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Exploring Inattention paradigm: The 'Less Can Be More' Effect in Consumer Attention

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Code available on https://github.com/BayesianBoi/Active-Inattention

Abstract {Molnar & Værbak}

This study investigates consumer inattention with a specific focus on how individuals interact with front-of-package calorie labels. The study empirically examines the theoretical framework of active inattention proposed by Orquin et al (forthcoming). The primary aim was to understand how consumers might actively or passively avoid engaging with these labels. Contrary to the anticipated anti-saliency effect, some of our findings suggested that increased label salience in fact may lead to heightened attention. The study also explored the correlation between health motivation, determined by survey scores, and label engagement. No significant link was found, suggesting a more complex set of factors influencing consumer attention beyond health consciousness. The study highlights the importance of ecologically valid research methodologies and contributes to the understanding of consumer inattention, underlining the complexity of factors involved in the attention paradigm and decision-making in consumer behaviour.

Keywords: *Eye tracking, Consumer Behaviour, Visual Attention, Anti-Salience Effect, Visual Marketing, Information-avoidance,* Nutritional *Labels*

Chapter 1: Introduction {Værbak}

In a world saturated with sensations, the human brain has to selectively prioritise and process tonnes of sensory information. This selection is crucial in visual perception, where attention serves as the filter and guide. Unlike a machine that handles details uniformly, our brains are wired to focus on specific aspects of our visual environment, making visual attention a central component in interpreting our surroundings. The role of visual attention extends into the field of visual marketing, where it is not just a component but a fundamental prerequisite for its effectiveness (Ungureanu et al., 2017).

The field of visual marketing uses visual signs and symbols to communicate with consumers. However, the effectiveness of this communication entirely depends on the consumer's visual attention, requiring their visual attention for effectiveness in both advertising and at the point of sale (Chandon et al., 2009; Gidlöf et al., 2017). Visual attention plays a crucial role not just in marketing, but also in guiding consumer behaviour and improving health and safety through food labelling (Rosenblatt et al., 2018; Tórtora et al., 2019), as well as in conveying warning messages on products such as cigarettes (Bansal-Travers et al., 2011; Popova & Ling, 2014) and alcohol (Giesbrecht et al., 2022). Consequently, a significant challenge in this field arises from consumers' failure to pay adequate visual attention. Studies have found that consumers often ignore advertising (Lee et al., 2015), ignore a majority of available products at the point of purchase (Clement et al., 2013; Gidlöf et al., 2017) and neglect vital information like nutritional and warning labels (Krischler & Glock, 2015; Orquin et al., 2020). Thus, visual inattention hampers effective marketing communication and poses a barrier to improving consumer well-being.

Historically, the field of visual marketing has predominantly focused on bottom-up models, where more salient elements are found to capture more attention, even when top-down motivation to process information is low (Burke & Leykin, 2014; Itti, 2005; Itti & Koch, 2001). Such an understanding has been integral in shaping current marketing strategies and designing digital and physical environments (Graham et al., 2012; Nohlen et al., 2022). Policy recommendations by organisations such as the OECD emphasise making crucial information more salient to reduce inattention (OECD, 2019). The concept that visually salient objects always attract more attention has also been widely applied in business tools used by companies like Neurons Inc. and Google Ads services among others (Google Ads, 2023; Neurons Inc., 2023). Although current bottom-up models vary in their underlying assumptions, they uniformly agree that visual salience positively influences visual attention (Itti & Koch, 2001; Kalboussi et al., 2021; Töllner et al., 2011; Yantis, 2005).

However, recent eye tracking studies have made observations where visual salience decreases, rather than increases, visual attention. Orquin et al. (forthcoming) re-analyzed published eye-tracking data (currently masked for review) and found that visual salience led to an expected increase in attention towards product attributes such as brand and product category. However, they found that making nutritional labels more salient resulted in decreased visual attention towards them. Similar contradicting results, in which an increase in object saliency decreased visual attention, have also been observed in digital retailing environments and advertisements (Gidlöf et al., 2018; Lee et al., 2015), even in instances where the specific features of the unwanted elements were not known in advance (Ma & Abrams, 2023).

These observations question the current understanding of visual inattention and have led Dr. Jacob Lund Orquin to challenge the prevailing consensus. In a forthcoming paper, Orquin et al. propose a novel differentiation of inattention that is not solely based on a dichotomy being that consumers either notice an object or they do not. The framework instead proposes a trichotomy theory of inattention that incorporates elements from information-seeking theory.

Research in the fields of marketing, behavioural economics, and social psychology has focused on understanding why consumers either seek or avoid information (Engel & Hertwig, 2021; Gabaix, 2019; Woolley & Risen, 2021). However, the frameworks used within these fields mainly rely on behavioural observations and have not integrated the mechanisms of visual attention. To explain why visual attention sometimes decreases when increasing the saliency of an object, Orquin et al. (forthcoming) propose the concept of 'anti-saliency', which is part of a broader inattention framework. Anti-saliency is a counterintuitive phenomenon observed in specific contexts such as digital and in-store shopping, where highly salient visual elements paradoxically receive less attention. This anti-salience effect suggests that more salient elements might be more easily ignored, especially if they conflict with the viewer's top-down goals or motivations (Orquin et al., forthcoming; Sharot & Sunstein, 2020). Such findings necessitate a re-evaluation of how we understand visual attention and its implications in consumer behaviour. The traditional notion of saliency as a straightforward attractor of attention is thus complicated by the realisation that what is salient is only sometimes what draws the most engagement. This realisation might be crucial in situations where the goals and motivations of the targeted group might conflict with the bottom-up saliency. For instance, current studies recommend that salient and sizable warning labels on cigarette packs can heighten the perceived danger of smoking (Bansal-Travers et al., 2011; Popova & Ling, 2014). Yet, a comprehensive study in Denmark in 2020 revealed that only about 20% of young Danish smokers notice these warning labels on cigarette packages

(Jarlstrup et al., 2023). Exploring the phenomenon of anti-salience could shed light on the reasons behind it.

This thesis aims to delve deeper into this revised understanding of visual inattention, specifically to the Orquin et al. (forthcoming) proposed trichotomy of inattention. We will describe and investigate the anti-salience effect further, examining how it impacts decision-making in purchasing contexts and challenges long-held beliefs about consumer attention. Our exploration will contribute to a nuanced comprehension of visual inattention, offering insights that could reshape marketing strategies and inform more effective communication and policy-making in the realm of consumer behaviour.

1.1 Trichotomy of Inattention {Værbak}

To understand and predict how inattention occurs, it is necessary to understand the underlying mechanisms of when and why consumers seek or avoid information. Classic theories on information-seeking suggest that individuals pursue information that helps them make decisions to gain rewards and avoid harm, essentially information that has practical or 'instrumental utility' (Stigler, 1961). An example of this is being offered the choice to know whether you are predisposed to a genetic illness, which can inform decisions on preventive measures (Sharot & Sunstein, 2020). However, instrumental utility is not the only driver of information-seeking behaviour as individuals frequently seek out information that does not have a direct impact on changing outcomes (Ibid).

Contemporary frameworks extend on the classic theories and propose two additional motives that determine whether individuals seek or avoid information. These contemporary frameworks are grounded in the idea that information is not inherently beneficial; instead, it possesses the ability to both positively and negatively alter an individual's actions (instrumental utility), affect (hedonic utility), and cognitive processes (cognitive utility) (Sharot & Sunstein, 2020). In this framework, it is argued that individuals seek or avoid information based on the value the information brings to their actions, affect and cognitive processes. Thus, the anticipated value of information can be positive, prompting *information seeking*, zero causing *information indifference*, or negative, leading to *information avoidance* (Ibid). However, theoretical models for information-seeking have primarily concentrated on the factors that motivate individuals to either seek or avoid information without considering the role of visual attention (Orquin et al., forthcoming). The theory proposed by Orquin et al. (forthcoming) aims to integrate the three key concepts of the Sharot & Sunstein (2020) framework: information seeking, information indifference, and information avoidance with mechanisms of visual attention and proposes three distinct types of visual inattention: involuntary, passive, and active inattention. See Figure *1* for the hypothesised effect of information-seeking on visual attention.

According to the theory proposed by Orquin et al. (forthcoming), information seeking is equivalent to top-down facilitation of visual attention. If a consumer believes nutritional labels help improve their food choices, the consumer is more likely to direct attention towards nutritional labels (thus guiding their actions). In terms of bottom-up factors, empirical evidence suggests that when a consumer is actively seeking information, increasing the saliency or size of the label has been found to facilitate increased attention to the information (Gidlöf et al., 2017; Orquin & Lagerkvist, 2015). However, a desire to find information does not always equate to successful attention. Factors such as visual clutter can impede the detection of sought-after information leading to what they term *involuntary inattention* (Chen et al., 2021; Graham et al., 2012). This occurs when a consumer wants to focus on specific information but is unable to do so due to difficulties in noticing it. Secondly, information indifference is characterised by a lack of deliberate effort to direct attention, often leading to what the Orquin theory terms *passive inattention*. This is understood as a scenario where visual attention is not engaged, stemming from the prioritisation of certain information over others that are deemed irrelevant. Interestingly, salient visual elements can capture attention even without active engagement, suggesting that enhancing the visibility or saliency of information can mitigate passive inattention (Burke & Leykin, 2014). Lastly, in the proposed theory, information avoidance is identified as an active suppression of visual attention. In this case, individuals consciously choose not to engage with certain information. Inattention arising from information avoidance is termed *active inattention*. Orquin et al. (forthcoming) propose that increasing visual saliency is ineffective in reducing active inattention. Attempting to make such information more visually salient might result in what is known as the *anti-salience effect*. This part of the proposed framework is the main focus of this paper.

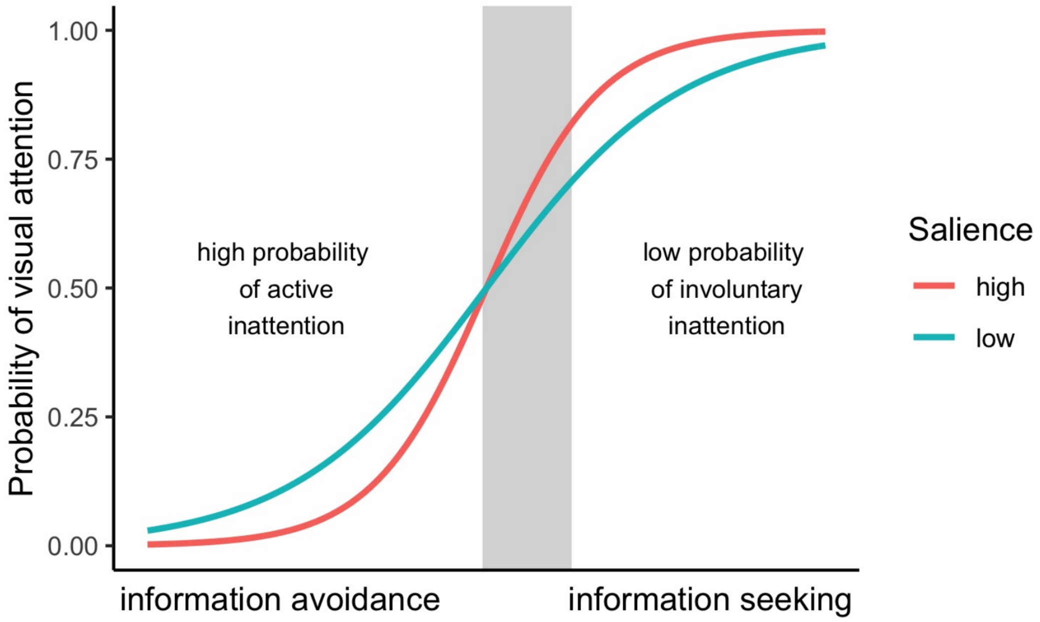

Figure 1 - From Orquin et al. (forthcoming). The figure shows the Orquin et al. (forthcoming) hypothesised effect of information seeking, indifference, and avoidance, as well as visual saliency, on the probability of visual attention (with the probability of not paying attention being the inverse of the probability of paying attention). The grey bar represents information indifference, which in the case of visual attention is the state where consumers are likely to exhibit passive inattention. To the right of the bar is the area of involuntary inattention and to the left is the area of active inattention.

1.1.1 Passive Inattention {Molnar}

Passive inattention arises from a consumer's inherent prioritisation of subjectively relevant information over what is perceived as irrelevant (Meißner et al., 2016; Orquin et al., 2013, forthcoming). This form of inattention reflects a top-down facilitation process where attention is selectively directed towards elements considered interesting by the individual, leading to an inadvertent disregard for other potentially valuable information (Sharot & Sunstein, 2020).

In the context of visual attention and consumer behaviour, passive inattention arises when consumers through a process of learning and habituation become adept at focusing on specific aspects of their environment that align with their needs or interests. This selective attention mechanism enhances efficiency in decision-making but simultaneously cultivates a form of inattention to elements deemed non-essential. For marketers and advertisers, this poses a unique challenge; products or messages that fall outside the realm of a consumer's defined interests risk being passively ignored, despite their potential relevance or value (Orquin et al., 2021; Orquin & Lagerkvist, 2015). To mitigate the effects of passive inattention, several strategies have been suggested. One approach involves disrupting the predictability of information presentation such as through disorganised retail shelving, which has been shown to broaden the scope of visual search and potentially increase consumer engagement with unfamiliar products (Ladeira et al., 2023; Walter et al., 2020). Another approach is enhancing bottom-up control by increasing the visual salience, size, and centrality of information, thereby capturing attention even in the absence of top-down facilitation. However, the latter approach might result in active inattention therefore it is crucial to understand the setting and intention when considering different options.

1.1.2 Involuntary Inattention {Værbak}

As proposed by Orquin et al. (forthcoming), involuntary inattention occurs when consumers struggle to find and hence pay attention to the information they are seeking. For instance, a customer might want to know the caloric content of a product, but if the backside of the product is cluttered with information, it could easily be missed. This situation illustrates how searching for information often resembles a visual hunt for specific items like a certain brand or product detail. Effectiveness in this visual search is influenced by two main factors: top-down and bottom-up control (Wolfe & Horowitz, 2017). Top-down control is where attention is directed towards objects matching the known characteristics of the target. For instance, if searching for a specific brand, products with similar colours to the brand are more noticeable (van der Lans et al., 2021). In contrast, bottom-up control is driven by visual aspects like the saliency of the information. This can reduce involuntary inattention, especially if the target stands out more than other objects (Itti & Koch, 2001).

1.1.3 Active Inattention {Molnar}

Active inattention refers to the intentional avoidance of information by consumers, a behaviour observed even when the information could benefit them or others. This concept encompasses various forms of information avoidance, such as deliberate ignorance and selective exposure (Engel & Hertwig, 2021; Golman et al., 2017; Sweeny et al., 2010).
A key driver behind this phenomenon is the top-down modulator of the consumer, in other words, inner motivation. For instance, consumers often avoid nutritional information to evade guilt associated with unhealthy eating (Bradu et al., 2013). Similarly, avoiding information can be a strategy to avoid responsibility, leading to behaviours detrimental to others (Dana et al., 2007).

Consumers employ various strategies to avoid unwanted information in the realm of visual information. These include selective exposure, biased interpretation, wishful seeing (Dunning & Balcetis, 2013), and motivated forgetting (Shu et al., 2011). Active inattention is particularly pronounced in situations involving dishonesty or self-interest. Several studies demonstrate how attention shifts towards self-beneficial information, often at the expense of accuracy (Hochman et al., 2016; Leib et al., 2019; Pittarello et al., 2019). Three underlying mechanisms of active inattention have been identified: inhibition of eye movements, suppression of attention, and disengagement of attention. Inhibition of eye movements involves consciously avoiding distracting stimuli, a skill that develops in late adolescence and diminishes with age (Luna et al., 2008; Noiret et al., 2017). Suppression of attention is a proactive approach, relying on prior knowledge to avoid certain information (Geng et al., 2019). Disengagement of attention is a reactive strategy employed when confronted with unexpected information (Cashdollar et al., 2013; Kristjánsson, 2012)

The concept of active inattention has significant implications for visual marketing. Strategies that increase the salience of information might inadvertently lead to greater avoidance due to an anti-salience effect. This necessitates a nuanced approach by marketers, taking into account the diverse attitudes of consumers towards information. Visual factors such as salience and predictability need to be carefully considered in light of these attitudes (Burke & Leykin, 2014; Graham et al., 2012; Nohlen et al., 2022).

1.1.4 Practical Implications of the Proposed Inattention Framework {Værbak}

Thus, in the realm of product labelling, designers face a challenge: striking a balance between reducing active inattention and inadvertently increasing passive inattention. This balance is crucial in creating effective labels that cater to the diverse needs of consumers. The proposed Orquin et al. theory suggests that efforts to reduce one form of inattention can unintentionally increase another. For instance, when a label's saliency is reduced to minimise active inattention (where consumers consciously avoid specific information), it may lead to an increase in passive inattention (where consumers overlook the label due to its lack of saliency). This outcome poses a significant challenge for designers who aim to make important product information both accessible and engaging to a broad audience (Orquin et al., forthcoming). The practicality of label design thus hinges on understanding the target consumer group. If the primary audience consists of individuals who tend to actively avoid certain information, a strategy that subtly integrates this information without overwhelming or deterring these consumers may be effective. Conversely, if the target group is more inclined to seek out the information, the design should ensure that such information is prominently shown. Furthermore, the design approach must adapt to the context in which labels are encountered. In digital shopping environments, the placement and presentation of labels may differ in effectiveness compared to physical retail settings (Gidlöf et al., 2018; Lee et al., 2015). This necessitates a thoughtful approach to ensure labels are not only informative but also contextually appropriate.

1.1.5 Choice of Methodology {Molnar}

For our study, eye-tracking was a clear choice as it surpasses traditional inspection techniques like questionnaires and offers a discreet and effective means to study cognitive processes behind attention whilst bypassing biases like social desirability among others. The complexity of consumer decision-making processes, often characterised by a significant gap between stated attitudes and actual behaviours (Grimm, 2010), presents a substantial challenge for researchers and marketers (Balcombe et al., 2017). Eye-tracking technology assists in bridging this gap by providing tangible evidence of what truly captures a consumer's attention, drives their interest, and influences their decision-making process in real-time (Beesley et al., 2019).

1.1.6 Visual Attention, Fasting and Highly Palatable Food {Værbak}

In our study, we aimed to provoke a top-down conflict among the participants. By first implementing a fasting period and then presenting an appealing food item, we intended to trigger an internal battle where participants had to balance their health-conscious choices with the temptation of hedonic food items. A significant amount of research indicates a link between blood glucose levels and specific cognitive and behavioural functions. In a fasted state, individuals are more likely to exhibit altered patterns of visual attention. When an individual is in a fasted state, characterised by lower blood glucose levels, their attention is disproportionately drawn to food-related stimuli (Goldstone et al., 2009; Mogg et al., 1998); especially towards high-calorie, palatable foods (Papies et al., 2008). Additionally, studies have found that eating high-fat, low-carbohydrate meals after fasting can increase the appeal of subsequent high-fat foods (Hopkins et al., 2016; Meule, 2020). The heightened interest and attention towards food stimuli can lead to quicker, more impulsive decisions regarding food choices, which can overshadow the usual considerations for health or dietary restrictions. This shift in visual attention is influenced by biological mechanisms, where orexigenic peptides in the hypothalamus, responding to low glucose levels, drive a preference for high-calorie, palatable foods (Goldstone et al., 2009).

Chapter 2: Methodological Approach

2.1 Participants and Technical Setup {Værbak}

All participants (N = 60; male = 20, female = 40) participated voluntarily in a laboratory room at the Aarhus-based Cognition and Behavioral Lab (CobeLab) in October 2023. The participants were recruited through the official CobeLab research participation recruitment system and were rewarded 85 DKK for their participation in the experiment. As the experiment involved rating meat-based products, it was listed as a requirement that the participants were not vegan or vegetarian. Furtherly, as half of the participants were asked to consume cake, it was listed as a requirement that they did not have any allergies to any of the ingredients. All participants signed a written consent form and none abandoned the experiments midway. The participants had a mean age of 25.7 (9.4) years.

The study was carried out using a table-mounted eye-tracker (EyeLink 1000) with a recording resolution of 1000 Hz monocular. The participants were seated 50 cm from the 1920 x 1200 pixels screen in a static head-mount. At this distance, the EyeLink eye tracker has an accuracy of 0.4°, which approximates a visual angle of 3.2°, and a capture rate of 80% - meaning that at least 80% of all fixations are captured correctly. For two of the participants, the head mount was not available. Therefore, an improvised mounting apparatus was used as a head stabiliser. The calibration and accuracy of the eye-tracking were inspected before proceeding with the experiment and deemed not to be an issue.

2.2 Stimuli {Værbak}

The study focused on nutritional labels as the primary product cue. Since the study took place in Denmark where front-of-package (FOP) nutritional labels are not mandatory nor widely implemented (Farrand, 2021), the study opted for a basic version of the Facts Up Front nutritional labels (Facts Up Front, 2012) to ensure the label was easily understandable on its own. This simplified variant displayed only the calorie content per 100g/ml[1].

The calorie label was chosen for various reasons. The study originally wanted to examine active inattention in the domain of the sustainability of a given product. However, the Danish labelling system does not currently have a sustainability label and introducing one for this study would not satisfy the naturalistic behaviour we wanted to examine. Therefore, it was

[1] Throughout the paper, we use the terms 'nutritional label' and 'calorie label' interchangeably. Specifically, we refer to 'calorie labels' when discussing the labels utilised in our experiment, which are based on a simplified calories-only version of the Facts-Up-Front labelling system. Conversely, we use nutritional labels when addressing the broader theoretical aspects.

considered to examine the active inattention using either the Danish organic label or Nøglehulsmærket, a Nordic-governed label related to the healthiness of the food product. However, both of these labels are generally viewed positively or neutrally by most consumers (Laasholdt et al., 2021; Landbrug & Fødevarer, 2019). There is no corresponding label indicating that a product is either unhealthy or non-organic. This absence of contrasting labels rendered them unsuitable for our study of active inattention. As the calorie label is on a continuous scale, it was suitable for the study of active inattention.

In our experiment, we used 60 images of food products as stimuli, evenly split between 30 low-calorie and 30 high-calorie food items. The pictures of the food products were obtained from BilkaToGo (*BilkaToGo.dk*, 2023), a Danish online grocery shop. To minimise the impact of brand familiarity on participants' choices, we used only Salling brand products. Salling is one of the few brands in Denmark that provides their own version of nearly all household products (Olesen, 2020), allowing us to select the stimuli consistently from a single producer. Each product was carefully selected in pairs to cover a range of food categories, with each pair including one high-calorie and one low-calorie food item. The pairs of products remained consistent throughout the experiment and consisted of low-calorie and high-calorie counterparts. For example, cereal products formed one such category - with oats as the low-calorie option and granola as the high-calorie counterpart. A full list of these categories and the food products can be found in Appendix *1*. The division of products into low-calorie or high-calorie was based solely on the caloric content of the product and the food categories were based on the ones found on BilkaToGo. The stimuli were arranged to mimic the layout of an online grocery store. All of the product names were kept consistent with the ones found on BilkaToGo.

We added calorie labels to the bottom-right corner beside each product. There were two versions of the calorie label: a basic version enclosed in a grey oval and a more salient version where the inside text and the surrounding circle were highlighted to increase the saliency. For low-calorie stimuli, the calorie labels were consistently non-salient. In contrast, for high-calorie items, we created two variants: one with the non-salient calorie label and the other with the salient label. This resulted in 60 pairs of images, each pair containing a low-calorie product with a non-salient label and a high-calorie product with either a non-salient or a salient label. Therefore, the experiment included 60 image pairs in total, split evenly between the two label types. See *Figure 2* for the experimental design setup and both versions of the calorie label. The prices displayed in the experimental setup were the actual prices from the webshop. However, we adjusted the caloric content on the labels to emphasise the health difference: increasing it for high-calorie products and decreasing it for low-calorie ones.

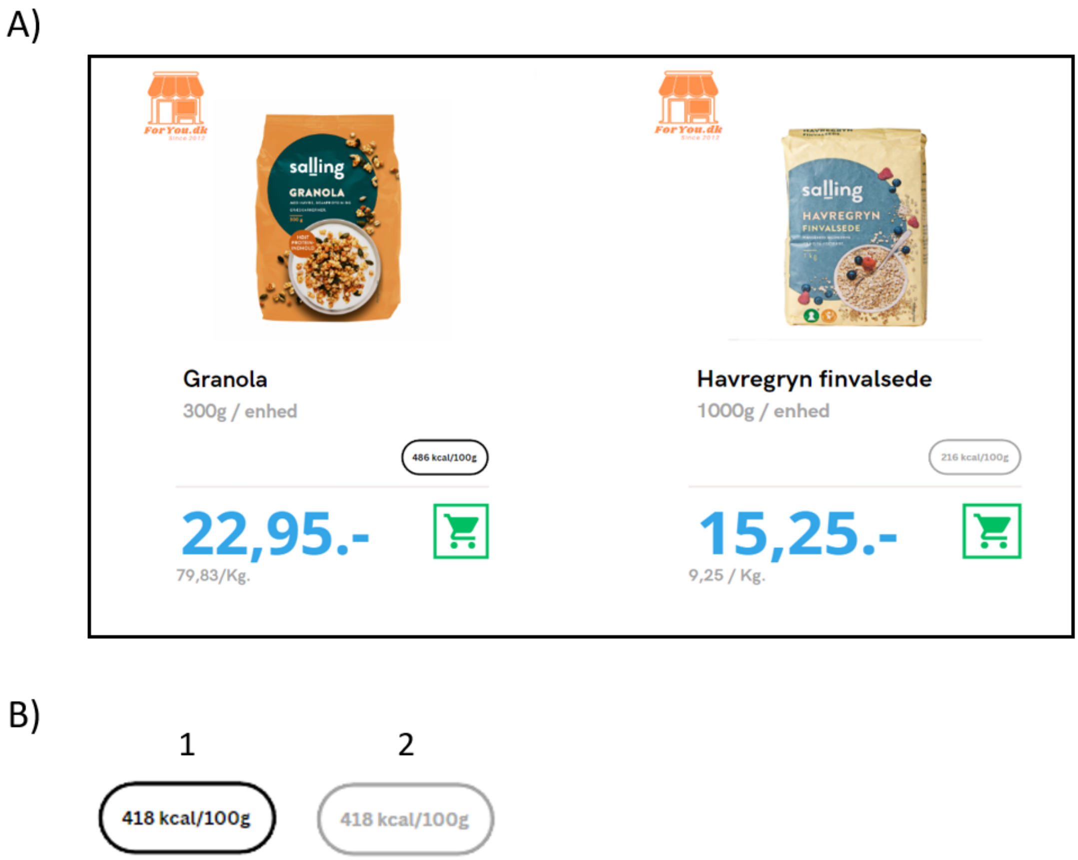

Figure 2 - A) shows an example choice-set in the experiment. In this case, the food category is cereal. The participant has to choose between the two shown food products by clicking on the shopping basket. In the shown example, the calorie label of the high-calorie product is more salient than the one for the low-calorie product. B) shows the two versions of the calorie label, with 1 being the more salient one.

2.3 Task and procedure {Værbak}

Participants engaged in an online shopping simulation, programmed using PsychoPy v. 2023.2.2 (Peirce et al., 2019). In this task, they chose between pairs of products based on personal preference by clicking on the shopping basket. The participants had unlimited time to decide on their choice in each trial. Before the experiment, an eye tracker was calibrated to record the eye gazes of the participants on the screen.

The participants underwent 30 trials, each featuring a pair of products randomly selected from the pool of 60 pairs. In the selection, 15 pairs were randomly chosen from the pair set that consisted of non-salient low-calorie and non-salient high-calorie products, and another 15 pairs were randomly chosen from the pair set that consisted of non-salient low-calorie and salient high-calorie products. Between each choice set, the participants were instructed to focus on a fixation cross in the middle of the screen to control for exposure bias. After the eye-tracking experiment, the participants were asked to fill out a survey asking questions regarding their nutritional habits. See *Appendix 2* for the list of questions.

2.3.1 Experimental groups {Værbak}

Before showing up for the experiment, the participants were assigned to one of two groups; Either an experimental group or a control group. The participants in the experimental group were instructed to refrain from eating food three hours before the experiment. Once they showed up for the experiment, they were asked for the amount of time since their last meal and were then given a small piece of cake and asked to eat it. Once the participant had eaten the small slice, the rest of the cake was placed next to the participant for the remainder of the experiment. This approach was implemented to induce a hedonic craving for food. The control group was not asked to refrain from food and was not offered any cake.

Chapter 3: Research Question {Molnar}

Contemporary literature questions the long-held belief that increased salience invariably garners more consumer attention. The notion of "anti-salience," as explored by Perkovic et al. (2022) and furthered by Orquin et al. (forthcoming), suggests a counterintuitive effect in digital settings - as shown in *Figure 3*. This discovery necessitates a reassessment of our understanding of visual attention dynamics, particularly in the context of consumer behaviour.

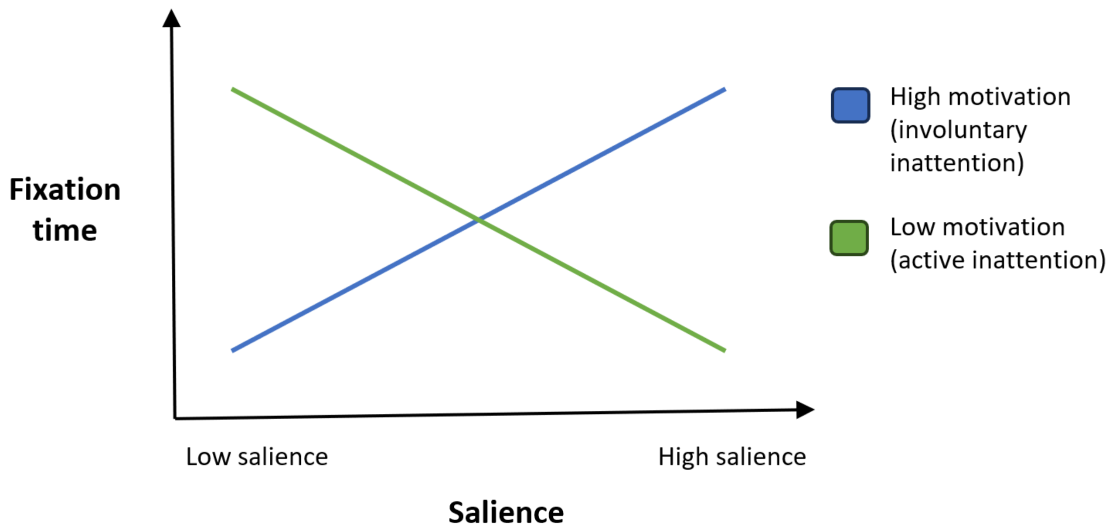

Figure 3 - Shows the Orquin et al. (forthcoming) hypothesised relation between the saliency of a product, the motivation of the consumer and the resulting fixation time. In the case of a highly motivated consumer, increasing the saliency of a product is hypothesised to increase the fixation time on the product. Conversely, the opposite effect is hypothesised for a lowly motivated consumer, which is the anti-salience effect.

3.1 Hypothesis:

We hypothesise a significant effect of the survey, the salience of calorie labels, and experimental conditions on dwell time. Participants in the experimental condition, who fasted for three hours before the experiment and were then given a small piece of food, are expected to demonstrate a heightened tendency to avoid gazing at salient calorie labels in the form of short dwell time or no fixation at all. This avoidance behaviour is anticipated to be a response to the combined effect of the fasting period and the subsequent consumption of a highly palatable food item, which may induce a conflict between immediate gratification and health consciousness. In contrast, the control group, which did not experience fasting or consume cake, is anticipated to show different dwell time patterns. Their engagement with calorie information is expected to be more neutral or less avoidant, reflecting the absence of the immediate, hunger-driven motivation that characterises the experimental group. This difference underscores the influence of top-down motivational factors in shaping consumer behaviour and attention allocation.

3.2 Research Question:

> *“ To what extent do top-down modulators such as health consciousness modulate consumer engagement with calorie labels based on their salience? “*

Chapter 4: Eye-tracking Data Analysis

4.1 Pre-processing {Værbak}

Before proceeding to the analysis, the data went through a preprocessing phase. The preprocessing was carried out in R v. 4.2.2 (R Core Team, 2021) using Rstudio v. 2023.09.1 (RStudio Team, 2020). Using the Tidyverse package v. 2.0 (Silge & Robinson, 2016), all of the participants' behavioural and survey data were aggregated into two files containing all of the data and analysed. For the captured eye-tracking data, we used the built-in algorithm in the EyeLink data viewer (EyeLink, 2023) to filter out the artefacts in the eye-tracking data. The eye-tracking data were then extracted from the program. Next, we used R to correct any formatting issues with the fixation coordinates and ensured their accuracy. All of the eye-tracking trials were inspected to verify that there were no missing data or other issues. The pre-processing analysis was primarily concentrated on two defined areas of interest (AOIs). The defined AOIs were manually measured and verified to ensure that they encased the exact boundaries of the caloric labels. Gaze data not falling within these specified areas was systematically excluded, as illustrated in *Figures 4* and *5*. There was a significant difference in the number of gazes directed towards the AOIs among the participants. While some participants displayed numerous fixations, others exhibited almost none. Seven of the participants did not fixate on the AOIs in any of their trials. From the defined AOIs, we derived the duration of attention on each AOI and the proportion of gaze time to the total duration of the trial. In our study, we specifically focused on examining the impact of high-calorie stimuli. Therefore, we chose to exclude the low-calorie stimuli from our primary analysis. This exclusion was crucial as the low-calorie stimuli, used primarily as a control, could have introduced an imbalance in the salience distribution. By focusing solely on the high-calorie stimuli, we ensured a consistent and clear comparison of salience effects.

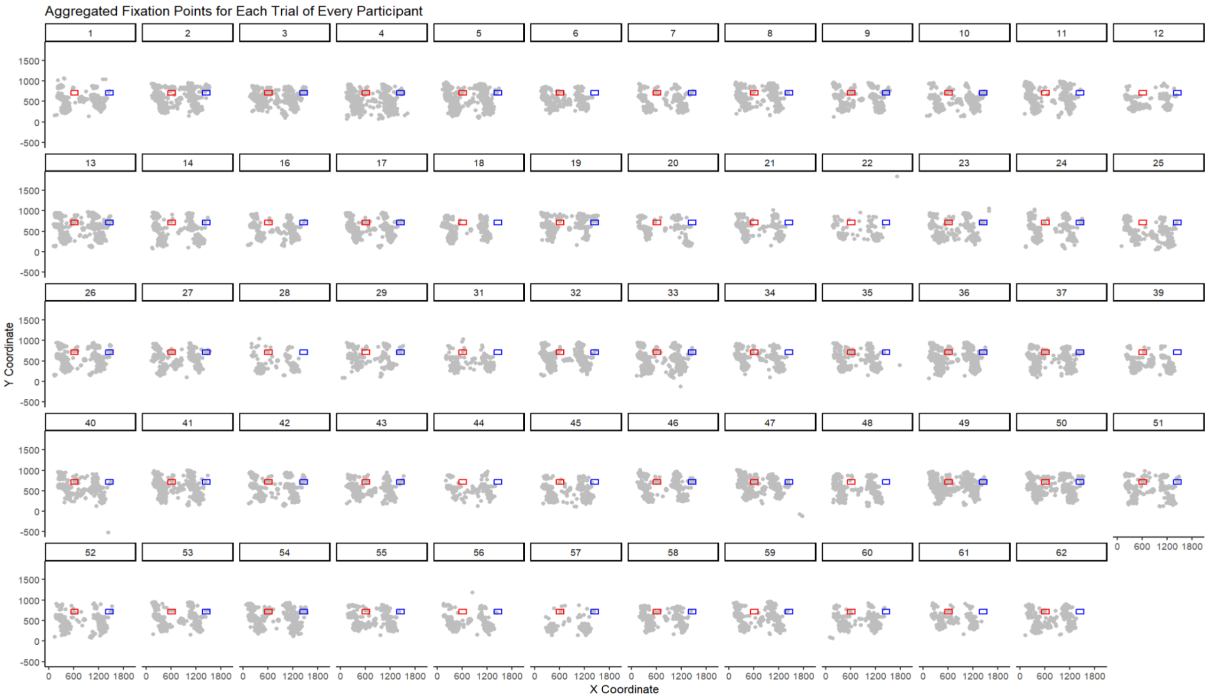

Figure 4 - Visual representation of the aggregated fixation points for each participant, highlighting the two areas of interest (AOIs) before filtering. The AOIs on the left and right products are marked in red and blue, respectively. Each subplot represents an individual participant.

Figure 5 - Visual representation of the aggregated fixation points for each participant, highlighting the two areas of interest (AOIs) after filtering. The AOIs on the left and right products are marked in red and blue, respectively. Notice the scale of the axis and the small number of gazes from some of the participants. Each subplot represents an individual participant.

4.2 Analysis of Eye-Tracking Data {Molnar}

In the study, we sought to examine the interplay between label salience, the health motivation of the participant and consumer attention using eye-tracking data. Our approach was informed by the hierarchical and complex nature of the dataset.

4.2.1 Theoretical Model Selection {Molnar}

Selecting the appropriate theoretical model was a central step in our research, particularly because our primary aim was to investigate the anti-salience effect. This focus distinguished our study from others that might explore correlations between questionnaire responses and dwell time, interactions between healthy food stimuli and dwell time or more general attention theories. We were not merely interested in these broader correlations or replications of established attention theories. Instead, our goal was to delve deeper into the unique dynamics of the anti-salience effect.

Our model selection process was greatly informed by the published and unpublished work of Dr Orquin, Dr Perkovic, and other key studies like one by Gidlöf et al. (2018), among others. These works provided critical insights and a strong foundation for understanding the nuances of visual attention and inattention. By thoroughly examining these prior studies, we were able to develop an appropriate approach that specifically targeted the anti-salience effect, ensuring that our experimental design and subsequent analyses were aligned with our research objectives. We triggered participants' top-down modulators, challenging their habitual choices through the presentation of high-calorie, visually appealing, and high-calorie food options. This approach was aimed at evoking a strong inclination towards choosing aesthetically pleasing food while simultaneously prompting them to consciously avoid high-calorie content. Subsequently, we incorporated salience into our model to capture variations in attention, with the expectation that higher salience would correlate with shorter dwell times. By adopting a between-subjects design, we were able to sidestep the complexities of a three-way interaction but were still able to focus specifically on modelling the anti-salience effect rather than merely the impact of salience.

In our analysis, we explored two distinct multilevel models to investigate the effects on dwell time:

$$\textit{Dwell time} \sim \textit{Salience} + \textit{Survey} + (1|ID)$$

&

$$\textit{Dwell time} \sim \textit{Salience} * \textit{Survey} + (1|ID)$$

In our study, we employed both additive and interaction models to thoroughly examine the effects on dwell time. The additive model was used to capture the unique contributions of individual variables. In contrast, the interaction model explored the combined effects of these variables. This dual-model approach was crucial to understanding whether the interaction between salience and survey variables provides significant explanatory power beyond their individual effects.

Our decision to utilise both models was informed by the previous studies that emphasise that different modelling approaches can yield varying results (Billard et al., 2014). Additionally, insights from preliminary literature reviews and prior research indicated that while interaction models can reveal complex relationships within data, they also increase the model's complexity. Specifically, introducing interaction terms can sometimes result in multicollinearity, particularly when main effects are strongly correlated, and can also lead to capturing variance that simpler models would attribute to main effects alone (Duncan & Kefford, 2021). Given the novel application of eye-tracking data in the domain of inattention research, employing both additive and interaction models was instrumental in achieving a comprehensive understanding of the data, while also addressing potential issues of multicollinearity and variance capture.

These complex evaluations, adhering to strict scientific criteria, were pivotal in ensuring accuracy and reliability. This commitment was especially important to avoid reporting misleading findings. Furthermore, after running our models, we conducted comprehensive assessments of their assumptions, explanatory power, and other key parameters.

During our analysis, we explored the potential of modelling fixation likelihood as a key variable. However, this approach proved to be inefficient in our case and did not yield any reasonable or informative results. We encountered issues such as minor effect sizes and p-values hovering around the 0.4-0.5 mark. Additionally, the methodology of predicting a categorical variable by another categorical variable presented significant limitations in our study's concept of modelling inattention, further diminishing the utility of this approach for our specific research objectives.

4.2.2 Visual Exploration of the Data {Molnar}

In line with "good science" practices, we first outlined a theoretical model in the previous section. That step enabled us to objectively analyse our data visually, focusing on identifying unique patterns and characteristics within it. By doing so, we ensured that our initial theories and hypotheses remained unbiased by the visual insights we gained from the data.

Our initial step in the data exploration process involved examining the distribution of the dependent variable. This aspect is crucial as it significantly influences the modelling approach.

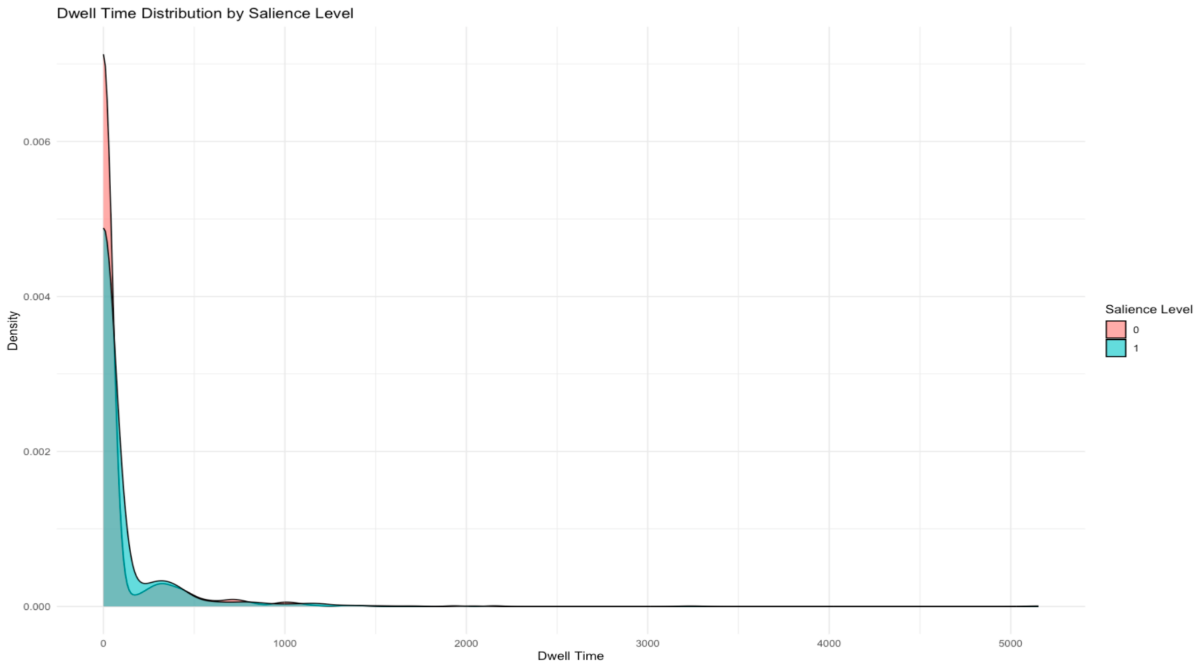

Figure 6 - Distributions of dwell time grouped by salience.

Upon inspection, it's evident that our dataset comprises a substantial proportion of zero values and exhibits traits indicative of a bimodal distribution - as seen in *Figure 6*. This pattern greatly deviates from the typical assumptions of a Gaussian distribution. However, a comprehensive evaluation of model assumptions will be conducted after the implementation of specific models.

Another central aspect of our visual analysis was to explore the relationship between *salience* and *dwell time* across the two conditions.

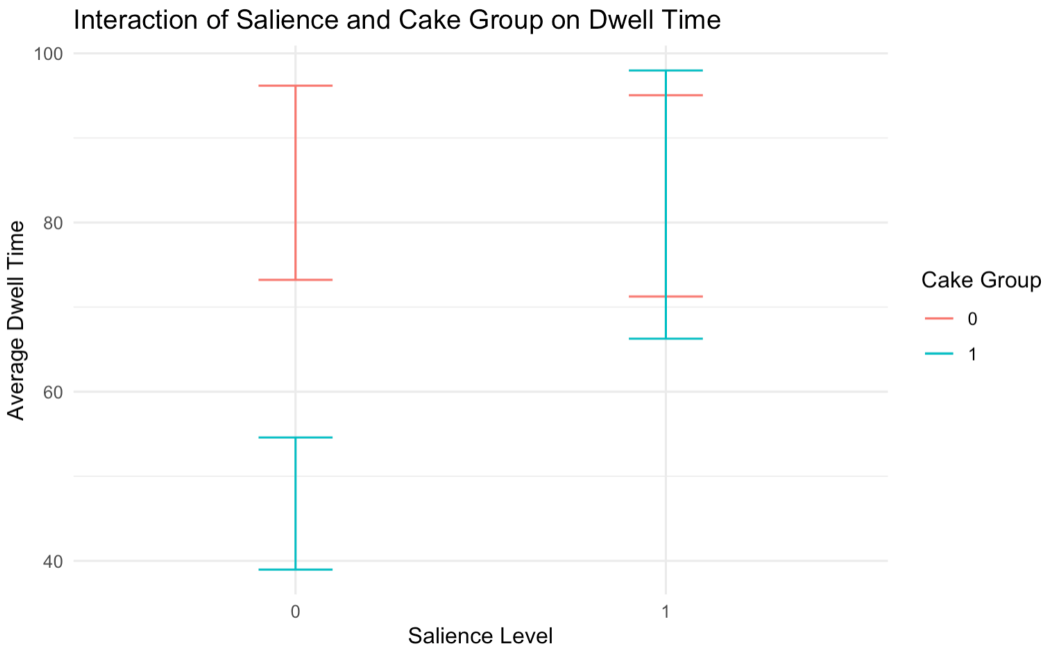

Figure 7 - Influence of visual salience on dwell time grouped by control and experimental groups.

Notably, there appears to be a distinctive difference between the groups when *salience* equals zero - as seen in *Figure 7*. An intriguing observation is that the group subjected to a three-hour fasting period followed by the consumption of a small piece of cake or sweets exhibited a reduced dwell time compared to the control group. This finding may suggest the effectiveness of our experimental group manipulation in contrast to the control group. However, it is also observed that in conditions of high salience, the intervals for the experimental group encompass or even exceed those of the control group, indicating a need for a more nuanced interpretation

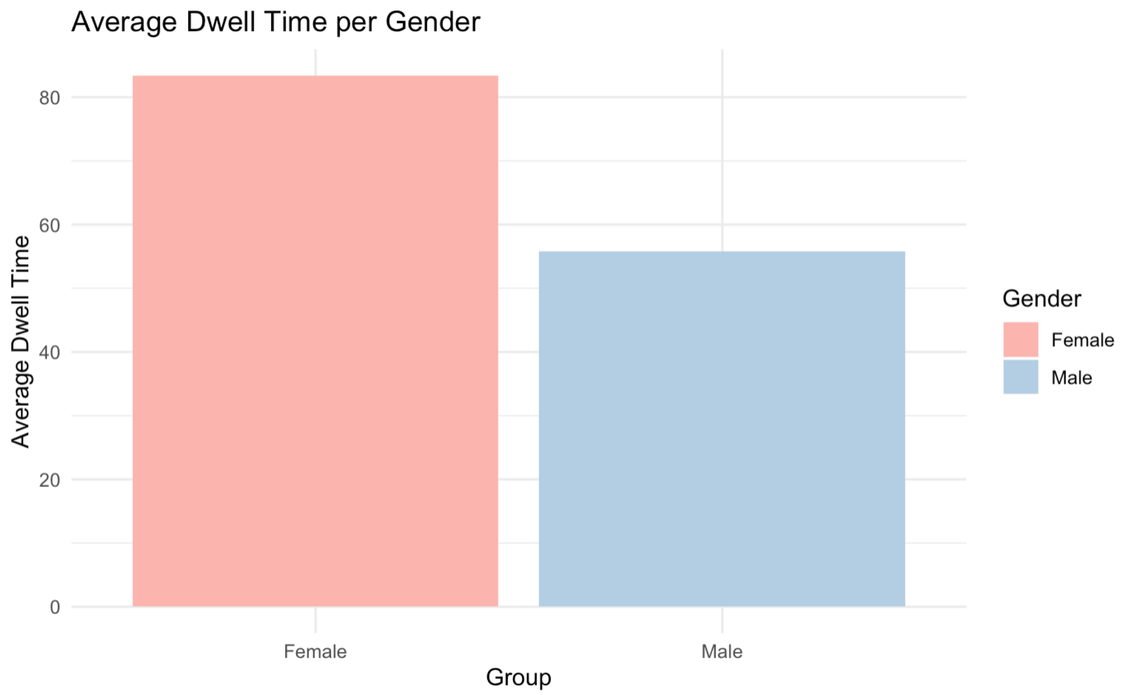

Figure 8 - Average dwell time grouped by gender

Next, we created a plot of dwell time per AOI, categorised by gender, where we observed patterns in how male and female participants allocate their visual attention. *Figure 8* highlighted clear differences in dwell times between genders across the different AOIs.

4.2.3 Initial Approach: Generalised Linear Mixed Models (GLMM) {Molnar}

We started our analysis using Generalised Linear Mixed Models (GLMM) to handle the random effects in our data. GLMMs, implemented using the lme4 package in R (Bates et al., 2015), allowed us to accommodate the individual differences among participants (ID) and the variations across trials. This approach was ideal for our within-subject data structure, with multiple observations per participant.

However, preliminary diagnostics revealed non-compliance with some of the GLMM assumptions such as normal distribution, particularly regarding the distribution of residuals and the number of 0 in our dataset. This necessitated an exploration of more appropriate modelling techniques.

4.2.4 Exploring Zero-Inflated Gamma Models {Molnar}

Considering the significant number of zero values in dwell times and the skewed nature of the data, we decided to delve into the literature and find more nuanced methods for the distribution of our outcome variable. We found a study by Wei et al. (2019) where they implemented Zero-Inflated Gamma Models for calcium imaging while measuring neural activity. Although the context of their study was different, the similarity in data patterns, particularly the frequent occurrence of calcium spikes at zero, resonated with the challenges we faced. This study inspired us to adopt the same modelling approach to our research, offering a more fitting method for interpreting our dataset.

These models, adept for datasets with excess zeros and continuous, skewed dependent variables were fitted using the glmmTMB package (Brooks et al., 2017). They provided a more appropriate way of modelling the attention allocation patterns in our data.

4.2.5 Assumption Testing and Model Diagnostics {Molnar}

We conducted thorough diagnostics for each model type. For the GLMMs, residual analysis and Q-Q plots were generated using base R graphics. For the Zero-Inflated Gamma Models, we utilised the DHARMa package for simulation-based diagnostics (Hartig, 2022), ensuring robust assessment of model fit and assumption adherence.

4.2.6 Model Selection and Comparison {Molnar}

For each of the experimental conditions, we focused on both no-interaction and two-way interaction models involving *salience* and *survey* output. Model comparisons were conducted using the Akaike Information Criterion (AIC) to determine the best-fitting models while balancing model complexity and goodness of fit. Afterwards, r-squared was calculated as another evaluator of the models' efficiency.

Chapter 5: Results

5.1 Behavioural Results {Værbak}

Comparing the two conditions, the experimental group had an average reaction time of 6.2 (SD = 4.1) seconds while the control group had an average reaction time of 5.5 (SD = 3.7) seconds. In terms of whether the participants chose the low-calorie or high-calorie product, both groups were centred around the base chance of either category of product with a mean of 50.56% towards the low-calorie choice for the experimental group and the control group chose the low-calorie option 49.78% of the times. Relatively large standard deviations, 13.1% for the experimental group and 12.6% for the control group indicate a wide range of individual preferences within both conditions. This variability suggests that while the groups as a whole did not differ in their propensity to choose between the two groups of food items, some of the participants were more inclined towards either of the two food item groups.

The mean aggregated survey results for the two conditions were 55.4 (SD = 22.4) for the experimental condition and 56.4 (SD = 26.4) for the control group. These similar means suggest that the survey results for the groups as a whole were not influenced by the short-term fasting of the participants.

The relationship between participants' survey responses, which reflected their attitudes and habits toward the consideration of food healthiness and usage of nutritional labels in everyday purchases and their actual product choices in the experiment was quantified using Pearson's product-moment correlation. For the experimental group, this correlation was not statistically significant ($p > 0.05$), suggesting no correlation between survey scores and product choices within this group. Conversely, for the control group, a significant correlation coefficient of 0.41 was observed ($p < 0.05$), pointing to a moderate association. For the combined sample, the correlation was significant with a coefficient of 0.33 ($p < 0.05$), indicating a mild overall relationship between health consciousness as reported on the surveys and low-calorie product selection. These results suggest that while there is some association between survey responses and choice behaviour in the control group and the overall sample, the survey scores were generally not strong predictors of the actual choices made by participants. See *Figure 9* for a scatter plot of all of the participants' survey results against the frequency of their low-calorie product choices

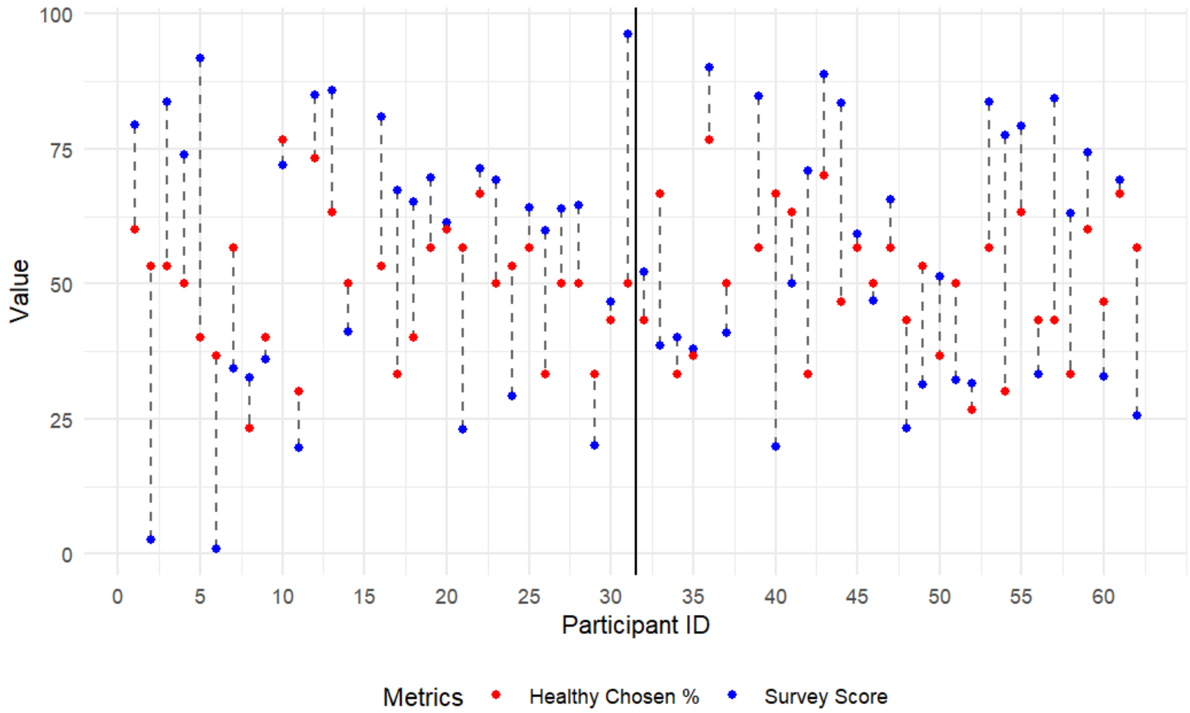

Figure 9 - Scatter plot showing the mean percentage of low-calorie product choices (red dots) against the average survey score (blue dots) for each participant. The line in the middle divides the two conditions in the experiment, with the control group on the left of the line, and the experimental group on the right side. The survey score is the mean score of the survey questions for each participant.

In terms of stimuli selection, a visual inspection of the chosen products from each pair was conducted to determine if there was a consistent preference for certain items within the product pairs. The bar plot, as seen in *Figure 10*, suggests a preferential bias towards or against some of the products. For instance, one of the most striking findings was the overwhelming preference for regular butter, which was chosen 86.7% of the time, in stark contrast to vegan spread, selected only 13.3% of the time. This disparity highlights a clear inclination towards certain products. See Appendix *1* for the full list of how much a product was chosen.

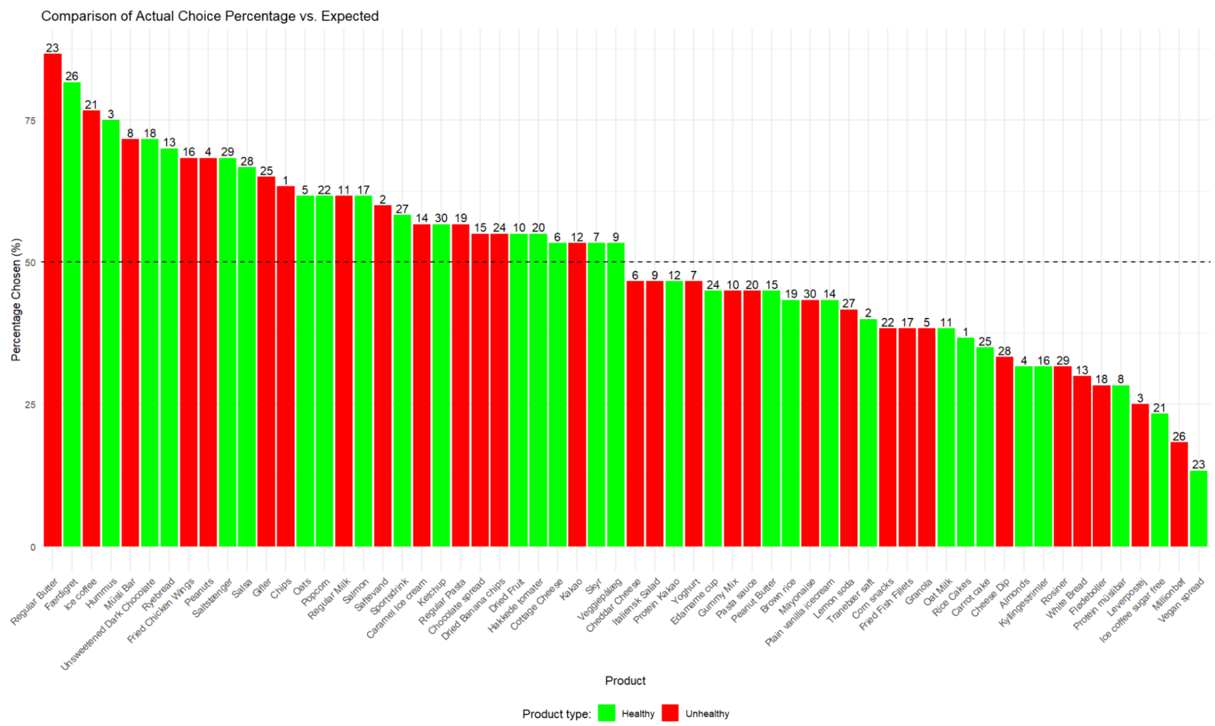

Figure 10 - A bar graph displaying the selection frequency of the stimuli compared against the base probability. Low-calorie products are marked with green bars and high-calorie ones with red. The height of each bar reflects the product's selection percentage with the base chance indicated by the dashed line. The numerical labels on the bars correspond to the product pairs. The graph suggests a preferential bias toward or against some of the products.

5.2 Eye-tracking Results {Molnar}

In the analysis of dwell time using Generalised Linear Mixed Models, we started with the experimental group. The model, which included *salience* and the *survey* score as fixed effects and participant ID as a random effect, yielded an intercept estimate of 23.0813 (SE = 50.5918, df = 29.5879, t = 0.456, p = 0.6516). *Salience* showed a significant positive association with *dwell time* (Estimate = 35.3467, SE = 16.6924, t = 2.118, p = 0.0345), suggesting that increased salience is associated with longer dwell times. The *survey* score, however, did not significantly predict *dwell time* (Estimate = 0.4273, SE = 0.8362, t = 0.511, p = 0.6133). The random effects component revealed a standard deviation of 90.03, indicating variability between participants. The conditional R-squared was 11.95%, suggesting that while the model accounts for some of the variance, much of it remains unexplained. Nonetheless, the model diagnostics highlighted issues with the assumption of normally distributed residuals, suggesting that the GLMM may not be the best fit for this data.

Turning to the control group within the GLMM framework, neither *salience* (Estimate = -1.5489, SE = 14.2663, t = -0.109, p = 0.914) nor the *survey* score (Estimate = 1.1440, SE =

0.9286, t = 1.232, p = 0.228) significantly predicted *dwell time*. The random effects suggested a higher variability among participants in this group than in the experimental group, with a standard deviation of 126.1. The conditional R-squared was 26.83%, indicating that other unmeasured factors may be influencing dwell time. Similar to the experimental group, the model diagnostics for the control group raised concerns about the normality of residuals.

We also examined interaction models for both groups. In the experimental group, the interaction between *salience* and the *survey* score was not significant (Estimate = 0.99477, SE = 0.75680, t = 1.314, p = 0.189), the same as in the control group (Estimate = 0.2809, SE = 0.5498, t = 0.511, p = 0.609). The conditional R-squared values remained unchanged from the non-interaction models, suggesting the interaction terms did not increase the explanatory power of the models. The diagnostics for these models suggested similar issues with the normality of residuals, indicating that alternative models might be warranted.

Given the significant number of zero dwell times and the right-skewed distribution of the data, Zero-Inflated Gamma Models were implemented. For the experimental group, the intercept was significant (Estimate = 5.514818, SE = 0.300239, z = 18.368, p < 2e-16) in the conditional model, but *salience* and the *survey* score were not significant predictors. The Zero-Inflation part of the model, however, indicated a significant effect of the intercept (Estimate = 1.91082, SE = 0.09948, z = 19.21, p < 2e-16), suggesting the presence of excess zeros. This could mean that there are factors not included in the model that leads to a zero dwell time, or that zero dwell time is a distinct state that needs to be accounted for separately from the positive dwell times. The Zero-Inflated Gamma Model handles this by having two parts: one that models the predictors of the positive dwell times and another that models the occurrence of zeros. For the control group, the Zero-Inflated Gamma Model's conditional model also showed a significant intercept (Estimate = 5.890202, SE = 0.235300, z = 25.033, p < 2e-16) but no significant effects for *salience* or the *survey* score. The zero-inflation component was significant for the control group as well (Estimate = 1.60944, SE = 0.08944, z = 17.99, p < 2e-16).

In the interaction models of the Zero-Inflated Gamma framework for the experimental group, the interaction term was borderline significant (Estimate = 0.0118875, SE = 0.0062532, z = 1.901, p = 0.0573), however, the effect sizes were extremely low. For the control group, neither the main effects nor the interaction term were significant. The DHARMa diagnostics for the Zero-Inflated Gamma Models indicated a significant dispersion problem for the experimental group, suggesting variance heterogeneity, while the control group's diagnostics did not reveal any significant dispersion issues.

Model selection, informed by the Akaike Information Criterion, favoured the Zero-Inflated Gamma Models over the GLMMs due to their better handling of the excess zeros and the skewed nature of the data. This was further corroborated by the conditional R-squared values which did not show improvement with the inclusion of the sophisticated models including interaction terms, emphasising the need to explore other factors that might influence dwell time.

In summary, the analysis results suggest that salience may significantly influence dwell time in the experimental group, whereas it appears to be non-significant for the control group. However, the models demonstrating this significance did not fully satisfy the necessary assumption criteria. The *survey* score did not prove to be a significant predictor for either group. Diagnostics highlighted the difficulties in fulfilling the GLMM assumptions, prompting the use of Zero-Inflated Gamma Models as a better-fitting alternative, even though some dispersion issues persisted. Nonetheless, these models did not yield any significant outcomes either.

Chapter 6: Discussion

6.1 Discussion of Hypothesis {Molnar & Værbak}

The primary aim of our study was to explore the concept of the anti-saliency effect in the context of consumer behaviour, particularly in how consumers interact with nutritional labels. Our hypothesis centred around understanding the types of inattention consumers exhibit towards these labels and the underlying reasons for such behaviour.

The core of our hypothesis revolved around the anti-saliency effect, which posited that highly salient calorie labels might be actively avoided by consumers. Contrary to this, our results showed an increased dwell time on more salient labels in the experimental group, however, it is important to mention that the model failed to fully satisfy assumptions for GLMM using Gaussian distribution. This outcome suggests a fundamental challenge to the concept of anti-saliency in this context. Rather than avoiding these labels, consumers appeared drawn to them. This raises a critical question: Is what we observed a manifestation of salience attracting attention supporting current attention theories, or is there a nuanced interplay where certain conditions or consumer mindsets might trigger an anti-saliency response, but our experimental design did not succeed in triggering them?

Furthermore, the lack of a significant relationship between health motivation (as measured by survey scores) and engagement with calorie labels implies a complex decision-making landscape. Consumers' interaction with labels may not be as straightforwardly influenced by top-down modulators as hypothesised. This finding opens up new avenues for exploring different areas that will be able to introduce an effect of inattention to specific stimuli.

The prevalence of zero dwell times, as highlighted by the Zero-Inflated Gamma Models, introduces an additional layer to our discussion. It suggests the existence of a segment of consumers who might consistently ignore nutritional information, possibly due to ingrained habits, lack of interest, or other unidentified factors discussed below. This observation necessitates further investigation into what were the reasons causing this to correctly categorise the type of inattention.

6.1.1 Distinguishing Anti-Salience from Passive Inattention {Molnar}

A critical aspect of our discussion revolves around distinguishing between active inattention (anti-saliency) and mere passive inattention. Our experimental design did not necessitate an explicit examination of involuntary attention. The Area of Interest (AOI) in our study was designed to be visible and easily accessible to all participants, ensuring that it was within the visual field and could be effortlessly engaged with.

Our results suggest that in one case increased salience of calorie labels attracted attention, challenging the concept of active inattention (however, the model afterwards failed to meet assumptions). Nevertheless, the occurrence of instances with zero dwell times might allude to passive inattention, where labels fail to capture conscious awareness due to habitual disregard or perceived irrelevance. Distinguishing between active and passive inattention is pivotal in fully grasping how consumers engage with nutritional information. It could be argued, following Perkovic et al. (2022), that zero dwell times are indicative of active inattention occurring during covert attention processes. This would suggest that influenced by top-down modulators, participants actively divert their attention away from the calorie label. For this inference to hold, significant differences in either the prevalence of zero dwell times or the influence of top-down modulators (survey) must be observed in the control group, as these are key in differentiating between the various types of inattention in our study. Given that our results did not reveal a significant difference, we are unable to attribute the observed effect to active inattention. To further explore this distinction, future studies could introduce some of the areas with stronger top-down modulators containing more weight to participants as described in section 6.4.1.

6.1.2 Label Placement {Værbak}

The placement of calorie labels within the webshop environment also warrants consideration. In our study, the labels were located in the bottom right corner of the webshop interface. This positioning could have influenced their visibility and the degree of attention they received. In a real-world context, such placement might not align with natural viewing patterns, potentially contributing to the observed inattention (Bialkova et al., 2020).
To address this, future studies could experiment with different label placements, such as integrating calorie information directly into the product image. This approach could enhance the naturalism of the label's presentation and potentially increase its saliency. Additionally, employing methods like the Itti Koch saliency map (Itti & Koch, 2001) could provide a more objective measure of label saliency, offering insights into how different label placements and designs impact consumer attention (Peschel & Orquin, 2013)

6.2 Methodological Considerations

6.2.1 External Validity and Participants' Representativeness {Molnar}

Our study predominantly recruited participants from the student participants pool of Aarhus BSS, with a mean age of 25.7. This demographic is highly immersed in digital environments that are saturated with advertising and attention-grabbing stimuli (Blumberg et al., 2013; Simola et al., 2014), which aligns with the core focus of our research. While such an age-homogenous sample might raise concerns about the generalizability of results, we believe that the particular relevance of this group to digital exposure somewhat alleviates these concerns.

In our study, we observed noticeable gender differences in engagement with calorie information (*Figure 8*). Females tended to spend more time examining calorie-related areas, suggesting a heightened interest or less familiarity with calorie details and, therefore, longer dwell time. In contrast, males progressed through the experiment more rapidly, raising questions about their information processing style, greater experience with such information or interest levels. Interestingly, a Wilcoxon rank sum test revealed a statistically significant difference in dwell times between genders (p-value = 0.05). Females had a mean dwell time of 83.37ms, while males had a mean of 55.82ms. This indicates a difference in engagement, with females showing greater attention to the calorie information.

Although our literature review did not find existing studies directly corroborating these specific findings, they offer a unique perspective on gender-specific interactions with health information. The behaviour observed in male participants could suggest naturally quicker decision-making due to experience rather than a lack of interest. This distinction is important, as it could imply different approaches to processing health information. While our findings are not definitive, they do suggest that further research in this area might be beneficial.

While the lab-based findings provide valuable insights, the question of generalizability to real-world purchasing behaviour remains open. The artificial setting of presenting two stimuli side by side in a controlled laboratory environment is not extensively reflective of the typical grocery shopping experience. Purchases in a naturalistic setting (both online and physical) involve more complex decision-making processes and environmental interactions, including factors such as salience within the environment, not only within a product.

To bridge this gap in ecological validity, future research could adopt more immersive methodologies. In physical shopping contexts, the implementation of portable eye-tracking devices, seamlessly integrated into participants' eyewear, would enable the capture of genuine consumer behaviour within the hustle and bustle of a supermarket. This approach would offer a more authentic glimpse into how consumers interact with products and make choices in real time. For the increasingly prevalent online shopping sphere, a more sophisticated experimental setup is necessary—one that replicates the scrolling and browsing experience of actual web pages, while still harnessing the precision of eye-tracking technology. Efforts to develop such advanced experimental designs and analysis techniques are underway at the EYEmab lab at BSS Aarhus. Incorporating these innovations in future studies would allow for a comprehensive understanding of choice behaviours in both physical and digital shopping environments, thereby enhancing the external validity of the research findings.

6.3 Experimental Design

6.3.1 Effectiveness of the Experimental Condition {Værbak}

The study design included an experimental condition that included a three-hour fasting period, intended to enhance hunger levels and possibly shift participants' preferences towards the hedonic food stimuli. Given that existing research indicates fasting can influence decision-making, our focus will be on examining the effectiveness of this priming approach within our experimental framework.

To evaluate the effectiveness of the priming in our study, we analysed behavioural outcomes, focusing on reaction times and product choices. The experimental group had an average reaction time of 6.2 seconds, slightly longer than the control group's 5.5 seconds. Both groups similarly leaned towards low-calorie choices, with the experimental group at 50.56% and the control at 49.78%, suggesting that the priming did not significantly influence preference for unhealthier options. However, large standard deviations in both groups indicate individual differences.

Further, we considered the impact of the experimental condition on subjective reporting in subsequent surveys. As mentioned earlier, during the inspection of *Figure 9*, we noticed variability in participants' selection of low-calorie options. When cross-referencing these choices with the survey scores, which may reflect participants' intention or belief about choosing low-calorie options, there does not appear to be a consistent alignment between the self-reported calorie choices and the actual selections made. This discrepancy may be indicative of a social-desirability bias, where participants' survey answers are influenced by what they think will be viewed favourably by others, leading to an over-reporting of healthy consciousness in the survey. Also, this disparity between stated health-conscious attitudes and actual choices made during the experiment may simply suggest that participants' decisions are influenced by factors other than the calorie content alone, such as taste preferences or habits.

In our study, we investigated the impact of a three-hour fasting period on decision-making. The effect of fasting duration on behaviour varies according to existing research: some studies suggest noticeable behavioural changes after short fasting periods, while others point to the necessity of longer durations for significant effects (Cameron et al., 2014). Our participants fasted for three hours, but in the absence of objective blood glucose level measurements, the precise influence of hunger on each individual's decision-making process remained uncertain. This limitation makes it challenging to conclusively determine the effectiveness of fasting as a priming method in our study.

Neurological research, particularly studies utilising electroencephalogram (EEG), has observed distinct brain responses to different food types. High-caloric foods typically evoke different neural responses compared to healthier choices (Sato et al., 2020; van Bochove et al., 2016). This phenomenon is linked to the dual regulation of food intake by the homeostatic and hedonic systems, the latter of which shares pathways with substance use disorders and influences overconsumption behaviours (Wilcox, 2021). Incorporating EEG into our study methodology could have provided an objective assessment of whether participants experienced a top-down conflict when making food choices, offering a more robust understanding of the fasting period's impact on decision-making.

6.3.3 Stimuli Selection and Potential Bias {Værbak}

An important aspect of our study's methodology is the selection of stimuli and the potential bias it may have introduced. The choice of products as stimuli was based solely on their calorie content. However, this approach may not have adequately accounted for individual preferences, leading to potential biases in participant responses.

The observed patterns of preferential choosing among participants suggest that some products were consistently favoured over others in certain pairs. This finding indicates that personal preferences might have played a significant role in the decision-making process, possibly overshadowing the intended focus on calorie content and label saliency. Such preferences could be influenced by a variety of factors, including familiarity with the product, perceived quality, or taste preferences. Reflecting on this, a more controlled approach to stimuli selection could have been beneficial. Conducting a pilot study to select relevant products within each category based on participant feedback might have resulted in a more representative set of stimuli. Alternatively, a pre-study where participants indicate their regularly purchased products could ensure that the experiment only includes items relevant to their usual shopping habits. This approach would likely reduce the impact of personal preference on product choice, focusing more directly on the influence of calorie content and label saliency.

Another potential improvement for future studies could be the use of a single, plain product consistently across all experimental conditions, altering only the saliency of the labels, as seen in Orquin et al (2020). Such a controlled approach would help isolate the effect of label saliency on choice, ensuring that preferences are based solely on the presented information rather than inherent product appeal.

6.4 Anti-salience in Consumer Behaviour

6.4.1 Nutritional Labels, Consumer Decision Making and Future Studies {Molnar}

In discussing the influence of calorie labels on purchase decisions, a key consideration is whether these labels significantly alter consumer perceptions or whether buyers rely more on their pre-existing knowledge of what products are preferred. Despite our controlled pairing of low-calorie and high-calorie options with corresponding calorie counts in the experiment, participants' inherent beliefs or lack of attention to calorie information may have overshadowed the intended effect of these labels. This observation leads to reconsidering the efficacy of anti-salience in the context of nutritional information. The concept, intriguing in theory, might not hold as much influence in real-world settings where consumers often base their decisions on ingrained perceptions rather than on-the-spot label evaluations. In Denmark, the infrequency of front-of-package nutritional labels further complicates this scenario, suggesting that Danish consumers might be unaccustomed to, or even dismissive of, such information.

Therefore we propose an exploration of anti-salience effects in the context of addictive substances like alcohol, nicotine, or even harder drugs which in our opinion offers a profound opportunity to understand how deeply ingrained habits and dependencies interact with information avoidance. Addiction, by its very nature, involves a complex interplay of psychological and physiological factors, truly triggering a top-down modulation. When presented with information about the harmful effects of these substances, individuals with an addiction might exhibit a strong anti-salience response, actively avoiding such information. This could be due to a variety of reasons, including denial, fear, or a subconscious reluctance to confront the reality of their dependency. Understanding this behaviour could lead to more effective strategies in public health messaging and intervention design. However, the challenge lies in ethically and practically conducting studies in these sensitive areas. A more feasible approach could for example involve examining decision-making in simulated driving scenarios shedding light on how individuals prioritise information when under stress or facing conflicting motivations. For instance, when presented with a laboratory-simulated computer task that simulates driving and requires reaching a destination urgently, such as a simulated emergency, participants might be more inclined to ignore or quickly divert their attention away from traffic signals that impede their progress. In this context, a red light, typically a salient and attention-grabbing signal, might become less effective. The duration of dwell time on more salient versus regularly salient traffic signals could provide insight into how urgency and motivation influence visual attention and decision-making processes.

Chapter 7: Conclusion

Our study aimed to explore the realms of inattention and anti-saliency effect, specifically within the context of consumer interactions with calorie labels. This exploration aimed to illuminate the dynamics of how consumers might actively avoid engaging with such labels. However, our findings presented a nuanced picture, challenging the initial hypothesis. Rather than demonstrating active avoidance, or anti-saliency, increased label salience in the experimental group unexpectedly drew more attention, suggesting that the relationship between salience and consumer attention is more complex than initially theorised. The model failed to meet the requirements for GLMM modelling using Gaussian distribution, nonetheless, the results should be considered when developing an experimental design for further inspection of the inattention paradigm.

The lack of a significant link between health motivation as a top-down modulator quantified by survey scores, and label engagement (dwell time) suggests that the interplay of factors regulating consumer attention towards calorie labels extends beyond simple health motivation. This complexity points to a richer decision-making landscape where factors beyond health motivation influence attentional engagement. The presence of zero dwell times, found in the Zero-Inflated Gamma Models, adds another layer to our understanding, indicating potential complete disengagement from nutritional information for reasons not captured within the scope of our study and analysis design. This observation suggests that nutritional labels may not be the most effective medium for exploring the paradigm of inattention. It points to the possibility that other contexts, where top-down modulators have a more pronounced impact, might be better suited for eliciting dilemmas that could lead to active inattention. Our study proposes several such areas where the interplay of decision-making factors could be more impactful in triggering this kind of attentional response.

Methodologically, the study navigated minor challenges related to external validity and participant representativeness. The use of a participant pool predominantly composed of Aarhus BSS students, while pertinent to the digital context of our research, raises questions about the broader applicability of our findings. The observed gender differences in engagement with calorie labels hint at potential variations in how men and women process such information, warranting deeper investigation into these gender-specific behaviours. Moving forward, should further exploration of active inattention in the realm of nutritional labelling be pursued, our study highlights the critical importance of adopting research methodologies that more accurately replicate real-life shopping scenarios. Adopting more ecologically valid approaches, such as eye-tracking in physical shopping environments or realistic online shopping simulations, would provide deeper insights into the mechanisms of consumer attention and decision-making. Initiatives at the EYEMaB lab at BSS Aarhus to develop such methodologies are a step in the right direction, promising to bridge the gap between laboratory findings and real-world behaviours.

In conclusion, our study adds a new dimension to the understanding of inattention and anti-saliency in consumer behaviour, particularly in the context of nutritional labels. While our results do not succeed in supporting the notion of anti-saliency, they open up new perspectives on areas to consider in further research on inattention and engagement.

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Appendix *1* (food categories)

Product 1 (healthy)	Chosen % of the time	Product 2 (unhealthy)	Chosen % of the time
Rice Cakes	36.7	Chips	63.3
Cranberry Juice	40.0	Cordial	60.0
Hummus	75.0	Paté	25.0
Almonds	31.7	Peanuts	68.3
Oats	61.7	Granola	38.3
Cottage Cheese	53.3	Cheddar Cheese	46.7
Skyr	53.3	Yoghurt	46.7
Protein müslibar	28.3	Müsli Bar	71.7
Veggie Spread	53.3	Mayonnaise spread	46.7
Dried Fruit	55.0	Gummy Mix	45.0
Oat Milk	38.3	Regular Milk	61.7
Protein Cocoa	46.7	Cocoa	53.3
Rye bread	70.0	White Bread	30.0
Plain vanilla ice cream	43.3	Caramel Ice cream	56.7
Peanut Butter	45.0	Chocolate spread	55.0
Chicken Strips	31.7	Fried Chicken Wings	68.3
Salmon	61.7	Fried Fish Fillets	38.3
Unsweetened Dark Chocolate	71.7	Chocolate covered marshmallows	28.3
Brown rice	43.3	Regular Pasta	56.7
Tomato sauce	55.0	Cream sauce	45.0
Ice coffee sugar-free	23.3	Ice coffee	76.7
Popcorn	61.7	Corn snacks	38.3
Vegan spread	13.3	Regular Butter	86.7
Edamame cup	45.0	Dried Banana chips	55.0
Carrot cake	35.0	Gifler	65.0
Microwave dish	81.7	Millionbøf	18.3
Sports drink	58.3	Lemon soda	41.7
Salsa	66.7	Cheese Dip	33.3
Saltstænger	68.3	Raisins	31.7
Ketchup	56.7	Mayonnaise	43.3

Appendix 2 (Survey questions)

Please indicate how much you relate to the following statements on a scale from 1 to 100 (where 1 means "not at all" and 100 means "very much"):

1. How often do you read the nutritional labels before deciding on a food product?
2. How conscious are you about the number of calories you consume when it comes to food?
3. How often do you make an effort to understand the dietary implications of different food products before making a purchase?
4. How frequently do you seek information about the health and nutritional benefits of different food items?
5. How concerned are you about the impact of your diet on your long-term health?
6. How often do you compare calorie content between similar food products before making a purchase?
7. How cautious or considerate are you when consuming high-calorie foods?