rangel, 2012; Navalpakkam, Kumar, Li, & Sivakumar, 2012) and a pertinent question to JDM and vision science is naturally whether a synthesis of these studies reveals an effect or not.

A second bottom-up factor which has been shown to influence eye movements is the relative *surface size* of stimuli. The relative surface size of a stimulus refers to the proportion of the visual environment occupied by the stimulus (for a review see Peschel & Orquin, 2013). The effect of surface size is most likely a consequence of the psychophysical properties of the visual system (Dehaene, 2003), since increments of the surface size exhibit a diminishing marginal increase on eye movements (Lohse, 1997). So far, no theories or models have incorporated surface size effects in decision-making, which might reflect that JDM researchers typically control for this feature in stimulus design. However, in natural decision situations, surface size varies substantially (Orquin et al., 2019) and it is, therefore, relevant to understand the magnitude of this feature on decision-makers' eye movements.

A third bottom-up factor is the *position effects*. The position of the stimuli in the visual environment has been shown to influence eye movements and have been proposed to correct for this effect in vision research models when estimating the influence of other variables of interest (Clarke & Tatler, 2014). In the context of JDM, two types of position effects have been examined: A left to right effect of reading direction (Chandon et al., 2009) and a centrality effect suggesting that decision-makers are more likely to attend to the middle of a row of two-dimensional arrays (Atalay, Bodur, &

Rasolofoarison, 2012; Meißner, Musalem, & Huber, 2016). The position effects have not been incorporated into models of decision-making, perhaps for the same reasons as surface size effects.

A fourth factor that has been examined is the influence of the *set size*. We define set size as the number of available alternatives (Meissner et al., 2016b) or attributes (Spinks & Mortimer, 2016) presented to the decision-maker. Increasing the set size may lead to increases in the visual complexity by the addition of more and different visual stimuli (Rosenholtz, Li, & Nakano, 2007). The visual complexity has been shown to increase the difficulty and amount of visual search (ibid.), but also the amount of attention consumers pay to print advertisement (Pieters, Wedel, & Batra, 2010). While visual complexity may lead to more search in absolute terms, decision-makers might, at the same time, look at a smaller proportion of stimuli since search difficulty is not a linear function of the set size (Wolfe & Horowitz, 2017). Another perspective on the set size is that it increases the decision complexity. Toolbox models predict those decision-makers should adapt to this phenomenon by using heuristics such as the satisficing or lexicographic decision rules in response to more alternatives or attributes (Gigerenzer & Gaissmaier, 2011; Payne, Bettman, & Johnson, 1992). Since the probability of finding a satisficing alternative is independent of the set size, we should expect a constant amount of search and, therefore, an increase in non-attendance as the set size increases. Similarly, if decision-makers adopt lexicographic decision rules, they must always search the most important attribute leading to the same prediction. From this perspective, set size may qualify both as top-down and bottom-up factors.

As mentioned above, top-down control is usually defined as goal-driven attention, which results in more fixations to relevant stimuli and fewer fixations to irrelevant stimuli (Land & Hayhoe, 2001). Previous research has identified a wide range of top-down factors that influence attention such as goals, task instructions, and preferences (for a review see Orquin & Mueller Loose, 2013). Some studies have suggested that top-down control is up to three times more effective in capturing attention compared to bottom-up control (Wedel & Pieters, 2006). In the context of decision-making, the challenge in quantifying top-down control is the definition of relevance. What is relevant to decision-makers at which to gaze? In inferential choices, relevance should be equal to the validity of the stimuli since the time spent gazing at invalid attributes is wasteful. The participants may be instructed on the validity of attributes (Krefeld-Schwalb & Rosner, 2019) or infer the level of validity themselves (Bialkova et al., 2014). In preferential choices, the relevance should be equal to the subjective preferences for either attributes or alternatives, e.g., some attributes may be more important to decision-makers (Meissner et al., 2016a) and some alternatives have higher subjective values than others (Kim et al., 2012).

Here we distinguish between the two types of relevance; the effect of task-defined stimulus validity (hereafter *task effects*) and the effect of subjective preferences (hereafter *preferential viewing*) on eye movements. Both effects are central to several theories and models of decision-making. Some decision rules, for instance, assume that information is searched in the order of its validity which, in terms of eye movements, has been taken to mean that they must have more fixations to more valid or more preferred information (Glöckner & Herbold, 2011). Two different versions of drift-diffusion models have been proposed, one version assuming an effect of preferential viewing (Towal et al., 2013) and the other version explicitly assumes no such effect (Krajbich & Rangel, 2010). Recent work has shown that, given limited cognitive resources, it is probably optimal for decision-makers to attend more to alternatives they prefer (Callaway & Griffiths, 2019).

The same resource-rational model also predicts another effect, namely that decision-makers should spend more time gazing at the eventually chosen alternative. This choice of gaze bias (hereafter *choice bias*) has been subject to much theorizing. The topic was introduced by Shimojo and colleagues (Shimojo et al., 2003) who presented the hypothesis of a feedback loop between preferential viewing and mere exposure, i.e., that decision-makers are more likely to look at alternatives they prefer and because they gaze more at these alternatives, come to like them even more. This feedback process, which they dubbed the gaze cascade, leads to an increased probability of fixating on the chosen option. Later simulation work has shown that the gaze cascade phenomenon may not be due to a feedback loop, but arises rather as a consequence of the relative threshold evidence accumulation processes (Mullett & Stewart, 2016). Several alternative models predict similar gaze bias effects, for instance, the parallel constraint satisfaction model assumes that decision-makers are more likely to fixate on the alternative with the highest network activation level, i.e., the ultimately chosen alternative (Glöckner & Herbold, 2011). The aDDM model also predicts a choice bias, but for a different reason; that decision-makers are more likely to choose alternatives that have received more fixations (Krajbich & Rangel, 2010).

To conclude, it is unclear whether the choice bias effect is a consequence of preferential viewing or a different mechanism, such as evidence accumulation, coherence maximization, or optimization under constraints. In preferential choice tasks, it is clear that the chosen alternative should be fixated on more since it is also the most preferred option. However, in non-preferential tasks, e.g., inferential or judgment tasks or tasks in which participants choose the least preferred option, these processes naturally differ, and it should be possible to disentangle the relative contribution of preferential viewing to the choice bias effect.

Study approach

In the following sections, we perform a meta-analysis on the top-down and bottom-up factors reviewed above. To the best of our knowledge, no previous meta-analyses have examined top-down and bottom-up control of eye movements. Our analysis, therefore, aims to further our understanding of eye movement control, in general, and of decision-making in particular. At the most general level, we wish simply to know the magnitude and robustness of the top-down and bottom-up factors. The mere existence (or non-existence) of these factors and whether they are moderated by task and stimulus type, furthermore, have implications for various models of decision-making.

So far, relatively few meta-analyses on eye movements have been published. Consequently, there are several unresolved methodological issues such as how to compare different eye movement metrics, dealing with multiple and different areas of interest (AOIs), and handling measurement validity across different eye tracker types. To handle these issues, we use a psychometric meta-analysis, which allows us to quantify the interference of measurement validity or multiple metrics.

Method

Literature Search

Web of Science was searched using the following terms: eye track* OR eye move* OR eye fix* AND decision-making OR choice. Grey literature, such as reports and unpublished work, was identified in the first 2,000 hits on Google Scholar. No restrictions on publication date or language were imposed. Additional literature was identified by searching the reference lists of the identified papers and through contact with the authors. Calls for unpublished studies were distributed to the relevant research communities via email lists published February 2018 at the following lists; EADM, SJDM, and EGPROC. The search resulted in 290 studies screened for eligibility. The last search was done on March 1st, 2018.

Inclusion Criteria

We included studies in which participants made decisions or judgments between discrete alternatives while their eye movements were monitored using eye-tracking technology. We did not include studies related to perceptual decision-making, such as categorizing or discriminating visual stimuli or studies on problem solving. We excluded studies where participants were selected based on clinical diagnosis or specific sociodemographic traits (i.e., visual disorders, age-related visual diseases, age restrictions; such as adolescents or infants). Studies using time constraints or time pressure manipulations were excluded from analyses. Eventually, 57 articles met all inclusion criteria and were included in the meta-analysis (see Figure 1).

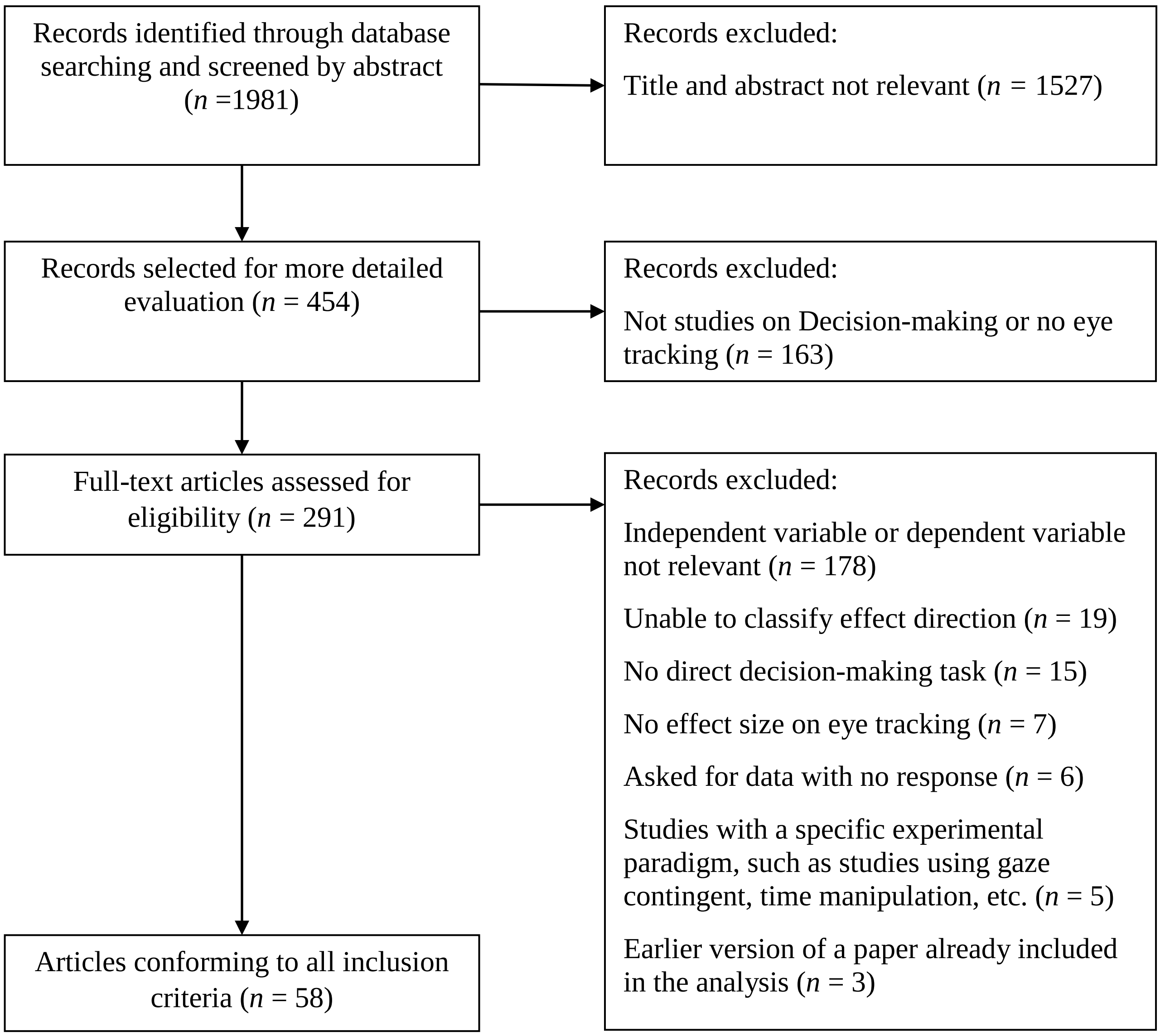


Figure 1. Flow diagram of the literature search.

Coding Procedure

The included studies were coded on their independent and moderator variables. All studies were initially coded by the first author and later by the second author. Any disagreement was resolved by discussion. To assess the agreement between coders a subset of 15 papers was used for comparison. Agreement for categorical variables was assessed using Cohen's measure of agreement (kappa). This measure assesses the similarity of raters' categorizations accounting for chance agreement (Lombard, Snyder-Duch & Bracken, 2010). Agreement for continuous variables was assessed using the intraclass correlation coefficient (Shrout & Fleiss, 1979). There was a high level of agreement (for categorical variables, median k = .89, range = .74-.92; for continuous variables, median ICC = .99, range = .56-1.00).

The independent variable was coded into two main groups: bottom-up control and top-down control, with bottom-up control divided into four dimensions: *position effect*, *visual salience*, *surface size*, and *set size*. Top-down control was divided into three dimensions: *choice bias*, *preferential viewing*, and *task instruction*.

Visual salience. We coded studies as visual salience if they operationalized one or more of the known dimensions of visual salience such as color, edge density, contrast, or motion (Itti & Koch, 2001). Some studies failed to indicate the direction of the salience manipulation, i.e., high vs. low levels of salience. In such cases, we contacted the original author and asked for clarification.

Surface Size. We coded studies that manipulated the relative surface size of alternatives or attribute, e.g., small vs. large alternatives or attributes (Lohse, 1997). Some studies manipulated the number of product facings, i.e., the number of the same product on a supermarket shelf (Chandon et al., 2009). We coded such manipulation as a surface size manipulation.

Position effect. We coded position effects into two different sub-classes: 1) studies that manipulated the position horizontally and reporting effect sizes on left vs. right (Kreplin et al., 2014),

2) studies that manipulated the centrality in one or two-dimensional arrays (Atalay et al., 2012, experiment 1A & 1B; Meissner, 2016a).

Set size. We coded set size as studies that manipulated the number of alternatives or attributes in a given choice task, e.g., studying the effect of a two- vs. three-alternative choice task (Hong et al., 2016).

Choice bias. We coded choice bias if studies reported the difference in eye movements between the chosen alternative and all other (not chosen) alternatives. Studies that operationalized the choice bias in specific time windows, e.g., the first 500 msec after stimulus onset or last 500 msec prior to choice (see Shimojo et al., 2003 for an example) were excluded. We categorized choice bias into two moderator subgroups: 1) preferential tasks where participants performed a preferential choice task, that is where participants were instructed to choose in accordance with their preferences and 2) inferential tasks where participants were instructed to choose in accordance with a predetermined goal, such as choosing the healthiest option.

Preferential viewing. We coded studies on preferential viewing if they measured the effect of preferences on eye movements. We categorized preferential viewing into two moderator sub-groups: 1) studies that demonstrated the effects of between-attribute preferences, e.g., when price is more important than flavor (Meissner et al., 2016a) and 2) studies that demonstrated effects of between-alternative preferences e.g., when preferring one alternative over another because it is cheaper and has a better flavor (Gidlöf et al., 2017; Meissner et al., 2016a).

Task instruction. We coded studies on task instruction if they presented participants with identical stimuli under different task instructions, e.g., presented participants with the same choice alternatives under a preferential choice task vs. a healthy choice task (Orquin et al., 2019). We categorized task instruction into two moderator sub-groups: 1) studies that demonstrated the effects of task instructions across attributes and 2) studies that demonstrated effects across alternatives.

Construct validity of the dependent variable

A concern in the current meta-analysis is that the included studies use different eye trackers since data quality varies considerably across different eye-tracking equipment. Precision, which is the reliability of an eye tracker, can vary as much as from .005° RMS in the best to .5° in the poorest remote eye-trackers (Holmqvist et al., 2015). Accuracy, which is the validity of an eye tracker vary from around .4° to around 2° (Holmqvist et al., 2015). With an accuracy of 2°, the measured fixation, will on average fall as far as 2° away from the true fixation point. Both accuracy and precision have been shown to influence the capture rate, i.e., the percentage of correctly recorded eye movements which determines the degree of false positive and false negative observations (Orquin & Holmqvist, 2018, 2019). The level of false positive vs. negative fixations has been shown to influence effect sizes (Orquin, Ashby, & Clarke, 2016). These differences in measurement validity across eye trackers may introduce bias in the meta-analysis, since studies with lower accuracy and precision have lower validity, which, on average, attenuate effect sizes (Hunter & Schmidt, 2004). To inspect whether there is an attenuated effect on the validity of the eye-tracking devices and potentially correct for this, we ran a regression analysis on all included effect sizes with the absolute observed effect size correlation as the dependent variable and reported precision and accuracy of the eye tracking equipment as the independent variables. We fitted different models using a step-up approach based on AIC and BIC, and the final model included the main effect of accuracy and a random intercept grouped by study. Since the accuracy and precision of eye trackers are correlated (r = .63), including the precision in the model did not improve; therefore, the model fit. Despite the noise introduced by analyzing across different study subgroups, the results suggest that studies using eye trackers with lower-level reliability, on average, yield lower effect sizes (see Table 1 and Figure 2).

Table 1. Parameter estimates for GLMM analysis of measurement reliability on absolute effect sizes.

Parameter	Estimate	SE	*t*
Intercept	.665	.090	7.477
Accuracy	-.553	.157	-3.516
Number of observations = 175			
BIC = -25.718			
Variance (Study) = .049			

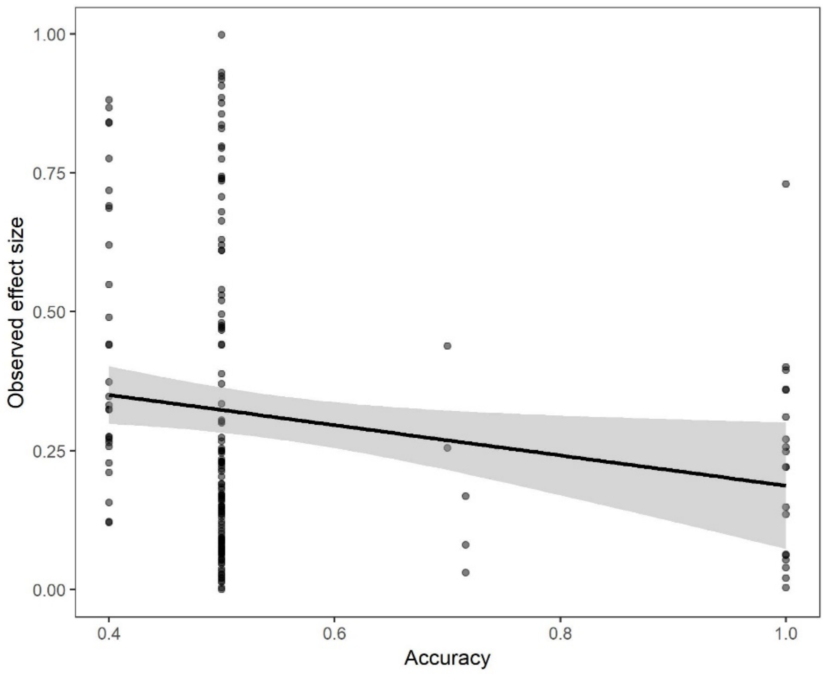


Figure 2. Plot of observed effect size and eye tracker accuracy.

Having demonstrated that the accuracy of an eye tracker diminishes effect sizes, the next step is to correct for this phenomenon. Psychometric meta-analysis offers a method for correcting the attenuating effects of artifacts, such as the lack of validity or reliability. The correction involves an artifact multiplier a_a, which is a measure of the expected attenuation of the true effect size ρ caused by the artifacts in study *i*. The observed study effect size ρ_0 is a function of the true effect size and the artifact multiplier, $\rho_0 = a_a\rho$. In the case of measurement validity, the artifact multiplier is the square root of the validity of the measurement, $a_a = \sqrt{r_{yy}}$.. From this calculation, it follows that the artifact multiplier, and, hence, the validity of the measurement, can be obtained as $a_a = \rho_0/\rho$. From our model, we know that the attenuated effect size, ρ_0, of study *i* can be expressed at the global level as $y_i = \beta_0 + \beta 1 accuracy$. Given perfect accuracy, i.e., accuracy equals zero, the expected effect size of study *i* is equal to the intercept β_0, which we will assume corresponds to ρ. From this calculation, it follows that the validity, r_{yy}, and, hence, the artifact multiplier can be obtained as the ratio of the attenuated effect size proportional to the unattenuated effect size:

$$a_p = \frac{\beta_0 + \beta_1 accuracy}{\beta_0} \quad (1)$$

For example, if a study uses an eye tracker with an accuracy of .50, this yields an artifact multiplier equal to, (.665 – .553*.50)/.665 = .584, meaning that studies with this level of accuracy will, on average, experience effect sizes that are 58.4 % of the true population effect size ρ. A full list of eye trackers and their construct validity can be found in Appendix 1. To compute the true average effect, ρ, we follow the psychometric meta-analysis method proposed by Hunter and Schmidt. We first compute the unattenuated effect sizes for each study, r_i^u, by dividing the observed attenuated effect size with the artifact multiplier that corresponds to the level of the eye tracker precision, $r_i^u = r_i/a_a$. Then, we weigh each study by its sample size and its level of unreliability, so that studies using poor eye trackers are corrected upwards, in terms of their effect sizes and variance (see Equation 3).

Multiple metrics

A second methodological issue in the present meta-analysis is that various studies included rely on different operationalizations of eye movements as their dependent variable, where 44 studies report the fixation likelihood, 64 studies report the total fixation duration, 48 studies report the fixation count, and 19 studies report the dwell count. However, to perform a meta-analysis, we need to compare studies across a common dependent variable. The many different eye-movement metrics stem from different research designs and research questions and, perhaps, also lack a consensus about when and why to use which metrics. Many studies on the bottom-up factors report fixation likelihood (whether an AOI is fixated or not) while studies on top-down factors often report fixation or dwell count. We focus on fixation likelihood and fixation count since they are easier to interpret than both the total fixation duration and the dwell count. The total fixation duration can, for instance, be difficult to interpret when there is a correlation between the fixation durations and the fixation count (Orquin & Holmqvist, 2018, 2019). The dwell count is similarly difficult to interpret if there is a correlation between the number of or the duration fixations per dwell and the probability of a dwell.

In order to inspect whether it would be meaningful to compare the effect sizes across different eye tracking metrics, we reviewed the identified articles for studies that reported multiple measures. We identified in total 44 studies N = 3105 reporting fixation likelihood along with one additional metric and 53 studies N = 3272 reporting fixation count along with one additional metric. The studies included manuscripts where we had access to data (k = 18), where we computed all eye tracking metrics. To investigate the strength of the relationship between metrics, we computed the correlation coefficient between all available metrics. We found a strong relationship between all the reported metrics (see Table 2). We also inspected the linearity of the relationship between fixation likelihood and fixation count against other metrics by plotting all observations (Figure 3).

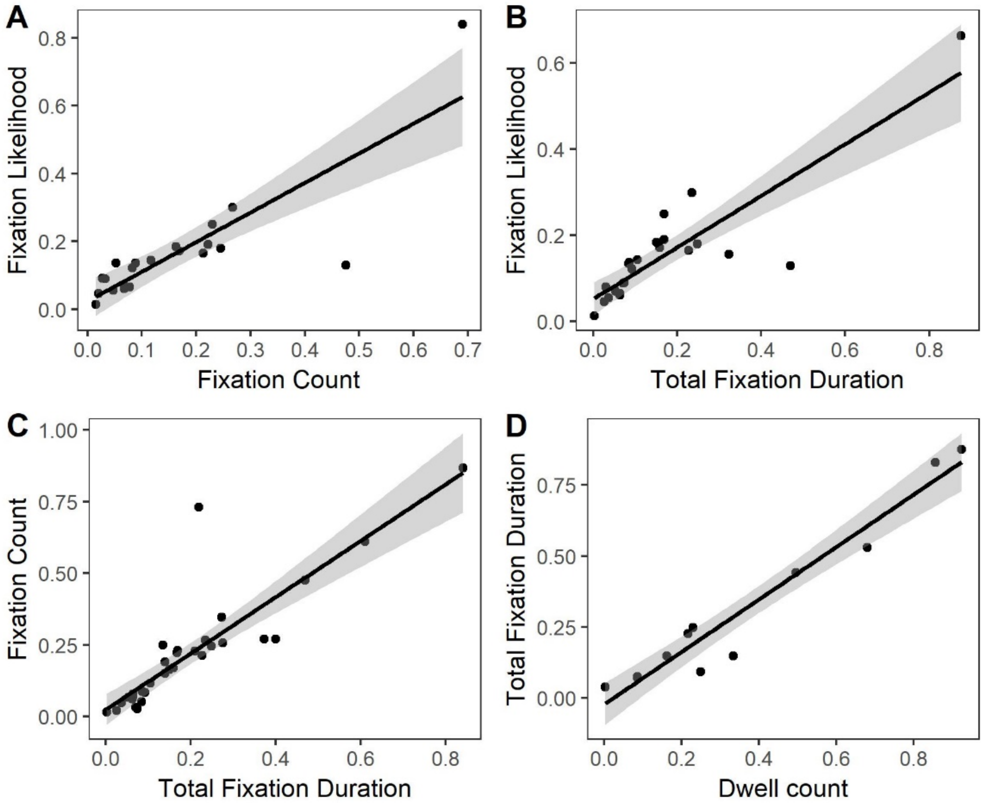


Figure 3. Scatterplots showing the relationship between effect sizes expressed in Fixation likelihood and A) Fixation count, B) Total Fixation Duration, and as expressed in Fixation count and C) Total Fixation Duration and as expressed in Total Fixation Duration and D) Dwell Count. The trend line in each plot represents the best-fitting linear regression line, and the shaded area around the trend line is its 95% confidence interval.

Since all eye movement metrics are highly correlated, we take this result as an indicator that all four metrics related to the same underlying construct, i.e., visual attention. One mechanism that might lead to differences in effect size estimates between fixation likelihood and the remaining metrics could be artificial dichotomization since fixations or dwells are categorized into a binary outcome (fixated or not fixated). Artificial dichotomization of a naturally continuous variable attenuates correlations with other variables (Hunter & Schmidt, 1990), and we should, therefore, expect effect sizes expressed in fixation likelihood to be slightly smaller. Correcting for artificial dichotomization requires knowledge about the true distributional split. Since none of the included studies provide information about the true distributional split of the dichotomization and since we do not have access to all data sets, we are unable to compute the artifact multiplier as proposed by Hunter and Schmidt (1990). Furthermore, since the distribution of the comparison metrics are both continuous and Poisson distributed, no such adjustments for dichotomization currently exist. Instead, we propose an empirically derived correction factor, a_m, to convert between the different metrics. Since we know that eye tracking metrics are highly correlated, we can express the correction factor by taking the ratio of the metrics between which we wish to convert, e.g., from fixation count to fixation likelihood. We express the metric correction factor a_m as:

$$a_m = \frac{|\bar{x}_{M1}|}{|\bar{x}_{M2}|} \tag{2}$$

Where $|\bar{x}_{M1}|$ and $|\bar{x}_{M2}|$ are the respective sample means of the absolute effect sizes for the metric that must be corrected to, *M1*, and the metric that must be corrected from, *M2*. We used the identified studies reporting multiple metrics as the empirical basis for the correction. We found, for instance, that correcting study effect sizes reported in fixation count to effect sizes in fixation likelihood yielded the correction factor, $a_m = .981$. This result means that effect sizes reported in fixation count result, on average, in effect size estimates that are 98% of the effect size when expressed in fixation likelihood. Table 3 shows an overview of the correction factor a_m when correcting to fixation likelihood (all bottom-up studies) and fixation count (all top-down studies). The correction factor is applied to each individual study effect size, but not to the study variance. When a study effect size is reported in the desired metric, e.g., fixation count for top-down studies, a_m takes the value 1 (see Equation 2).

Table 3. Metric correction factor a_m when correcting to either fixation count or fixation likelihood.

Correction to / Correction From	Fixation count (Top-down)	Fixation likelihood (Bottom-up)
Fixation count	1.000	1.019
Fixation likelihood	.981	1.000
Total fixation duration	1.016	.915
Dwell count	.950	.790

Computation of effect sizes

Effect size information was transformed into a common effect size, the Pearson's correlation coefficient *r* using the R package compute.es (Del Re, A. C., & Del Re, M. A., 2012). When multiple sources for computation of effect sizes were available, priority was given in decreasing order to other effect size measures such as eta squared, chi square, or odds ratio, means, and standard deviations, test statistics (e.g., *F*, *t*, wald), beta coefficient, or *p* values. For studies reporting effect sizes as correlations, no further computations were performed. If a study reported *p* values as a threshold value, e.g., $p < .05$, we used a conservative *p* value equal to .05. When studies reported effect sizes for multiple AOIs, we computed the average effect size across AOIs (for a similar approach, see Chita-Teigmark, 2016). Effect sizes were extracted from the available dependent variables.

Weighting of effect sizes, tests of heterogeneity

The effect sizes were analyzed with a psychometric meta-analysis following the Hunter and Schmidt approach. Individual effect sizes were corrected using the metric correction factor, a_m, to yield a common dependent variable. Studies on bottom-up factors were corrected to fixation likelihood, and studies on top-down factors were corrected to fixation count. The psychometric meta-analysis computes the true average effect size ρ based on the unattenuated correlation coefficients, r_i^u, weighted by sample size n_i, and corrected for validity by the artifact multiplier, a_a:

$$\rho = \frac{\sum_{i=1}^{k}(n_i a_a^2 a_m r_i^u)}{\sum_{i=1}^{k}(n_i a_a^2)} \tag{3}$$

To quantify the amount of variance, we report the 95% credibility interval of ρ. Where the confidence interval is an index of precision (based on the standard error) that tells us how precisely we have estimated the mean effect size the credibility interval is a measure of dispersion (based on the standard deviation) and indicates how widely the effects vary across populations. In other words, a credibility interval naturally takes into account the heterogeneity, as the degree of error in the estimated mean effect size is caused by sampling error (for more details on the distinction between credibility intervals and confidence intervals see Hunter and Schmidt, 2000). To inspect the degree of heterogeneity in the metaanalysis, we computed the I^2 statistic (Borenstein et al. 2011). The I^2 is the proportion of variance in the observed (attenuated) effect estimates explained by artifacts and sampling error:

$$I^2 = \frac{(T^u)^2}{(S^u)^2} \tag{4}$$

Where $(S^u)^2$ is the weighted variance of the unattenuated effect size ρ

$$(S^u)^2 = \frac{\sum_{i=1}^{k} n_i a_a^2 (\rho_i - \bar{\rho})^2}{\sum_{i=1}^{k} n_i a_{i\,a}^2} \tag{5}$$

and $(T^u)^2$ is the between-studies variance component of the unattenuated effect size ρ

$$(T^u)^2 = (S^u)^2 \frac{\sum_{i=1}^{k} n_i a_{accuracy}^2 v_i}{\sum_{i=1}^{k} n_i a_{accuracy}^2} \quad (6)$$

Results

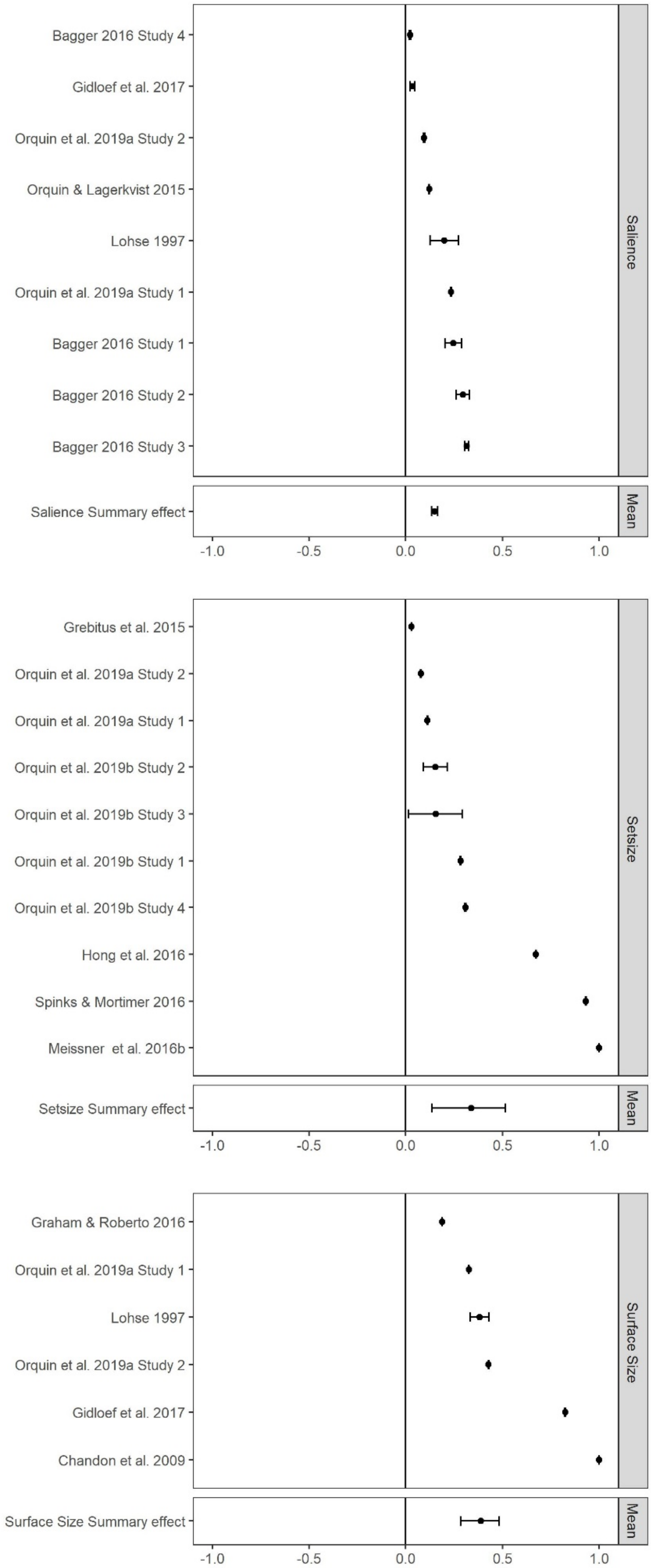
We analyzed each individual subgroup separately using a psychometric meta-analysis. Results on all bottom-up factors are presented in fixation likelihood and results on top-down factors are presented in fixation count (effect sizes on both metrics are comparable, see Table 2). The main results are presented in Table 4, with the most interesting results being the corrected effect size estimate, ρ, and the associated heterogeneity, I^2. We also present estimates of the uncorrected effect size, r, obtained from a bare-bones analysis, that is, ignoring differences in validity between eye trackers.

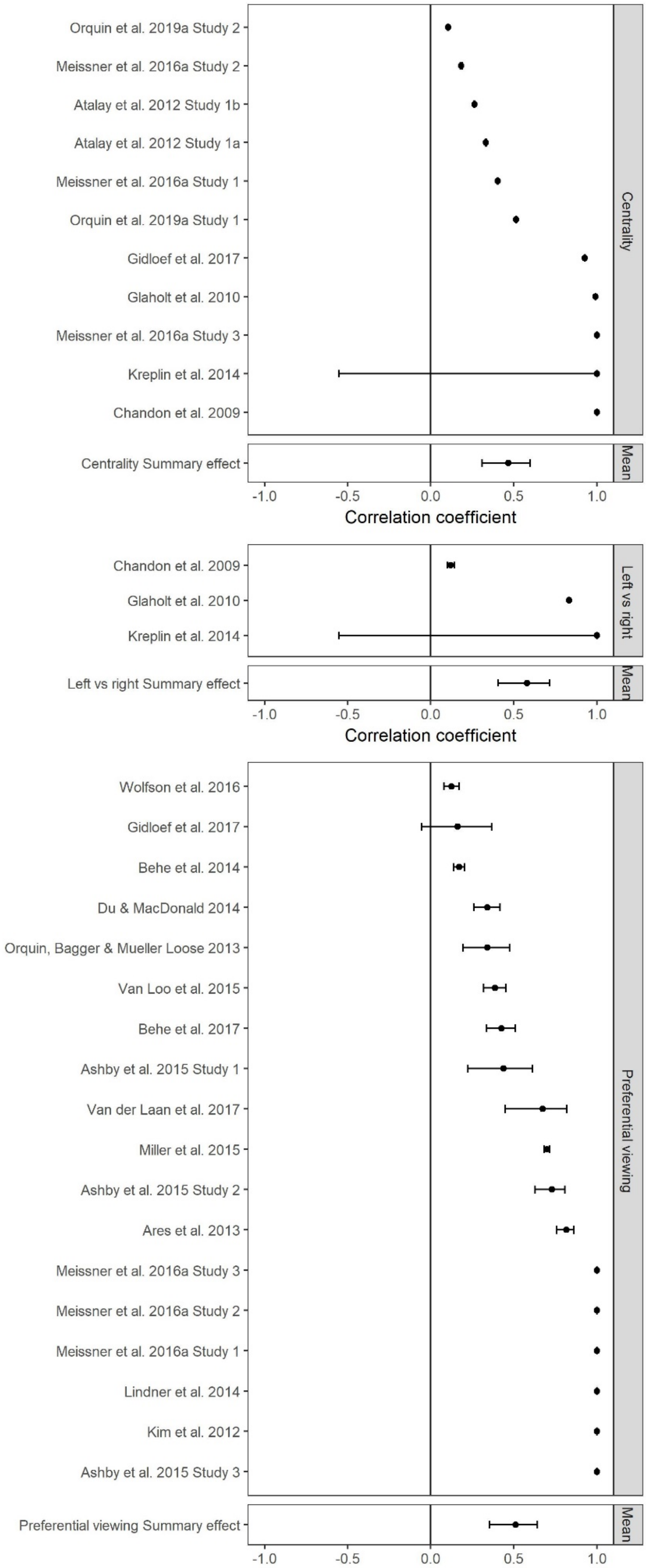
Besides the main effects, we perform four moderator analyses of set size, preferential viewing, task instruction, and choice bias. The moderator analysis was based on a hierarchical breakdown strategy (Hunter & Schmidt, 2004). Support for moderation was observed by a reduction in I^2 and changes in the corrected effect size estimates for the subgroup. We find support for moderation by attribute vs. alternative in preferential viewing and task instruction. In all moderator subgroups, the is I^2 reduced, and neither the confidence nor credibility intervals overlap between subgroups. For set size, we find some support; the I^2 increases in the subgroups but neither the confidence or credibility intervals overlap between subgroups. For choice bias, we find no support for moderation by inferential vs. preferential task subgroups (see Table 4). Figure 4 shows forest plots of the unattenuated effect sizes for each group.

Table 4. Main results of the meta-analysis divided into independent variable subgroups. *k* = number of studies, ρ = unattenuated effect size, *r* = attenuated effect size, *SD* = standard deviation of attenuated effect size, $CV_{95}LL$ = lower limit of the 95% confidence interval, $CV_{95}UL$ = upper limit of the 95% confidence interval, $CR_{95}UL$ = upper limit of the 95% credibility interval, $CR_{95}LL$ = lower limit of the 95% credibility interval, I^2 = within-group heterogeneity. Indented variables are moderators.

Independent variable subgroup	*k*	*N*	*r*	$\rho_{fixation\ likelihood}$	$\rho_{fixation\ count}$	*SE*	$CI_{95}LL$	$CI_{95}UL$	$CR_{95}LL$	$CR_{95}UL$	I^2
Salience	9	530	.086	.149	.146	.003	.143	.155	.133	.165	.830
Set size	10	610	.205	.340	.333	.037	.273	.402	.136	.515	1.995
Alternative	6	281	.333	.517	.507	.025	.480	.552	.395	.622	7.900
Attribute	4	329	.096	.174	.170	.030	.115	.231	.015	.324	8.189
Surface size	6	740	.272	.388	.381	.018	.359	.417	.284	.484	6.021
Left vs right	3	415	.085	.580	.569	.165	.325	.757	.404	.715	11.885
Centrality	11	912	.302	.466	.457	.029	.421	.509	.310	.598	9.417
Preferential viewing	18	1849	.332	.521	.511	.054	.428	.585	.352	.641	9.997
Alternative	7	390	.569	.831	.816	.026	.798	.832	.748	.866	8.918
Attribute	14	1624	.329	.510	.501	.03	.456	.543	.343	.631	9.791
Task instruction	26	1990	.272	.504	.495	.034	.443	.543	.348	.618	9.107

Alternative	12	787	.254	.741	.727	.036	.692	.758	.665	.779	6.118
Attribute	14	1203	.284	.451	.442	.026	.400	.483	.302	.563	8.287
Choice bias	18	625	.594	.787	.772	.047	.731	.807	.669	.845	1.932
Inferential	9	226	.526	.778	.763	.022	.745	.781	.695	.818	7.453
Preferential	11	443	.593	.755	.740	.032	.711	.767	.604	.835	12.768


Bagger 2016 Study 4
Gidloef et al. 2017
Orquin et al. 2019a Study 2
Orquin & Lagerkvist 2015
Lohse 1997
Orquin et al. 2019a Study 1
Bagger 2016 Study 1
Bagger 2016 Study 2
Bagger 2016 Study 3
Salience
Salience Summary effect
Mean
-1.0
-0.5
0.0
0.5
1.0
Grebitus et al. 2015
Orquin et al. 2019a Study 2
Orquin et al. 2019a Study 1
Orquin et al. 2019b Study 2
Orquin et al. 2019b Study 3
Orquin et al. 2019b Study 1
Orquin et al. 2019b Study 4
Hong et al. 2016
Spinks & Mortimer 2016
Meissner et al. 2016b
Setsize
Setsize Summary effect
Mean
-1.0
-0.5
0.0
0.5
1.0
Graham & Roberto 2016
Orquin et al. 2019a Study 1
Lohse 1997
Orquin et al. 2019a Study 2
Gidloef et al. 2017
Chandon et al. 2009
Surface Size
Surface Size Summary effect
Mean
-1.0
-0.5
0.0
0.5
1.0


Orquin et al. 2019a Study 2
Meissner et al. 2016a Study 2
Atalay et al. 2012 Study 1b
Atalay et al. 2012 Study 1a
Meissner et al. 2016a Study 1
Orquin et al. 2019a Study 1
Gidloef et al. 2017
Glaholt et al. 2010
Meissner et al. 2016a Study 3
Kreplin et al. 2014
Chandon et al. 2009
Centrality
Centrality Summary effect
Mean
-1.0
-0.5
0.0
0.5
1.0
Correlation coefficient
Chandon et al. 2009
Glaholt et al. 2010
Kreplin et al. 2014
Left vs right
Left vs right Summary effect
Mean
-1.0
-0.5
0.0
0.5
1.0
Correlation coefficient
Wolfson et al. 2016
Gidloef et al. 2017
Behe et al. 2014
Du & MacDonald 2014
Orquin, Bagger & Mueller Loose 2013
Van Loo et al. 2015
Behe et al. 2017
Ashby et al. 2015 Study 1
Van der Laan et al. 2017
Miller et al. 2015
Ashby et al. 2015 Study 2
Ares et al. 2013
Meissner et al. 2016a Study 3
Meissner et al. 2016a Study 2
Meissner et al. 2016a Study 1
Lindner et al. 2014
Kim et al. 2012
Ashby et al. 2015 Study 3
Preferential viewing
Preferential viewing Summary effect
Mean
-1.0
-0.5
0.0
0.5
1.0

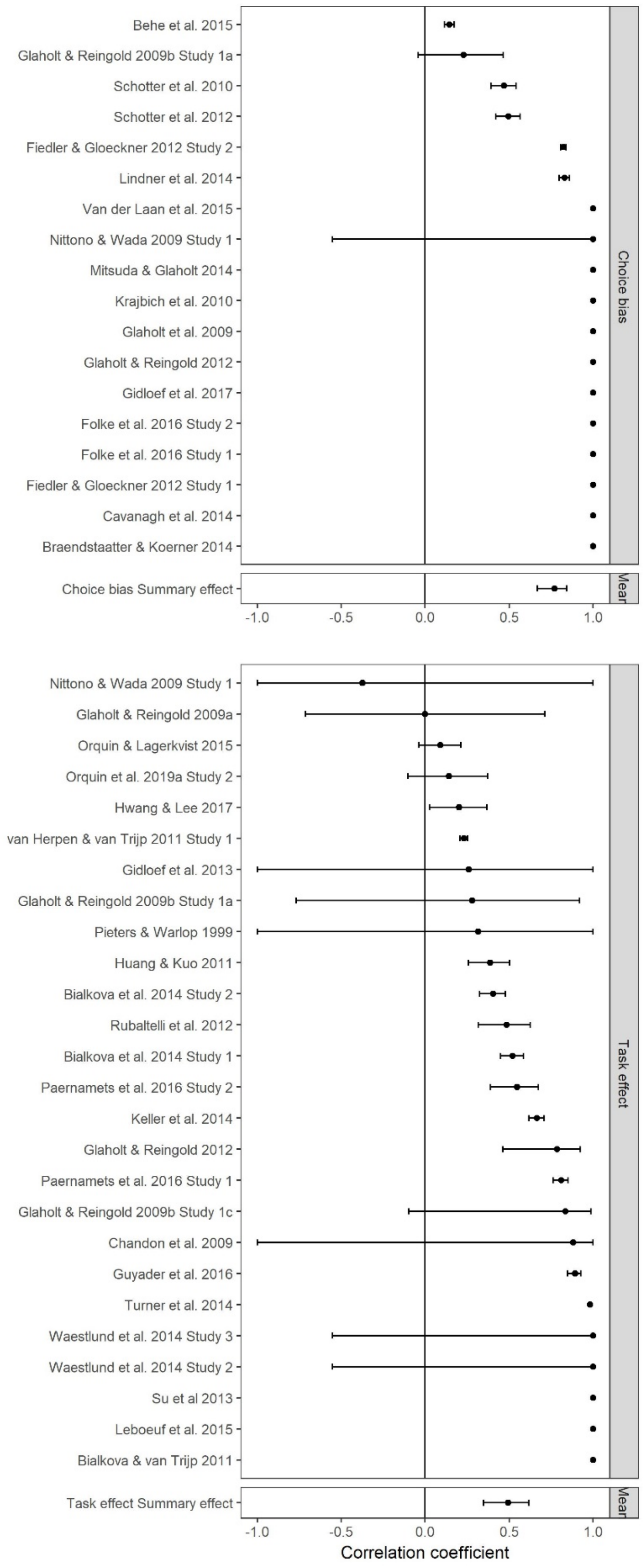


Figure 4. Forest plot of the unattenuated effect sizes for each of the seven subgroups. Error bars represent the 95% credibility interval of the mean.

Publication bias

We assessed the potential publication bias using a trim-and-fill analysis of the independent subgroup effect sizes (Duval & Tweedie, 2000). In addition, we plotted the Fisher's z transformed correlation coefficients of each study by its respective standard error (Figure 4). The symmetry of the plotted data (the funnel plot, see Figure 4) indicates whether there is a publication bias in favor of studies with higher standard errors (Egger, 1997). The trim-and-fill analysis resulted in a downward adjustment of the average effect size for most of the subgroups.

Additionally, for the subgroups Saliency, and Centrality, the adjusted confidence intervals crossed zero (Table 5). For the remaining subgroups, we took the results from the trim-and-fill to indicate that under the assumption of publication bias, the results of the present meta-analysis still provide robust estimates of the effect size. We also addressed a common concern regarding the use of trim-and-fill to assess publication bias, namely when there is between study heterogeneity, estimates may be biased (Johnson & Eagly, 2014). We did not find any immediate indications that between study heterogeneity bias, the results from the trim-and-fill analysis, which had similar I^2 values to the main meta-analytical models.

Table 5. Trim and fill analysis for each independent subgroup. Bias direction = expected direction of publication bias, Studies filled = the number of studies imputed, $r_{adjusted}$ = effect size after imputation, $CR_{95}LL$ = lower limit of the 95% credibility interval, $CR_{95}UL$ = upper limit of the 95% credibility interval.

Independent variable subgroup	Bias direction	Studies filled	$r_{adjusted}$	CR95LL	CR95UL
Salience	Left	2	.073	-.007	.154
Set size		0	.205	.040	.369
Left vs. right	Left	2	.020	-.275	.315
Centrality		0	.302	.200	.410
Surface Size		0	.272	.167	.377
Preferential viewing	Left	6	.238	.054	.422
Task instruction	Left	5	.218	.106	.330
Choice bias	Left	1	.570	.395	.739

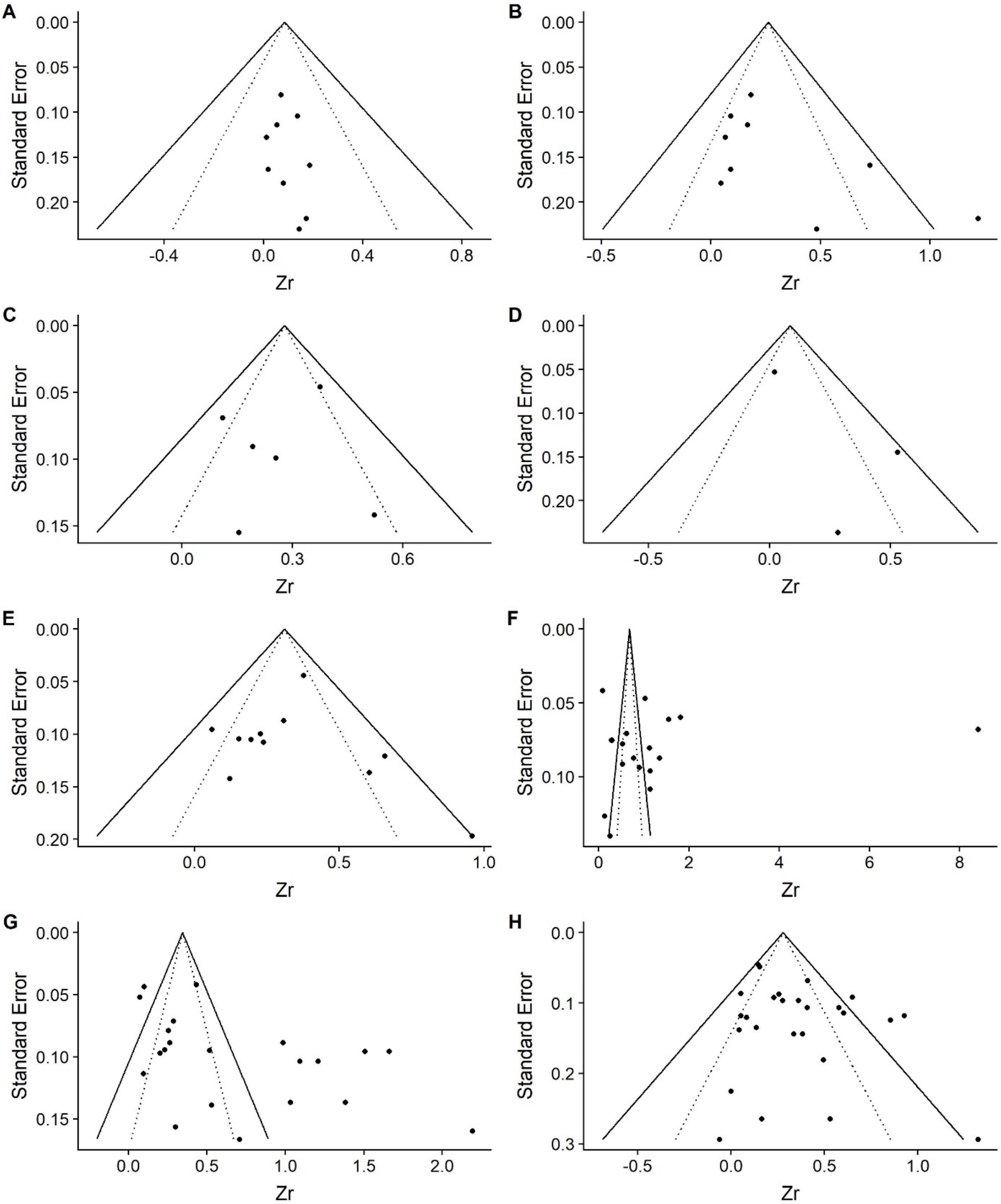


Figure 4. Funnel plots for each individual subgroup. Data are Fishers Z transformed correlation coefficients, A= Salience, B= Set size, C= Surface Size, D= Left vs, right, E= Centrality, F= Choice bias, G= Preferential viewing, and H= Task instructions. Dotted lines represent 95% confidence intervals; lines represent 99% confidence intervals.

Discussion

For the better part of our daily lives, we attend to and gather information using our eyes. We visually inspect food products in the supermarket or online, we read emails, task lists, memos, or software and spend considerable time looking at other people and our surroundings in an attempt to navigate our social and physical environment. Consequently, many of the decisions we make, small or large, are based on the visual information that we gather using our eyes. In this study, we attempt to answer how our eyes gather information during decision-making. We meta-analyze empirical studies on eye movements in decision-making and provide a quantitative overview of the factors driving eye movements in decision-making. We distinguish between internal or top-down factors such as preferential viewing, task instruction effects, and choice bias and external or bottom-up factors such as salience, surface size, set size, and position effects. We identify 107 effect sizes and perform a psychometric meta-analysis to control for issues related to the validity of each study.

Main findings

Except for salience, ρ = .15, the results show that all bottom-up factors have medium to large effect sizes ranging from ρ = .42 to .57. In comparison, all three top-down factors are large, ranging from ρ = .50 to .77, but not three times as large as previously hypothesized (Wedel & Pieters, 2006). Considering that there is no bottom-up free visual environment, it is reasonable to expect that all bottom-up factors influence eye movements at the same time. In laboratory environments, it is possible, and often desirable, to control for bottom-up factors, but in natural environments where no such control or counterbalancing takes place, the visual environment could account for a large share of variance in eye movements. The mounting evidence that demonstrates a causal effect of eye movements on decision-making (Ghaffari & Fiedler, 2018; Reeck et al., 2017; Pärnamets et al., 2015;

Shimojo et al., 2003), therefore, suggest an important role for the visual environment in guiding our decisions through our eye movements.

Regarding top-down factors, several findings have emerged. We decided to analyze studies on task instructions and preferential viewing separately since there is a clear qualitative difference between the two domains. In studies on task instructions, participants receive instructions concerning a specific decision goal, whereas, in preferential viewing studies, participants decide based on subjective preferences. The inspection of the effect sizes reveals that the main effect in the two types of studies are indistinguishable, i.e., similar effect sizes, $\rho_{\text{task}} = .495$ and $\rho_{\text{preferential viewing}} = .511$ and overlapping credibility and confidence intervals. This result suggests that it makes no difference to eye movements whether the relevance of information is defined according to an externally specified goal or according to preferences. Breaking down both groups by moderators reveal further similarities. Both preferential viewing and task instruction are moderated by the subgroups alternatives and attribute, and in both cases, there is a larger effect at the alternative level. These findings dovetail with the moderation of set size where we also find a larger effect on set size by alternatives than set size by attributes. The result implies that decision-makers are more likely to adapt to increases in set size by ignoring alternatives than by ignoring attributes. One interpretation is that decision-makers are more oriented towards compensatory than non-compensatory decision rules, e.g., more likely to use satisficing than the lexicographic decision rules.

Finally, we find that choice bias has a very large effect on eye movements. The choice bias effect is similar for preferential and inferential decision tasks, suggesting that eye movements are not driven by preferential viewing. Even in tasks where the chosen option is not the preferred option, decision-makers make more fixations to it. There could be several explanations for this finding. The choice bias might arise because of a) the gaze cascade phenomenon (Shimojo et al., 2003), b) an evidence accumulation process as proposed to, for instance, the aDDM model (Krajbich, Armel, &

Rangel, 2010), c) coherence maximization as proposed in the parallel constraint satisfaction model (Glöckner & Herbold, 2011), d) the result of a resource-rational process in which decision-makers prioritize attention (Callaway & Griffiths, 2019), or e) a mere consequence of a preparations for a motor response towards the chosen option (Hayhoe & Ballard, 2014). The specific mechanism behind choice bias remains unclear; but considering how large the effect is, and the number of models that imply this effect, we believe that a better, and eventually full understanding of the effect will help advance decision research.

Implications for other disciplines

Our findings have implications for several scientific disciplines. We have focused our discussion on judgment and decision-making but will turn a few other topics. Our meta-analysis is, to the best of our knowledge, the first to quantitatively summarize findings on top-down and bottom-up control of eye movements in any discipline, including vision science. Naturally, other disciplines may want to take stock of these findings and have to evaluate the generalizability of the findings to their respective discipline. Since JDM is a broad term, several disciplines such as cognitive psychology, behavioral economics, and consumer psychology are represented in the set of included studies. For these disciplines, our findings provide a useful framework for developing choice architecture interventions (Münscher, Vetter, & Scheuerle, 2016) based on bottom-up factors. Our findings also point to the possibility of measuring individual preferences in real time through eye movements – a technique that may become practically relevant once our devices have built-in eye trackers (Bulling & Wedel, 2019).

Given the high degree of variance in methodologies and stimuli, we expect that our results generalize well to other disciplines such as learning and education research, problem solving, or human-computer interaction. The disciplines studying eye movements in natural environments, e.g., driving, aviation, or other natural tasks, should be cautious when applying our findings since the vast majority of the included effect sizes were from laboratory-based studies. In general, our findings attest to an unexpectedly large influence of the visual environment on our eye movements. We believe that this pattern is likely to replicate in other disciplines as well.

Methodological contributions

So far, only a few meta-analyses have been published on eye movements, and no guidelines exist concerning how to deal with eye-tracking-specific issues in meta-analyses. To perform our analysis, we have developed procedures for how to handle issues related to multiple AOIs, multiple metrics, and eye tracker validity. The procedure for handling eye tracker validity showed that eye trackers with poorer accuracy, in general, lead to lower effect sizes. In our data, the difference in A_i between the best and worst eye trackers were spanning from .167 to .667. This result is a substantial difference. Accounting for eye tracker validity improved the precision of the synthesized effect sizes. This finding is, furthermore, an important methodological contribution which demonstrates the relevance of ensuring high-quality eye tracker data.

Regarding the multiple metrics such as fixation count, fixation likelihood, or dwell, count, we showed, first of all, that these metrics yield very similar effect sizes, and, second, that the effect sizes expressed in one metric can be converted to an effect size expressed in another metric. Regarding studies which report multiple AOIs, we propose to average the effect sizes across AOIs. An alternative would have been to weight the effect sizes depending on the relevance of the AOI to the research question, but this approach would have required precise and unambiguous predictions regarding the relevance of each AOI. Such precise predictions are rare but may become more frequent in the future since other researchers can now derive predictions based on our findings.

Limitations and future research

Several limitations deserve to be mentioned. Most importantly, several of the bottom-up factors included a low number of studies which casts some doubt about the precision of the results. The low number of studies also analyzed the publication bias less reliable, thereby, adding to the uncertainty. Another challenge is that the studies included varied substantially because of stimulus differences, e.g., high vs. low complexity stimuli, and because of task differences, e.g., risky gambles vs. consumer decision-making. These differences may have introduced additional heterogeneity into the synthesized effect sizes, but at the same time, serve to increase the generalizability of the findings (Cooper, Hedges, & Valentine, 2009).

Our findings call into question several assumptions about how decision-makers search for and gather information. Several existing theories and models make assumptions that imply only a subset of the identified top-down and bottom-up factors. While these models may work in a controlled laboratory environment, it is clear that they do not generalize to more natural environments. Future models should, therefore, strive to incorporate a wide set of the identified factors to balance between top-down and bottom-up control. Another important avenue will be to gain a better understanding of the phenomenon of choice bias. How does it arise and what does it imply about the attention-choice process? From a methodological perspective, future research may further develop our framework for correcting for eye tracker accuracy. We know that several factors contribute to the validity of eye trackers, e.g., accuracy depends on the stimulus and the AOI size (Orquin & Holmqvist, 2018) and other artifacts such as sample population and recording location also matter (Nyström, Andersson, & Holmqvist, 2013). By extending our framework to include these other artifacts, it will be possible to make more precise estimates of effect sizes in meta-analysis and individual studies as well as more realistic power analyses.

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Appendix 1 eye tracker reliability

Eyetracker	Accuracy	a_a
ASL6000	1	.167
ISCAN	1	.167
Nihon-Kohden EEG-1100	1	.167
SMI iView HED	1	.167
Tobii Glasses	1	.167
Unknown	1	.167
Easygaze	.7	.417
Eye gaze 97	.716	.404
Eye gaze tm	.4	.667
SMI RED	.4	.667
Tobii T120	.4	.667
Tobii X2	.4	.667
EyeLink 1000	.5	.584
EyeLink II	.5	.584
SMI Glasses	.5	.584
SMI iView	.5	.584
Tobii D10	.5	.584
Tobii T1750	.5	.584
Tobii T2150	.5	.584
Tobii T60	.5	.584
Tobii X1	.5	.584

3

The Visual Ecology of Product Packaging and its Effects on Consumer Attention[1]

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Abstract

Visual ecology is the study of how different species perceive their visual surroundings. We introduce the concept to consumer research and show that the micro-ecology of product packaging has a predictable visual ecology. Analyzing images of 158 consumer products, we show that brand-related packaging elements are visually conspicuous in terms of visual salience, surface size, and distance to center, while elements related to credence characteristics like sustainability and nutrition are visually inconspicuous. We show that the visual ecology of product packaging is a strong driver of consumer attention independently of consumer goals. Our findings suggest that the reason consumers regularly ignore sustainability and nutrition information is not lack of motivation, but because their visual environment acts as a barrier to attending this information. We conclude with a prediction for consumer attention given a policy intervention to increase the conspicuity of sustainability and nutrition information.

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Introduction

The human visual system has developed over eons to respond to particular features in our visual environment. A forager, for instance, takes advantage of this ability to detect ripe fruit in a crowded foliage because the fruit has a different color than the foliage (Hiramatsu et al., 2008). Our visual system is tuned to detect the color difference between red fruit and green foliage and directs our eyes to objects that stand out from the crowd. Other species respond to other features in their environment—from bees that see ultraviolet to dogs that see black and white (Land & Nilsson, 2012). The type and structure of the visual features animals respond to is termed their visual ecology (Cronin, Johnsen, Marshall, & Warrant, 2014). Each species has abilities according to their needs. Like the forager, consumers can take advantage of their visual abilities to detect differently colored objects in their environment, from car lights to traffic signs or promotion signs in the supermarket (Wedel & Pieters, 2008). What is different about consumers is that they navigate a visual environment designed by others to attract or distract their attention. The visual ecology of consumers is, in other words, a product of culture. This begs the question then, of what features in the visual environment consumers respond to and what is the structure and distribution of these features?

In this article, we address these questions in the context of product packaging. We begin by introducing known characteristics of the human visual system and discuss features in the environment that are likely to attract consumer attention. In the first of two studies, we examine the structure of these features in the context of product packaging. We find that within each product, packaging elements have highly predictable visual features. Packaging elements that are closely related to the brand are generally more visually conspicuous, while elements related to credence characteristics as sustainability and nutrition, which are not necessarily part of the brand positioning but have been added because such information is regarded as socially desirable, are less conspicuous in terms of color, size, and position. We show that these differences influence consumer attention to specific packaging elements. In the second study, we address some limiting conditions of the first study and show that the visual ecology of consumers exerts a strong influence on attention independently of consumer goals. We conclude with predictions of how a change in the conspicuity of packaging elements, due to brand repositioning or due to a policy intervention, might influence consumer attention.

Features that attract attention

A great deal is known about the human visual system and what features in the visual ecology we respond to. These ecological features are commonly referred to as bottom-up factors, and previous research has identified several such factors that influence attention. The most researched and canonical bottom-up factor is visual salience (salience for short). The concept captures the color differences discussed above, but also extends to other features such as the orientation and contrast of objects relative to their surroundings. Salience can be loosely defined as the conspicuity of a visual object relative to its surroundings. Several models of salience have been proposed based on different aspects of visual conspicuity such as contrast, color, edge orientation, or motion (Borji & Itti, 2013; Itti & Koch, 2001). Salience models take any visual scene as input layer and output a topographical salience map of the most conspicuous locations in the scene, i.e., those locations that are brighter, have sharper edges, or different colors than their surroundings. The salience map predicts the order and likelihood of each location in the map being looked at, with the most salient areas being the most likely to be looked at. Several studies have shown that salience maps can predict attention in tasks such as scene viewing (Foulsham & Underwood, 2008; Parkhurst, Law, & Niebur, 2002), visual search (Rutishauser & Koch, 2007), decision-making (Orquin & Lagerkvist, 2015; Towal, Mormann, & Koch, 2013), and consumer behavior (Lohse, 1997; Milosavljevic, Navalpakkam, Koch, & Rangel, 2012; Navalpakkam, Kumar, Li, & Sivakumar, 2012).

A second bottom-up factor is the relative surface size of objects, which has been shown to exert a robust effect on consumer attention (for a review see Peschel & Orquin, 2013). This effect is probably due to the object being more likely to attract attention by chance, but also to psychophysical properties of the visual system (Dehaene, 2003) since increasingly larger objects exhibit a diminishing marginal effect on attention (Lohse, 1997). Surface size effects have been shown in different consumer situations, for instance, are products with more shelf facings (Chandon, Hutchinson, Bradlow, & Young, 2009; Gidlöf, Anikin, Lingonblad, & Wallin, 2017), larger ads (Lohse, 1997), and larger elements within ads (Pieters, Warlop, & Wedel, 2002; Pieters & Wedel, 2004) more likely to be looked at.

A third bottom-up factor is object position. Position effects have been shown both in one and two dimensions. When information is structured in a one-dimensional arrays such as rows or columns, consumers typically read columns of information from top to bottom (Chen, 2010; Sütterlin, Brunner, & Opwis, 2008) and rows of information from left to right (Navalpakkam et al., 2012). This, of course, only holds in societies where the reading direction is from left to right. The position of an object not only influences when it is looked at, but also the likelihood of it being looked at. Many consumers ignore a large part of the available information and consequently, objects at the top or to the left are more likely to be seen. In two-dimensional arrays, consumers typically look at the middle of the array, while the corners often go unnoticed (Atalay, Bodur, & Rasolofoarison, 2012; Clarke & Tatler, 2014; Meißner, Musalem, & Huber, 2016). There is some evidence suggesting that positioning effects in two dimensional arrays depend on the object type, i.e. visual or textual (Otterbring, Shams, Wästlund, & Gustafsson, 2013). Positioning effects are well known in retailing where products in the middle of a shelf are chosen more frequently, presumably because they are seen more often than the products in the corners of the shelf (Chandon et al., 2009; Gidlöf et al., 2017). However, in the context of retailing, position effects may be a mix of both bottom up and top down factors since consumers believe that the more popular products are located in the middle of the shelf (Valenzuela & Raghubir, 2009, 2015) even though this is not the case (Valenzuela, Raghubir, & Mitakakis, 2013). Whether consumers hold similar beliefs about positioning of labels on product packaging remains to be shown. Besides these bottom-up factors, other less researched factors have been identified. Research shows that the amount of visual complexity or clutter affects the likelihood of consumers looking at an object (Pieters, Wedel, & Batra, 2010; Reutskaja, Nagel, Camerer, & Rangel, 2011). The predictability of object locations has also been shown to affect consumer attention (Orquin, Chrobot, & Grunert, 2017). In this article, we focus on salience, size, and position since these bottom-up factors are well understood and can be operationalized in an unambiguous way.

Top-down control

So far, we have discussed bottom-up factors as if these were the only factors influencing attention. However, this is not the case. Unlike other species, humans have an excellent capacity for attending to objects that are relevant to their goals and ignore objects that are irrelevant, irrespective of bottom-up factors. Humans can ignore irrelevant objects either based on known locations of the irrelevant object (Orquin et al., 2017) or based on peripheral vision (Wästlund, Shams, & Otterbring, 2018). Such goal-driven attention is commonly referred to as top-down control (Corbetta & Shulman, 2002). Previous research has identified a wide range of top-down factors that influence attention such as goals, task instructions, preferences, decision style, cognitive load, involvement, task complexity and mood (for reviews see Orquin & Mueller Loose, 2013; Orquin, Perkovic, & Grunert, 2018; Wedel & Pieters, 2008). What is important to our discussion is that top-down factors have been shown to dominate bottom-up factors. Some studies have shown that top-down control is up to 1.5 times more powerful in guiding consumers' attention compared to bottom-up control (Orquin & Lagerkvist, 2015). Some scholars have suggested that top down control account for 2/3 of attention (Wedel &

Pieters, 2006) or even that bottom-up factors such as salience play no role in natural environments and that attention is entirely a matter of top-down control (Tatler, Hayhoe, Land, & Ballard, 2011). If this holds, it could suggest that humans are, unlike other species, free of their visual ecology. For example, price or health-motivated consumers should be capable of ignoring irrelevant but eye-catching advertising in favor of cheap or healthy products, no matter how dull these products may look like. However, the view is difficult to reconcile with the malleability of consumer attention demonstrated in advertising (Wedel & Pieters, 2008), packaging (Peschel, Orquin, & Mueller Loose, 2019), instore (Otterbring, Wästlund, Gustafsson, & Shams, 2014), or online contexts (Menon, Sigurdsson, Larsen, Fagerstrøm, & Foxall, 2016).

The visual ecology of product packaging

If consumers are free of their visual ecology thanks to top-down control, how then do we explain visual marketing practices? Marketers not only believe in the power of bottom-up factors, they are willing to pay large amounts of money for the right visual marketing mix. A classic example is the higher price for differently colored ads in yellow pages books. The different color makes the ad more salient and more likely to be noticed (Lohse, 1997). In retailing, the shelf placement of products is determined by how much marketers are willing to pay for a central position in the middle of the shelf. More shelf facings, which increase the surface size, also cost more money. Both shelf location and size influence consumer attention and choice and are therefore worth paying for (Chandon et al., 2009). In online marketing, advertisers pay more for sponsored search results closer to the top of the page, which increases the chance of browsers seeing and clicking on the ad (Ghose & Yang, 2009). A similar position effect is also found on restaurant menus where dishes at the top of the menu are chosen more often (Dayan & Bar-Hillel, 2011). Naturally, other factors than bottom up attention may contribute to these examples, for instance, due to a limited cognitive capacity consumers may rely on heuristics about color ads or product positions to simplify the search process. Wästlund and colleagues provide evidence from instore eye tracking studies suggesting that such heuristics play an important role in consumer attention (Wästlund, Otterbring, Gustafsson, & Shams, 2015). The exact balance between bottom up and top down control remains an open question in many cases, but it seems plausible that marketers intuitively understand bottom-up factors and that it is worth paying for more salient, larger, and better positioned ads and products. At the very least, those marketers who have followed the marketing literature on these topics should understand these mechanisms (for reviews see Wedel & Pieters, 2006, 2008). It seems plausible then, that marketers use this knowledge when designing large-scale visual environments such as the shelf layout as well as small-scale environments such as product packaging. In the micro-ecology of product packaging, we might expect marketers to prioritize packaging elements, making some more visually conspicuous than others. It would, for instance, be reasonable to prioritize brand-related elements that drive the purchase (Klimchuk & Krasovec, 2012). If marketers converge in their priorities, we would consequently expect the visual ecology of product packaging to display certain predictable characteristics. Most notably, we would expect elements that are central to the positioning of the brand, like the brand name and key brand features, to be more salient, larger, and centrally positioned. In comparison, we would expect packaging elements that are more peripheral to the brand positioning or that have been added because they are viewed as socially desirable, to be less salient, smaller and more peripherally positioned. This would apply for credence characteristics like health and sustainability properties of the product, which have increasingly been added to packages in product categories like food (Fernqvist & Ekelund, 2014).

In this article, we address this issue with the following research questions: (i) does the visual ecology of product packaging have a predictable structure, (ii) does this structure influence consumer attention or are consumers free from their visual ecology thanks to top-down control, and (iii) what would happen if we changed the structure of the visual ecology according to a policy intervention?

Study 1

In Study 1, we use a representative design to examine the visual ecology of product packaging and its effects on consumer attention. We select 158 consumer products from different categories within dairy products and take high-resolution images of each product. We then categorize each packaging element as an area of interest (AOI) and measure each AOI on the three bottom-up factors discussed above: its relative visual salience, its surface size, and its distance to the center of the product. We then conduct an eye-tracking study mimicking a shopping trip, in which participants make choices from different product categories. In each category, participants first see an overview of the available products and then evaluate each product individually before making their decision.

Method

Participants. We recruited a representative sample of 123 Danish consumers (35.77 % men), age ranging from 21 to 59 (M = 37.85, SD = 11.61). We excluded participants who were not responsible for household shopping or who had a professional background in marketing or the food industry. From the total sample, we excluded 32 participants from the analysis due to low data sampling and the final sample included 91 participants. Participants had normal or corrected-to-normal vision and signed a consent form before beginning the study.

Materials and measures. The stimuli consisted of product images taken in a photo laboratory using a high-resolution digital camera. Each product was photographed from all four sides. The total stimulus sample contained 158 products from twelve different dairy product categories. We chose dairy products because it is a broad category (e.g. milk, butter, cheese, yoghurt etc.) and all products in the category are packaged. The study was based on four- and six-alternative choices. The study used an incomplete randomized block design with 24 versions. Each product was shown three times within the 24 versions. All products were grouped into choice sets of four or six products within the same category of foods, and each version consisted of five choice sets. For a complete description of the experimental versions and blocks see Supplementary Information 1. For each product, we defined eight areas of interest (AOIs) located on the front-of-pack (brand, category, fat percentage, organic label, Keyhole label, Guideline Daily Amount label, picture, logo). The organic label is a Danish sustainability/production method label (Ministry of Food, 2015) and the Keyhole (Ministry of Food, 2013) and Guideline Daily Amount (GDA) (Boztuğ, Juhl, Elshiewy, & Jensen, 2015) labels are nutrition labels. We defined the AOIs using Tobii Studio software with zero AOI margins in order to avoid assigning false positive fixations (Orquin, Ashby, & Clarke, 2016). We recorded eye movements using a Tobii 2150 eye-tracker (21 inches, 50 frames per sec) with accuracy = .5° and precision = .35°. For each AOI on each product, we measured the surface size of the AOI, its distance to the center of the product, and its visual salience. We extracted surface size information using the Tobii Studio software, which provides relative surface size measures and we measured distance from center as the Euclidean distance between the center of the product and the center of the AOI. We computed the visual salience of AOIs using a Matlab implementation of the Itti-Koch algorithm (Itti & Koch, 2001). The algorithm processes an input image at the pixel level based on color, contrast, and orientation, and outputs a ranking of the most salient locations in the image. The algorithm predicts that the highest ranked and hence most salient location is fixated first followed by the second highest ranked location etc. We transformed the salience ranks assigned to each AOI into a variable ranging from zero to one, where zero was the lowest visual salience and one was the highest visual salience. To ease the interpretation and comparability of the variables in the analyses, we range-standardized surface size and distance to center to a range between zero and one.

Procedure. We received participants individually in the laboratory and after completing the consent form, we seated them in front of the eye-tracker and assigned them randomly to one of the 24 experimental versions. Participants were not placed in a chin rest, but were instructed to minimize head movements. After calibration, participants completed two practice trials in which they were required to select their preferred product from a choice set of either four or six products. The practice trials used a different product category than the critical trials. After the practice trials, participants completed the critical trials which consisted of five choice sets from the twelve product categories. The critical trials followed a three-step protocol: overview, evaluation, and choice. In the overview phase, participants were presented with an image of the complete choice set to get an overview of all products. In the evaluation phase, participants had the possibility to inspect each product in detail. Participants could turn products on the screen to see the sides and the back of the product or skip products, using the keyboard. In the choice phase, participants were shown the same image as in the overview phase and were asked to choose their preferred product using the mouse (for an overview of the experiment phases see SI 2).

Results

Analysis of the visual ecology. We begin by analyzing the structure of the visual ecology of product packaging. We use the packaging element (categorical) to predict salience (metric), size (metric), and distance to center (metric) using generalized linear mixed models (GLMM). All models were estimated using the lme4 package in R. We fit models with and without packaging element as the independent variable using a step-up approach based on BIC. The packaging element was retained as a predictor for both salience, $F(7, 570) = 40.99$, $p < .001$, BIC = 412.58, size, $F(7, 501) = 94.37$, $p < .001$, BIC = 1048.25, and distance to center, $F(7, 480) = 30.47$, $p < .001$, BIC = 156.85. All models had a random intercept grouped by product. To better understand the structure of the environment, we illustrate the distribution of packaging elements in Figure 1 with box plots.

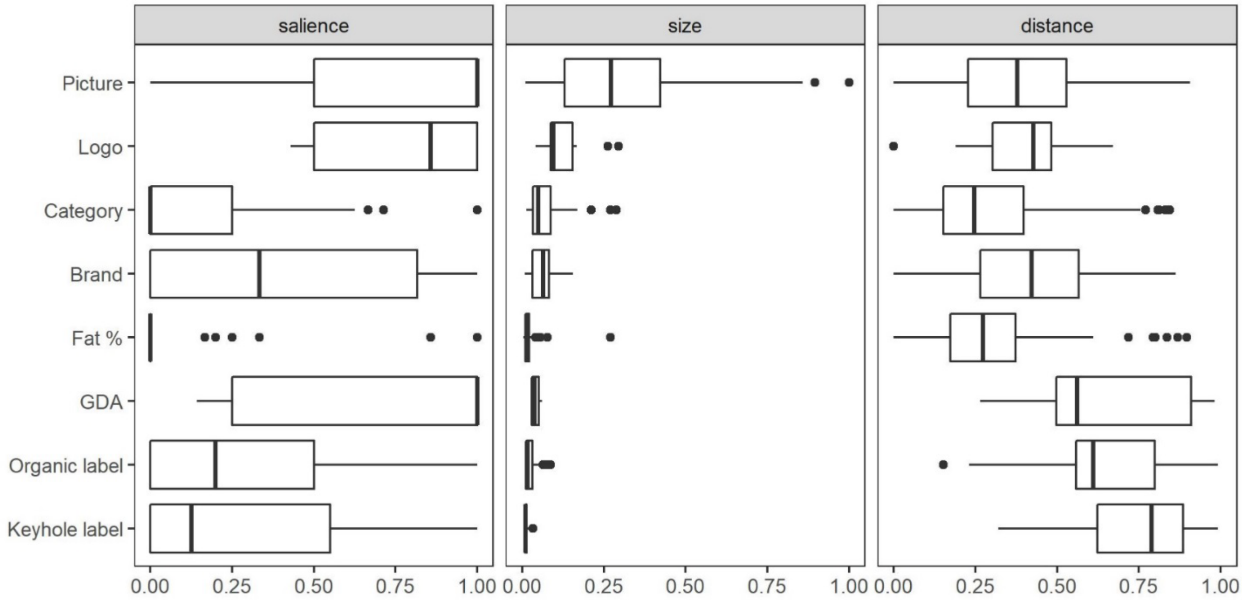

Figure 1. Box plot of the distribution of salience, size, and distance to center for each packaging element (578 data points). ‘GDA’ is a nutrition information label widely used in Europe. ‘Keyhole’ is a government-endorsed health symbol used on food products in the Nordic countries. The x-axis shows the range-standardized scores for salience, surface size, and distance respectively.

Analysis of fixation likelihood. We analyze the likelihood of participants fixating a packaging element during the product evaluation with a similar approach as above. The dependent variable (fixation selection) is a binary variable with the value one if an AOI is fixated and zero otherwise. The independent variables are packaging element size (metric), salience (metric), and distance to center (metric). The final model includes main effects of all variables and random intercepts grouped by participant, choice set, product, and packaging element. Table 1 shows the parameter and variance estimates for the final model.

Table 1. Parameter and variance estimates for fixation likelihood analysis in Study 1.

Parameter	Estimate	SE	*z*	*p*
Intercept	0.353	0.284	1.241	.214
Surface size	3.353	0.333	10.070	<.001
Distance	-2.512	0.133	-18.879	<.001
Salience	0.417	0.077	5.395	<.001
Number of observations = 9918				
BIC = 10864.4				
Variance (participant) = 0.380				
Variance (choice set) = 0.068				
Variance (product) = 0.308				
Variance (packaging element) = 0.500				

The analysis shows that the effects of salience, surface size, and distance to center are in the expected direction. More salient, larger, and more centrally positioned packaging elements are more likely to be fixated. Because the factors are additive, we compute a predicted fixation likelihood for each packaging element based on its average salience, size, and distance. We illustrate the predicted fixation likelihood against the observed fixation likelihood in Figure 2 together with a summary Figure of the structure of the visual ecology.

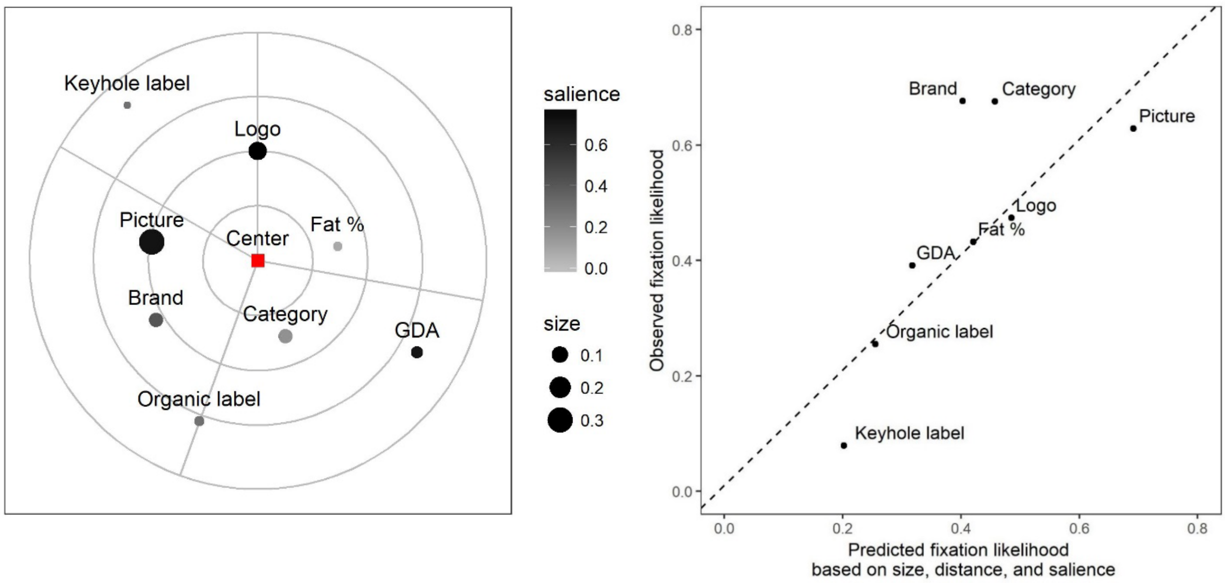

Figure 2. On the left, an illustration of the salience, surface size, and distance to center for each packaging element (578 data points). The salience, surface size, and distance to the center in the Figure correspond to the average values for the eight packaging elements. The angular position of packaging elements is arbitrary. On the right, an illustration of the predicted vs. observed fixation likelihood based on the combined effects of salience, surface size, and distance to center for each packaging element (9,926 data points).

Discussion

Study 1 shows that the visual ecology of product packaging has a predictable structure. Packaging elements central to the brand positioning such as the logo, brand, and picture are consistently more salient, larger, and more centrally positioned than packaging elements that relate to socially desirable credence characteristics like health and sustainability. Thus, the Keyhole (a government endorsed health symbol) and organic labels are consistently the least salient, smallest, and least centrally positioned packaging elements. We also show that this ecological structure plays a large role in determining consumer attention. All three bottom-up factors—salience, size, and distance to center—influence the probability of consumers fixating a product packaging element. The combined effects of the bottom-up factors explain consumer attention well, but Figure 1 suggests that there are additional factors that contribute to consumer attention. Specifically, the brand, category, and Keyhole label all deviate from the predicted level of attention shown as the dotted line. This is most likely due to top-down processes, such as consumers perceiving the brand and category as important and the Keyhole label as unimportant, which could facilitate attention to the former and suppress attention to the latter packaging element. Previous research has shown that consumers generally consider the brand as more important and the Keyhole label as less important. Specifically, previous studies have shown that this difference in subjective importance is associated with more attention to the brand and less to the Keyhole label, even when controlling for bottom-up factors such as size and salience (Orquin, Bagger, & Mueller Loose, 2013) or position on the package (Orquin et al., 2017). Two questions arise from this finding. First, is the deviation in attention due to interference from top-down control and second, is it possible, even in the case of interference, to guide consumers to attend the organic and Keyhole labels if these are prioritized in terms of salience, size, and distance to center? In Study 2, we examine the interaction of top-down and bottom-up processes more directly and whether it is possible to increase attention to functionally related packaging elements by enhancing their salience, size, and distance to center.

Study 2

Based on Study 1, we know that the visual ecology operationalized in terms of salience, size, and distance to center of packaging elements play a large role in determining how much attention a packaging element receives. The study also suggests that top-down factors, such as the perceived importance of packaging elements, may interfere with these bottom-up factors. An important question is therefore to what extent top-down control interferes with bottom-up control. Research on eye movement control processes is divided with regard to whether top-down control interferes with bottom-up control (Nordfang, Dyrholm, & Bundesen, 2013; Orquin & Lagerkvist, 2015; Tatler et al., 2011) which makes it difficult to make specific predictions. If top-down control processes interfere with bottom-up processes, this could attenuate the effects of salience, surface size, and distance to center under high top-down control due to, for instance, a ceiling or floor effect. Alternatively, top-down and bottom-up control could interact to facilitate the effects of bottom-up control (Bagger, 2016). In Study 2, we examine this question by manipulating the same bottom-up factors, salience, size, and distance to center of packaging elements and, a top-down factor, consumer health motivation, in a full-factorial experimental design. The three bottom-up factors are defined operationally as in Study 1 and the top-down factor is manipulated in three conditions: a control condition where participants are instructed to choose their preferred product, a health goal condition in which participants are instructed to choose the healthiest product, and a health priming condition in which participants are exposed to health information and instructed to choose their preferred product. Participants make choices between two toast bread products with a varying number of packaging elements, some of which are health-relevant (target labels) and some which are not (distractor labels). We use toast bread due to its ambiguous healthiness. If top-down control interferes with bottom-up control, we would expect either an attenuation or facilitation of salience, size, and distance to center under high top-down control, i.e. higher top-down interference in the health goal condition followed by the health priming condition and lastly by the control condition. We also expect participants' choices to conform to the top-down condition so that higher health motivation leads to more choices in favor of healthier products.

Method

Stimulus development. In order to generate target and distractor labels, we conduct a stimulus development study to identify labels relevant for forming health judgments of food products. The study uses a within-subjects design, in which participants assess whether a product with a given label is healthier than a product without that particular label (N = 225, M_{age} = 45.58, SD_{age} = 15.60, 52% females). Responses are binary with a value of zero indicating that the product is considered healthier and a value of one indicating that the product is not considered healthier with that label. Labels are presented individually and participants judge 39 labels in total. We compute mean judgments by averaging participants' health judgments with a score of zero indicating perfect agreement that a label implies healthiness and a score of one that it does not imply healthiness. We classify labels with a mean score < .4 as targets, and labels with a mean score > .7 as distractors. We exclude two labels with mean scores in the interval [.4 - .7] due to their ambiguity. Consequently, we identify four target and 33 distractor labels.

Participants. We recruit 76 participants with the help of a market research company (M_{age} = 44.84, SD_{age} = 13.25, 34% female). We exclude four participants due to imperfect vision, eye-tracker calibration problems, or being intoxicated. The final sample consists of 72 participants. Participants have normal or corrected to normal vision and provide informed consent before participating in the study.

Experimental design. We conduct a two-alternative choice experiment with a full factorial mixed within-between subjects design manipulating health motivation (control, health goal, and health priming) as a between-subjects factor, and target label salience (high, low), target label surface size (small, large), and target label distance to center (ranging from 463.42 to 208.22 pixels) as within-subjects factors. The position of target and distractor labels on each product is randomly sampled from 15 possible locations. The random positions ensure that participants have to actively search and fixate on labels rather than rely on peripheral vision which has been shown to play a large role in consumer behavior (Wästlund et al., 2018). Target labels are assigned as follows: A target product is chosen with an equal probability between the left and the right side. A target label is then drawn from the set of four target labels with the following probabilities P = (.8, .07, .07, .07). The target label with the highest validity in terms of healthiness is drawn with a probability of .8. To avoid that participants search for a single target, there is a .2 probability of the target not discriminating, i.e. being present on both products. In the event of the target not discriminating, a new target is drawn from the remaining set of targets and assigned to the target product. Two brands are then drawn from a set of seven brands and assigned to each product. Distractor labels are drawn from a set of 33 labels. In order to increase the external validity of each choice set, we vary the number of distractor labels presented in each choice set. The number of distractor labels is equal for products in the same choice set (either 2, 4, 6, 8, 10, 12, 14 distractors per product). The total number of labels (set size) per choice set therefore varies between six and 30 labels. All levels are presented twice, resulting in 140 trials.

Materials and measures. To avoid prior preferences influencing the results, the stimuli are images of mock toast bread. Products are presented on the left and right side of the screen. The salience of target labels is manipulated by controlling the contrast (transparency = 0% vs. 60%). The target label size is manipulated by increasing the surface size from 1.5×1.5 to 3.0×3.0 degrees of visual angle. All distractors are small (1.5×1.5) and have 0% transparency (for an example, see Figure 3). The experimental stimuli are presented using PsychoPy 2 (Peirce, 2009, 2007). We conduct a pre-test to ensure that all labels are readable at a distance of 60 cm from the screen. To prevent participants from foveating more than one label at a time, labels are separated horizontally and vertically by two degrees of visual angle. Eye movements are recorded using a desk-mounted EyeLink 1000 eye tracker with a monocular sampling rate of 1000 Hz and a screen resolution of 1920×1200 pixels. The screen subtends a visual angle of 46.5 degrees horizontally and 30.1 degrees vertically. Participants use a chinrest at approximately 60 cm viewing distance from the screen. Fixations are detected using a velocity, acceleration and motion-based algorithm (SR Research, 2008; Holmqvist et al., 2011) with velocity, acceleration, and motion thresholds of 30°/sec, 8,000°/sec^2, and 0.15° respectively. An area of interest (AOI) is drawn around each label. To avoid false positive fixations, the AOIs are the same size as the object.

Procedure. Upon entering the laboratory, participants are tested for color blindness, visual acuity and eye dominance. Participants failing either the color blindness or the acuity test are excluded from the experiment, but receive full payment for their inconvenience. We randomly assign participants to one of the three top-down conditions and they receive a short questionnaire corresponding to that condition. Participants in the health condition (N = 26) and the health priming condition (N = 26) receive the same questionnaire, which contain four vignettes concerning the four target labels and eight questions to ensure that participants have read the vignettes. Participants in the control condition (N = 24) receive a control questionnaire of similar length about shopping habits. After completing the questionnaire, participants are seated in front of the eye tracker and their head movements are restrained using a chin rest. Participants are calibrated using a 9-point calibration procedure performed at the beginning of the experiment followed by a 9-point drift validation test. A calibration offset < 1 degrees of visual angle is considered acceptable. After the calibration, participants in the health goal condition are instructed to choose the healthier product, while participants in the health priming and control conditions are instructed to choose the product they prefer. To control the location of the first fixation, every trial is preceded by a fixation cross presented at the center of the screen for 2000 ms. Participants complete 140 trials by indicating their choice of either the left or the right product by pressing the left or right arrow key. Trials last as long as participants need to make a choice. To test the validity of target and distractor labels, participants complete a post study questionnaire similar to the one in the stimulus development study.

Results

Manipulation check. To ensure the validity of the target and distractor labels we first inspect participants' responses to the post-experimental questionnaire. The results indicate that target labels have a stronger association with healthiness than distractor labels in all conditions. Table 2 shows the means and confidence intervals for targets and distractors in all conditions.

Table 2. Means and confidence intervals for target and distractor labels in the stimulus development and the three experimental conditions.

Condition	M_{target}	CI 95	$M_{distractor}$	CI 95
Stimulus development study	.33	[.29, .38]	.89	[.87, .91]
Health goal condition	.06	[.00, .12]	.85	[.79, .91]
Health priming condition	.04	[.01, .07]	.80	[.74, .86]
Control condition	.08	[.02, .14]	.80	[.76, .84]

Eye movement analysis. The likelihood of participants fixating target labels is analyzed in a similar way as in Study 1. The dependent variable (fixation selection) is a binary variable with the value one if the target label was fixated and zero otherwise. The independent variables are target label salience (binary), target label size (binary), target label distance to center (metric, 14 levels), set size (metric), and condition (categorical). The final model includes main effects of all variables except condition, and random intercepts grouped by participant and target label type. Table 3 shows the parameter and variance estimates for the final model.

Table 3. Parameter and variance estimates for fixation likelihood analysis in Study 2.

Parameter	Estimate	SE	*z*	*p*
Intercept	-0.245	0.215	-1.143	.253
Size	1.352	0.040	33.664	<.001
Salience	0.333	0.039	8.582	<.001
Distance	-0.445	0.055	-8.037	<.001
Set size	-0.017	0.002	-7.020	<.001
Number of observations = 14,896				
BIC = 16,299.4				
Variance (participant) = 0.380				
Variance (target label type) = 0.046				

Choice analysis. We then analyze the likelihood of participants choosing the target product across conditions. The dependent variable (target choice) is a binary variable indicating whether a participant chose the target product in a given trial. Fixation to the target label (binary) and condition (categorical) are used as independent variables. We use the same model selection approach as in Study 1. The final model includes main effects of fixation to the target label, condition, and an interaction between fixation and condition. The model includes a random intercept grouped by participant and by target label type. Table 3 shows the parameter and variance estimates for the final model. Figure 4 illustrates the effect of condition and fixation of the target label on the probability of choosing the healthier target product.

Table 4. Parameter estimates for choice likelihood analysis in Study 2.

Parameter	Estimate	SE	*z*	*p*
Intercept	2.041	0.236	8.630	<.001
Condition (health goal)	-1.397	0.328	-4.259	<.001
Condition (health priming)	-0.898	0.322	-2.791	.005
Fixation	0.891	0.105	8.505	<.001
Condition (health goal) × fixation	-0.591	0.128	-4.632	<.001
Condition (health primed) × fixation	-0.623	0.129	-4.820	<.001
Number of observations = 14,896				
BIC = 13,990.2				
Variance (participant) = 1.22				
Variance (target label type) = 0.01				

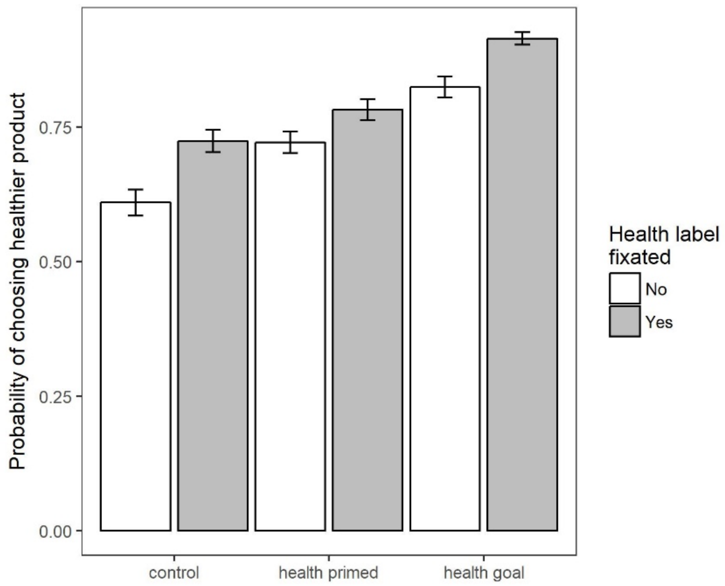

Figure 3. The probability of choosing the heathier target product depending on the condition and whether the target label was fixated. Error bars represent 95% confidence intervals (10,640 data points).

Follow up analysis. It is a common concern in consumer research that repeated measures designs create demand or learning effects which result in low external validity. Since Study 2 contains 140 trials per participant, we test the same model selection procedure on the first 10 trials for both the eye movement and choice data. The first 10 trials are less likely to be influenced by learning effects and therefore indicate whether the results are biased by the repeated measures experimental design. For the eye movement data, the final model for the first 10 trials is similar to the one on the complete data set, although all estimates are slightly larger, $\beta_{\text{size}} = 1.725$, $p < .001$, $\beta_{\text{salience}} = 0.474$, $p < .01$, $\beta_{\text{distance}} = -0.613$, $p = .01$ $\beta_{\text{set size}} = -0.040$, $p < .001$. For the choice data the final model for the first 10 trials retains the main effects of condition and fixation, but not their interaction – presumably because 760 are too few observations to adequately fit the interaction term. The estimates for the two main effects fall within the 95% confidence interval of the original estimates, $\beta_{\text{condition (health goal)}} = 1.172$, $p < .001$, $\beta_{\text{condition (health priming)}} = 0.314$, $p = .272$, $\beta_{\text{fixation}} = 0.795$, $p < .001$. A model free inspection of trial 1 and trials 1-5 reveal similar data patterns for both eye movement and choice data. The follow up analysis suggests that the repeated measures design does bias the results for the eye movement analysis, but not the choice analysis. For a more externally valid, albeit less precise, estimate of bottom up effects readers may therefore refer to the estimates in the follow up analysis.

Discussion

In Study 2, we examine the effects of the same bottom-up factors as in Study 1 (salience, surface size, and distance to center) under different levels of top-down control. We find that all bottom-up factors, including set size, influence fixation likelihood. Regarding top-down factors, we find no effect of health goal or health priming on fixation likelihood, either as main or interaction effects with bottom-up factors. Without the choice results, it would seem that the manipulation of the choice condition was unsuccessful, but the choice data reveal otherwise. The probability of participants choosing the healthier target product is highest in the health goal condition followed by the health priming and finally the control condition. In all three conditions, fixating the target label has a positive effect on choosing the target product. Interestingly, choice accuracy is above chance level in all conditions both when the target label is fixated and when it is not. This might be due to covert (peripheral) attention, i.e., participants fixating a point in proximity to a target allowing for indirect detection of the target (Wästlund et al., 2018). Overall, the results suggest that, in this study, top-down control does not interfere with bottom-up control. This could be due to a generally low level of top-down control. Orquin, Chrobot and Grunert showed that randomizing label positions suppresses top-down control so that participants are less capable of ignoring subjectively irrelevant labels and attending to subjectively relevant labels (Orquin et al., 2017). In this study we randomized label positions to mimic naturalistic packaging, and this might have suppressed the effect of health motivation on fixation likelihood. However, similar findings have been demonstrated in eye tracking studies conducted in supermarkets (Gidlöf et al., 2017). To conclude, our findings suggest that top-down control does not interfere with bottom-up processes to the extent previously assumed (Orquin & Lagerkvist, 2015; Tatler et al., 2011; Wedel & Pieters, 2006). Consumers are therefore not free from their visual ecology, but subject to its particular structure as we saw in Study 1. The influence of bottom-up factors is the basis for visual marketing practices (Wedel & Pieters, 2006, 2008) or it can, as Study 2 shows, be the basis for visually oriented behavioral interventions (Münscher, Vetter, & Scheuerle, 2016).

Predictions for a different visual ecology

Study 1 and 2 both show that the visual ecology plays an important role in determining consumer attention to product packaging elements. Furthermore, what consumers see influences what they choose. By combining the insights from both studies, it is possible to make predictions about what might happen if policy makers or producers decided to change the visual ecology of product packaging by enhancing the visibility of, for instance, sustainability or nutrition labels. Based on the fixed effect estimates from Study 1, we compute the expected fixation likelihood for the Keyhole label given a one or two standard deviation improvement in salience, surface size, and distance to center. We make the predictions for the Keyhole label because it is a simple behavioral intervention that helps consumers identify healthy foods within a category of food products. Noticing and incorporating the Keyhole label in consumer choices therefore has a great potential for enhancing healthy foods choice. Table 5 summarizes the levels of salience, size, and distance to center and the predicted fixation likelihood. Enhancing all three factors by 2 SD would result in a 42.4% fixation likelihood. One challenge related to enhancing salience, size, and distance to center of a packaging element is that it changes the entire visual micro-ecology of the product. Both salience and size are relative to other elements, and centralizing elements creates a competition with other packaging elements since there is only a limited amount of space in the middle of the product.

Table 5. Predictions for consumer attention to the Keyhole label in an enhanced visual ecology.

Setting	distance	size	salience	fixation likelihood
Current situation	0.746	0.012	0.264	15.7%
1 SD distance	0.549	0.012	0.264	21.3%
1 SD surface	0.746	0.018	0.264	17.9%
1 SD salience	0.746	0.012	0.627	18.0%
1 SD all	0.549	0.018	0.627	27.1%
2 SD all	0.352	0.023	0.991	42.4%

Another challenge related to these predictions is that producers might be concerned about crowding out brand-related packaging elements like the brand, logo or pictures on the product. While it is true that any change to a single packaging element is likely to influence all other elements, producers must keep in mind that brand-related packaging elements, particularly the brand itself, are close to ceiling in terms of consumer attention. Naturally, further studies might reveal how to strike an optimal balance in packaging design that benefits both the producer and the consumer in terms of attention to brand and functionally related elements.

Discussion

In this article, we have introduced the concept of visual ecology in consumer research. We have raised the question of whether the visual ecology of product packaging contains predictable structures and whether these structures influence consumer attention. In Study 1, we show that the visual ecology of product packaging does have a predictable structure and that packaging elements central to the brand are more conspicuous in terms of salience, size, and distance to center whereas elements referring to socially desirable credence characteristics such as sustainability or nutrition are the least conspicuous. This structure is probably due to marketers converging on the same priorities, namely to visually promote those packaging elements that drive purchases. We also show that the visual ecology explains consumer attention well, although some packaging elements—including the brand, category, and Keyhole label—are relatively over- and under-attended according to the predicted effects of the bottom-up factors. This over- and under-attendance is probably due to interference from top-down factors such as the perceived importance of the packaging element.

In Study 2, we examine the influence of top-down control on the effects of salience, size, and distance to center by manipulating consumer heath goals. Surprisingly, we find that in this study consumer goals do not interfere with the effect of the bottom-up factors on attention. Participants do, however, make different decisions depending on their goals. Participants instructed or primed with health goals are more likely to choose the healthier of the two products. Finally, we combine these insights to predict the effect of a policy intervention. We show that relatively small changes in the visual ecology of product packaging can lead to much higher levels of consumer attention to, for instance, sustainability or nutrition information.

To conclude, our findings show that the visual ecology of product packaging has a predictable structure favoring brand-related elements and that this leads consumers to largely ignore sustainability and nutrition-related elements. We believe that the concept of visual ecology has a lot to offer in consumer research, and with this article we take a first step in this direction. Future studies should extend the scope to other ecological features such as visual clutter and location predictability and address the limitations of the current studies. To examine a sufficiently wide range of products and maintain internal validity, it was necessary to conduct both Study 1 and Study 2 in the laboratory. Studies with mobile eye-tracking would be helpful to generalize the findings to a natural and incentivized environment. Currently such studies remain limited because the data quality of mobile eye-trackers makes it difficult to detect fixations to small objects such as packaging elements (Orquin & Holmqvist, 2017). These limitations introduce uncertainty in the parameter estimates in both studies and we must allow for this uncertainty when interpreting the predictions. Despite the limitations, we believe the studies present a strong case for studying the visual ecology of consumers. Understanding the visual ecology of consumers helps us explain why consumers regularly ignore sustainability and nutrition information (Graham, Orquin, & Visschers, 2012; Grunert, Wills, & Fernández-Celemín, 2010). Rather than blaming consumers for a lack of motivation, it would be more helpful to design policy interventions that address the visual ecology of consumers, for instance by increasing the visual conspicuity of sustainability and nutrition information.

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Supplementary information

SI 1.1 Overview of versions, blocks and categories. Each experiment version samples five blocks, one from each category of products. The products shown in each block are represented in SI 1.2 to 1.6.

Version	Milk	Cheese	Grated cheese	Yoghurt	Butter
Version 1	Milk 0.1% 1	Sliced - Mild 1	Grated 1	Neutral 1	Hard 1
Version 2	Milk 0.1% 2	Sliced - Mild 2	Grated 2	Strawbery 3	Hard 2
Version 3	Milk 0.1% 3	Sliced - Medium 1	Grated 3	Pear/Banana 1	Hard 3
Version 4	Milk 0.1% 4	Hard - Mild 1	Grated 4	Neutral 2	Hard 4
Version 5	Milk 0.1% 1	Hard - Medium 1	Grated 5	Pear/Banana 2	Liquid 1
Version 6	Milk 0.1% 2	Hard - Medium 2	Grated 6	Strawbery 1	Liquid 2
Version 7	Milk 0.5% 1	Sliced - Mild 3	Grated 7	Strawbery 2	Hard 5
Version 8	Milk 0.5% 2	Sliced - Medium 1	Grated 8	Pear/Banana 3	Hard 6
Version 9	Milk 0.5% 3	Sliced - Medium 2	Grated 1	Neutral 3	Hard 7
Version 10	Milk 0.5% 4	Hard - Mild 1	Grated 2	Neutral 4	Hard 8
Version 11	Milk 0.5% 1	Hard - Mild 2	Grated 3	Pear/Banana 4	Liquid 3
Version 12	Milk 0.5% 2	Hard - Medium 1	Grated 4	Strawbery 4	Liquid 4
Version 13	Milk 1.5% 1	Sliced - Mild 1	Grated 5	Pear/Banana 1	Hard 1
Version 14	Milk 1.5% 2	Sliced - Mild 2	Grated 6	Neutral 3	Hard 2
Version 15	Milk 1.5% 3	Sliced - Medium 2	Grated 7	Strawbery 1	Hard 3
Version 16	Milk 1.5% 4	Hard - Mild 2	Grated 8	Pear/Banana 2	Hard 4
Version 17	Milk 1.5% 1	Hard - Medium 3	Grated 1	Neutral 4	Liquid 1
Version 18	Milk 1.5% 2	Hard - Medium 4	Grated 2	Strawbery 2	Liquid 2
Version 19	Milk 3.5% 1	Sliced - Mild 4	Grated 3	Neutral 1	Hard 5
Version 20	Milk 3.5% 2	Sliced - Medium 3	Grated 4	Neutral 2	Hard 6
Version 21	Milk 3.5% 3	Sliced - Medium 4	Grated 5	Strawbery 3	Hard 7

Version 22	Milk 3.5% 4	Hard - Mild 3	Grated 6	Strawbery 4	Hard 8
Version 23	Milk 3.5% 1	Hard - Mild 4	Grated 7	Pear/Banana 3	Liquid 3
Version 24	Milk 3.5% 2	Hard - Medium 2	Grated 8	Pear/Banana 4	Liquid 4

SI 1.2 Milk category blocks showing the product ID combinations for each block.

Category	Block 1	Block 2	Block 3	Block 4
	1000	1005	1000	1001
	1001	1006	1002	1003
Milk 0.1%	1002	1007	1004	1005
	1003	1008	1006	1007
	1004	1009	1008	1009
	1100	1106	1100	1101
	1101	1107	1102	1103
	1102	1108	1104	1105
Milk 0.5%	1103	1109	1106	1107
	1104	1110	1108	1109
	1105	1111	1110	1111
	1200	1206	1200	1201
	1201	1207	1202	1203
Milk 1.5%	1202	1208	1204	1205
	1203	1209	1206	1207
	1204	1210	1208	1209
	1205		1210	
	1300	1305	1301	1300
	1301	1306	1303	1302
Milk 3.5%	1302	1307	1305	1304
	1303	1308	1307	1306
	1304			1308

SI 1.3 Cheese category blocks showing the product ID combinations for each block.

Category	Block 1	Block 2	Block 3	Block 4
Medium	2401	2408	2401	2403
	2403	2411	2404	2405
	2404	2416	2406	2407
	2405	2417	2408	2411
	2406	2418	2416	2417
	2407	2419	2418	2419
Mild	2301	2305	2302	2301
	2302	2306	2304	2303
	2303	2307	2306	2305
	2304	2308	2308	2307
Sliced Medium	2100	2106	2101	2100
	2101	2107	2103	2102
	2102	2108	2105	2104
	2103	2109	2107	2106
	2104	2110	2109	2108
	2105	2111	2111	2110
Sliced Mild	2000	2004	2000	2001
	2001	2005	2002	2003
	2002	2006	2004	2005
	2003	2007	2006	2007

SI 1.4 Grated cheese category blocks showing the product ID combinations for each block.

Category	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7	Block 8
Grated cheese	2600	2605	2610	2616	2612	2600	2601	2611
	2601	2606	2611	2617	2614	2602	2603	2613
	2602	2607	2612	2618	2616	2604	2605	2615
	2603	2608	2613	2619	2618	2606	2607	2617
	2604	2609	2614	2620	2620	2608	2609	2619
			2615			2610		

SI 1.5 Yoghurt category blocks showing the product ID combinations for each block.

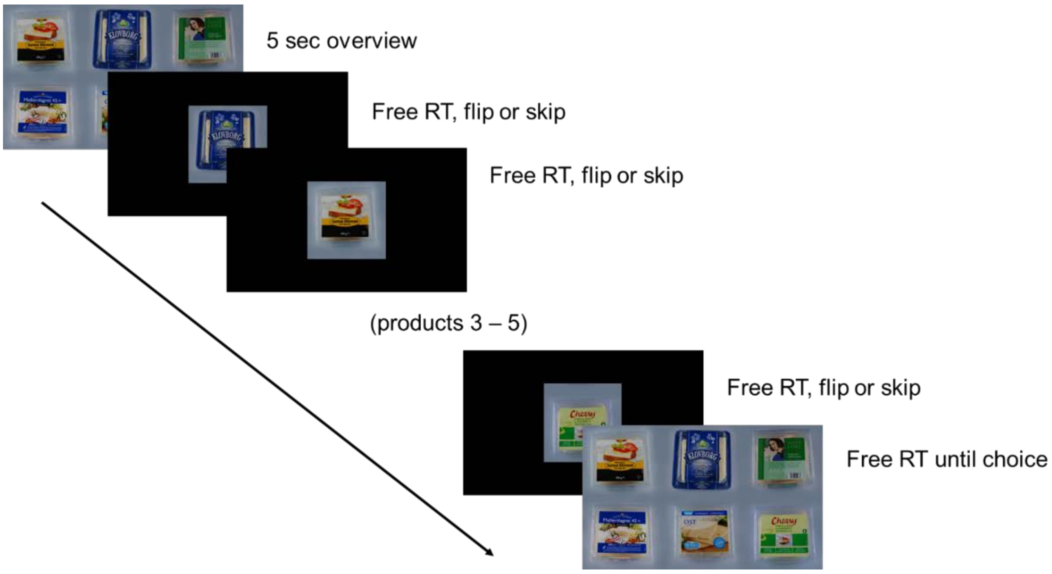
Category	Block 1	Block 2	Block 3	Block 4
Plain	3000	3007	3000	3001
	3001	3008	3002	3003
	3002	3010	3004	3005
	3003	3011	3007	3008
	3004	3012	3010	3011
	3005	3013	3012	3013
Pear-banana	3200	3205	3200	3201
	3201	3206	3202	3203
	3202	3207	3204	3205
	3203	3208	3206	3207
	3204	3209	3208	3209
Strawberry	3100	3105	3100	3101
	3101	3106	3102	3103
	3102	3107	3104	3105
	3103	3108	3106	3107
	3104	3109	3108	3109

SI 1.6 Butter category blocks showing the product ID combinations for each block.

Category	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7	Block 8
Hard	4000	4004	4000	4001	4008	4012	4008	4009
	4001	4005	4002	4003	4009	4013	4010	4011
	4002	4006	4004	4005	4010	4014	4012	4013
	4003	4007	4006	4007	4011	4015	4014	4015
Liquid	4100	4104	4100	4101				
	4101	4105	4102	4103				
	4102	4106	4104	4105				
	4103	4107	4106	4107				

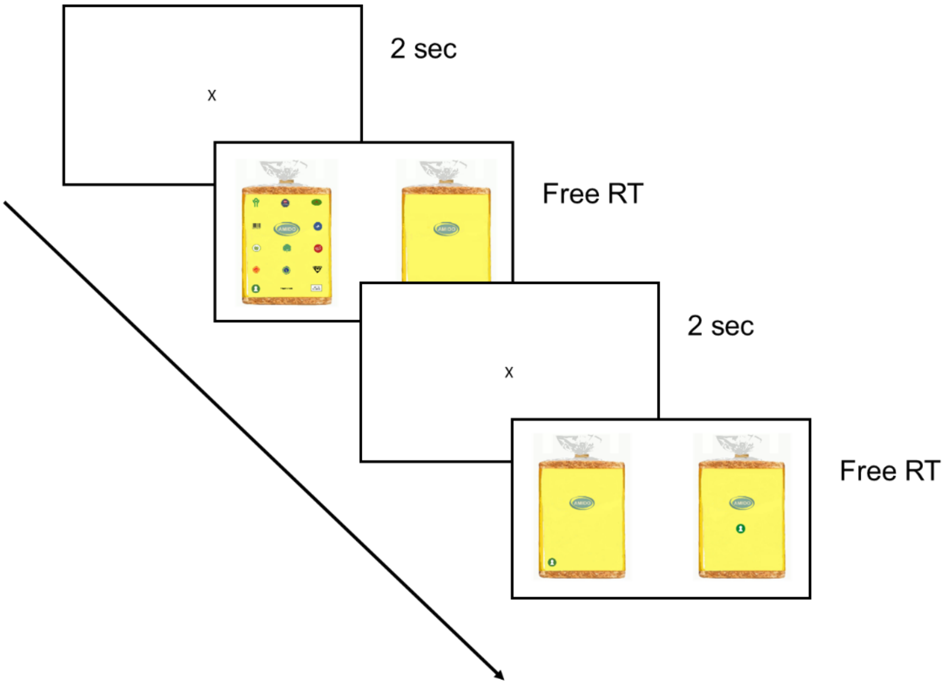
SI 1.7 Examples of product images used in Study 1. From left to right: liquid butter/margerine, skimmed milk, and fruit yoghurt.

SI 1.8. Experimental flow in Study 1.



SI 2.1 Examples of product stimuli in Study 2. On the left a product with a single target (Keyhole label), brand, and no distractors. On the right a product with the same target label and brand and 13 distractor labels.

SI 2.2 Experimental flow in Study 2.



4

Perceptual Grouping of Nutritional Information can Optimize Visual Attention[1]

Under review in Food Quality and Preference

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Abstract

Guiding consumers' attention to food labels is paramount for many stakeholders who wish to influence consumers to eat healthier. However, most research has shown that labels are often overlooked by the consumer. In order to enhance consumers' utilization of labels, the label needs to capture attention. This paper investigates whether perceptual organization of food labels can capture consumers' attention. This phenomenon is tested in three separate studies. In Study 1, the hypothesis was tested by analyzing 419 product packages for the prevalence of perceptual organization. A prevalence of perceptually grouped nutritional labels was observed when product characteristics allowed it. Furthermore, a predicable positional structure was observed in which groupings appeared at specific positions of the package. To test the phenomenon of perceptual grouping, two experimental studies manipulating grouping of nutritional labels on product packaging were conducted. Study 2 revealed that perceptual grouping can influence consumers' eye movements if they are directed toward one element of the group. In Study 3, when participants were under time pressure, this effect disappeared. While the effect of perceptual grouping is inconclusive at this point, our findings point toward a direction in which purely perceptual manipulation is capable of guiding consumer attention. This paper gives some interesting aspects for future research in the area of perceptual manipulation.

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Introduction

Acquiring a healthy diet is a goal for many consumers, and the World Health Organization considers nutrition labeling an essential part of its global strategy on diet and health (World Health Organization, 2014). From a public policy perspective, in order to guide consumers toward informed decisions, food labels are viewed as a tool to empower consumers. The success of food labeling depends on the ability of consumers to detect, read, and understand nutritional information (Mackison et al., 2010). Until recently, most research on healthful food choices has concentrated on consumers' ability to understand nutritional information in situations of forced exposure to food labels (Bialkova & van Trijp, 2011). However, in a real-world situation, before consumers can decode and process food labels, they need to pay attention to them. Past research shows that many labels are rarely considered in the consumer's decision process (Graham, Orquin, & Visschers, 2012; Grunert & Wills, 2007), and even consumers motivated to select healthful foods are sometimes unsuccessful in accurately acquiring the information. As most food choices are often made in the spur of the moment in complex decision environments with products constantly competing for consumers' attention (Wästlund, Otterbring, Gustafsson, & Shams, 2015), it seems reasonable to assume that attention is an important factor in limiting the effect of food labels. To increase the likelihood that consumers include food labels in their decision-making process, it is crucial to capture consumers' attention.

Factors influencing visual attention

It is universally recognized that visual attention is driven by two main controls of attention: goal-directed attention and stimulus-driven attention (Corbetta & Shulman, 2002). Goal-driven attention is influenced by top-down factors, while stimulus-driven attention is determined mostly by the bottom-up factors. The former guides attention based on consumers' individual preferences or task-related goals, for example, searching for the organic label on multiple alternatives. The latter guides attention based on differences in the external visual environment, irrespective of consumers' current goals or dietary constraints (Itti & Koch, 2002; Theeuwes, 2010). Previous research has found that a higher share of attention on packaging information increases the likelihood of choosing that product alternative (Armel, Beuamel, & Rangel, 2008; Bialkova & van Trijp, 2011; Milosavljevic, Navalpakkam, Koch, & Rangel, 2012; Nordfang, Dyrholm, & Bundesen, 2013; Pärnamets et al., 2015). Recently, a range of studies has investigated consumers' visual attention on food labels utilizing eye-tracking methodologies. For instance, bottom-up factors, such as the label format or its position on the package, influence the probability that the label attracts consumer attention (Pieters & Wedel, 2004; Van Herpen & Van Trijp, 2011; Gaschler, Mata, Störmer, Kühnel, & Bilalić, 2010; Orquin, Bagger, Lahm, Grunert, & Scholderer, 2019). Further, color-coded labels have been found to increase attention to nutrition information and facilitate its processing (Antúnez, Giménez, Maiche, & Ares, 2015; Cecchini & Warin, 2016; Enax, Krajbich, & Weber, 2016). Moreover, Graham, Orquin, and Visschers (2012) have proposed six aspects that are used to attract consumers' attention: surface size, order of presentation, position on product, visual clutter (complexity), saliency, and simplifying heuristics. Concerning decision-making, Orquin, Perkovic, and Grunert (2018) propose six similar principals: saliency, set size (complexity), surface size, positioning effect, emotional stimuli, and unpredictable location. Currently, most research has focused on optimizing food labels in terms of their salience, color, or position; few have addressed the issue that the industry partners may have other objectives, such as using knowledge about visual attention to divert attention to hide unfavorable information from consumers (Visschers, Hess, & Siegrist, 2010). Furthermore, considering that many product packages contain a large number of informational cues, for example, brand, pictures, flavor description, and other visuals, centered at the front of the package, while embedding socially desirable information such as nutritional labels in a cluttered and minute enumeration corner of the product or at the back (Fernqvist & Ekelund, 2014; Orquin et al., 2019;

Visschers et al., 2010). With this knowledge in mind, remarkably few studies have focused on alternative organizations of food labels, such as the role of perceptual organization of food labels in consumer decision-making. The influence of perceptual organization manipulating the decision-making process was investigated decades ago (Bettman & Kakkar, 1977; Bettman & Zins, 1979; Jarvenpaa, 1989; Payne, Bettman, & Johnson, 1993; Russo, 1977). More recent perceptual grouping has been found to influence the visual search in decision-making (Ettlin & Bröder, 2015; Perkovic, Bown & Kaptan, 2018). According to Gestalt psychologists, this effect may arise from humans' tendency to organize their visual environment. For instance, when the spatial positions of dots are altered such that pairs of dots are more proximal to each other than they are to other dots (Figure 1), the entire array tends to be seen as four groups of two dots rather than as eight independent dots. Another reason may be due to how the human visual system operates and how we perceive the world. For humans to attend to specific objects, the eye must be relatively still, also known as a fixation. For the eye to move to a new target, it relies on saccades, which are rapid eye movements toward a target location (Duchowski, 2007). When making a saccade, we lose visual acuity and, therefore, are "blind" while saccading. Research in marketing suggests that consumers' visual search takes place in two ways: a global and a local search, which is indicated by long and short saccades, respectively (Wedel, Pieters & Liechty, 2008). When consumers inspect a product package, which is a local search, we would expect short saccades, which may create a spill-over effect leading objects in proximity to have a higher fixation likelihood. That is to say, perceptual grouping may work to attract attention due to regulation in the human visual system. This begs the question of whether purely perceptual manipulation of nutritional labels can guide consumers' attention to information given in proximity.

This paper addresses this question in the context of product packaging. By analyzing 419 dairy product packages, it examines the prevalence of perceptual grouping on contemporary product packaging. A prevalence of perceptual grouping was observed on products containing more than two nutritional labels, and a positioning effect was observed where the grouping of labels is more likely to appear at the bottom of the packaging. To test the influence of perceptual grouping, two experimental studies were conducted manipulating grouping of nutritional labels on product packaging.

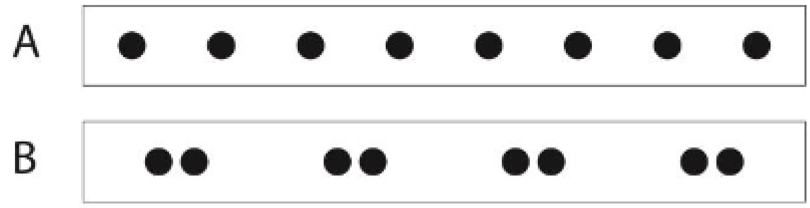

Figure 1. Example of perceptual organization based on Gestalt principals.

Study 1

To investigate the prevalence of perceptual organization of nutritional label on current product packages, Study 1 analyzed the total quantity of products utilizing perceptual grouping of nutritional labels on the front of the package in the Danish dairy sector. Since previous literature has introduced the concept of visual ecology, in which product packaging holds a predictable structure (Orquin et al., 2019), the positioning of food labels was analyzed as well.

Method

To obtain estimates of the prevalence of label grouping on the front of the package, we manually counted the number of products where label grouping occurred. We counted a label grouping as two or more nutritional labels, such as the organic label, or the Nordic keyhole, positioned less than two visual degrees from each other, which is approximately the size of your thumbnail if you outstretch your arm. Two visual degrees is the minimum with which we can experience high visual acuity

(Henderson, 2003). The keyhole label is a publicly administrated nutritional label that identifies healthier alternatives within a product category (Ministry of Environment and Food of Denmark). The sample included all available products in the dairy section in three of the largest supermarket chains in the country of investigation. The reason for our choice of case is that dairy products include both healthy and unhealthy products, such as yogurt that can be either plane or with added fruit, have reduced fat, or be sugar-free. This natural variation in healthiness makes this category perfect for investigating health label grouping, while also controlling for unhealthy products that normally do not have nutritional labels. To ensure that the counting performed by the author was unbiased, an independent coder blind to the study hypothesis was used in one supermarket. The intercoder reliability was assessed by means of intra-class correlation (Shrout & Fleiss, 1979) and was very high ICC = .987, CI_{95} = [.952, .997]

Table 1. Number of products, number of labels present on front of package, prevalence of perceptual grouping, and the position of labels on front of package.

Category	# of products	≥one label	≥ two label	Grouping of labels	Positioning of labels		Positioning of grouped labels	
					Top	Bottom	Top	Bottom
Milk	107	66	37	21	55	58	1	20
Yogurt	128	48	23	15	23	18	3	15
Cheese	184	67	38	28	15	52	4	23

Note. Some products' position labels both at the bottom and the top; in such cases, both are counted in the positioning, which is why the amount of top and bottom position may not sum to the total number of products.

Results

The field data indicate that the grouping of labels is prevalent if a product contains two or more labels (from these, 65% of product packages had a grouping of labels). However, out of the total quantity of available products in the dairy section, 23 percent carried two or more labels. In terms of the visual ecology of the packaging, this study found a strong positioning effect in which nutritional labels are positioned farthest from the center of the product with an almost equal distribution between top and bottom (57% at the bottom). However, for labels that are grouped in proximity, the distribution becomes skewed toward the bottom of the product, with 88 percent being positioned at the bottom.

Discussion

Study 1 partially confirms the assumption that perceptual grouping is a common practice among marketers. When product packaging allows for potential grouping effects, grouping also becomes more prevalent, 65 percent of product packages group labels in proximity. It seems that there may be two reasons for this. First, brand-related packaging elements such as the logo, brand, and pictures occupy a large portion of the available packaging surface. Thus, nutritional labels are consistently left to the least central positions, that is, bottom corners. Second, grouping of labels makes it easier for the consumer to search and locate relevant nutritional information, which is why grouping of labels occurs only if both signal a healthier product, such as organic and keyhole labels. In terms of the positioning of labels, for two out of the three categories, the study found the positional distribution to be equally divided between the top and the bottom of the package; the last category (cheese) mainly makes use of the bottom of the package. Inspection of the shapes of the packaging of the three categories reveals that yogurt and milk have rectangular shaped packages, whereas cheese has a quadratic shape. Whether there are any structural properties for the former to position labels at the top is unknown. However, grouped labels tended to be positioned near the bottom of the package (88%). This is an interesting observation given previous studies and well-known practices in retailing suggesting that bottom positions, in general, receive less attention than, for instance, top or center positions (Atalay, Bodur, & Rasolofoarison, 2012; Orquin et al., 2019).

Study 2

Study 1 found evidence to support perceptual grouping of nutritional labels as a commonly used practice in food marketing. In Study 2, we were interested in testing experimentally whether perceptual grouping of nutritional labels would likely increase participants' attention toward the grouped information.

Method

Participants. We recruited 38 participants (M_{age} = 23.95, SD_{age} = 4.76, 70.3% female). Due to a bug in the computer software, 20 participants were lost. The result was a final sample of 18 participants. Participants had normal or corrected-to-normal vision. Participants gave informed consent and received DKK 50 for completing the study. Due to the loss of participants, a post-hoc power analysis was conducted using the "pwr" package in R (Champely, 2017). The power analysis revealed that the power to detect a small-sized effect (d = .2) with the sample size of 18 and an alpha level at .05 is .92, therefore, it was decided to continue with the sample of 18 participants.

Experimental design. The study used a 2x2 within-subjects fractional factorial design manipulating presentation (grouped and ungrouped) and label position twice for 16 unique choice sets, resulting in 64 trials.

Materials and measures. To avoid familiarity with the product influencing the experiment, the stimuli were images of mock toast bread. Products were presented randomly on either the left or the right side of the screen. All labels were 1.5x1.5 degrees of visual angle in size. Each product alternative consisted of a set of four labels and one brand, each label was drawn from a set of 32 food labels, originally obtained from Study 1, following a uniform distribution, and the brand was drawn uniformly from a set of five fictional brands. The price of the product was randomly sampled from a set of eight prices, all with the same number of digits. The first label drawn would be assigned as the target label; this is the label subject to the experimental manipulation, that is, whether it was grouped or ungrouped with the second label drawn, which is assigned as the grouped label. The following two labels were assigned as distractor labels.

To increase the likelihood that participants fixated the target label, the saliency was manipulated in favor of the target label, such that all other labels were less salient.

Saliency was manipulated by increasing the transparency to 60 percent for all labels beside the target label. Labels were conditionally positioned to the target label, such that the target label was randomly positioned in one of the four corners of the product (as based on Study 1, these positions were found to be an ecologically valid position). The grouped labels were then positioned at the horizontally opposite corner (in the ungrouped condition) or 1.5 visual degrees toward the horizontal center of the product in the grouped condition (see Appendix A for details). The two distractor labels were then randomly assigned to the two remaining corners of the product. The brand was always positioned in the middle of the product. Eye movements were recorded using a table-mounted Tobii T60XL eye tracker with a temporal resolution of 60 Hz and accuracy = .4° and precision = .22°. Stimuli were displayed on a 24-inch widescreen monitor with a resolution of 1920 x 1200 pixels. Participants were seated approximately 60 cm from the screen using a chin rest. Fixations were detected using the I-VT algorithm with a minimum fixation duration of 60 ms. Areas of interest (AOIs) were drawn around each label with a margin of 0° to avoid falsely assigning fixations stemming from neighboring labels in the grouped condition (see Orquin, Ashby, & Clarke, 2016).

Procedure. On arrival at the lab, participants were seated in front of the eye tracker, and their head movements were restrained by a chin rest. Participants were calibrated using a nine-point calibration procedure. After calibration, participants were instructed to choose the product they prefer by indicating with a keypress assigned to “yes” and “no.” To control the location of the first fixation, every trial was preceded by a fixation cross presented at the center of the screen for 1000 ms. Participants completed 64 trials by indicating their choice by pressing the left or right arrow key for yes or no. Trials lasted as long as it took the participants to make a choice.

Results

Homogeneity of attention to labels. To assess whether labels were meaningfully different from each other in capturing participants’ visual attention, two one-way ANOVAs were performed, with dependent variables being time to first fixation and the fixation likelihood (the term fixation likelihood is described in more detail in a section below) and the independent variable being labels. Both analyses indicated that there was no meaningful difference among the labels since neither the time to first fixation, F (3,2713) = 1.045, p = .372 nor the fixation likelihood, F (3,4444) = .796, p =

.496 reached significance. This means that participants start their visual search on the product randomly in relation to the label information.

Saccadic length. To understand participants' search behavior and to test the assumption that participants apply short saccades, the saccadic length was analyzed. In visual research, a saccade is classified as short if it is less than two visual degrees (Tatler, Baddeley, & Vincent, 2006). For the experimental material, a two-degree visual angle will correspond to a saccade between the two grouped labels. A saccade around 10 visual degrees would correspond to horizontal saccading between each corner of the product. The analysis of saccadic length was assessed by plotting participants' saccadic length and the frequency of occurrence. A strong bias toward shorter saccades was observed, which was hypothesized to lead to a greater likelihood of grouped stimuli to be fixated compared to ungrouped stimuli. Figure 2 shows the frequency of saccadic length.

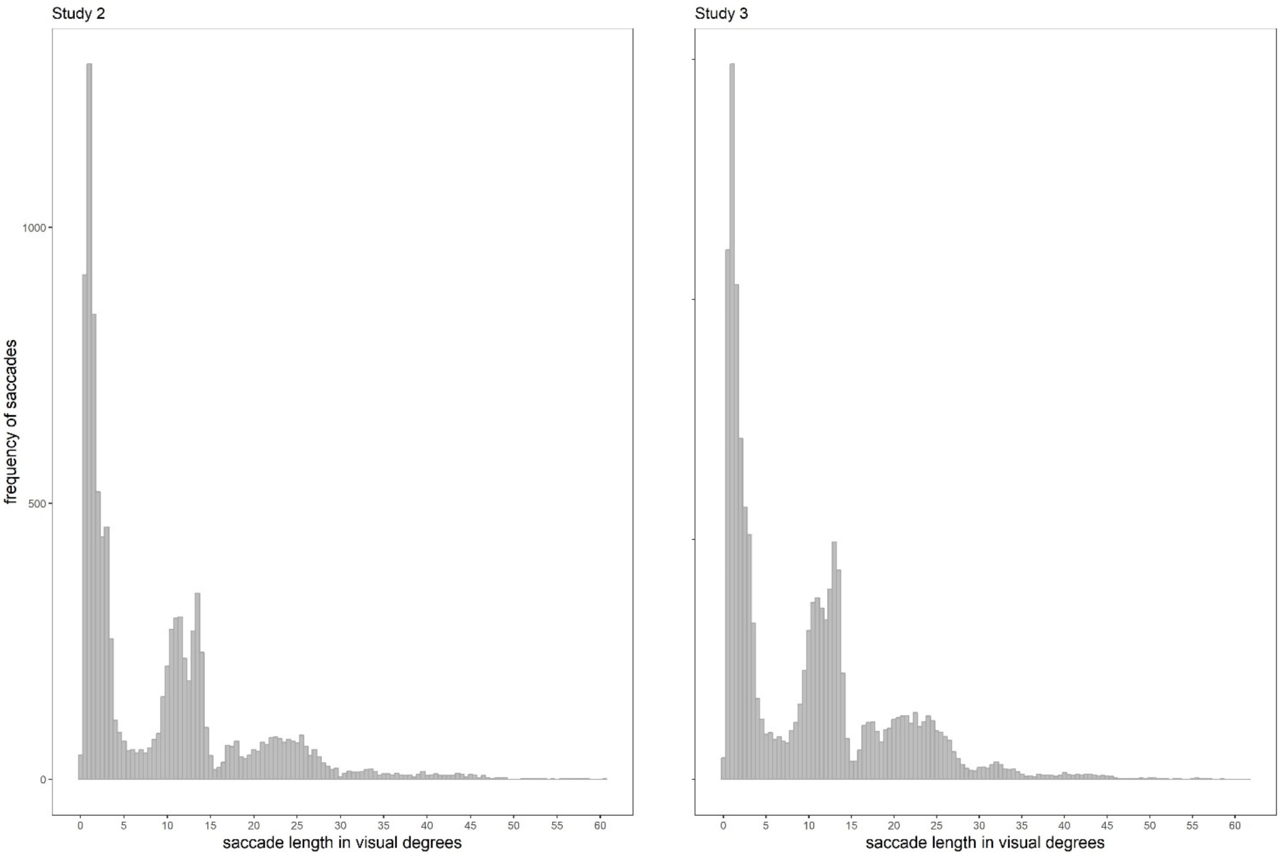

Figure 2. Plot of saccadic length for Studies 2 and 3, respectively.

Analysis of fixation likelihood. The likelihood of participants fixating the grouped label in each trial was analyzed using a generalized linear mixed model (GLMM). The dependent variable (fixation likelihood) is a binary variable with the value 1 if an AOI is fixated and 0 otherwise. All models were estimated using the lme4 package in R (Bates, Sarkar, Bates, & Matr, 2007). Models were fitted using a step-up approach based on BIC. The best-fitted model contains the main effect of trial and random intercepts grouped by participant, indicating no significant main effect of condition, label, or position. The list of models considered for model selection can be found in Appendix B.

Effect sizes were computed directly from the observed data by means of Cohen's *d*, where the mean differences are divided by the pooled standard deviation: $\sqrt{\frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1 n_2-2}}$, where n_i and s_i refer to the sample size and standard deviation of the two experimental conditions (grouped vs. ungrouped). No effect was observed in fixation likelihood between the two conditions, Cohen's d = .049, CI_{95} = [-.069, .166]. Mean fixation likelihood and standard deviation for the two conditions are shown in Table 3.

Table 2. Parameter and variance estimates for fixation likelihood analysis in Study 2.

Parameter	Estimate	SE	*t*
Intercept	.737	.071	10.427
Trial	-.004	.122	-5.394

Number of observations = 1113

Analysis of conditioned fixation likelihood. Since the saccadic analysis indicated that participants apply shorter saccades and this did not affect the fixation likelihood directly, it was analyzed whether the likelihood of participants fixating the grouped label was conditioned on fixating the target label. That is, if a participant fixates the target label, would it increase the likelihood that she fixates the grouped label in the grouped condition contrary to the ungrouped condition? Effect sizes were computed in a way similar to the analysis of fixation likelihood. A small effect was observed of the likelihood of conditioned fixations to the grouped label between conditions, d = .189, CI_{95} = [.02, .356]. The mean conditioned fixation likelihood and standard deviation for the two conditions are shown in Table 3.

Table 3. Conditioned fixation likelihood for the target 2 label given a fixation on target 1 across studies and conditions.

		Fixation likelihood		Conditioned Fixation likelihood	
Study	Condition	M	SD	M	SD
2	Ungrouped	.613	.488	.776	.418
	Grouped	.636	.482	.849	.358
3	Ungrouped	.522	.500	.813	.391
	Grouped	.461	.499	.827	.379

Analysis of position. To ensure that the observed effect of conditioned probability was not due to any positioning effect, an analysis of the effect of positioning on fixation likelihood was conducted. Effect sizes were computed in a way similar to the fixation likelihood analysis. The largest difference in fixation likelihood was observed between the bottom right and top left, d = .359 CI_{95} = [.237, .470]. Contrary to the reading direction, bottom right receives a higher fixation likelihood than top left. Figure 3 illustrates the positioning effect.

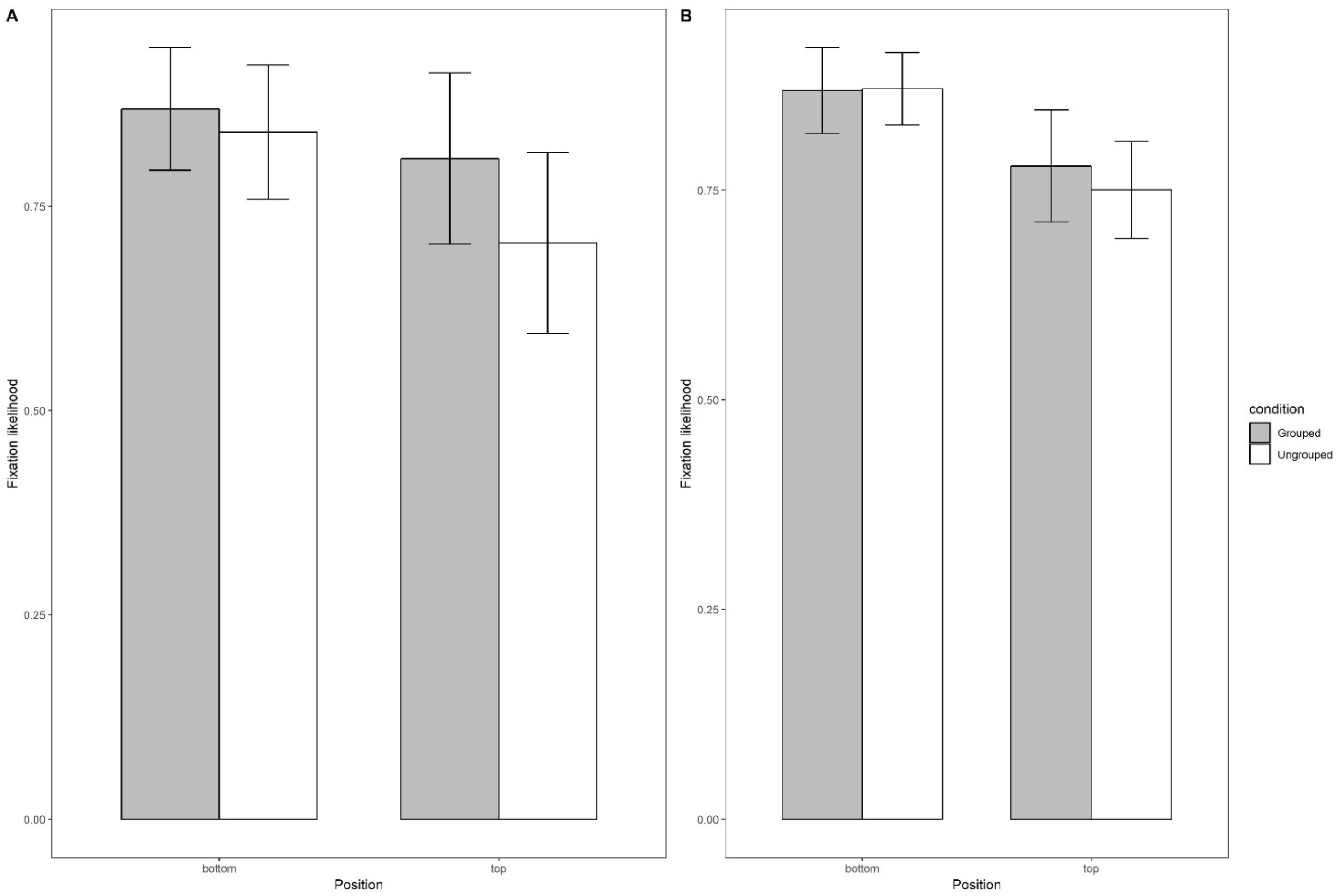

Figure 3. The probability of fixating the grouped elements depending on the condition and the vertical position in which they appear. Error bars represent 95% confidence intervals for A) Study 2 and B) Study 3.

Discussion

The analysis of fixation likelihood revealed that fixating the grouped label was not more likely in the grouped condition compared to the ungrouped condition. However, when controlling for the fact that participants fixated the target label, the fixation likelihood increased significantly in the grouped compared to the ungrouped condition. This indicates that grouping of stimuli increases the likelihood of fixating nearby labels. It can be hypothesized that participants are more likely to perceive the grouped labels as one unit, or it could be an artifact of participants favoring shorter saccades, which will force participants involuntarily to fixate objects in proximity. Irrespective of the mechanism, the outcome is the same, namely a higher likelihood of fixating grouped elements. A position effect was observed for stimuli at the bottom being more likely to be fixated, especially in the grouped condition. At first glance, this is an unintuitive finding given the rich literature confirming a higher fixation likelihood for stimulus presented at the top of the screen (Chen & Pu, 2010; Sütterlin, Brunner, & Opwis, 2008). However, as Study 1 suggested, there is an overrepresentation of grouped nutritional labels to be positioned at the bottom of product packages. This observation could be an ecologically learned cue guiding consumers toward the bottom of the product to find relevant information for their decision-making process.

Study 3

In Study 2, a conditioned grouping effect was observed. However, with both conditions receiving a high fixation likelihood (Table 3), it was hypothesized that this effect could stem from the experimental procedure where participants had all the time they needed to make a decision. This may have driven participants to be overly systematic in their approach. Study 2 indicated that labels positioned at the bottom of the stimuli had a higher fixation likelihood. Since positioning was randomized only twice, it might be possible that some labels had a higher likelihood of ending at the bottom. Since a real-life supermarket is a distracting and noisy purchasing environment, consumers are often too rushed or confused to search intentionally for nutritional information (Otterbring, Wästlund, & Gustafsson, 2016). To increase the ecological validity, it was experimentally tested whether an imposed time constraint could increase the likelihood of grouped stimuli being fixated. Furthermore, to ensure that positioning did not influence the outcome, we chose to increase the design from Study 2 to a full factorial design presenting all labels at each location. It was hypothesized that in a time-pressured decision environment, participants would have a higher likelihood of fixating grouped elements since it requires fewer saccades to identify grouped labels.

Method

Participants. A total of 34 participants were recruited for the study (M_{age} = 27.21 SD_{age} =8.93, 44.12% female). Three participants were excluded due to the loss of data or lack of useful eye-tracking data. The result was a final sample of 31 participants. Participants had normal or corrected-to-normal vision. Participants gave informed consent and received DKK 60 for completing the study.

Experimental design. The experimental design was similar to that of Study 2, with the exception that a time constraint was imposed on participants and that it follows a full factorial design, positioning of labels resulting in a total of 128 trials.

Materials ad measures. The experimental materials were similar to those of Study 2.

Procedure. The experiment follows the same procedure as Study 2; however, participants were instructed to imagine that they were in a hurry and needed to make a decision fast. Further, they were instructed that the screen could terminate at any time.

Results

Manipulation check. The effect of the time constraint manipulation was assessed using total decision time. The results indicate that our time constraint worked, as participants used 1620 ms. (SD = 1810) to make a decision in Study 3; in contrast, participants in Study 2 used 2345 ms. (SD = 1788) to make a decision, equal to a moderate Cohen's $d = .403$, $CI_{95} = [.336, .468]$.

Homogeneity of attention to labels. The analysis of participants' eye movements on labels was assessed similarly to Study 2. Both metrics indicated that there was no meaningful difference among the labels since neither the time to first fixation nor the fixation likelihood reached significance $F_{\text{time to first fix}}(3,7977) = 0.249$, $p = 0.862$; $F_{\text{fixation likelihood}}(3,15968) = 0.136$, $p = 0.939$). This means that participants start their visual search on the product randomly in relation to the label information.

Saccadic length. The same pattern of saccadic length was observed in Study 2, indicating a preference for participants to have shorter saccades. Figure 2 shows the frequency of saccadic length.

Analysis of fixation likelihood. The analysis was conducted in the same manner as in Study 2. The best-fitted model contains the main effect of condition and trial with random intercepts grouped by participant, indicating no significant main effect of label or position. Table 4 shows the parameter and variance estimates for the final model. There was a small effect of condition on fixation likelihood toward the ungrouped labels, $d = .123$, $CI_{95} = [.060, .186]$. The mean fixation likelihood and standard deviation for the two conditions are shown in Table 3. The list of models considered for model selection can be found in Appendix B.

Table 4. Parameter and variance estimates for fixation likelihood analysis in Study 3.

Parameter	Estimate	SE	*t*
Intercept	.556	.006	8.873
Condition	-.009	.002	-.559
Trial	-.001	.000	-5.328
Number of observations = 3,866			
BIC = 3,638.172			
Variance (participant) = .108			

Analysis of conditioned fixation likelihood. The conditioned fixation likelihood analysis was conducted in the same manner as in Study 2. A small effect of conditioned fixation likelihood was observed, d = .038, CI_{95} = [.006, .139]. The mean conditioned fixation likelihood and standard deviation for the two conditions are shown in Table 3. To investigate this further, the probability of looking at any combination of labels was assessed. Interestingly, no other conditioned fixation likelihood was above chance level (.33). That is, any combination of potential conditional fixation likelihood, that is, from target to distractor, or distractor to distractor, was not meaningfully different from chance, irrespective of condition, indicating that if the target label was fixated, the likelihood of participants fixating the grouped labels was significantly higher than chance.

Analysis of position. The analysis of position was assessed in the same manner as in Study 2. Since the experimental design accounts for any random positioning effect, effects of position are less likely to come from random factors. The largest difference in fixation likelihood was observed between bottom left and top left, d = .333, CI_{95} = [.267, .392]. Splitting it by top and bottom, a moderate effect of d = .238, CI_{95} = [.175, .300] was observed in favor of the bottom position. Investigating the same positioning effect as Study 2 between bottom right and top left, it yielded a moderate effect of d = .242, CI_{95} = [.179, .302]

Discussion

While the analysis of fixation likelihood revealed a small effect of condition on the fixation likelihood, this was of the ungrouped condition, contrary to the expected outcome. The analysis of the conditional probability revealed no difference in fixation likelihood between the two experimental conditions. As with Study 2, Study 3 revealed a larger fixation likelihood to labels positioned at the bottom of the package, which again points to consumers learning from the environment and expecting valid cues to be positioned near the bottom, as the field data from Study 1 confirms.

General discussion

This paper tests the effect of perceptual grouping in the context of product packaging. The hypothesis was that positioning nutritional labels in short proximity would increase attention toward these as a function of properties from Gestalt. While most research on food labels has been concentrated around optimizing locally, that is, utilizing bottom-up processing (Orquin et al., 2018; Orquin & Loose, 2013; Wedel & Pieters, 2008), little focus has been given to perceptual organization, that is, Gestalt principals such as proximity. Study 1 was conducted to investigate the prevalence of perceptual organization of nutritional labels on current product packages. The field data in Study 1 found evidence for perceptual grouping of nutritional labels on product packages if grouping was possible, that is, two or more labels prevalent on the product. Whether this is due to a strategic design property or an artifact of visual ecology (Orquin et al., 2019), where key selling points such as pictorials and brand occupy a large portion of the available space, whereas elements referring to socially desirable credence characteristics such as sustainability or nutrition are given a less prominent location, is unknown. However, Study 1 confirms the latter, namely that the position of nutritional labels follows a predictable ecology, where they are overrepresented at the bottom of the product, a position known as the least favorable for influencing attention (Chandon et al., 2009; Gidlöf et al., 2017; Orquin et al., 2019; Sütterlin et al., 2008). Study 2 experimentally tested the influence of perceptual manipulation of nutritional labels by means of proximity. The perceptual manipulation showed no evidence for increasing fixation likelihood. However, the analysis indicated that if participants had fixated the target label, the likelihood of fixating the other was significantly higher in the grouped compared to the ungrouped condition. Study 2 provided evidence that perceptual manipulation could increase consumers' attention if one of the grouped elements were fixated. Additionally, Study 2 provided evidence for a positioning effect in which grouped stimuli positioned at the bottom of the product had a higher fixation likelihood. This is an interesting finding for two reasons: First, it is contrary to what previous research would lead us to expect, where the bottom usually receives poor fixation likelihood; second, it points to participants maybe relying on some sort of ecological cues, such as learning from the environment that nutritional information is usually to be found at predictable locations. Similar effects have been found in natural environments, where consumers learn cue validities of healthful foods in the supermarket (Perkovic & Orquin, 2018). This is coherent with the findings of Study 1, where there was a prevalence of grouped elements being positioned at the bottom. Since Study 2 only partially randomized the position of grouped labels, it cannot be ruled out that this effect stems from a design effect, which is why the position of labels was fully factorially positioned in Study 3. In Study 3, it was tested whether a time constraint would increase participants' use of grouped elements involving a higher fixation likelihood. Imposing a time constraint did change the distribution of fixation likelihood; however and contrary to expectations, perceptually distanced labels were more likely to be fixated compared to labels in closer proximity. When controlling for the conditional probability, no effect in fixation likelihood was observed between the two conditions. As in Study 2, an increased fixation likelihood to labels positioned at the bottom of the package was observed, since Study 3 insured full randomization of position, that is, if a position effect is observed, it is not due to a random factor in the positioning of labels; it may be an indication that consumers learn where to expect nutritional information from the environment. One of the limitations of this paper is that it tested purely perceptual manipulation and its effect on eye movements on food labels without any processing costs, task manipulation, or decision relevance. This paper’s findings cannot provide a clear picture of the effect of perceptual manipulation on product packaging; however, it seems that, under the right circumstances, grouping has the potential to guide eye movements. Future studies should try to implement decision relevance as an experiment factor to test the interaction between perceptual manipulation and decision relevance. While Study 2 found a positive effect on fixation likelihood for grouped stimuli, no such effect was confirmed when, in Study 3, a time constraint was imposed on participants. While the main reason for the deviation in results is unanswered, the author speculates that participants may have been more systematic in their processing of stimuli and, therefore, on average, equally likely to fixate the labels in both conditions. Future research could investigate whether bottom-up factors, such as position, saliency, or size, could be used to attract attention to the grouped stimuli. To test the phenomena of perceptual grouping on product packaging while maintaining internal validity, it was necessary to keep both experimental designs simple. Despite the limitations, I believe that this paper presents an interesting use of perceptual manipulation and sets the stream for future studies. If perceptual grouping does indeed attract attention, it may help consumers navigate and more efficiently choose the best product for their purpose.

Managerial implications

Without compromising brand-related elements, product designs and marketers alike can utilize grouping of nutritional labels to increase the likelihood that consumers notice the information. As a potential benefit, it could decrease the visual clutter and simplify the design further since grouped information requires less space than two separately positioned labels.

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Appendix A

A 1. Example of experimental stimuli for the grouped and ungrouped conditions.

Appendix B

B.1 List of potential models for model selection for study 2

Model	LL	DF	N	BIC	deltaBIC
selection ~ +(1 | ParticipantName)	-590.61	3	1113	1202.26	8.92
selection ~ condition + (1 | ParticipantName)	-592.88	4	1113	1213.82	20.48
selection ~ AOI + (1 | ParticipantName)	-592.79	4	1113	1213.64	20.3
selection ~ trial + (1 | ParticipantName)	-582.64	4	1113	1193.34	0
selection ~ trial + position + (1 | ParticipantName)	-581.28	5	1113	1197.63	4.29

Note. Selection = fixation likelihood, condition = the experimental condition (grouped vs. ungrouped), AOI = the unique label used, trial = the order of trials, ParticipantName = the unique ID for each participant, position = the relative position of labels on the product.

B. 2 List of potential models for model selection for study 3

Model	LL	DF	N	BIC	deltaBIC
selection ~ +(1 | ParticipantName)	-1812.36	3	3866	3649.5	16.34
selection ~ condition + (1 | ParticipantName)	-1802.57	4	3866	3638.18	5.02
selection ~ condition + AOI + (1 | ParticipantName)	-1827.26	17	3866	3794.94	161.78
selection ~ AOI + condition + AOI * condition + (1 | ParticipantName)	-1848.37	30	3866	3944.54	311.38
selection ~ condition + trial + (1 | ParticipantName)	-1795.93	5	3866	3633.16	0
selection ~ condition + trial + position + (1 | ParticipantName)	-1793.23	6	3866	3636.02	2.86

Note. Selection = fixation likelihood, condition = the experimental condition (grouped vs. ungrouped), AOI = the unique label used, trial = the order of trials, ParticipantName = the unique ID for each participant, position = the relative position of labels on the product.

5

The Effect of Fixation Order on Choice[1]

Working paper

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Abstract

The vast majority of the decisions we make as consumers happen in visual environments, from searching on google to choosing a product in a supermarket. In situations in which we have to make use of our eyes, information processing occurs sequentially, that is, in order to mentally process information, attention is focused on one option at a time. Whenever options appear in sequence, our decision-making may be vulnerable to potential order effects. In one laboratory and one quasi-experimental field study, we show how the perceptual order can influence consumer choices as a primacy effect, where products seen first are more likely to be chosen compared to products seen later. However, this effect arises merely as a function of how consumers search for information. As set sizes become large, participants are more likely to ignore a growing percentage of products. We computed the probability of choice given fixation order across set size and found a primacy effect on consumers' choice for large set sizes, but no effect for the smallest set sizes. Our findings suggest that the importance of perceptual order arises as consumers truncate their search as a response to increasing information load.

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Introduction

The vast majority of the decisions we make as consumers happen in visual environments, from searching on Google to choosing a product in a supermarket. Both these examples rely on the consumers to utilize their eyes in order to process the available options. In situations where we have to make use of our eyes, information processing occurs sequentially, that is, in order to mentally process information. Therefore, attention is focused on one option at a time. Whenever options appear in sequence, our decision-making may be vulnerable to potential order effects. The order in which information is encountered has a strong impact on judgments of alternatives. One way order effects influence consumers' choices is by the order of presentation, which dictates the direction of comparison. One of the most well-known effects on presentation order is the anchoring effect (Tversky & Kahneman, 1974), which proposes that information presented first serves as an anchor for later judgments that are adjusted to the original anchor. However, sometimes information appearing early in a sequence has a stronger effect on judgment than does subsequent information (a primacy effect), whereas at other times later items dominate earlier items (a recency effect). This is known as the serial position effect (Murdoch Jr, 1962). The serial position effect is one of the most robust findings in psychology. In the traditional version, participants have to remember sequences of information. In such cases they show a preference to information placed at the beginning and/or end of the ordered list, known as primacy and recency effect, respectively. One caveat from serial position effect studies is that the position is temporal and temporary and the dependent variable is usually memory or recall, which makes it of less relevance for studying consumer decision-making. However, similar effects of positioning are found in decision-making with dependent variables being choice or judgment. For instances in online domains, Anesbury, Nenycz-Thiel, Dawes, & Kennedy (2016) found that consumers frequently choose products from the first category page and consistently use the default display option chosen by the retailer. Similar results are found in for instance; restaurant menus, as consumers tend to order items near the top of a menu more often than when those same items are at the bottom (Dayan & Bar-Hillel, 2011; Ditmer & Griffin, 1994; Miller, 1980), in voting, candidates that are listed at the top receive a greater proportion of votes compared to when the same candidate is listed in any other position (Koppell & Steen, 2004), in risk assessment, Bergus, Levin, & Elstein (2002) found that the order of presenting information about a treatment to patients alter their perception of the treatment. Patients presented with information about risk first perceived the treatment more positively compared to the situation where information about risk was presented last. A similar effect was found by Kwak and Huettel (2018), in which participants were more prone towards risk aversion, when the riskless option was presented first. The concept of order effect has been found in visual consumer research as well. For example in an eye-tracking study of reading yellow pages, participants tended to fixate and choose ads that were presented at the top of the list (Lohse, 1997). In a later study, Hoque and Lohse (1999) manipulated an online interface to match the traditional offline yellow pages and found evidence of a primacy effect in such an online context as well.

By now, it seems fair to argue that the visual environment can influence how consumers search for and intake information. The abovementioned findings showcase one important aspect in consumer decision-making; that the presentation order in every sequence dictates the direction of the comparison, leading to potential order effects (Bruine de Bruin & Keren, 2003). This is not a trivial point, since the order of information intake is subject to changes in decision preferences, which means that how we search for and integrate visual information plays a crucial role in how we decide. If we consider that the visual presentation of information can influence the order of perception and that order of perception may be equal to the order of information integration, then it follows that the spatial positioning may influence what consumers choose. In fact the spatial position is widely recognized to influence consumers' decision-making. Compelling evidence from both laboratory and field experiments indicate that shelf position to influences both consumers' attention and choice, in favor of products that are placed at eye height or in the middle of the shelf (Atalay Bodur, & Rasolofoarison, 2012; Chandon Hutchinson, Bradlow, & Young, 2009; Valenzuela & Raghubir, 2009). These findings may be explained by the beliefs held by consumers about the psychical positioning of products on the shelf applied by marketers, specifically that the bestselling products are positioned in the middle. In an eye tracking study where position was perfectly correlated with price ranking, Pan, Zhang, and Law (2013) provide useful insights into the effect of position on attention, suggesting that individuals attend mainly to items at the top and bottom of the page, this may be generalizable to the shelf level as well. Interestingly in a later study Ert and Fleischer (2016) found that even when position is uncorrelated with relevance, the same positioning effect emerges.

It seems fair to summarize the evidence of positioning in decision-making and conclude that it indeed seems to influence the order of perception as well as choice. Yet, the boundaries and the nature of these effects are poorly understood in consumer decision situations such as online and regular supermarkets. In this paper, we aim to investigate consumers' search behavior and how this influences the perceptual order of information integration in simultaneously presented visual environments, free of mere position effects', that is, the position in which information occurs is uncorrelated with its decision value. We first analyzed consumers' search behavior in a laboratory experiment by means of a realistic shopping task environment resembling an online supermarket. In order to resemble a real shopping experience as much as possible, a preferential choice task was used asking participants to choose the product they prefer. Furthermore, to ensure a sufficient variation in the number of available products, the study manipulated the set size. Next to test the order effect in natural environment we conducted a quasi-experiment in a regular supermarket.

Study 1

In order to understand how the perceptual order affect consumers' choices we re-analyzed a subset of the original data presented in Orquin, Perkovic, Bagger, & Todd (2018 under review). The study design makes it perfect to investigate perceptual order since it utilized a controlled discrete choice experiment in which participants choose their preferred product free of mere position effect. Furthermore it manipulated the set size to test whether larger set sizes influenced consumers' search behavior differently than smaller set sizes.

Method

Participants. The study originally recruited 78 Danish participants through a consumer panel provider. Seven participants were excluded after the experiment due to insufficient data quality resulting in a total sample of 71 participants (M_{age} = 45.73, SD_{age} = 15.12, 19 women). Since the current paper was only interested in preferential choice conditions, we only used participants from this condition, resulting in a total sample of 32 participants. Participants had normal or corrected to normal vision and full color vision. All participants provided a written informed consent and received a gift card of DKK 150 for participation.

Experimental design. The study utilized a within subjects design manipulating set size (3, 6, 9, 12, 15, 18, 21, 24, and 27 products) in a discrete choice experiment. There were 10 trials for each set size, resulting in 90 trials in total.

Materials and measures. Stimuli consisted of 56 discrete products of ready meal products. All products were real consumer products sold at online supermarkets. Each product included an image, brand name, content in grams or kilograms, and a price. Stimuli were presented rectangularly and occupied 5.1° horizontally and 8.2° vertically and were separated by 0.8° horizontally and vertically. Product presentation were created by means of Adobe Photoshop and were always located on a grid starting in the middle of the screen and extending horizontally and vertically as the set size increased. The products were randomly located on the grid to avoid correlating product location and product quality.

Eye movements were recorded using a table mounted Tobii T60XL eye tracker with a temporal resolution of 60 Hz and accuracy = .4 and precision = .22. Stimuli were displayed on a 24-inch widescreen monitor with a resolution of 1920 x 1200 pixels. Participants were seated approximately 60 cm from the screen using a chin-rest. Fixations were detected using the I-VT algorithm with a minimum fixation duration of 60 ms. Areas of interest (AOIs) were drawn around each product with a margin of 0° to avoid falsely assigning fixations stemming from neighboring products (see Orquin, Ashby, & Clarke, 2016).

Procedure. Upon arrival to the laboratory, participants were seated in front of the eye tracker. The study utilized a preferential choice task in which participants were instructed to choose the product they preferred. After the nine-point calibration, the experiment begun. Instructions were presented on the screen and participants completed the task at their own pace. The participants indicated their choices with a mouse click on the chosen product. A fixation cross was displayed before each trial for 500 ms and the order of trials was fully randomized. We kept the first fixation in the data, since the order of presentation of each alternative was randomized and thus on average should not influence attention at stimulus onset.

Results

Individual level order effects. We begin by analyzing the effect of fixation order on choice at an individual level. For each participant and each trial, we denote the fixation order of the chosen product as *k* and the search set that is, the total number of seen products as *n,* and the set size as *N*. To understand whether participants are more likely to choose the first or the last seen product we fit a beta-binomial distribution to each participant as a function of fixation order *k* given the consideration set *n*. As the name suggests, the beta-binomial distribution is essentially a binomial distribution with a parameter for over dispersion, θ. When the θ = 2 and *p* = .5, the beta-binomial becomes a discrete uniform distribution ranging from zero to *N*. By adjusting *p* and θ, the beta-binomial distribution can become either left or right-skewed, u or inverse u-shaped, or uniform. The beta-binomial therefore lends itself for studying *order* effects with the small caveat that one has to subtract one from *N* and *k* to make the data consistent with the distribution. Furthermore, the distribution cannot be fitted to samples with less than two fixated products, which in our data means excluding 13 trials from the analysis. To ensure that these transformations to the data would not bias the estimated parameters we first conducted a parameter recovery. We simulated data consistent with the given data set, but assuming no *order effects*. We then applied the transformation and exclusion and fitted the beta-binomial distribution to the resulting data set. The simulation showed that the transformation and exclusion did not bias the parameter estimates. We then fitted the beta-binomial distribution to each participant by means of maximum likelihood using the r package “bbmle” (Bolker, 2017). The obtain estimates are show below in Figure 1. The average estimates were p =.53, SD=.05 and θ =1.93, SD=.39.

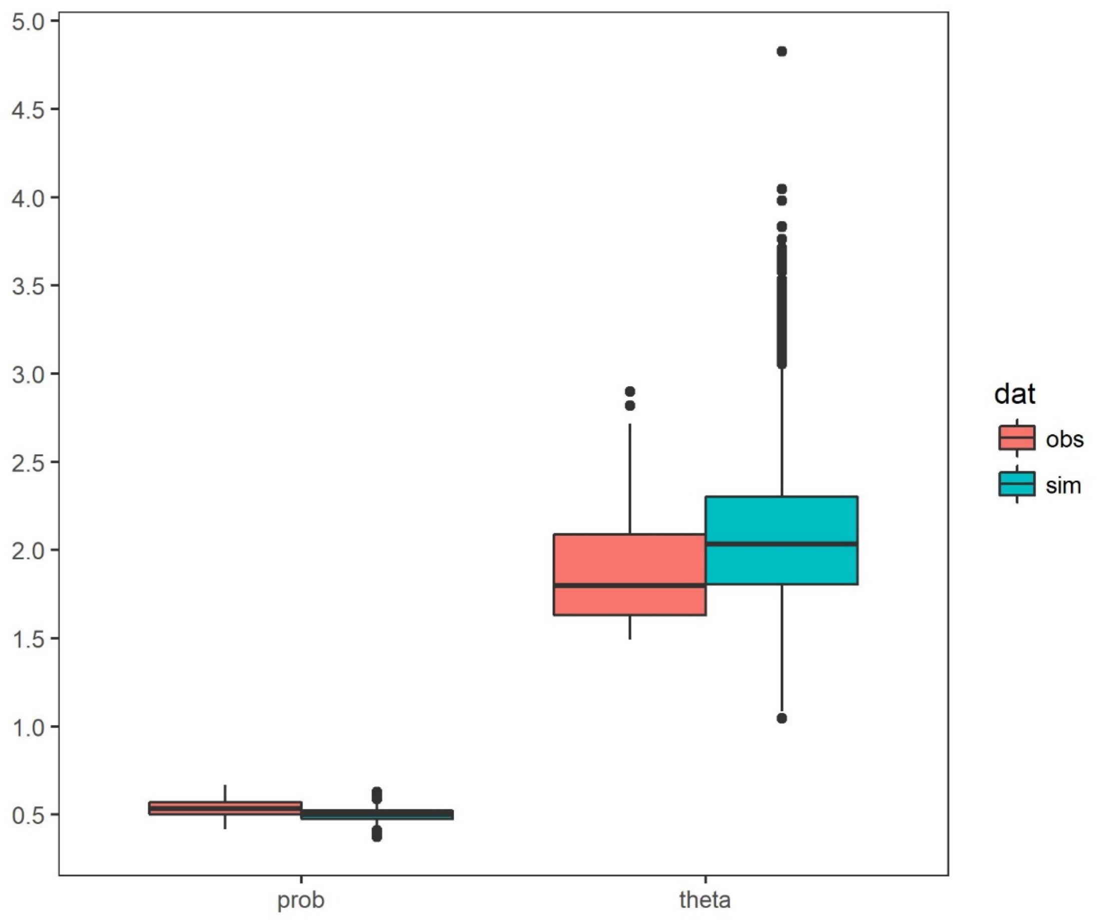

Figure 1. Box plot of observed and simulated p and θ coefficients, red boxes illustrates observed data, and blue boxes illustrate simulated data.

To understand whether any of the participants were meaningfully different from uniform (no *order effect*) we simulate the confidence interval for a data set with 90 observations and $p = .5$ and $\theta = 2$. We generate 10,000 data sets and fit the beta-binomial to each resulting in a distribution of p and θ. We then compute the 95% confidence interval for our simulated distribution parameters p CI_{95} = [.48,.61] and θ CI_{95} = [1.37, 2.83]. We then compare the observed parameter estimates to our simulated confidence interval. In the absence of order effects, we would expect parameter estimates not to differ from our simulated confidence interval. As Figure 1 shows, most of the participants fall within the simulated 95% confidence interval, and none of the participants fall outside the confidence level on both distribution parameters. We take this to suggest that there is no support for an order effect at the individual level.

Analysis of order effects at an aggregate level. The above analysis suggests that the order effects such as those that occur in Google or online grocery shopping are not due to a psychological primacy effect. Consumers are not more likely to choose the first product they see over the second product. How then could order effects arise in the absence of a psychological primacy effect? One possible explanation is that order effects will arise in the aggregate due to a Simpson's paradox: Even if consumers are equally likely to choose the first, second, third, etc. product they see, they do not always look at the same number of products. The consumer will always see at least one product, often see two products, sometimes see three etc. Because we do not choose what we do not see, this might create an order effect on average. To test whether this is the case we plotted the probability of choosing a product given the fixation order for each of the nine set sizes. We fitted the data by a beta-binomial distribution, with starting parameters obtained from the analysis of individual effects. Results are presented in Figure 2. Figure 2 shows a clear primacy effect for the larger set sizes, but no effect, or even a recency effect, for the smallest set sizes. According to our hypothesis, this might be due to participants fixating all products in the smaller set sizes, but truncating search in the larger set sizes.

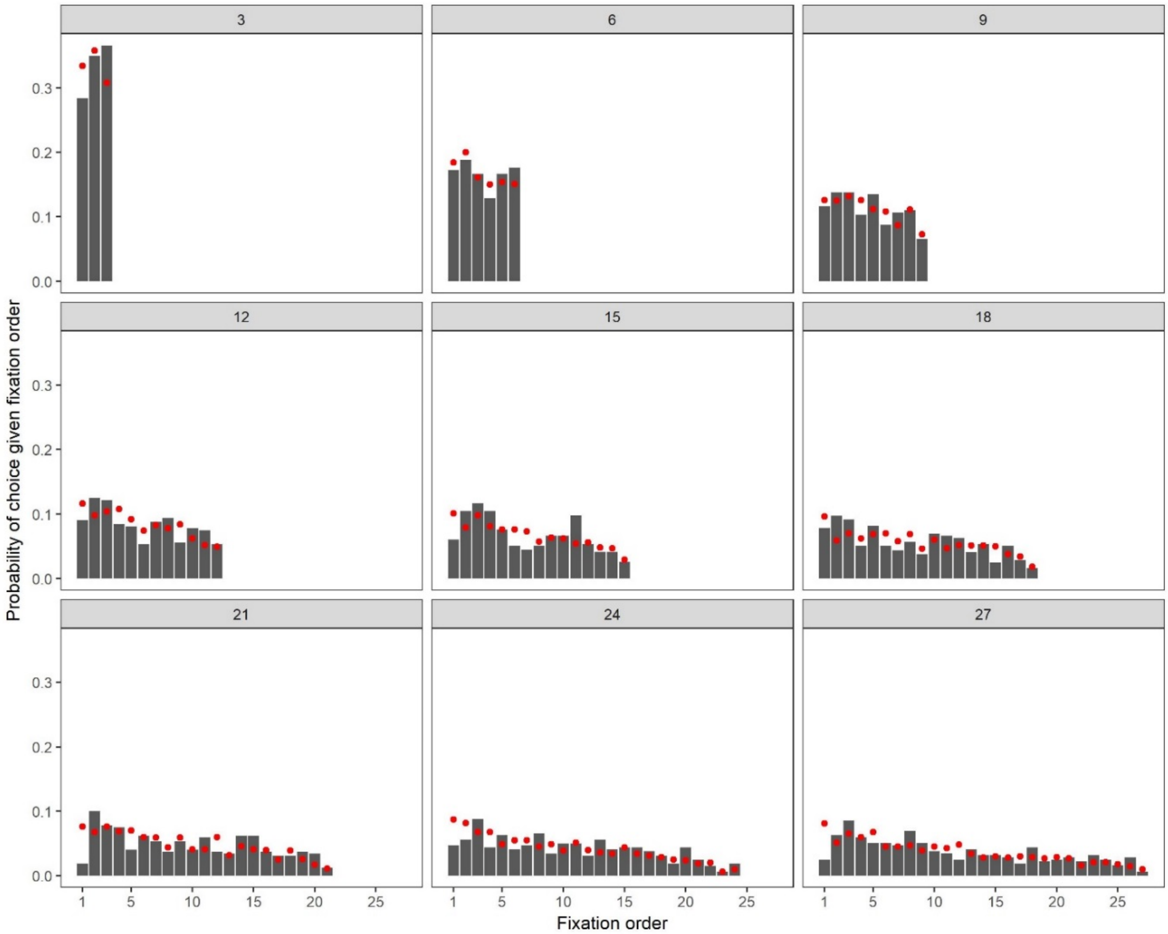

Figure 2. Probability of choice given fixation order across set sizes. Bars represent observed data and red dots represent the predictions from the simulation.

To explore this, we analyze participants' consideration sets as a function of the set size. We propose that there are at least three ways that consumers can adapt to an increase in set size by altering their visual search behavior. The first response is by linearly increasing the consideration set as a function of the set size. We can also imagine search rules with a diminishing marginal increase as well as search rules with an upper limit, i.e. the consumer searches all information up to a certain point after which no additional information is taken into consideration. We define a *diminishing marginal search rule* as any model that captures a diminishing marginal increase in the search space as a function of the set size. Third, we define a constant limit search rule as having an upper search space limit, so that when the set size is below the limit, everything is fixated, whereas when the set size is larger, no additional information is fixated. We analyze participants' consideration set as a function of set size implementing the above search strategies as follows: the linear search rules is approximated with an intercept, *k*, so that the probability of fixating a product is equal to P(f) = *k*. where p=1. The diminishing marginal search rule was approximated by a power law and an exponential function respectively. For both functions the set size, *N*, factors into the equation. For the power law function as:

$$P(f) = w_1 N^{-w_2}$$

where w_1 and w_2 are free parameters. The exponential function was defined as:

$$P(f) = w_1 e^{-w_2 N}$$

The constant limit search rule was implemented as:

$$P(f) = \begin{cases} 1, & N \leq l \\ \frac{l}{m}, & N > l \end{cases}$$

We fitted the model with a maximum likelihood function using the 'bbmle' package. The likelihood functions had a binomial probability distribution. The best fitting model was identified using the ΔBIC value, where $\Delta BIC_i = BIC_i - BIC_{min}$. Considering the higher model complexity of the power law and exponential models, we selected the linear model when $\Delta BIC_{linear} < 2$. The constant limit model was selected when $\Delta BIC_{linear} > 2$ and $\Delta BIC_{constant\ limit} < 2$ (Burnham & Anderson, 2002; Lewandowsky & Farrell, 2011). When neither of these conditions were met, the power law and exponential models were selected based on the smallest ΔBIC. The majority of participants were best described by the exponential model (N = 25) and a subset by the linear (N = 4) and power law (N = 3) models. None of the participants were identified as using the constant limit search model. The model fit measures for each individual are shown in Appendix 1.

Next, we fitted the exponential model across all participants. The estimated parameters were a=1.03, b=.012, -LL=9517.17, BIC= 19050.27. The BIC also known as the Bayesian Information Criterion, is a criterion for model comparison among a set of models, where the model with the lowest BIC is preferred. The BIC balance the level of fit (quantified in terms of the log-likelihood) with model complexity. Figure 3 shows the observed consideration set for each set size and the predicted consideration set by the exponential function. As Figure 3 shows, the predicted consideration sets fall inside the observed confidence intervals. The Figure shows that when set sizes are low i.e., 3 and 6, participants fixate all products. As set sizes become large participants are likely to ignore a growing percentage of products.

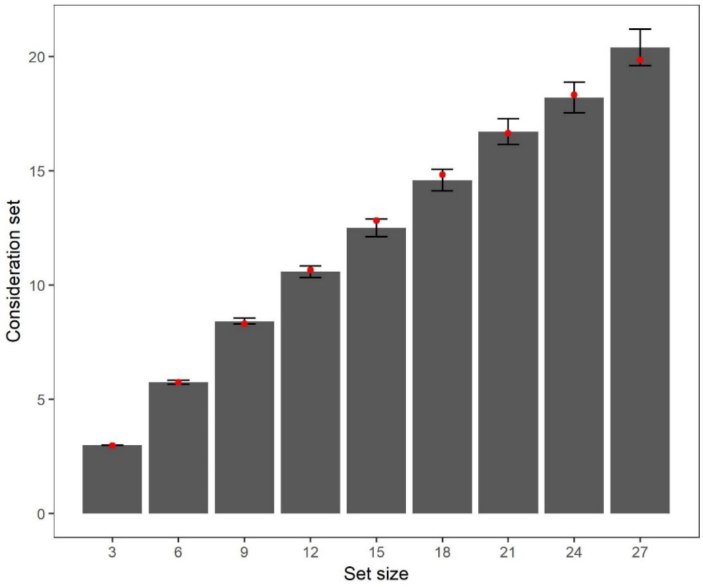

Figure 3. Observed and predicted consideration set by set size. Observed consideration set is presented as bar and predicted are the red dots. Error bars represent 95% confidence interval.

Next, to test the aggregation hypothesis we simulate the choice process for each set size using the parameters from the two previous analyses. First, we simulate the consideration set, *k*, by drawing from a binomial distribution with probability, $p = ae^{bN}$, where *N* is the set size. We then simulate the fixation order of the chosen product by drawing uniformly from 1 to *k*. We iterate 10,000 times for each of the nine set sizes. We then compute the probability of choice given fixation order across set sizes. Figure 2 shows that the simulation results resemble the observed data well, R2 = 88.13. This suggests that order effects can arise in the aggregate even though no such order effect occur at the individual level.

Discussion

In Study 1 we analyzed the effect of fixation order on consumer choices in an eye tracking study using a realistic shopping task environment resembling an online supermarket. No evidence was found of an order effect at the individual level. However, in the aggregated data we observed a primacy effect, where products seen first have a higher probability of being chosen. This effect was further investigated by consumers' search behavior. We found that when set size was low i.e. below 6 products, participants were fairly good at sampling almost all available products, given little influence of the order. When set size on the other hand increases, participants are more likely to ignore a growing percentage of products. When computing the same aggregated probability of choice given the order of fixation across set size, we found a pattern in which order effects arise as set sizes increase. We take this to imply that the importance of order arises as consumers truncate their search as a response to an increase in information load. In this study we presented stimuli randomly across the screen, that is, there is no correlation between relevance and position, meaning that participants are unable to rely on the order of information as a decision heuristic.

Study 2

Study 1 found an order effect that arises in the aggregate as a function on how participants react to increase in information load. To test the boundaries and the ecological validity of our findings in situations where information overload naturally occurs we choose to conduct study 2 in a supermarket by means of mobile eye tracking.

Method

Participants. We recruited in total 60 consumers (M_{age} = 24.25, SD_{age} = 5.27, 29 women). Seven participants were excluded due to poor data quality. Participants had normal or correct to normal vision. After completion of the study, which lasted approximately 15 min., participants received a voucher of 100 SEK for their participation. Participants gave informed consent.

Experimental design. The study utilizes a quasi-experimental design varying the set size between three different food categories, namely cereals, rice cakes, and pasta. The set sizes were 12, 15, and 56 for the three categories. Since the study utilizes a naturalistic environment, set sizes could potentially vary within categories due to products being sold out during the days of recording. We believe that a natural occurring heterogeneity in set sizes is beneficial to the hypothesis and these will be taking into account as random variables.

Materials and measures. The stimuli consisted of all available products in the pasta, rice cake and cereal category in one supermarket in Lund, Sweden. Eye movements were recorded using Tobii eyeglasses II with a binocular sampling rate of 50 Hz. Since participants wear the equipment during their shopping, there was a possibility that the equipment was moved around too much on the head, why the pre-study calibration becomes invalid. Because of this, we always checked the calibration at the end of the recording. The eye tracking data was analyzed frame-by-frame for dwells (Holmqvist et al., 2011) from selected segments of the gaze-overlaid video, namely around pasta, cereal, and rice cake shelves. Coding started when the first fixation falls on the category and terminates when a decision is reached. Four independent coders, using Tobii Pro Lab software, performed the initial coding. To ensure standardization of coding, a subset of the data (three videos) was coded by all individual coders. Interrater reliability was high (Cohen's kappa = .828).

Procedure. Upon entering the supermarket, participants were met by the researchers. Participants were informed about the study procedure without disclosing the study hypothesis. Participants were calibrated using the Tobii calibration tool. After the calibration, participants were instructed, in addition to their ordinary shopping, to buy one item from each category of interest. After completion of the eye tracking study, participants filled out a questionnaire, including questions regarding their preference for various food attributes, their familiarity with the present supermarket and the categories included in the study (this is not relevant for the present hypothesis).

Results

Since Study 2 was conducted as a quasi-experiment, it has some limitations in terms of data points. Since each participant only has three data points, meaning that modelling on the individual level will be an extreme overfitting of the data, which is why we choose only to pursue the answer of the order effect at the aggregate level.

Analysis of order effects at an aggregate level. The analysis was conducted in a similar manner as Study 1. With one exception, that we fitted the data by a beta-binomial distribution, with starting parameters set to .5 and 2 for prob and theta respectively. Results are presented in Figure 4. Inspecting Figure 4 gives rise to a similar order effect as the laboratory study in Study 1, in which participants are more likely to choose the third and fourth alternative in their search. This could be an effect of participants orienting themselves at the beginning of their search. The simulation also captures this effect by indicating an almost zero probability of choosing the first product seen. Calculating the cumulative probability for the first five products seen indicates that these stands for 53.2% of the total probability of choice which is almost similar to that of Study 1 (52.4%).

Analysis of familiarity. One of the limitations of collecting field data is the lack of control of participants' level of familiarity of the store environment. Therefore in order to test if store familiarity influences participants' search behavior, we ran a regression analysis on the influence of familiarity on number of products dwelled.

Table 1. Parameter and variance estimates for number of products dwelled in study 2.

Parameter	Estimate	SE	*t*	*p-value*
Intercept	13.180	1.086	12.141	<.000
Store familiarity	-.592	.500	-1.184	.239

Number of observations = 126

The regression analysis indicates that store familiarity did not influence the effect of search, why it is not to be considered a problem for the present papers hypothesis.

Follow up analysis. Since the study of perceptual order in natural environments is found to be influenced by the positioning effect, we calculated the choice distribution of participants for each shelf and presented them as heat maps in Figure 5. For two out of the three product categories, choices were distributed fairly heterogenetic between participants, in other words, we did not observe any correlation between mere position and choice. This is therefore an indication that the visual environment did not influence participants' choices.

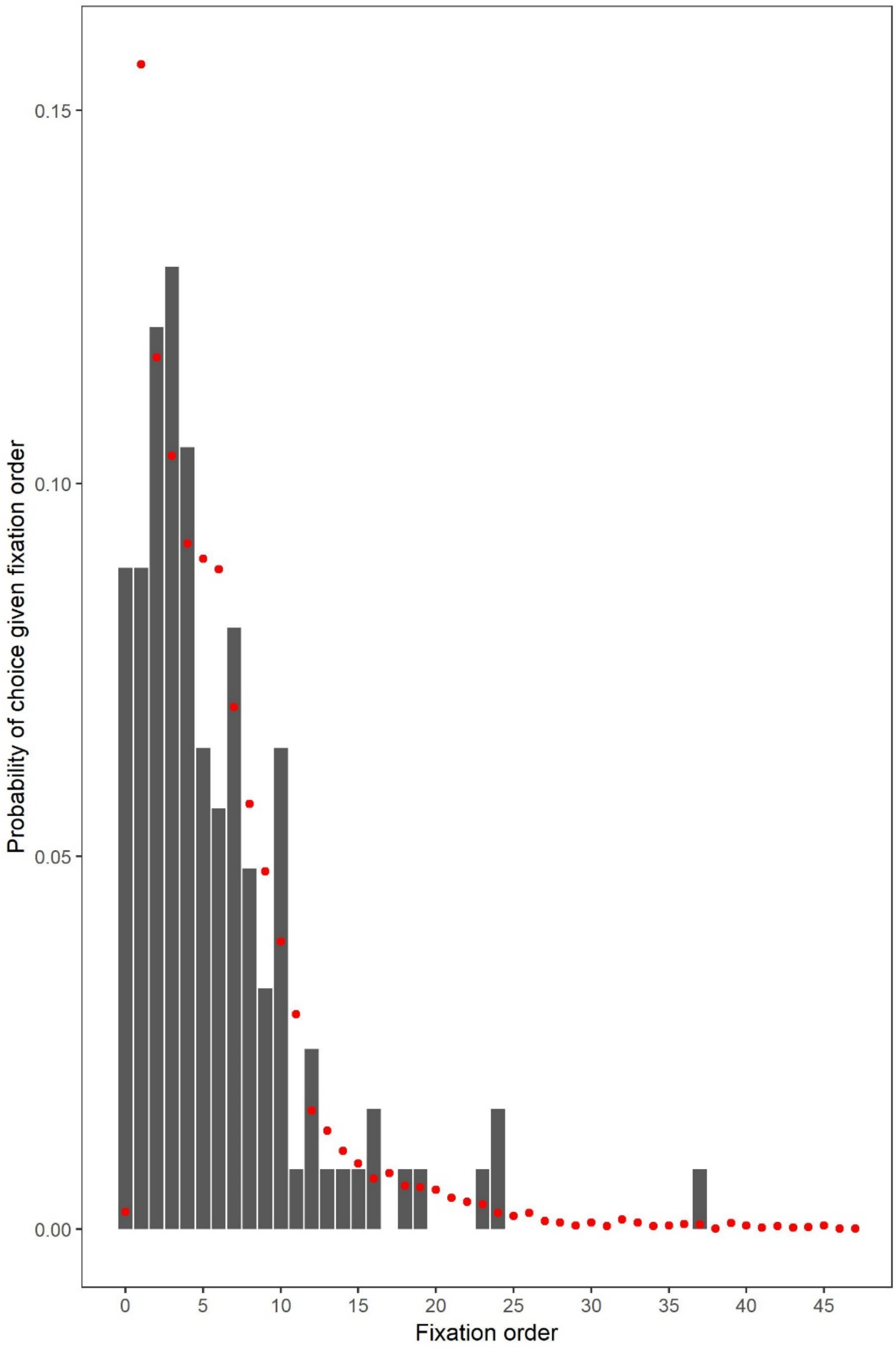

Figure 4. Probability of choice given fixation order. Bars represent observed data and red dots represent the predictions from the simulation.

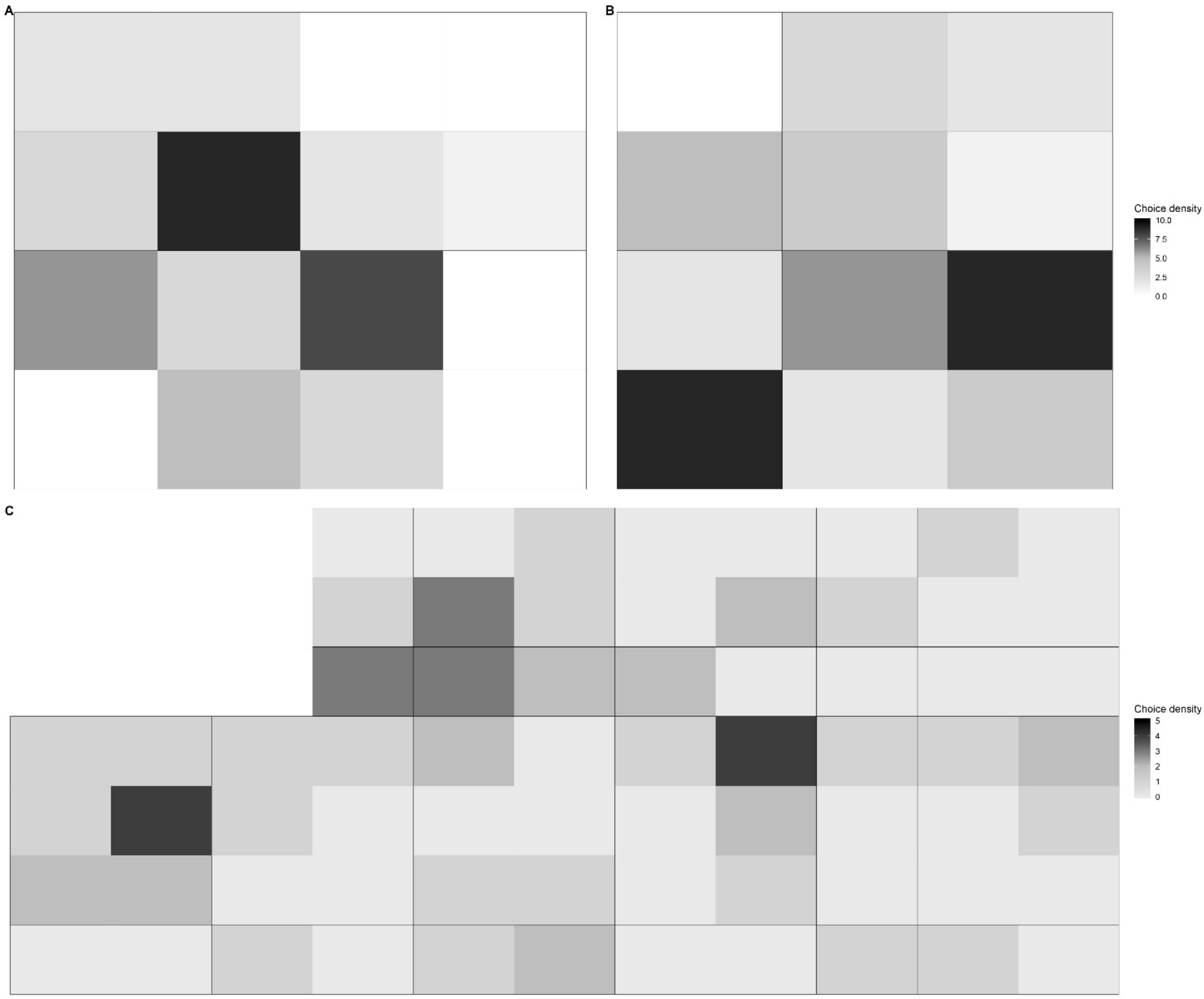

Figure 5. Proportion of choice distributions for A) cereals, B) rice cakes, and C) pasta.

Note: Darker cells indicate greater number of choices. The empty spacing at the upper left corner of Figure C) indicates products other than pasta.

Discussion

The findings from Study 2 indicate that the order of fixation is highly predictable for consumers' choice, in which products seen among the first are more likely to be chosen, in particularly the third and fourth product seen. This could be an effect of visual orientation on the shelf. This effect is even robust without controlling for the orientation phase which previously has been shown to influence consumers' eye movements (Gidlöf et al., 2013). Study 1 controlled for the predictability of positioning, that is that the order of fixation was internally exposed from the participant and not an artifact of the environment. Study 2, on the other hand, was conducted in a supermarket, which is known to hold some predictability about importance and placement (Dreze, Hoch, & Purk, 1994; Valenzula & Raghubir, 2009). It cannot be ruled out that participants knew this structure and therefore guided their visual search towards relevant products earlier in their decision-making phase. However, store familiarity did not influence the number of products dwelled. Further, the follow up analysis of choice distributions also indicated that choice distributions were heterogeneity distributed over the shelf. The results from Study 1 and 2 give a clear story about the importance of fixation order on consumers' choice probability. We chose not to analyze the effect of set size between product category, since previous research has found a high degree of heterogeneity between product categories, making analysis between categories nearly impossible (Gidlöf, Wallin, Holmqvist, & Møgelvang-Hansen, 2013).

General discussion

We analyzed the effect of fixation order on consumer choice in two eye tracking experiments, first a lab experiment using a realistic shopping task environment resembling an online supermarket and second a quasi-experimental field study in a traditional supermarket. In Study 1, we analyzed order effect at the individual level by fitting a beta-binomial distribution. We found no evidence for an order effect at an individual level. Since our initial analysis did not support an order effect, we hypothesized that an order effect potentially arises in the aggregate as a function of how consumers sample information. We analyzed how consumers constitute their search set as set sizes increase. We found when set sizes are low, i.e. below 6 alternatives participants fixate on all products. As set sizes become large, participants are more likely to ignore a growing percentage of products. To test the aggregation hypothesis, we computed the probability of choice given fixation order across set size and found a primacy effect on consumers' choice for large set sizes, but no effect for the smallest set sizes. We take this to imply that the importance of primacy arises as consumers truncate their search as a response to increasing information load. Study 2 we tested the assumption in a traditional supermarket setting. We found a similar effect of fixation order on choice, as in Study 1. To ensure that the order of presentation did not influence the results in the supermarket, we calculated the distribution of chosen objects across each shelf position, and there was no correlation between mere position and choice, why we believe this to be a robust finding across different contexts. Further, to insure that store familiarity did not influence participants' search behavior, we regressed store familiarity with number of products dwelled, and found no support for familiarity to influence number of products dwelled. Both studies indicated that the first fixation did not influence choice. Similar results have been found in a study by Van der Laan et al. (2015), where a manipulation of the location of the first fixation towards a product did not influence its likelihood of being chosen. We speculate that the first fixation both on monitors and on supermarket shelfs in particular is stochastic in terms of decision relevance. The first fixation may be used as purely visual orientation. This may explain why it takes participants additionally one or two fixations to locate products with high value. That consumers search for information as a function of the set size have been proposed by others as well (Horstmann, Ahlgrimm, & Glöckner, 2009; Lohse & Johnson, 1996; Reutskaja et al., 2011). However to propose a causal chain where a primacy effect arises, as a function of truncated information search is a new and interesting aspect in understanding consumer choices. We propose that this primacy effect arises in the aggregate due to a Simpson's paradox i.e. even if consumers are equally likely to choose the first and the last product they see, they are not always looking at the same number of products. Since unattended products do not enter the consideration set and will be unchosen, this gave an observed primacy effect on average. This is an interesting finding for marketers who wish to influence consumers' choice. If they can capture attention earlier in the decision phase, marketers will on average increase the likelihood of being chosen, especially in situations where they are fighting for attention, such as the case for most retail stores.

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Appendix

Table A1

Individual estimates fitted by beta-binomial distribution, by ID probability and θ with respective standard errors.

ID	*P*	θ	SE_P	SE_θ
11	0.4990356	2.001552	0.033	0.354
13	0.5216284	2.450311	0.031	0.452
16	0.5159422	1.896117	0.033	0.326
18	0.5958172	1.637403	0.035	0.315
19	0.6669629	1.545348	0.038	0.381
22	0.5595202	1.788213	0.034	0.327
24	0.5341211	2.898888	0.030	0.561
25	0.4921127	2.533963	0.032	0.489
27	0.5647300	1.524078	0.036	0.293
28	0.5267404	1.707835	0.035	0.305
32	0.4920346	1.878863	0.034	0.337
33	0.4740410	2.197886	0.032	0.395
36	0.5863380	1.613101	0.034	0.276
38	0.5803357	1.655218	0.034	0.306
40	0.5112740	2.121189	0.033	0.383
42	0.4587376	2.017057	0.033	0.343
43	0.5466727	1.746295	0.038	0.379
44	0.5371613	1.804616	0.036	0.356

46	0.5771831	1.523601	0.035	0.284
48	0.5006207	2.146094	0.033	0.384
53	0.4577365	2.818503	0.031	0.556
54	0.5598784	1.789658	0.034	0.324
59	0.5921434	2.079383	0.035	0.467
60	0.5234805	2.716539	0.032	0.542
62	0.6250390	1.666732	0.035	0.329
67	0.5449692	1.677732	0.037	0.335
68	0.5532233	1.607330	0.036	0.294
71	0.4361438	1.586265	0.035	0.280
73	0.5709039	2.062397	0.033	0.399
74	0.5716296	1.518471	0.035	0.269
77	0.5027890	1.493752	0.036	0.278
79	0.4174659	2.062767	0.033	0.372

Appendix

Declarations of Co-Authorship

AARHUS BSS SCHOOL OF BUSINESS AND SOCIAL SCIENCES
AARHUS UNIVERSITY

Declaration of co-authorship*

Full name of the PhD student: Erik Stoltenberg Lahm

This declaration concerns the following article/manuscript:

Title:	A Meta-Analysis of Eye Movements in Decision-Making
Authors:	Erik S. Lahm, Jacob L. Orquin

The article/manuscript is: Published ☐ Accepted ☐ Submitted ☐ In preparation ☐

If published, state full reference:

If accepted or submitted, state journal:

Has the article/manuscript previously been used in other PhD or doctoral dissertations?

No ☒ Yes ☐

The PhD student has contributed to the elements of this article/manuscript as follows:

- A. Has essentially done all the work
- B. Major contribution
- C. Equal contribution
- D. Minor contribution
- E. Not relevant

Element	Extent (A-E)
1. Formulation/identification of the scientific problem	B
2. Planning of the experiments/methodology design and development	A
3. Involvement in the experimental work/clinical studies/data collection	B
4. Interpretation of the results	B
5. Writing of the first draft of the manuscript	A
6. Finalization of the manuscript and submission	C

Signatures of the co-authors

Date	Name	Signature
	Jacob L. Orquin	

In case of further co-authors please attach appendix

Date: 15/07/2019

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Signature of the PhD student

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Declaration of co-authorship*

Full name of the PhD student: Erik Stoltenberg Lahm

This declaration concerns the following article/manuscript:

Title:	The Visual Ecology of Product Packaging and its Effects on Consumer Attention
Authors:	Jacob L. Orquin, Martin P. Bagger, Erik S. Lahm, Klaus G. Grunert, Joachim Scholderer

The article/manuscript is: Published ☒ Accepted ☐ Submitted ☐ In preparation ☐

If published, state full reference:

If accepted or submitted, state journal: Journal of Business Research

Has the article/manuscript previously been used in other PhD or doctoral dissertations?

No ☐ Yes ☒ If yes, give details: Martin P. Bagger used a subset of the final manuscript in his doctoral dissertation. The manuscript has changed dramatically since, by introducing a new scope, a new analysis and an additional study, why the manuscript in the present thesis is of major changes.

The PhD student has contributed to the elements of this article/manuscript as follows:

A. Has essentially done all the work
B. Major contribution
C. Equal contribution
D. Minor contribution
E. Not relevant

Element	Extent (A-E)
1. Formulation/identification of the scientific problem	C
2. Planning of the experiments/methodology design and development	C
3. Involvement in the experimental work/clinical studies/data collection	B
4. Interpretation of the results	C
5. Writing of the first draft of the manuscript	C
6. Finalization of the manuscript and submission	D

Signatures of the co-authors

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Signature of the PhD student

Declaration of co-authorship*

Full name of the PhD student: Erik Stoltenberg Lahm

This declaration concerns the following article/manuscript:

Title:	The Effect of Fixation Order on Choice
Authors:	Erik S. Lahm, Kerstin M. Gidlöf, Annika Wallin, Jacob L. Orquin

The article/manuscript is: Published ☐ Accepted ☐ Submitted ☐ In preparation ☒

If published, state full reference:

If accepted or submitted, state journal:

Has the article/manuscript previously been used in other PhD or doctoral dissertations?

No ☒ Yes ☐

The PhD student has contributed to the elements of this article/manuscript as follows:

- A. Has essentially done all the work
- B. Major contribution
- C. Equal contribution
- D. Minor contribution
- E. Not relevant

Element	Extent (A-E)
1. Formulation/identification of the scientific problem	B
2. Planning of the experiments/methodology design and development	A
3. Involvement in the experimental work/clinical studies/data collection	B
4. Interpretation of the results	B
5. Writing of the first draft of the manuscript	A
6. Finalization of the manuscript and submission	A

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