A model of goal-based inattention in consumer choice

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Abstract

Consumer attention is limited, while available product information is abundant. Consequently, most information remains unattended, but which information and why? Here, we present a novel model of goal-based inattention in multi-attribute, multi-option consumer choice environments. The model explains three key patterns of consumer inattention: inattention to goal-irrelevant attributes, inattention to goal-relevant attributes that are difficult to locate, and inattention for the sake of avoiding goal-relevant attributes. By integrating insights from marketing, social psychology, and economics, we assume consumers choose based on their goals by weighing product attributes in a utility function according to their goal relevance. We also assume that attention to attributes creates goal competition, which modulates the weights so that attended attributes become more equal while unattended attributes receive zero weight. Consumers select the level of attention or inattention to each attribute a priori but choose a posteriori according to the modulated weights. In other words, consumers anticipate imminent goal competition and select the attention levels that best align their future choices with their current goals. The model makes novel predictions about how changes to consumer environments or consumer beliefs about attribute correlations may help reduce information avoidance of relevant attributes, such as health and sustainability information.

Keywords: consumer search, visual attention, multi-attribute choice, information avoidance, goals

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Many consumer choices happen in multi-option, multi-attribute choice environments such as physical or digital retail stores. Such environments are typically information-rich, and previous research shows that consumers only attend to a limited number of choice options and attributes (Lu & Hutchinson, 2024; Orquin et al., 2020). Therefore, an important question in consumer research is why consumers attend to some options and attributes and not to others. Many different classes of theories assume that consumers attend to options and attributes that are relevant to the choice and ignore those that are irrelevant (Bettman et al., 1998; Hauser, 2014; Martinovici et al., 2023; Ursu et al., 2023). With practice, consumers, for instance, become increasingly efficient in ignoring options and attributes that are less relevant to their subsequent choice (Meißner et al., 2016), and a meta-analytic synthesis of extant research shows a robust positive effect of information relevance on attention (Orquin et al., 2021).

However, there is also evidence that consumers are sometimes inattentive towards relevant information. For instance, they often fail to request information about the ethical attributes of products (Ehrich & Irwin, 2005; Zane et al., 2016), even when they report that this information is relevant to them. Similarly, many consumers believe they should attend to food calorie information during dietary choice, yet they avoid restaurants that display calorie information on their menus (Woolley & Risen, 2021). Remarkably, when faced with calorie information, those consumers who would have avoided it often use the information to select healthier food options (Woolley & Risen, 2018).

In this article, we present a novel model of goal-based inattention in decision-making that integrates insights from marketing, social psychology, and economics to explain when and why consumers are attentive or inattentive to product attributes during product choice. Specifically, the model aims to explain three ubiquitous patterns of consumer inattention during visual search. For brevity, we will refer to this as *visual inattention* although the term has previously been used as a synonym for a neurological condition known as hemispatial neglect (Kooistra & Heilman, 1989).

The first pattern of inattention is that consumers are inattentive to irrelevant product attributes. For instance, a price-conscious consumer will search for and attend to price attributes but will be inattentive to attributes such as product ingredients or production methods perceived as irrelevant. The second pattern of inattention is that consumers are inattentive to relevant attributes when these are difficult or costly to find. Even though price-conscious consumers care about getting the best deal, they usually fail to attend to the highly relevant unit price attribute because it is typically less visible than the selling price. The third pattern of inattention is that consumers are sometimes inattentive to relevant attributes to regulate their emotions or choices. A consumer who believes that calorie information is relevant may, for instance, search for and attend to this attribute when shopping for groceries in a supermarket but be inattentive to this attribute when ordering a meal in a fast-food restaurant.

In the following sections, we describe the three patterns of consumer inattention in more detail. We then review recent findings from vision science concerning the cognitive mechanisms that may lead to visual inattention. Following that, we describe how existing theories explain aspects of the three patterns of inattention. We then present a novel model of goal-based inattention in multi-option, multi-attribute choice environments that aims to explain all three patterns of inattention. Finally, we evaluate the goal-based inattention model using simulations and discuss what the model teaches us about the three patterns of consumer inattention.

Three patterns of inattention

The present article aims to explain the three patterns of consumer inattention as described above. The first pattern of inattention is that consumers are inattentive to irrelevant attributes. This effect is the flip side of value-based attention capture (Anderson et al., 2011; Gluth et al., 2018) or preferential viewing (Orquin et al., 2021), which is the robust finding that consumers attend more to rewarding or preferred stimuli while filtering out less preferred stimuli. This pattern is evident in studies that measure consumer search using eye-tracking technology. In one approach, consumers make repeated choices between two or more choice options that vary on several attributes. Based on the choice data, researchers can then estimate a random utility model that reveals the relevance of each attribute to consumers. A consistent finding from this type of research is that consumers visually attend to those attributes that are relevant to their choice and are inattentive to those that are irrelevant (Edenbrandt et al., 2022; Meißner et al., 2016; Orquin et al., 2013). Furthermore, consumers become increasingly efficient at ignoring irrelevant attributes, resulting in faster and more consistent choices over time (Meißner et al., 2016; Orquin et al., 2013). A different approach is to measure option or attribute relevance through preference ratings. This approach has been applied in physical and digital retailing and shows that consumers are more attentive to preferred products while less preferred products are mostly unattended (Gidlöf et al., 2017; Lu & Hutchinson, 2024). Some studies using preference ratings suggest no effect of preferences on attention in simple binary choices (Krajbich et al., 2010). However, the finding is probably limited to specific experimental paradigms, and meta-analytic estimates suggest that preferential viewing has a robust effect size correlation, $r = .36$, across studies and contexts (Orquin et al., 2021).

The second pattern of inattention is that consumers are inattentive to relevant attributes when they are difficult or costly to find. A consumer may, for instance, wish to know the unit price of a food product. Still, retailer practices such as making unit prices very small and of low visual salience make them challenging to detect and reduce the chances of consumers attending to unit price information (Bogomolova et al., 2020). Similarly, reducing the salience of actual or fictitious product attributes reduces visual attention to those attributes, even when consumers find them relevant (Orquin & Lagerkvist, 2015; Peschel et al., 2019). Another example is the 'fine-print effect,' in which unfavorable license or contract information is hidden in plain sight in lengthy and complex contracts. Only one in 1,000 consumers access such license agreements on retail websites, and those who do only read a small portion (Bakos et al., 2014). A policy report on consumer search in telecommunications shows that consumers often have difficulties finding relevant information on websites due to layout, and that consumers believe companies rely on information overload as part of their business model. The report recommends, among other things, that telecommunication businesses present product unit prices and provide a summary of standard contracts in plain language and a larger font size (Harrison et al., 2011).

The third pattern of inattention is that consumers are sometimes inattentive to relevant attributes that could otherwise benefit them, such as calorie, health, or nutrition information (Nordström et al., 2020; Reisch et al., 2021; Thunström et al., 2016; Woolley & Risen, 2021), but also attributes that could benefit others, such as CO^2 emissions, animal welfare, or unethical production conditions (Bell et al., 2017; Edenbrandt et al., 2021; Reisch et al., 2021). This pattern is known as information avoidance and it is studied in different research disciplines and under different names, including deliberate ignorance, willful blindness, willful ignorance, strategic ignorance, ethical blind spot, and selective exposure (for reviews see Golman et al., 2017; Hertwig & Engel, 2020; Sweeny et al., 2010). Recent reviews have proposed several reasons why consumers may want to avoid information. Relevant reasons include emotion regulation and regret avoidance, which, for instance, explains why many prefer not to receive information about their genetic predisposition to a lethal type of cancer or a family member's genetic predisposition to a severe incurable disease (Reisch et al., 2021). Emotion regulation could be part of the reason why many consumers avoid calorie and nutrition information since nutrition knowledge could lead to negative feelings of guilt when, for instance, indulging in unhealthy foods (Bradu et al., 2014). Another reason for information avoidance is eschewing responsibility. Consumers who choose not to receive calorie or nutrition knowledge are more likely to over-consume food (Thunström et al., 2016). Similarly, people who choose not to know about the consequences of their actions are more likely to behave in ways that benefit themselves yet harm others (Dana et al., 2007).

A limited number of studies have related information avoidance more directly to visual inattention. In one study, participants were asked to report which of the six dice was closest to a previously shown fixation cross (Pittarello et al., 2015). In the pay-for-accuracy control condition, participants were paid based on how accurately they reported the outcome closest to the fixation cross. In the pay-for-report condition, the authors varied whether the die second closest to the fixation cross had a higher or lower value than the closest die. Since participants were paid based on the number of dots on the die they reported, it created an incentive for reporting an incorrect die if it had more dots. When participants were paid for accuracy, they made fewer mistakes and attended mainly to the correct die. On the contrary, when they were paid based on the reported die value, they made more mistakes by reporting an incorrect but higher-paying die and attended more to this incorrect die. Other studies using similar methodologies have replicated the link between dishonesty and increased attention to self-serving information (Hochman et al., 2016; Leib et al., 2019; Pittarello et al., 2019). Additionally, a recent study shows that participants can learn statistical regularities about where information appears and use this insight to visually attend to rewarding information and avoid unrewarding information despite being clearly instructed to search for both types of information (Børsting et al., 2024). These findings suggest that information avoidance is linked to visual inattention, although the mechanisms behind it remain unclear.

Mechanisms of visual inattention

To explain the three patterns of inattention in terms of visual processes, we need to consider the cognitive mechanisms behind visual inattention. The goal-based inattention model builds directly on evidence from vision science and assumes that visual attention occurs when attention is *facilitated* while visual inattention occurs when attention is *not facilitated* or when it is *suppressed*.

Visual attention to attributes is facilitated when the attribute is goal-relevant or when it has visual properties that guide attention (Wolfe & Horowitz, 2017). The former factor represents top-down control, where higher-level cognitive processes, such as knowledge, goals, and expectations, influence the direction and prioritization of attention within a visual scene. The latter factor, called bottom-up control, refers to any dimension of the visual scene that can be sufficiently described in terms of its physical visual properties (Theeuwes, 2010). One important dimension of the visual scene is the differences between stimuli in visual features like color, contrast, or motion, which is known as salience (Itti & Koch, 2001). Another important dimension of the visual scene is spatio-temporal regularity, which allows people to predict when and where a target stimulus is likely to appear and which features the stimulus is likely to have (Boettcher et al., 2022). Bottom-up control guides attention, and the cost of finding information, measured in the time it takes to find it, decreases when information stands out, for instance, because of high visual salience, or when it is predictable in terms of its likely features or locations (Boettcher et al., 2022; Wolfe & Horowitz, 2017). Recent evidence shows that another process called suppression may also lead to visual inattention. Suppression results in below-baseline levels of visual attention that is, below the level one would expect if a stimulus was not facilitated. Studies have shown that people can learn to suppress visual attention to locations with high probabilities of task-irrelevant distractor objects (Geng et al., 2019). The learning process can happen without any awareness of the statistical regularity, and learning is not limited to spatial locations but extends to predictable features. People can, for instance, learn distractor colors and their distribution and are more likely to suppress high probability distractor colors (Chetverikov et al., 2017). In a real-world context, this suggests that consumers may be able to suppress attention to an irrelevant, and therefore distracting, attribute if they know where the attribute is likely to appear or what it will look like.

Although suppression of attention has rarely been studied in consumer contexts, some findings suggest that consumers may rely on learned suppression to reduce distraction from advertising. Advertising is intuitively presumed to be unrelated to most online tasks (Resnick & Albert, 2016), and many consumers, therefore, attempt to reduce distraction from advertising. Research on online behaviors suggests that consumers can learn the locations of advertisements on websites and reduce attention to those locations (Loranger, 2013). Consumers can also learn the features of advertisements and ignore website elements that appear to be advertisements, that is, all elements intended to stand out (Resnick & Albert, 2014). Consequently, designers are advised not to make important website content too salient (Pernice, 2018). The effect is corroborated by controlled experiments on animated and static advertising formats, suggesting that consumers are less likely to attend to high-salience animated advertising compared to low-salience static advertising (Lee et al., 2015). Presumably, animated advertising gives away the ad, since legitimate content is rarely animated. In reaction to consumers' inattentiveness to advertising, advertisers have begun to rely on so-called native advertising, which disguises itself as legitimate content (Campbell & Marks, 2015; Wang et al., 2019). Native advertising is located with legitimate content and uses the same features, making it difficult to distinguish content from advertising. In vision science terminology, reducing the feature and spatio-temporal regularity of advertising makes it difficult to distinguish it from content and may prevent consumers from suppressing visual attention to advertising.

Research on consumer food choice corroborates the notion that consumers can learn to suppress attention based on location. Orquin et al. (2018) performed several eye-tracking studies in which participants made repeated choices between four food products with different attributes such as brand, flavor, price, and nutrition label. The authors manipulated the location of the nutrition label on the products: in one condition, the label appeared in a predictable location on products (e.g., always in the lower left corner of products), while in another condition, label locations were unpredictable. In the first two experiments, participants did not perceive the nutrition label as relevant, and predictable locations reduced attention to the nutrition label compared to unpredictable locations. In a third experiment, participants were instructed to make healthy food choices and informed that the nutrition label was relevant to their choices. In this experiment, participants perceived nutrition information as relevant. This reversed the effect of location predictability, leading to nutrition labels in unpredictable locations attracting less attention than labels in predictable locations. These findings can be explained in terms of facilitation and suppression of attention: when the nutrition label appears in predictable locations, participants learn these spatio-temporal regularities and use the knowledge to either facilitate or suppress attention to those locations, depending on whether they perceive the nutrition label as relevant or irrelevant.

Existing theory on consumer inattention

Existing theories, such as Industrial Organization models (Ursu et al., 2023) and Rational Inattention Theory (Caplin & Dean, 2015; Joo, 2023; Matějka & McKay, 2015), examine how consumers prioritize their limited attention and thereby provide an account of the first and second patterns of inattention. Broadly speaking, these models assume that consumers search for information to reduce uncertainty about, for instance, which is the better product, where a product is located, or whether a product contains a specific attribute. Wedel et al., 2023 distinguish six consumer tasks that differ in the type of uncertainty that consumers need to reduce: in localization tasks, consumers aim to reduce uncertainty about a known object's spatial location; in identification tasks, consumers aim to reduce uncertainty about an object's identity in relation to other objects, in specification tasks consumers aim to reduce uncertainty about the presence of specific attributes, in inference tasks consumers aim to reduce uncertainty about the consequences of these attributes and their decision outcomes, in valuation tasks consumers aim to reduce uncertainty about the value of product attributes in relation to current goals, and in integration tasks consumers aim to reduce uncertainty about the overall utility of a choice option in relation to other options.

While reducing uncertainty is important to consumer choice, it is also costly, and consumers, therefore, need to balance the costs and benefits of search. Rational inattention theory formalizes this idea, proposing that consumers have limited cognitive resources and, therefore, cannot process infinite information (Joo, 2023; Sims, 2003). Given this constraint, consumers must decide how to allocate their attention effectively. Rational inattention theory proposes that consumers optimally allocate their attention. This means they choose to focus on information that is most relevant to their decision-making processes or that provides the most significant value given their goals and preferences. They also choose not to pay attention to specific details or pieces of information to conserve cognitive resources for more critical decisions or tasks. Rational inattention theory also assumes that consumers dynamically adjust their attention allocation based on changing circumstances. When attention costs are relatively low, or the potential benefits of processing specific information are high, individuals may choose to allocate more attention to that information.

Ursu et al. (2023) propose that the search cost is a function of consumer demographics, such as age, gender, and income; the visual choice environment, such as how centrally options and attributes are located on the screen, and consumer search efficiency, although they do not explain what influences consumer search efficiency. van der Lans et al. (2021) show that consumer search efficiency depends on the ability to visually reject options that the consumer is not searching for (i.e., reducing the duration of erroneous gazes) and that this, in turn, depends on the color congruence between the target option and competing options. When target and competitor options are visually similar, consumers are less able to reject competitor options.

Uncertainty reduction and costly search provide a theoretical framework for Patterns 1 and 2, explaining why consumers are inattentive to irrelevant information and why they are inattentive to relevant but costly or difficult-to-find information. However, they do not explain Pattern 3; that is, why consumers sometimes are inattentive to relevant information that is neither costly nor difficult to find. One potential answer to this is dynamic inconsistent time preferences, which imply that consumer preferences for present and future consumption can be inconsistent over time. A common approach is to model dynamically inconsistent consumer choices as a function of two or more utility functions. Gul and Pesendorfer (2001) present a theory of temptation and self-control choice. They model an agent who is tempted when choosing from a set of choice options (referred to as a menu), and the agent anticipates the temptation in an ex-ante period in which the agent can choose between different menus that include or do not include the temptation. To avoid the temptation and reduce the burden of self-control, the agent can commit to a menu that excludes the temptation. The authors present an example of a consumer who has to decide what to eat for lunch. The consumer has the option of ordering a vegetarian dish or a hamburger. While not hungry in the morning, the consumer prefers a healthy, vegetarian dish, but at lunchtime, the consumer prefers a hamburger. To lessen the impact of hunger on the choice, the consumer can limit the lunchtime options, for example, by selecting a vegetarian restaurant.

Beyond the example of hunger, Gul and Pesendorfer (2001) do not explain when or why consumers will change their preferences. One possibility is that consumers have a clear ranking of goals, such as choosing a meal that is healthy and, if possible, also tasty.

However, consumers may not be able to implement these goals accurately. Exposure to food stimuli may, for instance, lead them to overweight taste relative to health, resulting in a less healthy meal than intended. In goal systems theory, attention to means activates associated goals, which can inhibit conflicting goals:

> "...whereas one may step into a restaurant with a very specific plan to have a light dinner and thus pursue one's weight control concerns, exposure to food-related stimuli (e.g., the smell of freshly cooked food, the items on the menu, and the sight of appetizing courses served to other patrons) may activate the goal of food enjoyment. This latter goal may, in turn, result in the inhibition of the weight control goal and promote unplanned (or impulsive) eating contrary to one's initial plans" (Kopetz et al., 2012, p. 215)

According to this view, the overweighting of taste relative to health could, therefore, result merely from paying attention to taste attributes, which increases the activation of the taste goal and decreases the activation of the conflicting health goal. Preferences for healthy or tasty meals may, therefore, change not just as a function of hunger but in a matter of seconds as consumers attend to information that changes goal activation.

In the model by Gul and Pesendorfer, 2001, consumers commit to their primary goal by eliminating choice options from the menu before their goals can change. However, another solution might be to avoid attending to information that activates the conflicting goal. Evidence shows that people sometimes shield their primary goals by avoiding paying attention to information that conflicts with the primary goal (Cole & Balcetis, 2021; Isaacowitz, 2006). In the studies by Mischel and Ebbesen (1970) and Mischel et al. (1972), participants who avoided looking at the tempting food were better at resisting the temptation. Similarly, if attention to calorie information increases the activation of health goals, avoiding such information may help consumers pursue hedonic eating goals when they wish to do so.

An important, yet often implicit, assumption in theories about goals, temptations, and self-control is that choices require trade-offs between goals. For example, it is assumed that consumers must choose between a healthy meal or a tempting but unhealthy meal (Gul & Pesendorfer, 2001), which leads to a health vs. taste goal conflict (Kopetz et al., 2012). However, in reality, many food options can serve both goals, such as gourmet or home-cooked meals, and in some cultures, consumers even perceive health and taste to be positively correlated attributes (Werle et al., 2013). A line of research has shown that consumers can learn attribute correlations and adapt their decision and search processes to reflect their environment (Perkovic & Orquin, 2018; Pleskac & Hertwig, 2014). However, learning is sometimes incomplete, which can lead to misbeliefs about attribute correlations, such as the unhealthy = tasty belief (Kunz et al., 2023). A complete theory of when and why consumers avoid information, therefore, has to factor in beliefs about attribute correlations in the environment.

In the next section, we present a novel goal-based inattention model that integrates the above ideas. Specifically, we will assume that consumers search to reduce uncertainty about product utility (Wedel et al., 2023), that search is costly and limited (Sims, 2003), that search costs depend on search efficiency which is determined by the visual environment (van der Lans et al., 2021), that attention to information can change goal activation (Kopetz et al., 2012) and thereby the utility function, that consumers anticipate their dynamic inconsistency (Gul & Pesendorfer, 2001), have beliefs about attribute correlations (Perkovic & Orquin, 2018; Pleskac & Hertwig, 2014), and use attention and inattention to attributes to align future choices with current goals. A conceptual overview of the model is presented in Figure 1.

Model setup

The goal-based inattention model assumes that consumers visually search product options and attributes to reduce uncertainty about product utility (Wedel et al., 2023), and that product utility is a function of how well a product represents a means to achieve current goals (Van Osselaer et al., 2005). We represent the importance of goals through attribute weights, for instance, the weight of health attributes relative to taste attributes. Attributes are sometimes associated with multiple goals, which is known as equifinality (Kopetz et al., 2012). For example, an attribute signaling that a food product is vegan could serve both a dietary and a sustainability goal. On the other hand, a single goal can

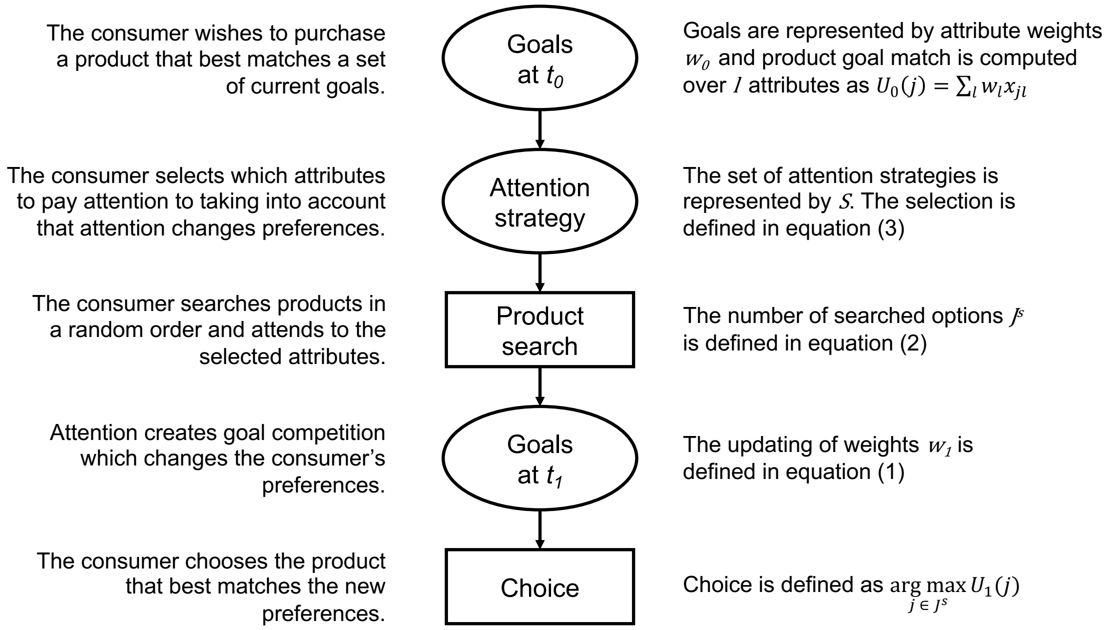

Figure 1. Conceptual overview of the goal-based inattention model, illustrating the search and decision processes and corresponding model parameters.

also be associated with multiple attributes which is known as multifinality. For example, both a vegan and a CO^2 emission attribute could serve a sustainability goal.

However, in the following, we assume for simplicity that each attribute is associated with a unique goal, for instance, calorie information to a health goal, taste information to a hedonic eating goal, and price to a budget goal. This allows us to describe the goal utility of a choice option j with L attributes $\{1, ..., l\}$ through the attribute weights $\{w_1, ..., w_l\}$ using an additive utility function, $U(j) = \sum_{l \in L} w_l x_{jl}$.

Attention strategy

Attention to the description of a tempting food option can increase the activation of a previously less important hedonic eating goal, leading to competition with a primary health goal (Kopetz et al., 2012). We represent such a shift in goals by an update in attribute weights before attention at t_0 and after attention at t_1. If a consumer chooses not to pay attention to attribute l then the corresponding attribute weight at t_1 takes the value zero $w_{1l} = 0$. For attributes that are attended, the weights at t_1 are re-scaled with a softmax function with a temperature parameter $\tau > 1$ reflecting an increased competition between goals:

$$w_{1l} = \begin{cases} \frac{e^{w_{0l}/\tau}}{\sum_{l \in L} e^{w_{0L}/\tau}} & \text{if attention to } l \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

For example, before searching the restaurant menu, a consumer may have a health goal twice as important as a hedonic eating goal and three times as important as a price budget goal. However, after visually attending to the health and taste attributes but not the price attribute, the goals change in activation levels reflected in more equal weights for the health and taste attributes and a weight of zero for the price attribute.

The model assumes that consumers select between different *attention strategies* that determine the level of attention for each attribute, allowing them to *facilitate*, *not facilitate* (i.e., pay sporadic attention to), or *suppress* (i.e., never pay attention to) attributes. For each available attribute, the consumer must choose whether to facilitate, not facilitate, or suppress that attribute, and the set of possible attention strategies S is thus 3^L. We will assume that if a consumer facilitates attention to an attribute, then that attribute is always attended to. If an attribute is not facilitated, then the attribute will still be attended to with some probability e. This parameter reflects the finding that selective attention is prone to errors (Araujo et al., 2001; Morvan & Maloney, 2012; Nowakowska et al., 2021). The noisy visual attention process implies that a product attribute has some chance of being attended to even when a consumer does not facilitate attention to that attribute. However, if the consumer chooses to suppress attention to an attribute, then visual attention is suppressed below the chance-level (Geng, 2014), in the model represented by $e = 0$.

Search, stopping, and choice rules

The model assumes that consumers search a fixed number of products and then choose the best product they see (Santos et al., 2012). Options are attended in a random order, and the within-option search is defined by the chosen attention strategy s. The number of options searched depends on the attention strategy, where strategies that imply attending to more attributes or difficult-to-locate attributes reduce the number of options searched. This leads to a trade-off between more precise information about the utility of fewer products and less precise information about the utility of more products. Some attributes are easier to locate than others because they have predictable locations or features or because they are visually dissimilar from other attributes (van der Lans et al., 2021). The difficulty of locating an attribute is represented as its visual guidance $g = (0, 1]$, and the cost of attending the attribute is the inverse of the guidance g^{-1}. Values close to zero (but not including zero) indicate that it is very difficult to locate an attribute, while values close to one indicate that it is very easy to locate an attribute. There is no cost of not facilitating or suppressing attention since these processes contribute little or nothing to the total search time. The number of searched options J^s given attention strategy s is a function of the number of attended attributes and their level of guidance:

$$J^s = \frac{n}{k + \sum_{l \in L} I_l^s g_l^{-1}} \tag{2}$$

where I_l^s is an indicator function that takes the value 1 if attribute l is attended to given attention strategy s otherwise, 0 and n and k are scaling parameters that jointly control the maximum number of options that a consumer is willing to search. After stopping, the consumer chooses the option from the set of searched options J^s that maximizes the updated utility function U_1. The model assumes that consumers protect their primary goal by choosing the attention strategy s from the set of possible strategies S that maximizes current utility U_0:

$$\arg\max_{s \in S} U_0(\max_{j \in J'} U_1(j)) \tag{3}$$

In other words, consumers anticipate that attention modulates goal competition and select the attention strategy that best aligns their future choices with their current goals. The process is illustrated in Figure 2. Panel A shows how the attribute weights at $t = 0$ change as a function of two attention strategies that either facilitate attention to both attributes (strategy FF) or facilitate attention to attribute A1 and suppress attention to attribute A2 (strategy FS). Panel B is an example of an environment where the two attributes are uncorrelated. In this environment, the smallest loss in terms of U_0 is achieved by selecting strategy FF. Panel C is an example of an environment where attributes are negatively correlated. In this environment, the smallest loss in terms of U_0 is achieved by selecting strategy FS.

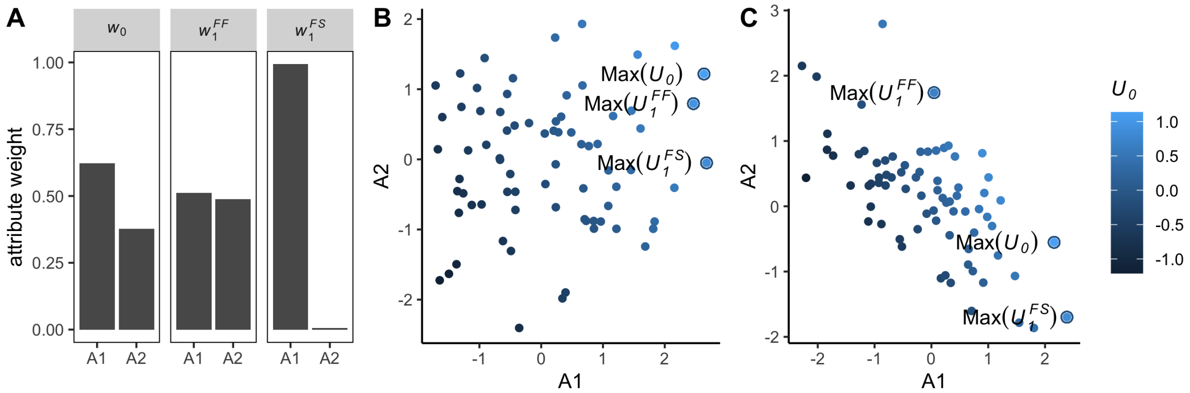

Figure 2. (A) Attribute weights before attention (w_0), weights after attention to both attribute A1 and A2 (w_1^{FF}), and weights after attention to only attribute A1 (w_1^{FS}). (B) Scatter plot of choice options in an environment where attributes are uncorrelated. The color indicates option values according to U_0, with lighter shades of blue indicating higher U_0. (C) Scatter plot of choice options in an environment where attributes are negatively correlated. The color indicates option values according to U_0, with lighter shades of blue indicating higher U_0.

Model simulation

Method

We generate model predictions by simulating data for 12 choice options with three attributes. In the baseline scenario, the three attributes are uncorrelated and normally distributed with $M = 0$ and $SD = 1$, with t_0 weights $\{0.48, 0.29, 0.23\}$, and model parameters $\tau = 20$, $e = .25$, $g = \{1, 1, 1\}$, $n = 50$, and $k = 3$. The parameters are chosen to produce search sets J^s between 10 and 20 products (Thomas et al., 2021). With three attributes, there are 27 possible combinations of the three attention processes: facilitation (F), no facilitation (N), and suppression (S). We name attention strategies according to their attention processes, for instance, FFF when all three attributes are facilitated or FFN when attributes 1 and 2 are facilitated and attribute 3 is not facilitated. We exclude those strategies where none of the attributes are facilitated since they imply no search (e.g., SSS, SSN, SNS, etc.), resulting in 19 attention strategies to be tested. In each simulation iteration, data is first generated for 12 IID choice options. The utility of each option is then computed according to each of the 19 attention strategies based on the re-scaled weights following equation (1). Attention strategies in which one or more attributes are not facilitated are subject to erroneous attention with probability e. Utilities for attention strategies where one attribute is not facilitated (e.g., FFN) are computed by sampling the utility from said attention strategy with probability $1 - e$ or from the corresponding attention strategy in which the attribute is facilitated (FFF) with probability e. Utilities for attention strategies where two attributes are not facilitated (e.g., FNN) are computed by sampling the utility from said attention strategy or the three corresponding attention strategies (FFF, FFN, FNF) with probabilities $(1 - e) * (1 - e)$, $(1 - e) * e$, $(1 - e) * e$, and $e * e$, respectively. The stopping point J^s is then computed for each attention strategy based on equation (2), and random subsets of size J^s options are selected. The loss function is computed for each attention strategy according to equation (3) as the difference in t_0 utility between the chosen option and the option that maximizes U_0 that is, $U_0(\max_{j \in J^s} U_1(j)) - \max_{j \in J^s} U_0(j)$. Data is simulated 10,000 times for each scenario, and losses are averaged over simulations. [1]

Rather than exploring the entire space of combinations of attribute weights and environment dimensions (guidance, attribute correlations, and attribute SD), we focus on some scenarios that reveal important properties of the goal-based inattention model. Table 1 contains an overview of the examined scenarios and the simulation results indicating which of the 19 attention strategies best reduces the loss in terms of t_0 utility. Figure 3 contains a complete overview of the loss in terms of t_0 utility for each of the 19 attention strategies across scenarios. The default parameter setup described above is referred to as the *baseline* scenario. The *low guidance*, *zero weight*, and *trade-off* scenarios examine the effect of changing a single simulation parameter: the level of guidance of attribute 2, setting the weight of attribute 3 to zero, and a negative correlation between attribute 1 and attribute 2. The *trade-off w. high SD* and *trade-off w. low guidance* scenarios examine the effect of attribute SD and guidance in a trade-off scenario.

[1] The code for running the simulation is available on
https://osf.io/j2wxz/?view_only=a5d5961c32c540b0af3752a0794f76bd

Table 1

Simulation results identifying the best attention strategy (right-most column) depending on attribute weights at $t = 0$, the level of attribute guidance g, the correlation between attribute A1 and A2, and attribute standard deviations.

scenario	w_0	g	r_{A1A2}	SD	strategy
baseline	{0.48, 0.29, 0.23}	{1,1,1}	0	{1,1,1}	FFN
low weight	{0.62, 0.38, $5e$-50}	{1,1,1}	0	{1,1,1}	FFS
low guidance	{0.48, 0.29, 0.23}	{1,.3,1}	0	{1,1,1}	FNF
trade-off	{0.48, 0.29, 0.23}	{1,1,1}	$-.7$	{1,1,1}	FSF
trade-off w. high SD	{0.48, 0.29, 0.23}	{1,1,1}	$-.7$	{1,2,1}	FFF
trade-off w. low guidance	{0.48, 0.29, 0.23}	{.3,1,.3}	$-.7$	{1,1,1}	FFN

Results

The simulation shows that the baseline and low-weight scenarios produce the first pattern of consumer inattention. In the baseline scenario, the goal-based inattention model predicts the smallest loss in terms of t_0 utility when consumers facilitate attention to the two most important attributes and do not facilitate attention to the least important attribute (FFN). By not facilitating attention to the least important attribute, the consumer can search for more options, thereby increasing the expected utility of the best option in the set. The reason for this is that the expectation of the best option X_n from a set of n normally distributed options increases when n increases since $E[X_n] = n\Big[F(x)\Big]^{n-1} f(x)$. In the low-weight condition, the least important attribute has a near zero weight, and the model predicts the smallest loss when consumers suppress attention to the least important attribute (FFS). The reason is that while the least important attribute has a near zero weight at t_0, it has a low weight at t_1 ($5e$-50 vs .001). The weight change introduces a small imprecision in the estimate of U_1 relative to U_0 if a consumer attends to the attribute accidentally. To avoid imprecision in U_1, it is therefore better to suppress the attribute.

The low guidance scenario produces the second pattern of inattention. When the attribute with the second-highest weight has a low level of guidance, the smallest loss is achieved by not facilitating attention to that attribute (FNF). Because the attribute has such a low level of guidance, its opportunity cost in terms of the number of searched options is very high. By not facilitating the low-guidance attribute, the consumer can instead search for more options.

The trade-off scenario produces the third pattern of inattention. When the two attributes with the highest weight are negatively correlated, the smallest loss is achieved by suppressing attention to the attribute with the second-highest weight (FSF). To understand why, one should recall that a negative correlation implies that there are likely no options that score high on both attributes. According to U_0, a consumer must choose an option that trades off a high value on the most important attribute with a lower value on the less important attribute. If a consumer attends to both attributes, the attribute weights will be more equal, and the consumer must choose an option with similar values for both attributes. If, instead, the less important attribute is suppressed, the consumer must choose the option with the highest value on the most important attribute (for a visual intuition, see Figure 2). This means that the difference between U_0 and U_1 is smaller when the less important attribute is not attended, and it is therefore advantageous to suppress attention to that attribute. The trade-off with high SD scenario shows that when the attribute with the second-highest weight has a higher standard deviation ($SD = 2$), the lowest loss is achieved by facilitating attention to all three attributes (FFF). The reason is that a large SD changes the distribution of option utilities and, thereby, the expectation of the option with the highest value $E[X_n]$, making it advantageous to attend to the attribute. The trade-off with the low guidance scenario shows that when the attributes with the highest and lowest weight have lower levels of guidance compared to the attribute with the second-highest weight, the lowest loss is achieved by facilitating attention to the two attributes with the highest weight (FFN). The reason is that although attending to instead of suppressing the second attribute (FFN) produces a larger deviation between U_0 and U_1, it outweighs the opportunity cost of searching for fewer options (FSF).

Implications

The goal-based inattention model provides a unified account of the three patterns of consumer inattention. The first pattern of inattention is that consumers are inattentive to irrelevant and less relevant attributes. This pattern has previously been explained by

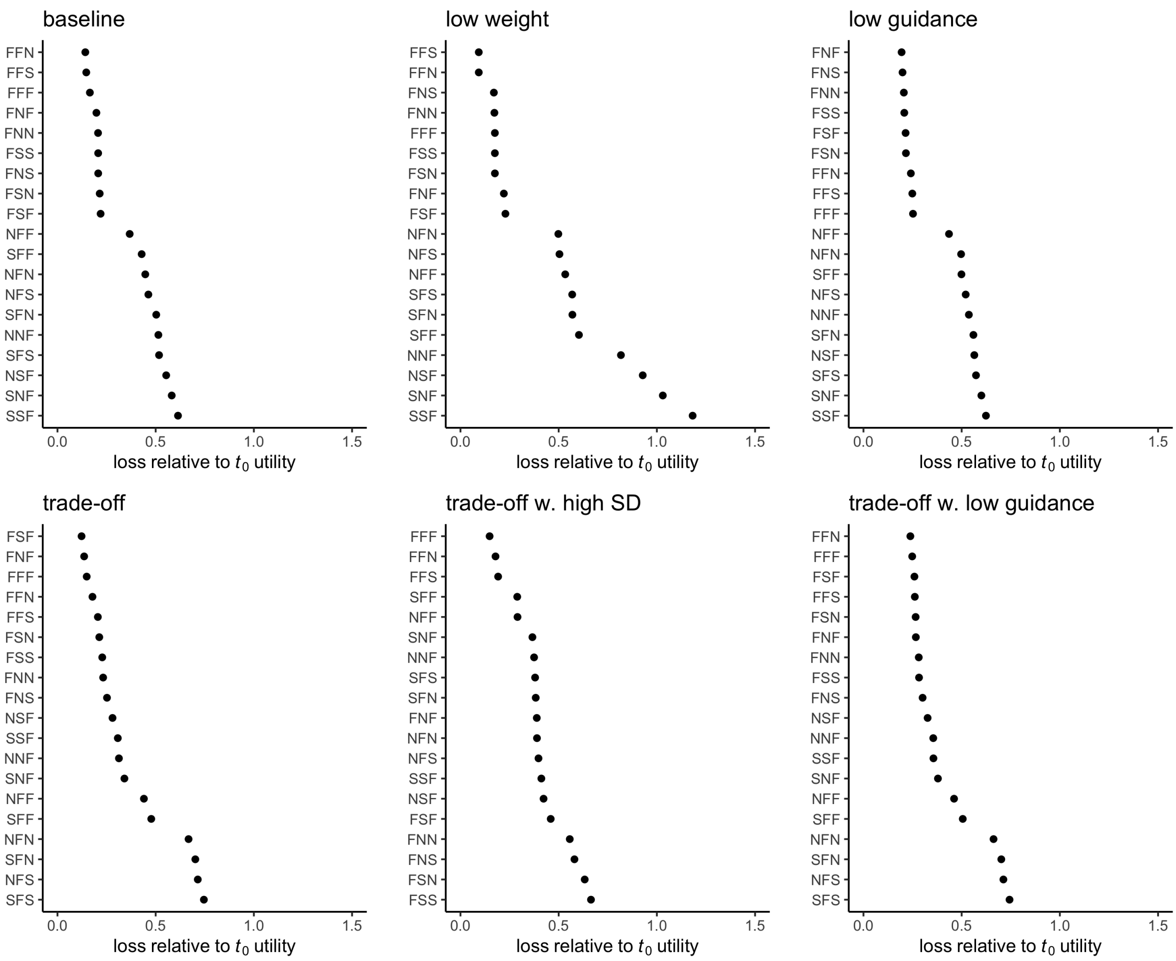

Figure 3. Simulation results for six scenarios: baseline, low guidance on attribute 2, zero weight on attribute 3, trade-off with a negative correlation between attribute 1 and 2, trade-off with high SD for attribute 2, and trade-off with low guidance on attribute 1 and 3.

different theories, including strategy selection models (Bettman et al., 1998), structural IO models (Ursu et al., 2023), and in a broad sense, Rational Inattention theory (Sims, 2003). The goal-based inattention model and Rational Inattention theory both explain this pattern as a result of a trade-off between the costs and benefits of search. Although a less relevant attribute may inform the consumer and potentially improve choices by reducing the loss in terms of t_0 utility, the benefit of searching for this additional attribute may not outweigh the opportunity cost of searching for fewer choice options. The second pattern of inattention is explained through the same trade-off mechanism. When an attribute becomes more difficult to locate it may push the balance between the benefit it provides and the increased cost of searching for it. The third pattern of inattention has previously been explained by theories about self-control in social psychology (Kopetz et al., 2012) and economics (Gul & Pesendorfer, 2001) and more recently by models of information avoidance (Golman & Loewenstein, 2018). Similar to self-control theories, the goal-based inattention model assumes that consumers can have multiple goals that compete against each other. Specifically, the model suggests that the third pattern of inattention occurs because consumers shield their most important goal against a less important goal.

The goal-based inattention model makes several novel predictions concerning consumer attention. First, the model suggests that consumers may be using attention suppression to reduce distraction from irrelevant attributes with zero weight and to shield their main goals from secondary goals. Current work in vision science emphasizes the role of suppression in reducing visual distraction (Geng et al., 2019), but the goal-based inattention model suggests that suppression may also play an important role in goal shielding. This casts new light on earlier findings related to self-control and visual attention. The seminal work by Mischel and colleagues demonstrated that children divert visual attention away from a tempting food to increase patience for a delayed but larger amount of the same tempting food (Mischel & Ebbesen, 1970; Mischel et al., 1972). Findings from adults have revealed similar patterns: people who crave chocolate but do not permit themselves to eat it attend significantly less to chocolate stimuli (Werthmann et al., 2013). It is possible that both children and adults in these examples used suppression of attention to shield themselves from temptations, thereby strengthening their goal pursuit.

Second, the model suggests several novel ways of reducing the suppression of attention to relevant information and thereby ways of reducing information avoidance. Information avoidance is not necessarily a challenge to consumer well-being, but it can become problematic when consumers avoid attributes that would benefit themselves such as calorie, health, or nutrition information (Nordström et al., 2020; Reisch et al., 2021; Thunström et al., 2016; Woolley & Risen, 2021), or attributes that could benefit others such as CO^2 emissions, animal welfare, or unethical production conditions (Bell et al., 2017; Edenbrandt et al., 2021; Reisch et al., 2021). Previous work has focused on techniques that either change consumers' attitudes or their possibilities of avoiding information (Hua & Howell, 2022; Woolley & Risen, 2021). However, the model suggests that the necessary condition for avoidance is whether consumers believe there is a negative correlation between the most important attributes. If marketers or policymakers can change consumers' beliefs about attribute correlations, they may be able to reduce information avoidance. Consumers generally believe that unhealthy foods taste better than healthy foods (Raghunathan et al., 2006), which is to say, consumers believe that health and taste are negatively correlated. This belief in a negative health-taste correlation could be the factor that leads many consumers to avoid calorie information when they pursue taste-oriented goals, for instance, when visiting or planning to visit a restaurant (Woolley & Risen, 2021). Beliefs about attribute correlations could stem from heuristic inferences, such as the availability heuristic (Tversky & Kahneman, 1973). It may, for instance, be easier to recall examples of unhealthy foods that are very tasty (e.g., candy, ice cream, etc.) and examples of healthy foods that are less tasty (e.g., mixed green salad) while examples of healthy and tasty foods are more difficult to recall (e.g., gourmet or home-cooked meals). Another possibility is that consumers observe correlations between attributes in the environment and form beliefs through a process of statistical learning (Perkovic & Orquin, 2018). A recent study suggests that differences in the frequencies of healthy and tasty foods across consumer environments can lead to misbeliefs about the correlation between health and taste (Kunz et al., 2023). Regardless of the mechanism, it seems that a promising avenue is to increase consumers' exposure to examples of healthy and tasty foods, which may help consumers change their belief from a negative into a positive correlation between health and taste. If successful, such interventions will, according to the goal-based inattention model, reduce information avoidance of calorie and health information and improve healthy food choices.

A second finding that may help reduce information avoidance is the prediction that increasing the standard deviation of the avoided attribute leads to facilitation instead of suppression of attention. The reason is that a large SD changes the distribution of option utilities, making it advantageous to attend to the attribute. Marketers and policymakers can increase an attribute's standard deviation by increasing its range or, in the case of ordinal attributes, by increasing the number of attribute levels (e.g., going from a five- to a six-star rating system). Findings from discrete choice experiments suggest that increasing the attribute range or number of levels sometimes increases the importance of the attribute in consumer choice (Verlegh et al., 2002). However, it remains unclear under which circumstances range, and the number of levels increases attribute weights (Bestard & Font, 2021). In many cases, it is difficult for marketers or policymakers to increase the actual range of an attribute such as price or calories, but this may not even be necessary. Assuming that consumer search is incomplete, one approach could be to expose consumers to more extreme values of an attribute to change their sampling and thereby beliefs about the attribute (Kunz et al., 2023).

A third finding relevant to information avoidance is that decreasing the level of guidance of the two not-suppressed attributes leads to the facilitation of the otherwise suppressed attribute (FFN). The reason is that while attending to the attribute produces a larger deviation between U_0 and U_1, this outweighs the opportunity cost in terms of searched options. In the context of food packaging, this suggests that attributes that are commonly avoided (e.g., nutrition or calorie labels, CO^2 emission labels, etc.) need to be much more visually prominent than other product attributes. Currently, attributes such as brand and logo occupy a large share of product surface at the expense of the visual prominence of these attributes (Orquin et al., 2020).

Limitations and future research

The goal-based inattention model makes several assumptions about the consumer environment and consumer search. Concerning the environment, the model assumes that attribute guidance is constant across products. Previous research has shown that levels of guidance, measured in terms of visual salience, surface size, and position on products, are relatively consistent for different attributes (Orquin et al., 2020). However, it is clear from this research that there is considerable variance across products in these measures, and it remains an open question exactly how regular attribute guidance must be for consumers to choose an attention strategy. More research is needed concerning the structure of consumer environments, both to describe the visual structure but also to understand how consumers observe and sample information from their environments to form beliefs about attribute distributions and correlations. The model makes several assumptions about consumer search. First, the model assumes that consumers use a fixed sample search process. The assumption is based on empirical findings suggesting that while consumers may decide to stop searching sequentially (product by product), there is nevertheless an upper limit to how many products they will search (Reutskaja et al., 2011; Thomas et al., 2021). Second, the model assumes that consumers are sophisticated planners who anticipate a change in goal activation and choose the best attention strategy accordingly. Future research can relax this assumption by allowing consumers to be more or less sophisticated, for instance, in terms of anticipating a change in goal activation or in terms of the number of attention strategies they can choose from. Third, the model describes goal competition with a softmax function, see equation (1), but more research is needed to determine whether the choice of this particular re-scaling function is adequate. One potential oversimplification of this function is that it does not distinguish between types of goals, for example, hedonic vs. healthy eating goals. This is important as looking at an appetizing picture of food may activate a hedonic goal more strongly than looking at a calorie label activates a healthy eating goal. Future research can relax the assumption that all goals compete on equal terms by allowing attention to activate goals more strongly than others.

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