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Trust, Time, and Tables:

How the Shielding Effect of Brands Influences Product Evaluations

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Abstract

This research builds on the Dual Process Theory to examine how time constraints and brand familiarity affect customer decisions, focusing on the usage of the Nutri-Score and Nutritional Information Table. Understanding these characteristics is essential for healthy eating habits as snacking has become more common and obesity rates have increased over the past years. Our findings reveal that low time pressure supports more analytical evaluations, whereas time constraints compel consumers to rely on heuristics. Brand familiarity further modifies these behaviors, increasing the likelihood that consumers will rely on heuristic processing when they recognize a brand, leading to less detailed evaluations of product attributes, although it does not result in quicker decisions.

Keywords: Consumer behavior, Nutri-Score, Brand familiarity, Time pressure, Heuristic processing, Systematic processing, Food labeling

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1 Evolution of Food Consumption and Labeling

Eating habits have changed significantly in recent decades, driven by factors such as economic growth, urbanization, technological advances, and increased global trade. This has led to a dietary landscape that is very different from that of previous generations. It is characterized by an increase in overall calorie intake, changes in food composition, and variations from regional food preferences (FAO 2024).

1.1 Global Trends and Challenges in Food Consumption

Improvements in food production, supply, and distribution have significantly increased the number of calories consumed by people worldwide since the 1960s (Appendix 1). This increase is particularly noticeable in fast-growing countries in Asia and Africa, where the availability of food has improved access to a variety of food sources (Roser, Ritchie, and Rosado 2023). However, this pattern masks inequalities: high-income countries consume far more calories than low-income countries, underlining the persistent disparities in global food distribution (Appendix 2). These regional differences highlight the complex links that exist globally between dietary practices, economic status, and food availability (Roser, Ritchie, and Rosado 2023).

1.1.1 Shift to More Industrially Processed and Energy-Dense Food Products

In many developing countries, rising salaries and urbanization have contributed to a "dietary transition" characterized by enhanced consumption of high-energy, low-nutrient food products frequently associated with the Western diet (Popkin, Adair, and Ng 2012). This diet typically includes high levels of refined grains, red meat, sugary drinks, and processed snacks, often combined with the expense of fruits, vegetables, and whole grains (Popkin, Adair, and Ng 2012). Consequently, there is a higher intake of fats, refined carbohydrates, and processed foods, while people deprioritize fiber- and nutrient-rich options such as fruits and vegetables

(Popkin 2001). This transition is particularly prevalent in urban areas of Asia, Latin America, and Africa, where modernized lifestyles have led to dietary changes that mirror those in high-income countries (Popkin 2001). The shift toward processed foods has also been driven by big lifestyle changes that prioritize convenience, as more people have less time to prepare meals at home due to longer working hours (Quash 2023). The growing consumption of processed foods has been linked to increasing rates of obesity, type 2 diabetes, and cardiovascular disease, emphasizing the significant public health risks associated with changing dietary patterns (World Health Organization 2024).

1.1.2 The Various Consequences of Malnutrition

As seen in many developing countries, where undernutrition and overnutrition coexist within the same population or even household, the balancing act of malnutrition is becoming more common. However, lack of nutrients is still widespread in low-income and more rural populations, creating an inequality that makes public health efforts more difficult (Grimmelt et al. 2022). This twofold burden highlights the challenges of the food transition; access to high-energy, low-nutrient foods is widespread, but access to quality food remains uneven across socio-economic lines. Addressing this issue requires actions that address both ends of the nutritional spectrum, promoting food labeling and consumer education to support healthy dietary choices (Popkin, Adair, and Ng 2012).

1.1.3 Shift in Animal- and Plant-Based Foods

In many high-income Western countries, the consumption of animal products and industrial sugars has fallen sharply due to increasing recognition of their health and environmental implications (Southey 2020). For example, in the UK and US, consumers are increasingly selecting plant-based alternatives, leading to food labeling policies that prioritize sustainability and health. Labels that highlight these are well received by consumers, bringing food labeling into line with modern buyer values ("Trends Impacting the Healthy Eating" 2024). This shift reflects a global rethinking of dietary impacts and highlights the growing demand for transparency in food labeling to support eco-conscious and health-focused choices (Grimmelt et al. 2022).

1.1.4 Increased Consciousness of Health and Ecological Impact

The COVID-19 pandemic has significantly boosted the trend toward healthier eating, with consumers recognizing more and more the link between nutrition and their overall well-being. A McKinsey survey detected that 50% of consumers now prioritize a healthy diet, particularly by limiting their intake of sugar, fat, and salt (Grimmelt et al. 2022). Almost half of the respondents acknowledged difficulties in identifying the specific actions they need to take to make healthy and sustainable choices, indicating a gap in easily accessible, clear guidance (Appendix 3). While health is generally considered more important than sustainability when making food choices in the mentioned survey, this confusion has left many people feeling "hungry and confused" about what makes a truly good diet (Grimmelt et al. 2022). This lack of clarity is further compounded by frustration with retailers, as many consumers feel that grocery stores are not providing enough support for their shift towards a more health-conscious diet (Appendix 4). Such demand for transparency and a broader selection of health-oriented products underscores the significance of effective food labeling systems, which can provide consumers with clear and reliable information to make informed choices (Grunert and Wills 2007).

1.2 Expansion of the Snacking Category

One notable change in eating behavior is the decline of traditional meals in favor of more frequent, smaller meals or snacks, such as crisps, fruit, and cheese. This development reflects a general shift towards greater convenience and flexibility, as consumers are increasingly turning to snacks to quickly satisfy their nutritional needs and keep up with their busy schedules (Appendix 5). Snacking behavior is on the rise, particularly among younger professionals and population groups who have little time for traditional meals due to changing working hours (Quash 2023). On the other hand, the rise in health consciousness has also driven the demand for healthier snacks, as Nielseniq (2023) reports that the snack sector has seen significant growth, with annual sales of over $135 billion. Despite the assumed popularity of snacks, only 25% of respondents were ‘very aware’ of the daily nutritional value of proteins in their snacks, indicating a gap in nutritional knowledge (TalkerResearch 2024). However, this increase in snacking has also raised some nutritional concerns. Some people use snacks to fulfill specific nutritional needs, but others frequently consume high-calorie, low-nutrient varieties, which can lead to an unbalanced diet. Unintentional snacking can have negative consequences, such as poor food choices and low energy levels (TalkerResearch 2024).

1.3 The Start of Food Labeling

Due to the increasing complexity of offered products, front-of-pack labeling (FOPL) systems were developed to simplify nutritional information and enable quicker, more informed food choices and easier product comparisons (Porter and Earl 1990). The first step to protect consumers from misbranded and contaminated foods was by implementing the Pure Food and Drug Act of 1906 in the United States. The consequence was that food labels needed to contain accurate descriptions to provide clear nutritional information to the consumers. The Federal Food, Drug, and Cosmetic Act reinforced these requirements by mandating the inclusion of key nutritional information, such as a comprehensive list of ingredients, on food labels (Allison 2022). These early developments are the basis for the nutritional labels we know today and already show the importance of honesty between food producers and consumers (Nermae 2021). The research found that FOPL systems like the Nutri-Score have an impact on consumer behavior and encourage even those to make healthier purchase decisions that lack detailed nutritional knowledge (Julia and Hercberg 2017). This need for a correct FOPL applies especially when considering processed foods with unclear health benefits (Facioni et al. 2020). This becomes even more important keeping in mind the developments of increasing obesity and diabetes rates and the desire for healthy food options (Grimmelt et al. 2022).

1.4 The Transition to FOPL

Building on the history of food labeling, FOPL was introduced to address the limitations of traditional back-of-pack labels. The detailed and often complex information on the back of food packages can be time-consuming and may require numeric interpretation (Li, Wang, and Zhang 2022). In contrast, FOPL is designed to give quick and accessible insights into the nutritional quality of a product. This is especially important for individuals with lower education or numeracy skills, who may find back-of-pack information difficult to understand and use effectively (Kotler and Keller 2016; Rothman et al. 2006). By placing clear, simplified information on the front of the packaging, FOPL can help consumers to make informed food choices more easily, which is especially beneficial at the point of purchase (Roberto et al. 2021). This part of the paper will explore the key features and design principles of FOPL, provide recommendations for effective FOPL design, and examine its limitations.

1.4.1 Key Features and Design Principles of Front-of-Pack Labeling

To improve the effectiveness of FOPL, various design principles and labeling types have been developed to meet different consumer needs and improve dietary choices. These vary across several dimensions which are further explained in the following (Appendix 8). Summary indicators, like the Nutri-Score and the Health Star Rating, provide an overall health rating for products and may help consumers make quick assessments of their nutritional quality. In contrast, nutrient-specific labels, such as Chile’s ‘High in’ warnings, focus on individual nutrients like sugar, sodium, and fat (Roberto et al. 2021). Real-world evidence shows that nutrient-specific warning labels can significantly reduce purchases of unhealthy products, such as decreases in sugary drink purchases (Taillie et al. 2020). Additionally, interpretive labels, like the traffic light system, offer visual cues that try to guide consumers in assessing the healthfulness of a product. Studies have proven the effectiveness of these labels by observing significant increases in purchases of healthier items and a simultaneous decline in the desire for less healthy ones (Cawley et al. 2015; Sutherland, Kaley, and Fischer 2010). Noninterpretive labels, such as the Guideline Daily Amount, present nutrient data without any additional guidance (Talati et al. 2019), however, studies indicate that interpretive labels are more effective in promoting healthier choices (Cawley et al. 2015; Sutherland, Kaley, and Fischer 2010).

Threshold-based labels only appear on products that meet a certain health standard, clearly marking healthier options, while non-threshold-based labels are displayed across all products regardless of nutritional quality (Roberto et al. 2021). Evidence suggests that threshold-based systems can help consumers easily identify healthier options; for example, the Health Star Rating system in Australia is associated with small but positive shifts in purchases toward products that meet health standards (Shahid, Neal, and Jones 2020). Symbols, colors, and visual elements in FOPL systems, such as the color-coded Nutri-Score letters, make nutritional information instantly recognizable and easier to interpret. Real-world evidence underscores the effectiveness of clear visual symbols; Chile's black octagonal 'High in' labels, for instance, attracted significant consumer attention and contributed to reduced purchases of labeled products (Taillie et al. 2020).

1.4.2 Recommendations for Effective Front-of-Pack Labeling Design

Roberto et. al (2021) suggest that Front-of Pack-Labeling (FOPL) should be prominent and easy to spot, utilizing bold colors and distinct shapes (e.g., stop signs) to attract attention.

Also, visibility is important in busy shopping environments where quick decisions are essential. Labels should convey simple, clear messages without relying heavily on numeric details. Numeric-heavy labels like the GDA are less effective, especially for those with low numeracy, as simpler information helps in faster decision-making (Roberto et al. 2021). Leveraging symbols and color-coding (e.g., red for caution, green for health) aligns with intuitive thinking, allowing consumers to process information faster and more easily (Roberto et al. 2021). Adding emotional cues like "high in" or "warning" reinforces health messages, making the potential risks clearer. Emotional messaging has been shown to push consumer awareness and intention to avoid less healthy products (Grummon et al. 2019). Additionally, phrases like "high in" or "avoid" make health risks clear and have been proven effective in reducing purchases of sugary drinks and other unhealthy items (Grummon and Hall 2020). Displaying FOPLs on all products, not just healthy ones, helps consumers make balanced choices by highlighting both healthier and riskier options (Roberto et al. 2021).

1.4.3 Limitations of Effective Front-of-Pack Labeling

FOPL systems, while designed to improve public health, also come with certain limitations and unintended consequences. For instance, Moorman, Ferraro, and Huber (2012) have shown that the introduction of mandatory food labeling, such as the U.S. Nutrition Facts label, could not always lead to an improvement in the overall nutritional quality of products. While labeling prompted some healthier reformulations, especially in processed foods like French fries and hot dogs, the nutritional quality of many labeled products may decreased as manufacturers shifted ingredients. Companies were often more inclined to improve the nutritional quality of new brands rather than make changes to established products (Moorman, Ferraro, and Huber 2012).

Another unintended effect observed in FOPL implementation is the reformulation of high-sugar products with noncaloric sweeteners. According to a study in Chile (Quitral et al. 2019), the majority of products in specific categories, like dairy (67%) and cereals, contained at least one noncaloric sweetener, a significantly higher percentage than in countries without such labeling requirements, such as Brazil (14%) and the United States (21%) (Sambra et al. 2020). Although this shift may align with FOPL's goal to reduce sugar intake, it raises concerns about the potential health effects of increased noncaloric sweetener consumption, especially for children. Additionally, there is a risk that certain FOPL designs could unintentionally stigmatize consumers: proposals for graphic warning labels in the United States have sparked discussions around whether such labels may contribute to negative perceptions of certain body types or food choices (Hayward and Vartanian 2019). The impact of labeling on stigmatization is still under-researched, but it highlights the need for sensitivity in FOPL design, particularly for labels that use negative framing to encourage behavior change. The effectiveness of FOPL can also be limited by inconsistencies in the underlying nutritional criteria. Systems like the Nutri-Score and the Health Star Rating rely on category-specific thresholds, which allow comparisons within product categories (e.g., comparing different types of ice cream) but may complicate cross-category assessments (Julia and Hercberg 2017).

In summary, FOPL is a valuable approach to guiding healthier food choices by providing clear, accessible nutritional information. However, various limitations, such as potential ingredient shifts or inconsistencies in nutritional standards, highlight the need for ongoing adjustments to enhance its effectiveness. To meet diverse consumer needs and maintain its public health impact, FOPL requires continuous refinement (Roberto et al. 2021).

2 Introduction to Consumer Behavior

Consumer purchasing decisions are shaped by social, cultural, and personal factors. These factors are important for strategies in marketing practices as they help businesses adapt their products according to consumer needs (Kotler and Keller 2016).

2.1 Understanding the Concept of Consumer Behavior

Consumer behavior refers to the processes involved when “individuals, groups, and organizations select, buy, use, and dispose of goods, services, ideas, or experiences to satisfy their needs and wants” (Solomon and Russell 2023, 179). The concept of a holistic marketing approach requires an understanding of consumers’ circumstances and how they change over time (Kotler and Keller 2016). As a consequence, marketers need to consider not only what their customers want but also why and how they want it and in what ways their needs are changing over time. Three main variables impact consumer behavior: cultural, social, and personal influences. Each of these factors has a unique impact on customer preferences and the decision-making process:

Cultural factors reflect societal values, perceptions, and preferences. Nationalities, religions, and ethnic communities are examples of subcultures that further refine these preferences. As already observed, “when subcultures grow large and affluent enough, companies often design specialized marketing programs to serve them” (Kotler and Keller 2016, 181). Social factors, particularly family and peer groups, play a major role in shaping consumer behavior. Intergenerational interactions encourage brand loyalty across generations, and families, the most powerful social unit, have a significant impact on purchasing decisions (Moore, Wilkie, and Lutz 2002). From regular grocery shopping to major purchases like cars and vacations, family structures have an impact on a variety of decisions (Rick, Small, and Finkel 2011). Reference groups provide societal standards that shape attitudes and behaviors, supporting consumers in making more informed decisions. Additionally, factors such as age, profession, personality, and lifestyle significantly influence purchasing behavior. Consumer needs vary across different stages of the family life cycle, from single adulthood to marriage, parenthood, and retirement. A young adult, for instance, may place a higher priority on convenience and entertainment, whereas a parent with young children might focus more on nutrition and products suitable for the family (Du and Kamakura 2006). Psychological life-cycle stages, such as becoming a parent or entering midlife, also trigger shifts in consumption habits (Kotler and Keller 2016). Additionally, personal traits like personality and self-concept shape consumer behavior. Attributes such as self-confidence, socialbility, and adaptability affect how individuals engage with marketing messages. For instance, individuals with high self-confidence are more inclined to explore new or unfamiliar brands, while those who are less adaptable typically prefer familiar and trusted options (Kassarjian 1971).

Furthermore, lifestyle and personal values - how individuals live, prioritize activities, and spend their time and money - significantly influence consumer choices. A person's lifestyle is reflected in their daily actions, interests, and preferences. According to Kotler and Keller (2016), consumers who feel they are constantly short on time are more likely to engage in multitasking and prioritize convenience. Time-pressed consumers often gravitate toward products and services that offer convenience and efficiency, such as ready-to-eat meals, highlighting how lifestyle plays a pivotal role in shaping purchasing decisions. Recognizing these patterns allows marketers to craft strategies that align closely with the specific needs and priorities of varied consumer segments, making their approach more relevant and effective (Solomon and Russell 2023).

In summary, understanding cultural, social, and personal factors is essential to successfully predicting consumer behavior and developing marketing strategies. Building on this, the next section will explore the decision-making process in more depth, investigating how these factors influence consumer decisions and how marketers can influence decision-making.

2.2 The Decision-Making Process

The consumer decision-making process goes through a series of stages that lead consumers to recognize a need to evaluate their satisfaction after making a purchase. Understanding these different stages assists marketers in tailoring their strategies to influence consumer behavior at various deciding points (Kotler and Keller 2016).

2.2.1 The Different Stages of the Decision-Making Process

The five-stage model consists of problem recognition, information search, evaluation of alternatives, purchase decision, and post-purchase behavior (Appendix 6; Kotler and Keller 2016). The process starts with problem recognition, which can be initiated by internal factors like hunger or external influences such as advertising. This understanding forms a need for a solution (Solomon and Russell 2023). The consumer then searches for information, either internally (based on memory) or externally (by looking at reviews, advertising, or advice) (Blackwell, Engel, and Miniard 2006). Consumers then evaluate alternatives by comparing options based on factors like price, quality, and brand reputation. Decision rules may be compensatory, where trade-offs are made, or non-compensatory, where certain criteria must be met (Hoyer, Pieters, and Maclnnis 2018). The purchase decision stage involves the consumer making a choice, although external influences such as discounts or the opinions of others can still influence the final decision (Schiffmann and Wisenblit 2018). Lastly, post-purchase behavior involves the valuation of satisfaction or dissatisfaction with the purchase. As noted by Oliver (2013), satisfied consumers are more likely to remain loyal, while dissatisfaction is likely to lead to complaints or product returns.

2.2.2 Factors That Influence the Decision-Making Process

Various psychological, social and situational factors influence how consumers move through these stages (Appendix 7). Psychological factors such as motivation, perception, and attitudes are crucial in decision-making. Maslow's hierarchy of needs explains how motivation varies according to urgency, with basic needs leading to faster decisions (Maslow 2017). Perception also influences how consumers interpret marketing messages and often leads to different ways of processing information (Schiffmann and Wisenblit 2018).

Social variables such as family and reference groups have a considerable impact on individual decisions. Solomon and Russel (2023) argue that recommendations from credible sources frequently outperform advertising, especially for high-involvement purchases. Similarly, situational considerations like time constraints and the shopping environment influence decision-making processes. According to Dhar and Nowlis (1999), when faced with time constraints, consumers rely more on heuristic cues, such as brand familiarity or simpler labeling systems, to make decisions. Customers can undertake in-depth assessments in low-pressure environments (Babin and Attaway 2000). Recognizing these traits enables marketers to tailor their methods to specific scenarios, enhancing engagement and successfully guiding customers through the decision-making process.

2.3 The Role of Food Labeling in Consumer Decision-Making

To help consumers make healthier choices during their grocery shopping, it is necessary to label products with clear and easy-to-understand information about their nutritional content (Grunert and Wills 2007). In today’s fast-paced world, where consumers are often stressed and overwhelmed by the multitude of options available in the supermarket, front-of-pack labeling systems simplify decision-making by providing quick, clear information (Grunert and Wills 2007; Julia and Hercberg 2017). The Nutri-Score, for example, grades products from A to E, enabling consumers to assess health information at a glance, particularly when time is limited (Julia and Hercberg 2017). At the same time, macronutrient tables provide more detailed information for those who prefer a rather analytical decision-making process and desire to go into more detail (Hodgkins et al. 2012). These labeling systems are central to Europe's health initiatives, where governments and organizations promote standardized labels to address diet-related issues like obesity (Southey 2020). By simplifying choices, especially when time or cognitive resources are limited, labeling has become a crucial tool in today's complex and overwhelming food environment (Li, Wang, and Zhang 2022).

3 The Effectiveness of Nutri-Score and Nutritional Information Table

Due to the increasing health awareness of consumers, food labeling has become an important tool for guiding healthier dietary choices. The two labeling systems, Nutri-Score and the Nutritional Information Table, also referred to as NIT, aim to guide consumers in making more informed choices and adopting healthier eating habits (Li, Wang, and Zhang 2022). However, their format, effectiveness, and complexity vary significantly, particularly when consumers are under time pressure (Food Dive 2017). This chapter explores the two labels and how consumers can rely on them in the decision-making process.

3.1 Nutri-Score

In 2017, France officially implemented the Nutri-Score as a front-of-pack nutrition label, under the leadership of Professor Serge Hercberg (Julia and Hercberg 2017). It is an FOP labeling system that was developed to simplify nutritional labeling comprehension and therefore support healthy food choices among consumers. The Nutri-Score categorizes food products based on their nutritional profile by using a combination of letters and colors to represent their healthiness. Products with a higher nutritional value are assigned an A and a green color, while those with a lower value receive an E and are marked red. This labeling system aims to simplify complex nutritional information and can help consumers make quicker and more informed decisions (Julia and Hercberg 2017). This system has been adopted in other European countries, including Belgium, Germany, and Spain (Bundesministerium für Ernährung und Landwirtschaft, n.d.).

3.1.1 Nutri-Score in Detail

The system is based on a scoring algorithm that balances “favorable” and “unfavorable” nutritional attributes of a food product per 100 grams or milliliters. It operates on a negative vs. positive point system where unfavorable components including saturated fats, sodium (a component of salt), energy (kJ), and sugars are given negative points, while the favorable components like protein, fruits, or vegetables contribute to positive points (Julia and Hercberg 2017) (Appendix 9**)**. All points, positive and negative, are assigned to a score. The final score is calculated by deducting the positive points from the negative points, giving a single value that represents the nutritional balance of the product. The result is categorized into one of five Nutri-Score levels: A (green) to E (red), with A indicating a more balanced nutrient profile (e.g., lower sugars and saturated fats, higher protein), while E represents a less favorable balance, typically with more nutrients like sugars and saturated fats (Julia and Hercberg 2017) (Appendix 11, 12).

In addition, the Nutri-Score system includes specific adjustments for beverages, cheese, and added fats. These thresholds were set to create clearer distinctions in food categories, such as water, juices, and sugary beverages. It provides a detailed classification to help consumers make more informed decisions (Julia and Hercberg 2017). The visualization is intended to effectively inform customers about nutritional ingredients instantly and affect their food consumption decisions (Li, Wang, and Zhang 2022).

3.1.2 Advantages of Nutri-Score

The Nutri-Score aims to make it easier for consumers to assess the nutritional value of products by providing a simple, color-coded label (Julia and Hercberg 2017), allowing consumers to make quick assessments without the need for detailed nutritional knowledge. Research suggests that the label is widely understood and effective across various cultural and social groups (Egnell et al. 2018). By integrating meaningful colors with an easy-to-understand, graded format, the design is intended to enhance its effectiveness under time pressure (Egnell et al. 2018). Research has shown that heuristic labels or simple summary labels, which need the least amount of cognitive work, may be very useful and preferred under time pressure due to limited cognitive resources (Li, Wang, and Zhang 2022) or when decision times are short storefront (Egnell et al. 2018). A label on the front of the package helps consumers quickly understand the nutritional value of a product and its impact on their health (Włodarek and Dobrowolski 2022). Additionally, the Nutri-Score is especially effective in encouraging the purchase of healthier products by increasing the overall nutritional value of selected products (Julia and Hercberg 2017). Furthermore, FOPLs such as the Nutri-Score support consumers in comparing the nutritional characteristics of different products compared to scenarios where FOPL are not used (Egnell et al. 2018).

3.1.3 Disadvantages and Limitations of Nutri-Score

However, the Nutri-Score might overlook important health aspects such as the glycemic index, which evaluates carbohydrate-rich foods by measuring their impact on blood sugar levels compared to a glucose reference (Atkinson, Foster-Powell, and Brand-Miller 2008). This is critical for individuals with disease entities such as diabetes. Also, it may not fully account for the degree of food processing or specific dietary recommendations, potentially leading to misleading results as it favors highly processed foods, which have been modified to improve their Nutri-Score rating (Włodarek and Dobrowolski 2022). Additionally, the Nutri-Score does not fully calculate the content of vitamins, minerals, or other bioactive compounds. Products rich in these nutrients, such as naturally occurring sugars in fruit juices, might receive a lower rating due to their huge sugar portion. In contrast, a soft drink with no added sugar but artificial sweeteners, which have uncertain long-term health effects, can receive a better Nutri-Score despite lacking nutritional value (Włodarek and Dobrowolski 2022). Furthermore, the Nutri-Score calculates the overall rating of a product based on specific ingredients and calories per 100 g. However, it does not account for typical portion sizes. For instance, products with higher Nutri-Score ratings might be consumed in greater quantities, especially when sold in large packages, as portion control is not explicitly addressed. Moreover, high-energy products like nuts may receive lower scores despite being a nutritious component of a balanced diet when consumed in appropriate amounts (Włodarek and Dobrowolski 2022).

Although the Nutri-Score simplifies the evaluation of a product's nutritional value and supports decision-making under time constraints (Li, Wang, and Zhang 2022), it still has notable limitations, as discussed above. In the following chapter, detailed nutritional tables will be explored, providing a more detailed breakdown of nutritional content.

3.2 The Nutritional Information Table

In contrast to the Nutri-Score's simplified approach, the Nutritional Information Table is employed within the food industry to deliver comprehensive insights into a product's nutritional profile. This system emphasizes clarity, transparency, and standardized documentation to help consumers in making healthier, more informed dietary decisions (Food and Agriculture Organization of the United Nations & World Health Organization 2024).

3.2.1 Nutritional Information Table in Detail

Consumers can use nutritional tables, which provide a detailed, standardized depiction of a product's nutritional profile, to compare food items and potentially make healthier food choices (Julia and Hercberg 2017) (Appendix 13). As specified in the EU Regulation (EU) No 1169/2011 on food information to consumers, the following nutrients must be included in the nutrition label per 100g or per serving (Europäisches Parlament und Rat der Europäischen Union 2011): energy (in kJ and kcal), carbohydrates, sugars, proteins, salt, and optional nutrients.

While all of the components are vital for energy provision and the maintenance of cellular structure, consistent over-consumption of each can not only elevate the risk of chronic diseases but also organ dysfunctions (Romieu et al. 2017; Briggs, Petersen, and Kris-Etherton 2017; Harvard T.H. Chan School of Public Health 2013; Franz et al. 2010; Wu 2016; Hunter, Dhaun, and Bailey 2022). Optional nutrients, like fiber or specific vitamins and minerals, can be included in the nutrition label to provide consumers with additional information, but they are not mandatory. However, this is only required if these nutrients have been added to the product or if there is a nutrition or health claim referring to their presence (Europäisches Parlament und Rat der Europäischen Union 2011).

3.2.2 Advantages of the Nutritional Information Table

Nutrition Information Tables provide consumers with a comprehensive breakdown of specific nutrients, making them a useful tool for nutritional knowledge by offering clear information on several components. Studies show that individuals who follow a diet tend to read Nutrition Information Tables more frequently, possess a higher level of nutritional knowledge, and demonstrate greater interest in the impact of specific nutrients (Giró-Candanedo et al. 2022). Moreover, diet-conscious consumers exhibit increased attentiveness to nutrient content and are more aware of ingredients they may need to reduce, for example, sugar, in order to make healthy food decisions (Wongprawmas et al. 2021).

In general, reading Nutrition Information Tables before buying something seems to be linked to eating healthier nutrients, such as less sodium, sugar, energy, and saturated fat (United States Department of Agriculture, Economic Research Service 2023; Ollberding, Wolf, and Contento 2010; Post et al. 2010; Zhang et al. 2017). Further evidence from studies that label usage among students seems to correlate with increased consumption of healthier options, such as vegetables, whole fruits, and yogurt, while simultaneously a reduced consumption of sugary and fatty foods, including chips, cake, and soda (Pfledderer et al. 2024). Moreover, the regular use of Nutrition Information Tables is not only associated with healthier nutrient consumption, but it may also support long-term health by helping individuals make dietary adjustments that align with chronic disease prevention goals, for example, less fast food and added sugar (Graham and Laska 2012; Kollannoor-Samuel et al. 2017). For consumers with specific health concerns, Nutrition Information Tables serve as a practical tool for nutrient monitoring, facilitating choices that can contribute to sustained health improvements over time, like a reduced risk of conditions of diabetes or cardiovascular diseases (Kollannoor-Samuel et al. 2017).

3.2.3 Disadvantages and Limitations of the Nutritional Information Table

Research by Li, Wang, and Zhang (2022) indicates that Nutrition Information Tables require significant cognitive effort and often result in lower accuracy when identifying healthier options compared to simpler systems. Additional studies show that alternative labeling formats like color-coded labels are processed more efficiently by directing the attention of consumers to the key nutrients (Kelly et al. 2009; Siegrist, Leins-Hess, and Keller 2015). Research further suggests that standard, detailed nutrition tables may cause consumers to spread their attention, which results in less focused eye movements and lack of healthiness ratings (Jones and Richardson 2007). As the interpretation of the information on nutrients in tables is rather complex, they seem to be more beneficial for consumers with higher nutritional knowledge to make informed decisions (Drichoutis, Lazaridis, and Nayga 2005).

Besides the challenge of interpreting numerical information, Nutrition Information Tables seem to be difficult for consumers under time pressure. As shown in research, complex structures requiring detailed calculations can overwhelm consumers with limited cognitive resources, especially during fast purchase decisions (Li, Wang, and Zhang 2022). Beyond their low performance under time constraints, Nutrition Information Tables might not be compatible with heuristic processing. Unlike color-coded labels, which use visual cues to support fast, intuitive decision-making, Nutrition Information Tables present information in a monochrome, numerical format. This structure complicates automatic processing, which requires consumers to engage in a more analytical approach to interpret nutritional content accurately (Ma and Zhuang 2021) a result, detailed nutrition labels tend to be less favored by consumers due to the increased cognitive effort (Alonso-Dos-Santos et al. 2019).

3.2.4 Comparison of Nutri-Score and the Nutritional Information Table

The Nutri-Score, as a FOPL, aims to simplify complex nutritional information through its intuitive color-coded scale, potentially allowing for quick and informed decisions at the point of purchase (Julia and Hercberg 2017). This system has proven to be effective in time-constrained environments, as it guides individuals with limited nutritional knowledge or numeracy skills (Li, Wang, and Zhang 2022). As the other extreme, the Nutritional Information Table aims to provide a more comprehensive breakdown of specific nutrients such as fats, sugars, and proteins (Giró-Candanedo et al. 2022). They might be especially useful for consumers who require precise information to manage health conditions (Hunter, Dhaun, and Bailey 2022; Wu 2016). However, their detailed structure demands higher cognitive effort and more time to interpret (Ma and Zhuang 2021). In summary, it becomes apparent that while the Nutri-Score works on simplicity and accessibility, the Nutritional Information Table rather serve consumers who need more precise, tailored information. Both systems complement each other by addressing the specific and varying needs of each consumer, providing a balance between simplicity and detailed nutritional information (Roberto et al. 2021).

4 Dual Process Theory as a Theoretical Framework

The longstanding idea that cognitive processing is divided into two main categories, traditionally known as intuition and reason is nowadays well known under the term "Dual Process Theory" (Chaiken and Trope 1999). This theory has become an important framework in social and cognitive psychology as well as decision-making research, aspiring to understand how individuals form judgments and make decisions (Barrouillet 2011; Evans 2008). There are many approaches to the Dual Process Theory, but all have the differentiation between fast and slow cognitive processing in common (Kahneman 2011; Kahneman and Frederick 2002; Evans 2008). Given Kahneman's significant contribution to the development and popularization of the Dual Process Theory, as well as his focus on how individuals make judgments and choices under various constraints (2011), this paper will primarily explore his approach to understanding how time pressure and brand familiarity influence product evaluation. The Dual Process Theory divides cognition into two fundamentally distinct but complementary parts, known as System 1 and System 2, first named by Stanovich and West (2000).

4.1 System 1

System 1 operates fast and under minimal effort in situations that require immediate reaction, responding heuristically, unconsciously, and emotionally to stimuli and situations (Evans 2008; Kahneman 2011). Since it operates automatically without conscious awareness and cognitive engagement, it is responsible for our spontaneous reactions and quick judgments. This allows individuals to respond to familiar situations by using mental shortcuts that developed through past experiences, among others (Kahneman and Frederick 2002; Tversky and Kahneman 1974; Kahneman 2011; Evans 2008). Examples of system 1 processing are *reading a word on a sign, understanding sentences in one’s mother language, or answering 2+2* (Kahneman 2011).

System 1 originated as a diverse range of cognitive processes including innate abilities that we share with animals while other rapid responses rely on previous and learned experiences that have become automatic actions (Evans 2008; Kahneman 2011). Even though this efficient evaluation is evolutionary advantageous as it allows fast decision-making with minimal effort, it is also error-prone. It operates automatically and cannot be “deactivated” automatically because intuitive thinking errors, heuristics, and falling for bias are hard to prevent (Kahneman 2011).

Heuristics are pivotal in Dual Process Theory since they are associated with System 1 processing (Kahneman and Frederick 2002; 2005). They are mental shortcuts or rules of thumb, enabling individuals to make fast decisions with little to no effort leading the attention of individuals to certain features without using analytical processing to solve the faced problem. Heuristics are efficient and useful, but they are also prone to systematic errors, better known as biases, due to the reliance on simplified processing (Kahneman 2011; Evans 1990; 2008; Tversky and Kahneman 1974). Evans (2008) presented that individuals rather accept conclusions that align with their values even if they are logically invalid but reject logically valid ones that conflict with their beliefs. These results highlight the conflict between heuristic processing and analytical reasoning, emphasizing the relationship between the fast, intuitive responses of System 1 and the slower, analytical processing of System 2. Kahneman and Tversky (2011; 1974) were important researchers studying heuristics in their behavioral economics work in the 1970s. They aimed to prove that many decisions are not made through a series of steps but rather through mental shortcuts. Based on their approach, the following key types of heuristics notably influence processing and decision-making:

The *Representativeness Heuristic* occurs when individuals assess the chance of an occurrence or label an object based on its similarity to a mental stereotype, sometimes neglecting statistical information such as base rates. An emphasis on superficial similarities might lead to skewed judgments (Kahneman and Frederick 2002; Kahneman 2011; Tversky and Kahneman 1974). The *Availability Heuristics* impacts judgments based on how readily an example comes to mind. These heuristics impact decision-making by biasing judgment toward recent or emotionally charged information, among others, often leading to over- or underestimation and, thus systematic bias. The reason behind this is that factors such as familiarity or the latest occurrences impact the retrieval a lot more than frequency and probability (Tversky and Kahneman 1973; Kahneman 2011; Tversky and Kahneman 1974). The *Anchoring Heuristic* is the propensity to depend significantly on a beginning value, or "anchor," when estimating outcomes. Adjustments are frequently insufficient, resulting in biased outcomes dependent on the beginning point. For example, setting a price in sales and limiting objectivity by relying strongly on the first impression (Tversky and Kahneman 1974; Saleem and Amjad 2023).

Besides these three heuristics, Tversky and Kahneman (1974) analyzed in their paper "Judgement under Uncertainty: Heuristics and Biases", there are two more highly relevant biases for the field of consumer behavior, especially the field of branding. The *Affect Heuristic* is a mental shortcut in which judgments are based on quick emotional responses or "gut feelings," rather than deeper examination (Slovic et al. 2002; 2007). At this point, individuals do not react consciously; their cognitive processing engages in memory recall for similar past events and their emotional accompaniments (Epstein 1994; Kahneman 2011; Slovic et al. 2007). According to Darke, Chattopadhyay, and Ashworth (2006), this heuristic holds particular interest in analyzing consumer choices when brand familiarity and emotional associations remain strong (Hoyer and Brown 1990). Once a brand evokes positive feelings based on previous experience or effective marketing, consumers are more likely to choose a familiar brand without evaluating further options (Hoyer and Brown 1990). While heuristics speed up decision-making in everyday settings, they frequently induce biases, resulting in poor consumer decisions (Kahneman 2011).

4.2 Interaction of Systems 1 and 2

After analyzing the role of System 1 in human decision-making, the question arises if and how these irregularities can be overcome. Kahneman (2011) explained that these cognitive alterations cannot always be avoided, as System 2 might not be aware of them happening. Evans (2008) argues further that System 1 provides initial judgments that can be overridden by System 2 if prompted or if the cognitive ability of the respective individual is high enough. In other words, the initial judgments of System 1 can either be accepted or modified from System 2 (Stanovich 1999; Evans 2008; Finucane et al. 2000). Examples like the following underline the interaction of both systems. *A bat and a ball cost $1.10 in total, including that the bat costs $1 more than the ball. The task is to calculate how much the ball costs.* Almost everyone instinctively answers with 10 cents, but this is incorrect; the correct answer is 5 cents. The high rate of errors shows how much individuals trust their intuition (System 1) and how seldom System 2 screens the output of System 1 (Kahneman and Frederick 2002).

4.3 System 2

System 2 is usually engaged when System 1 reaches its limits and requires a more detailed and specific solution. In these cases, individuals face tasks beyond intuitive processing, necessitating effort, reflection, logical reasoning, or complex problem-solving. Therefore, System 2 operates in a slow, effortful, analytical, and reflective way (Kahneman 2011; Kahneman and Frederick 2002; 2005; Evans 2008; Tversky and Kahneman 1974). Additionally, in contrast to System 1, it processes information sequentially. For this processing mental engagement and concentration are necessary, unlike System 1 which relies on intuition and past experiences. Examples of this systematic thinking include *doing a tax declaration, solving complex mathematical tasks, and comparing specific product details* (Kahneman 2011). However, time pressure can disrupt System 2's slow processing, resulting in decisions that would not have occurred in the absence of time pressure (Finucane et al. 2000). In summary, System 1 and System 2 represent two distinct processing types that often operate in tandem, with System 1 characterized by fast, heuristic, and effortless processing and System 2 operating more deliberate, analytical, and slower. Therefore the division of work between System 1 and 2 is highly efficient, minimizing effort and optimizing performance (Kahneman and Frederick 2002; Tversky and Kahneman 1974; Evans 2008).

5 Identification of Research Gap: Role of Brand Familiarity & Time Pressure

Consumer food selection behavior has gained significant attention since diet-related health issues including obesity have become more prevalent (Thorndike et al. 2012; Sonnenberg et al. 2013). To address this, governments have introduced techniques such as traffic light labeling systems (TLLs), which simplify nutritional assessments and promote healthier choices (Freire et al. 2017; Becker et al. 2015). However, their effectiveness remains mixed, since brand familiarity sometimes overshadows nutritional cues, especially under time restrictions (Ikonen et al. 2020; Velasco Vizcaíno and Velasco 2019). Time pressure increases reliance on heuristic signals such as brand trust, decreasing engagement with comprehensive information (Chen et al. 2023). This chapter investigates how brand familiarity and time pressure combine to influence consumer response to nutritional labels, with a focus on the Nutri-Score and Nutritional Information Tables.

5.1 Brand Familiarity and Its Impact on Decision-Making

Brand familiarity forms the basis for consumer decision-making, especially for low-involvement or regularly purchased items (Becker et al. 2015). Defined as the knowledge and recall of a brand based on past exposure, brand familiarity allows consumers to use mental shortcuts, or heuristics, to make rapid judgments (Hoyer, Pieters, and Maclnnis 2018; Chaudhuri and Holbrook 2001). This is consistent with System 1 thinking, which is intuitive and automatic, as opposed to analytical System 2 thinking, which is connected with high-level choices (Tversky and Kahneman 1974; Kahneman 2011; Becker et al. 2015).

According to Velasco Vizcaíno and Velasco (2019), consumers tend to trust known companies, making it easier to evaluate alternatives. For example, Hoyer and Brown (1990) state that brand familiarity is a useful signal since it allows for rapid judgments without needing extensive information processing. Ma, Wang, and Da (2021) demonstrate that known brands trigger long-term memory, reducing decision effort, especially in unexpected or mismatched situations such as brand expansions. This cognitive efficiency can be explained by the "halo effect", in which well-known brands are immediately associated with positive characteristics such as healthfulness (Chandon 2013). Jo, Nakamoto, and Nelson (2003) found that known brands can “shield” consumers from negative product evaluations, even in the presence of warnings from traffic light labeling (Velasco Vizcaíno and Velasco 2019).

5.1.1 Psychological Underpinnings of Brand Familiarity

The "mere exposure effect" (Zajonc 1980) is one of the well-established psychological mechanisms that underlie the positive affective responses of familiar brands, operating mainly via System 1 cognitive processing (Kahneman 2011; Evans 2008). According to this effect, a person's liking of a brand increases with exposure, regardless of whether they are aware of or knowledgeable about the specifics of the product (Mandler 1980). Hoyer and Brown (1990) develop this idea further, noting that the effect is particularly impactful in low-involvement circumstances, where "[r]ecognition is taken to be the process of perceiving a brand as previously encountered" (141). In such circumstances, the consumer interprets a familiar brand as superior or trustworthy, thereby reducing some of the risk associated with the purchase (Baker et al. 1986; Janiszewski 1988). As demonstrated by multiple tests where participants preferred well-known brands over superior non-familiar alternatives, this System 1 heuristic dependence on familiarity can skew customer choice (Hoyer and Brown 1990; Evans 2008), emphasizing that simple exposure reinforces established buying habits by influencing both initial and future selection actions (Becker et al. 2015).

5.1.2 Brand Familiarity as a Heuristic in Food Choices

Brand familiarity frequently makes food choices easier, particularly when nutritional information is complicated. When a brand is well-known customers are more likely to trust it, as shown in studies on front-of-pack labels (Becker et al. 2015; Freire et al. 2017; Cowburn and Stockley 2005; Chandon 2013). According to Velasco Vizcaíno and Velasco (2019), TLLs only influence healthier choices for unknown brands; for well-known brands, their influence is less pronounced. This is consistent with research by Jacoby, Chestnut, and Silberman (1977), who found that consumers rely less on contextual information like nutritional data and more on memory and prior experiences. Further research on brand loyalty shows that familiarity strengthens both purchase loyalty, where consumers repeatedly buy the same brand, and attitudinal loyalty, where a favorable view of the brand builds over time (Velasco Vizcaíno and Velasco 2019). Chaudhuri and Holbrook (2001) note that these forms of loyalty impact consumer behavior, as trust in the brand fosters a lasting perception of quality that can overshadow nutritional information in future purchase situations. Similarly, Lanero, Vázquez, and Sahelices-Pinto (2020) contend that heuristic thinking dominates low-effort contexts like food purchases, minimizing cognitive effort by relying on familiar brands for trust-based efficiency.

Researchers have also described a form of cognitive anchoring in which the consumer's brand perception, based on memory, lessens the impact of objective health indicators (Robertson, Andersson, and Lunn, 2022; Grunert and Wills 2007). Findings from Zhang (2020) further support this by demonstrating that familiar brands demand less attention allocation, reinforcing the brand’s dominance in decision-making processes, particularly in situations when product information compete for cognitive resources. An example of this is in a supermarket setting, where consumers face choice overload with numerous options available, making the recognizable and familiar brands more appealing as they simplify the decision-making process.

5.1.3 Limitations and Biases Introduced by Brand Familiarity

Even though brand familiarity is a useful heuristic that makes decision-making easier, in some situations it can also lead to serious biases, particularly when quality levels vary throughout companies. Customers may frequently ignore essential product qualities when relying solely on familiarity, which could have detrimental effects on their decision-making when it comes to health (Hoyer and Brown 1990). As a result, consumers might become less responsive to health-related cues that would normally discourage them from buying high-calorie or low-nutrient items when they become accustomed to a particular brand (Jabs and Devine 2006).

The potential negative effects of brand familiarity highlight a serious tension between consumer autonomy and branding's persuasiveness. Erdem and Swait (1998) assert that because familiarity serves as a quality signal that reduces perceived risk and information processing demands, consumers' opinions of a brand's dependability are closely linked to its brand equity. Due to the protective effect of brand familiarity on product quality assessments (Jo, Nakamoto, and Nelson 2003), familiar brands can avoid investigation even when objective health signals point to a problem (Ikonen et al. 2020; Freire et al. 2017; Velasco Vizcaíno and Velasco 2019). As pointed out by Lanero, Vázquez, and Sahelices-Pinto (2020), heuristic processing can lead to overconfidence in brand-related claims. This effect can occur even when those claims are unregulated or ambiguous, as consumers have shown to trust brand cues without verifying supporting information.

5.2 The Role of Time Pressure in Decision-Making

Time pressure is generally accepted as one of the most influential external factors affecting consumer behavior (Huseynov and Palma 2021). Simply put, time pressure limits the amount of time available to make a decision, which compels consumers to adjust their strategies, often leading them to rely more on heuristic cues, like brand familiarity or simplified nutritional labels, without conducting a thorough analysis (Thorndike et al. 2012; Suri and Monroe 2003). According to Chen et al. (2023), time pressure reduces the ability to process detailed and contradictory information, compelling consumers to prioritize fluency, enabling faster and less thorough decision-making. Under such conditions, costumers resort to heuristic processing due to limited cognitive resources, particularly when information complexity increases. Additional research also indicates that consumers who are under time pressure tend to make decisions more rapidly but with less detail by selecting information that is easier to obtain (Payne, Bettman, and Johnson 1988; Park, Iyer, and Smith 1989). As Cao, Isa, and Perumal 2023) further highlighted, time constraints amplify information overload, stress, and perceived risks, often leading to more impulsive or less critical decisions, especially in situations involving promotions or time-sensitive offers. This section looks at how consumers choose foods based on time restrictions and the trade-offs they make between heuristic and analytical processing.

5.2.1 Impact of Time Constraints on Nutritional Label Use

The tendency to switch to heuristics under time pressure is well-documented in consumer behavior research: when time is limited, consumers often rely on decisions based on easily recognizable cues rather than performing a thorough evaluation of detailed product attributes, including nutritional information (Huseynov and Palma 2021; Nowlis 1995). Finucane et al. (2000) already detected this switch from analytical to heuristic processing, proving that System 2 thinking can be disrupted by time pressure, which happens as a result of consumers simplifying their decision-making process due to the restricted cognitive capacity (Payne, Bettman, and Johnson 1988). Sonnenberg et al. (2013) observed that when nutritional information is available but complicated, buyers under time constraints are more likely to employ heuristics and favor clear, color-coded labels such as Nutri-Scores over more in-depth breakdowns. This tendency is supported by Cowburn and Stockley's (2005) research, which believes that simple and familiar labels aid consumers' comprehension and reduce the cognitive burden that complex information requires. Chen et al. (2023) expand on this, noting that heuristic reliance becomes more dominant under time pressure because consumers experience cognitive overload, preventing them from effectively comparing complex or conflicting cues.

Nutrition labels vary significantly in their visual attributes, informational content, and processing characteristics, such as fluency (Sanjari, Jahn, and Boztug 2017; Hodgkins et al. 2012). Simplicity, which facilitates quick and intuitive System 1 processing, is a key attribute of summary food labels and traffic light labeling systems. Those labels are easier to process as they reduce the information complexity and provide the customer with an easily summarized overview of the nutritional information (Hersey et al. 2013; Sanjari, Jahn, and Boztug 2017). If people are given more time and if they evaluate the product more in detail, they use System 2 processing, focusing on the specific attributes of the product. Therefore, System 2 thinking is more closely associated with detailed food labels such as the nutrient table (Sanjari, Jahn, and Boztug 2017; Dhar and Gorlin 2013). This distinction between System 1 and System 2 processing, as emphasized by Ma, Wang, and Da (2021), reflects the cognitive mechanisms involved in decision-making under time constraints.

5.2.2 Impact of Time Constraints on Nutritional Decision-Making

Time constraints have a significant influence on customer behavior, particularly how consumers interact with nutritional information and make brand choices. Under pressure, clients choose to expedite their decision-making processes, often at the expense of full nutritional studies. This tendency toward simpler, heuristic-based decision-making may result in less nutrient-dense alternatives, such as a greater reliance on convenience meals or established brands (Jabs and Devine 2006; Meyers-Levy and Tybout 1989). Such selections demonstrate an adaptive approach in which well-known brands and unambiguous labeling systems fit into pre-existing cognitive frameworks, allowing for faster judgments while reducing mental strain (Balcombe, Fraser, and Falco 2010; Nowlis 1995).

The preference for simplicity under time constraints is evident in the frequent use of heuristic cues which offer a straightforward method of assessing healthfulness without detailed scrutiny (Thorndike et al. 2012). These cues are especially tempting when consumers encounter complicated information and must make rapid judgments. According to studies, under such settings, consumers choose easy-to-understand labels, often bypassing less vital information in favor of more digestible data (Huseynov and Palma 2021; Freire et al. 2017). This trend emphasizes the significance of label design, as clear, visually intuitive cues not only improve decision speed but also reduce stress associated with time-sensitive decisions, especially for those with limited nutritional knowledge (Suri and Monroe 2003; Roberto et al. 2012; Cao, Isa, and Perumal 2023).

Furthermore, the diversity in heuristic processing is impacted by the decision's intricacy and perceived dangers. When faced with short choices among commonly purchased commodities, customers usually depend on recognizable brands to lessen cognitive load and perceived risks (Park, Iyer, and Smith 1989). However, when faced with new brands or health indicators that are comparable across alternatives, the desire for clear, easy-to-read cues rises, demonstrating a greater requirement for simplicity in decision-making processes (Lin and Jia 2023; Hoyer and Brown 1990). As a result, time-pressed customers may choose simple labeling and well-known brands, skipping over the product's thorough health information (Balcombe, Fraser, and Falco 2010; Cowburn and Stockley 2005). The following chapter illustrates how time constraints reshape consumer interaction with nutritional labels and may influence their brand preferences, highlighting the trade-offs between speed and depth in dietary choices.

5.3 Hypothesized Interaction Between Brand Familiarity and Time Pressure

The following chapter discusses the complex dynamics of consumer product evaluation and decision-making, examining the impact of temporal constraints and varying degrees of brand familiarity. The significance of this study is underscored by its exploration of decision-making processes in diverse contexts, a topic of heightened relevance in light of increasing obesity rates and the trends for convenient snacking options (Thorndike et al. 2012; Quash 2023; Sonnenberg et al. 2013). While previous research has individually addressed the substantial influence of brand familiarity (Velasco Vizcaíno and Velasco 2019) and time constraints (Li, Wang, and Zhang 2022) on consumer processing and decision making, this study aims to investigate the interactive effects of these variables, illustrated in Figure 1.

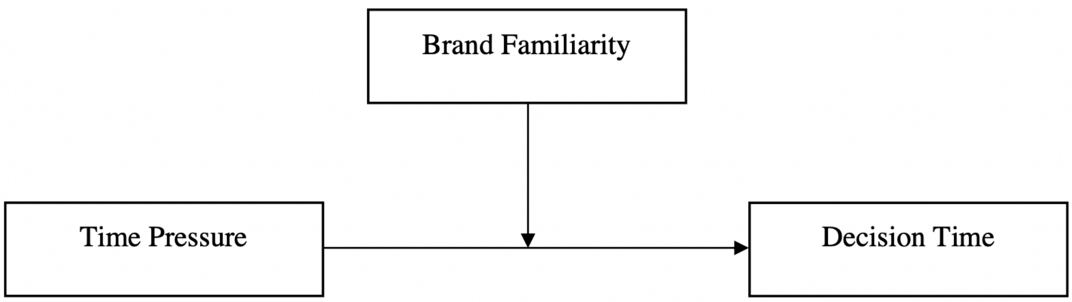

Figure 1: *Hypothesized Model for the Influence of Time Pressure and Brand Familiarity*

5.3.1 Heuristic Processing and Brand Familiarity Under Time Constraints

When making selections under time constraints, customers often focus on indicators they are familiar with and can recognize immediately. This focus on brand recognition speeds up the process, which is advantageous for customers who are more likely to trust well-known companies and avoid in-depth reviews (Hoyer and Brown 1990; Velasco Vizcaíno and Velasco 2019). Customers can make judgments more quickly and simply based on their trust in a brand rather than by attentively examining every feature of the product thanks to brand familiarity, which serves as a cognitive shortcut (Meyers-Levy and Tybout 1989), equalling System 1 processing (Tversky and Kahneman 1974). When consumers are pushed for time, they often use their limited cognitive resources to ignore complex nutritional information in favor of familiar cues as "[t]ime limitations are one of the most critical external factors influencing consumer behavior” (Huseynov and Palma 2021, 17), pushing consumers to filter out seemingly less important information (Robertson, Andersson, and Lunn 2022). Additional findings also show that time pressure amplifies the reliance on brand familiarity, as consumers facing limited decision time are even less likely to engage with detailed information (Chen et al. 2023). Therefore, we hypothesize that under conditions of high time pressure, customers who are familiar with a brand will make decisions more rapidly compared to those less acquainted with the presented brands (H1).

5.3.2 Continued Reliance on Brand Familiarity in Low-Pressure Contexts

Customers who are very familiar with a brand, even in the absence of time constraints, are more likely to make sudden selections based on their faith in well-known businesses rather than performing thorough comparisons. Even when there is plenty of time, their faith in the brand makes careful consideration seem superfluous, enabling simple decisions (Meyvis and Janiszewski 2002; Chaudhuri and Holbrook 2001). According to studies, brand familiarity provides a reliable alternative and lessens the mental effort needed for comparisons, which helps in decision-making processes (Hoyer and Brown 1990; Zhang 2020). When consumers have plenty of time, they nevertheless often select well-known brands over complex characteristics like nutritional information because they feel safer with well-known brands (Robertson, Andersson, and Lunn 2022). Because brand familiarity triggers memory-based cognitive processes, it allows consumers to retrieve pre-established positive associations quickly, further reducing the need for analytical comparisons and evaluations (Ma, Wang, and Da 2021). Chaudhuri and Holbrook (2001) add that brand trust allows consumers to streamline their decision-making, regardless of time constraints. Consequently, we propose that even in the absence of time constraints, consumers familiar with a brand are more inclined to rely on heuristic processing, thereby making faster decisions than those who lack familiarity with the presented brands (H2).

5.3.3 Nutritional Labels as Heuristic Tools for Low-Familiarity Brands

Consumers have shown to use straightforward nutritional indications to make judgments more quickly and heuristically, often relying on visual indicators, such as FOPLs, as a method of assessing a product's healthfulness (Becker et al. 2015). Nutri-Scores offer an easy-to-understand, color-coded system that reduces the mental effort needed to interpret detailed nutritional information, making them especially helpful when time is limited (Freire et al. 2017). Research shows that consumers without brand familiarity use accessible, situational cues to guide their choices efficiently: according to Sonnenberg et al. (2013), color-coded labels make health information more comprehensible and efficiently replace brand-based trust, which speeds up and enhances decision-making. Additionally, based on the findings from Balcombe, Fraser, and Falco (2010), customers may more readily evaluate unknown items because of the rapid reference that simpler indicators like Nutri-Scores offer. As predicted in H3, customers with low brand familiarity are therefore more inclined to rely on heuristic cues when under a lot of time pressure, which leads to quicker decisions compared to those experiencing low time pressure.

As a consequence, the participants in the high time pressure condition will also report a higher reliance on the Nutri-Score, resulting in more heuristic decisions than the low time pressure group.

5.3.4 Analytical Processing in Absence of Time Pressure for Low-Familiarity

In low-time-pressure situations, consumers who are not familiar with a brand tend to take a more analytical approach, carefully examining the information available to make thoughtful choices (Meyvis and Janiszewski 2002), aligning with System 2 processing (Kahneman 2011). Without the quick shortcut of brand familiarity, these consumers are more likely to scrutinize products, increasing the chance that they will notice any discrepancies between simplified cues, like Nutri-Scores, and the more detailed nutritional information in full tables (Meyvis and Janiszewski 2002). Research in consumer behavior shows that, under low time pressure, consumers lacking brand familiarity are more inclined to assess products based on the specific information at hand rather than relying on quick, heuristic decisions (Menon, Raghubir, and Schwarz 1995). When given time to think things through, consumers who are not very loyal to a brand look more closely at nutritional data and become more conscious of discrepancies between simplified and detailed labels (Sonnenberg et al. 2013; Freire et al. 2017). Consequently, we propose that under conditions of low time pressure, customers unfamiliar with a brand are more likely to allocate more time to evaluating products with conflicting nutritional information than non-contradicting ones, in contrast to those under high time pressure (H4).

6 Methods

In the following section, we will explain the methodology of the experiment, providing a descriptive analysis of the participants, the distribution of the groups, the material utilized, the applied study design as well as the procedure and the results.

6.1 Participants

We published our survey from the 27th of October 2024 until the 10th of November 2024, collecting a total of 559 responses. After filtering out incomplete answers, as well as cleaning up misleading data (such as outliers and suspectable artificially generated answers), we subjected the residual values to a filter threshold of 3. We have classified the suspected artificially generated messages by the fact that they were all generated within a very short time window in the middle of the night in the European time zone. We used the 280 valid responses remaining from the procedure for further analysis.

40.7% of participants identified as male, 57.9% as female, and 1.5% as either gender nonconforming or electing to conceal their gender identity. The average age of the participants was around 26, ranging from 18 to 55. Most respondents (84.3%) were German, with smaller percentages described as French (5%), Portuguese (2.1%), Italian (1.1%), and other nationalities (7.5%). Smartphones (82.1%) and computers (17.1%) were the most popular devices used by survey respondents, while 0.7% used tablets. Regarding education levels, 47.9% of participants held a bachelor's degree, 35.4% a master's degree, whereas the remaining ones had either completed high school (10.7%), an apprenticeship (5.4%), or another kind of education (0.7%). On a scale of 1 (= very unfamiliar) to 7 (= very familiar), participants rated their knowledge of nutrition and healthy eating with a mean of 4.88 (*SD* = 1.269) and their familiarity with the Nutri-Score system with a mean of 4.52 (*SD* = 1.665).

Two further variables were created to reflect the conditions that were given to each participant to evaluate our hypotheses, showing whether participants were exposed to high (BF) or low brand familiarity (NBF) and whether they were in a high (TP) or low time pressure (NTP) condition, resulting in a randomized distribution (Table 1).

			BF vs. NBF		
			BF	NBF	Total
TP vs. NTP	TP	Count	78	68	146
		% of Total	27.9%	24.3%	52.1%
	NTP	Count	71	63	134
		% of Total	25.4%	22.5%	47.9%
Total		Count	149	131	280
		% of Total	53.2%	46.8%	100.0%

Table 1: *Crosstabulation of distribution into 2x2 design (Source: SPSS)*

6.2 Materials

The current study used two types of nutritional labels to examine how participants understand and process health-related information about snack foods. In particular, we used the Nutri-Score system due to its simple look and interpretability, as this label is presumed to initiate heuristic System 1 processing (Julia and Hercberg 2017; Sanjari, Jahn, and Boztug 2017). In addition, a Nutritional Information Table has been provided to encourage deeper engagement with the product for decision-making. Because of its thorough and quantitative breakdown, this table requires systematic or analytical System 2 processing, requiring greater mental effort (Sanjari, Jahn, and Boztug 2017; Dhar and Gorlin 2013).

In order to adequately assess the healthiness of the product, participants should preferably deal with both of these types of data. To further investigate reliance on labeling systems, we introduced a manipulation with four scenarios where the Nutritional Information Table and Nutri-Score provided conflicting information on the product's nutrient profile. For example, participants come across nuts with a high-fat content that are given a less favorable Nutri-Score (level D) or cereal with a high sugar content that is given a good Nutri-Score (level A). The purpose of this design was to determine which label participants would be more inclined to trust when presented with conflicting information. Additionally, to establish a baseline for understanding, we included four products (such as rice waffles, yogurt, chips, and cookies) that displayed consistent information. These products displayed either a positive or negative Nutri-

Score paired with corresponding favorable or unfavorable nutritional values, and both the score and the Nutritional Information Table showed agreement.

6.3 Design

To test the hypotheses regarding the roles of brand familiarity and time pressure in decision-making, we implemented a 2 (brand familiarity: high vs. low) x 2 (time pressure: high vs. low) factorial design. This resulted in four experimental groups, where participants were exposed to products from either familiar, well-known brands or unfamiliar, AI-generated brands with or without a timer counting down from 20 seconds.

In the high brand familiarity condition, participants examined eight snack products from renowned international brands such as *Nesquik* and *Activia*, designed to facilitate decision-making due to their perceived familiarity (Figure 1; Appendix 14-20). Whereas in the low-familiarity condition, eight snack products from AI-generated brands were presented (Figure 2; Appendix 21-27), ensuring that respondents had no prior exposure or familiarity with the brand, thus requiring them to focus solely on the available nutrtional information for product evaluation.

Participants in the high-time pressure condition experienced a cognitive burden resulting from the time constraint. We instructed participants to make their choice within the given time, simulating real-world situations where quick decisions are occasionally necessary, such as while shopping in a store. A 20-second countdown timer was displayed at the top of the simulation screen to create a sense of urgency, allocating five seconds for participants to respond to each of the four questions. This specific time is based on the findings of Finucane et al. (2000) who discovered that analytical thinking takes more than 5 seconds. As such, with a time pressure of up to 5 seconds per question, heuristic processing is activated. The goal of this manipulation was to trigger heuristic System 1 processing because prior studies have demonstrated that time constraints impair cognitive function, causing participants to depend on readily available cues like Nutri-Score and brand recognition (Morley et al. 2013; Wansink and Chandon 2006; Sanjari, Jahn, and Boztug 2017; Finucane et al. 2000). In contrast, participants in the low-time pressure group had unrestricted time to make a decision, allowing them to conduct a more comprehensive analysis of the data. The purpose of this condition was to encourage participants to apply analytical System 2 processing, evaluating the health-related characteristics of each product by examining the Nutritional Information Table in its totality as well as the Nutri-Score.

6.4 Procedure

Participants were recruited via online social media sites such as WhatsApp, Instagram, and LinkedIn, and were randomly allocated to one of four experimental conditions. A series of eight food products from the snack category in two blocks (contradicting or non-contradicting) was shown to each participant in a randomized order with the particular Nutri-Score and Nutritional Information Table (Figure 2 and 3). To give a diversified presence in the snack market, the product set included flavored yogurt, cookies, chips, rice cakes, granola, cornflakes, a nut bar, and macadamia nuts. After evaluating each product, participants were prompted to complete a comprehensive post-evaluation questionnaire. The questionnaire was designed to capture key aspects of their decision-making process, including their healthiness perceptions ("How healthy do you think the shown product is?" on a scale ranging from 1 (very unhealthy) to 7 (very healthy)), purchase intentions based on products' healthiness ("How likely are you to purchase this product if you were looking for a healthy product?" on a scale ranging from 1 (very unlikely) to 7 (very likely)), confidence levels ("How confident are you in your healthiness rating?" on a scale ranging from 1 (very unconfident) to 7 (very confident), and brand familiarity ("How familiar are you with the shown brand?" on a scale ranging from 1 (very unfamiliar) to 7 (very familiar)).

Figure 2: *Example of food images presented, illustrating a flavored yogurt paired with the Nutri-Score and NIT in agreement for the high-familiarity condition (Source: Own Survey)*

Figure 3: *Example of food images presented, illustrating a flavored yogurt paired with the Nutri-Score and NIT in agreement for the low-familiarity condition (Source: Own Survey)*

To explore the cognitive process behind the decision-making, participants were asked whether they based their decision on a quick assessment or a more detailed analysis of the provided information. They responded using a 7-point likert-scale ranging from "very quick assessment" to "very detailed analysis". We included this item to differentiate between heuristic and systematic processing and to understand the extent to which time pressure or brand familiarity influenced participants' decision-making approaches in our explorative analysis. Participants were also asked to evaluate the importance of the Nutri-Score and detailed Nutritional Information Table in their decisions by indicating, on the same 7-point scale, how critical either the simplified or detailed nutrition label was to their judgments. Those questions provided deeper explorative insights into the role of both the Nutri-Score as a heuristic and the NIT as an analytical tool, in varying time-pressured environments.

In addition to these product-specific questions, participants were asked several behavioral questions designed to control for individual differences that could impact their decision-making. They rated their knowledge of nutrition and healthy eating on a scale from 1 (not knowledgeable at all) to 7 (very knowledgeable), which aimed to test for prior nutritional knowledge. To determine whether prior exposure to the Nutri-Score system influenced their Nutri-Score reliance during the study, the survey also asked participants to indicate their familiarity with the particular labeling system using a 7-point likert scale. Finally, participants provided demographic information, including their age, gender, education level, and nationality, and used device for the study. Collecting this data allows us to understand the diversity of the sample, identify potential demographic influences on decision-making behavior, and ensure the generalizability of our findings across different population segments.

After completing the evaluation of all eight products and answering the questionnaire for each, participants were thanked for their participation and provided with a debriefing statement that explained the overall purpose of the study. The data collected were anonymized and securely stored for subsequent analysis, which focused on assessing the effects of brand familiarity and time pressure on participants' product evaluations.

6.5 Results

SPSS Statistics (Version 29.0.2) was used as data analysis tool for the analysis of the study data to investigate how brand awareness and time pressure affect consumer decision-making. For this study, the use of a repeated measures ANOVA was chosen because of its strong capacity to manage within-subjects variability, making it ideal for psychological investigations in which behavioral changes over time (such as learning effects) must be precisely monitored. Furthermore, the methodology allows for an in-depth investigation of interaction effects between variables like brand familiarity and time pressure, crucial for dissecting the nuances in consumer behavior. Ware and Johnson (2013) reinforce the use of repeated measures ANOVA in consumer psychology for studying how several factors interact to influence decision-making under stress and time constraints.

Prior to hypothesis testing, assumption checks were performed to ensure the unrestricted interpretability of the statistical methods employed. The Kolmogorov-Smirnov and Shapiro-Wilk tests showed significant findings ($p < .05$, Table 2 and 3) for both time pressure and brand familiarity, indicating a violation of the assumption of normalcy. ANOVA, however, is comparatively resistant to small departures from normalcy, especially when sample numbers are larger (N > 30 per group). Given the sufficiently large sample sizes in this study (Table 1) and the minor deviations observed upon graphical inspection, proceeding with the ANOVA remains a statistically valid approach.

		Kolmogorov-Smirnov			Shapiro-Wilk		
	TP vs. NTP	Statistic	df	p	Statistic	df	Sig
Decision Time	TP	.061	146	.200*	.964	146	<.001
	NTP	.100	134	.002	.943	134	<.001

*This is a lower bound of the true significance.

Table 2: *Tests of Normality for Time Pressure (Source: SPSS)*

		Kolmogorov-Smirnov			Shapiro-Wilk		
	BF vs. NBF	Statistic	df	p	Statistic	df	Sig
Decision Time	BF	.092	149	.004	.941	149	<.001
	NBF	.106	131	<.001	.902	131	<.001

Table 3: *Tests of Normality for Brand Familiarity (Source: SPSS)*

The Levene's Test yielded conflicting results with respect to the homogeneity of variance assumption. Product-specific timing metrics showed severe violations, with variations being unequal between groups for some measures ($p < .05$, Appendix 28), even if total decision submission times indicated that the assumption held ($p > .05$, Table 4). Despite these variations, the ANOVA was carried out, utilizing the test's robustness with sizable and comparable sample sizes (Table 1).

		Levene Statistic	df1	df2	p
Decision Time (Total)	Based on Mean	2.383	1	278	.124
	Based on Median	2.149	1	278	.144
	Based on Median and with adjusted df	2.149	1	277.475	.144
	Based on trimmed mean	2.377	1	278	.124

Table 4: *Test of Homogeneity of Variance (Source: SPSS)*

To account for the repeated-measures design of this study due to the presentation of eight different products, the assumption of sphericity was evaluated using Mauchly's Test. The data showed a significant breach of sphericity (Mauchly's $W = 0.26$, $\chi^2(27) = 369.18$, $p < .001$), necessitating the modifications of the degrees of freedom for repeated-measures ANOVA by corrective procedures. The Huynh-Feldt ($\varepsilon = .74$) and Greenhouse-Geisser ($\varepsilon = .71$) corrections were used to make sure the statistical analyses were robust. The significance of the dataset's major effects and interactions was interpreted using these modifications. The results of the adjusted ANOVA tests revealed a significant main effect of the particular product ($F(4.998, 1379.37) = 93.48$, $p < .001$, partial $\eta^2 = .25$) and a significant interaction between the product and time pressure ($F(4.998, 1379.38) = 5.73$, $p < .001$, partial $\eta^2 = .02$) under Greenhouse-Geisser corrections. However, neither the three-way interaction of product * time pressure * brand familiarity nor any significant interactions between the product * brand familiarity were discovered, suggesting that these characteristics had no discernible impact on decision-making in the scenario that was being studied (Appendix 29). Even in the event of sphericity breaches, the results' validity is guaranteed by the statistical corrections used to derive these conclusions.

The Omnibus test results provide preliminary interpretability of the statistical methods employed for the research hypotheses, paving the way for a more thorough examination. Each significant effect and interaction has been linked to a specific hypothesis, illustrating how time constraints and brand familiarity influence customer decisions. This approach allows for a systematic exploration of how these factors specifically affect decision-making processes, ensuring that each hypothesis is considered in light of robust empirical evidence.

7 Results and Discussion

7.1 Hypothesis 2

The purpose of the analysis of Hypothesis 2 was to determine whether consumers who are familiar with a brand (BF) are more likely to employ heuristic processing triggered by the shown brand, which speeds up decision-making even when there are no time limitations (NTP), than consumers who are unfamiliar with the brand (NBF).

7.1.1 Results of Hypothesis 2

To test this notion, the high familiarity and low familiarity groups' decision times under low time pressure were compared with a repeated measures ANOVA. The removal of time limitations resulted in nearly identical mean decision lengths for both familiarity groups in the low-time-pressure condition: the high familiarity group took an average of 26.38 seconds (SD = 1.05) to make a decision, while the low familiarity group took an average of 26.92 seconds (SD = 1.12), suggesting that brand familiarity had less of an impact on decision speed. In the low time pressure scenario, the mean difference between both familiarity groups was -0.54 seconds (SD = 1.56, p = .73), which was not statistically significant. A more detailed analysis on a product level also revealed no significant differences in decision time for any product (Appendix 42). These results suggest that the observed differences in decision durations for familiar and unknown products cannot be adequately explained by brand familiarity. The primary effects of time pressure and brand familiarity, as well as their interaction, were evaluated by further analysis using univariate tests. The effect of brand familiarity was also insignificant in the low-time-pressure scenario ($F(1, 276) = .12$, $p = .73$, partial $\eta^2 = .000$), suggesting that brand familiarity had no apparent influence on decision time when there were no time limitations, leading us to reject this hypothesis.

Additional explorative analyses were conducted to explore the hypothesis that brand-familiar customers are more likely to use heuristic processing, even when there are no time constraints. The high and low brand familiarity groups' heuristic and methodical decision-making techniques differed significantly, according to additional research on processing types of participants' product judgements. In the low-time-pressure condition, analytical processing became more prevalent among participants with low brand familiarity ($M = 4.33$, $SD = .21$, $p < .001$) compared to those with high brand familiarity ($M = 3.64$, $SD = .20$, $p < .001$). Interestingly, whereas high time pressure had a greater impact on processing style ($F(1, 275) = 23.08$, $p < .001$, partial $\eta^2 = .08$) than high brand familiarity ($F(1, 275) = 11.23$, $p < .001$, partial $\eta^2 = .04$), familiarity continuously regulated decision-making strategies, with highly familiar individuals showing less reliance on systematic cues (Appendix 35), even for products with contradicting nutritional information (Appendix 43). These results support the initial idea that, even in the absence of outside time limitations, brand familiarity can serve as a heuristic cue and encourage quicker product assessments.

In addition to this, the explorative consideration of the reliance on the Nutri-Score as a heuristic cue showed a lower dependence on the score when there is low time pressure ($M = 3.33$, $SD = .16$, $p = .01$), but this reliance increased when participants were unfamiliar with the brands ($M = 3.76$, $SD = .16$, $p = .20$). Nevertheless, the presence of a brand had no significant influence on reliance on the Nutri-Score in both time pressure groups (TP: $p = .21$; NTP: $p = .58$; Table 5). Familiar brands may not significantly reduce Nutri-Score reliance because the Nutri-Score provides information about nutritional quality that participants may still find relevant, even if they trust the brand. Similarly, unfamiliar brands do not increase Nutri-Score reliance substantially because the cue's utility does not depend on brand recognition but rather on its role as a general decision aid.

						95% Confidence Intervall for Difference	
TP vs. NTP	BF vs. NBF	BF vs. NBF	Mean Difference	Std. Error	p	Lower Bound	Upper Bound
TP	BF	NBF	-.386	.303	.205	-.983	.211
	NBF	BF	.386	.303	.205	-.211	.983
NTP	BF	NBF	-.174	.314	.579	-.792	.444
	NBF	BF	.174	.314	.579	-.444	.792

Table 5: *Pairwise Comparisons for Reliance on Nutri-Score (Source: SPSS)*

The further investigation of reliance on the Nutritional Information Table offered a deeper perspective on systematic versus heuristic processing: under low-time-pressure settings, a significant effect was noted, with low-familiarity participants exhibiting much higher table reliance (M = 5.36, SD = .25) than high-familiarity participants (M = 4.30, SD = .23). These findings were significant (F(1, 274) = 9.77, p = .002, partial η^2 = .03), supporting the notion that familiarity reduces the reliance on analytical processing (Table 6). Even if the decision duration we assessed does not confirm our Hypothesis 2, this finding nevertheless suggests that participants with low brand familiarity may compensate for their lack of heuristic cues by engaging in more detailed and systematic evaluations, such as consulting the NIT when evaluating a product, even if not reflected significantly in their decision times.

						95% Confidence Intervall for Difference	
TP vs. NTP	BF vs. NBF	BF vs. NBF	Mean Difference	Std. Error	p	Lower Bound	Upper Bound
TP	BF	NBF	-.620	.326	.058	-1.261	.021
	NBF	BF	.620	.326	.058	-.021	1.261
NTP	BF	NBF	-1.054*	.337	.002	-1.718	-.390
	NBF	BF	1.054*	.337	.002	.390	1.718

Table 6: *Pairwise Comparisons for Reliance on Nutritional Information Table (Source: SPSS)*

Lastly, the variables of the participants' confidence in their judgments, their product's health perception, and the likelihood of purchase based on the product's healthiness were further analyzed within the low-time-pressure group, comparing participants in low and high familiarity contexts. No significant differences were found across these variables between groups based on their familiarity with the presented brands except for product related variations in decision confidence (Appendix 44-46). However, when examining evaluations on the level of individual products, one significant difference was observed: the confidence rating for macadamia nuts from a familiar brand was significantly higher than those from a non-existing brand in the low-time-pressure condition (mean difference = .76, p = .02, Appendix 47). This suggests that some branded products might gain more confidence and potentially even trust because of familiarity, but not all of them. This could be linked to the "shielding effect" of brand familiarity, which holds that choosing specific products boosts confidence in a well-known brand if consumers trust into this company. Despite this observation, the analysis revealed no further significant differences in the levels of judgment confidence, likelihood of purchase, or perceived healthiness of the product between participants who were highly familiar with the brand and those with low brand familiarity, when considered for each individual product (Appendix 48-50).

The findings show that brand familiarity has no discernible effect on decision speed in the absence of time restrictions. A minor trend indicated that familiar individuals made decisions more quickly, but this effect was insignificant, underscoring the importance of situational considerations such as time pressure in triggering heuristic processing as presented in the results of Hypothesis 3. However, exploratory results showed that brand familiarity influences cognitive strategies, with less reliance on systematic cues like the Nutritional Information Table among familiar participants. Unfamiliar individuals, on the other hand, completed more thorough assessments. In relaxed settings, familiarity by itself does not speed up decision-making, but it consistently promotes the processing of heuristic cues, highlighting its function as a cognitive shortcut in consumer behavior.

7.1.2 Discussion of Hypothesis 2

The results of this study indicate that when time limitations are removed, brand familiarity does not significantly influence decision speed. This observation challenges Hypothesis 2, which suggested that consumers familiar with a brand are more likely to engage in heuristic processing and thus make faster decisions, even in the absence of time constraints. It appears that brand familiarity alone is insufficient to accelerate decision-making, as evidenced by the comparable decision durations for the high and low brand familiarity groups under low time pressure. Interestingly, this outcome counters the “shielding effect” of brand familiarity, which posits that recognizable brands might reduce the need for systematic processing by fostering trust and minimizing perceived risks (Velasco Vizcaíno and Velasco 2019; Jo, Nakamoto, and Nelson 2003). As proposed by Ikonen et al. (2020), the described effect could imply that consumers may overlook some product attributes, such as low nutritional value or potentially harmful qualities, since brand familiarity acts as a cognitive filter. However, it seems that brand familiarity was not a strong enough heuristic signal to significantly alter decision-making processes in this study, as no evident differences were observed in decision speed when time constraints were absent. One argument is that the immediate usefulness of the heuristic shortcuts would be diminished since even brand-aware consumers would likely opt for more extensive evaluations in relaxed settings when speed is not an issue. This reasoning aligns with the Dual Process Theory, which suggests that System 2 processing dominates and enables consumers to make thoughtful, analytical judgments when they are not under time or cognitive pressure (Kahneman 2011; Evans 2008). Customers appear to rely more on product-specific knowledge in these situations than on heuristic cues and shortcuts such as brand familiarity. Chen et al. (2023) argue that heuristic reliance is context-sensitive, particularly when cognitive resources are unconstrained, diminishing its likelihood to act as dominant cue under relaxed time conditions.

Even though there was minimal difference in decision speed, the exploratory data provided important insights on the cognitive strategies utilized by individuals with different levels of brand knowledge: regardless of the time conditions, participants with high familiarity consistently demonstrated reduced reliance on systematic signals, such as the Nutritional Information Table, compared to their counterparts with low familiarity. This finding is consistent with the mere exposure effect, which states that familiarity increases brand trust while decreasing the perceived need for more critical product assessment and evaluation of alternative information sources (Zajonc 1980; Zhang 2020). As a result of their trust, buyers are more inclined to depend on heuristic cues rather than in-depth investigation (Hoyer and Brown 1990). Furthermore, this behavior mirrors the "shielding effect" described earlier, such as nutritional warnings, reinforcing the prominence of the brand over objective product attributes (Velasco Vizcaíno and Velasco 2019; Ikonen et al. 2020; Jo, Nakamoto, and Nelson 2003). Conversely, participants with low brand familiarity demonstrated compensatory behavior by focusing more on systematic and extensive information, such as the Nutritional Information Table. Comprehensive nutritional information tends to impact customers who lack heuristic anchors, like brand recognition, more significantly according to research by Freire et al. (2017).

The further examination of the impact of time pressure revealed that even in situations with low time constraints, brand familiarity influenced decision-making strategies, according to the exploratory data. Familiar participants tended to rely on quick assessments based on heuristic nutritional information (e.g. the Nutri-Score) rather than detailed judgments. This behavior is aligned with the theory that familiarity serves as a cognitive anchor facilitating decision-making by reducing perceived risk and cognitive load, according to Tversky and Kahneman's (1973) research on heuristic biases, even in the absence of time pressures (Velasco Vizcaíno and Velasco 2019). Because well-known businesses are usually seen as reliable and trustworthy, customers may develop opinions about them without doing extensive investigation (Hoyer and Brown 1990; Zajonc 1980). On the other hand, the systematic approach adopted by unfamiliar participants supports Meyers-Levy and Tybout's (1989) findings that analytical processing is triggered in the absence of heuristic cues. Unfamiliar participants appeared to rely on detailed information to compensate for the lack of brand-based shortcuts, reflecting deliberate effort to minimize uncertainty. This is in line with a study by Payne, Bettman, and Johnson (1988) that focused on using System 2 processing in situations where heuristic cues are either nonexistent or insufficient. Therefore, under low time pressure, the strong interaction effect between table dependence and brand familiarity supports the notion that unfamiliar customers use analytical processing to reduce ambiguity and conduct more thorough product evaluations. This observation is consistent with research by Grunert and Wills (2007), who found that consumers who are unfamiliar with a product are more likely to base their selections on specifics.

The exploratory study of Nutri-Score reliance explored the importance of heuristic processing in greater detail. Although Nutri-Score dependability was generally higher among those who were unfamiliar with the brand, brand familiarity had no significant effect on reliance in both time pressure conditions. Nutri-Scores, as a heuristic tool, provide universally accessible nutritional quality information that remains effective regardless of brand familiarity. Even without brand-derived cues, they enable evaluations for participants unfamiliar with the brands. The study results evidenced this role, which is particularly significant in high-time-pressure scenarios. Previous studies by Becker et al. (2015) and Julia and Hercberg (2017) corroborate these findings, highlighting the importance of simplified labeling systems like Nutri-Scores in lowering cognitive load and boosting decision-making effectiveness for various consumer groups, particularly in situations where time is crucial. The fact that brand presence has no discernible impact on Nutri-Score reliance may be an indication of the labels' wider applicability, as they are intended to be simple to understand and universally relevant. According to (Chandon 2013), Nutri-Scores and other simplified cues efficiently direct customer choices by removing the need for complex evaluations, which makes them especially useful for both known and unknown consumers.

Additionally, the exploration of the use of the Nutritional Information Table shows that brand familiarity has a substantial impact on reliance when time pressure is low: participants unfamiliar with the brands relied more on systematic processing and used specific cues in the form of the NIT. Accordingly to the Dual Process Theory, analytical System 2 processing dominates in the absence of heuristic signals (Kahneman 2011; Evans 2008). High-familiarity participants, however, relied less on systematic signals due to heuristic strategies. Since high- and low-familiarity groups' decision durations were comparable despite their varying dependence on systematic signals, the explorative analysis suggests that processing techniques might not always affect speed. This backs up earlier research that consumers without heuristic anchors need more specific information, such as nutritional tables (Freire et al. 2017; Grunert and Wills 2007). The observation that the "shielding effect" is lessened in low-pressure settings suggests that brand familiarity also has less of an influence when time constraints are removed, encouraging more in-depth evaluations even among brand-conscious consumers.

Product-specific findings added an extra layer of depth to the analysis: when it came to macadamia nuts, known brands received far higher judgement confidence ratings than unknown ones. This is consistent with the "halo effect," which states that favorable associations with a brand boost consumers' trust in its associated goods (Thorndike et al. 2012; Chandon 2013). However, the lack of similar effects for other products suggests that the strength of brand familiarity's influence varies by the product type itself, potentially reflecting differences in how consumers perceive and trust individual brands. Velasco Vizcaíno and Velasco (2019) emphasized that the protective effect of brand familiarity is contingent on the consumer's prior experiences and the product's context, which may explain these variations.

This study's interplay between systematic and heuristic processing highlights the significance of conditional decision-making strategies. The Dual Process Theory provides a robust framework for assessing these findings (Kahneman 2011). When time limitations are relaxed, especially in the absence of heuristic indicators, customers appear to shift to System 2 processing. Those who were already familiar with the brand, however, continued to apply heuristic strategies compared to unfamiliar participants, indicating that brand familiarity promotes cognitive comfort – even if it is not reflected in faster decision durations. These findings also support those of Robertson, Andersson, and Lunn (2022), who noted that brand familiarity often reduces the cognitive load required for decision-making, which may cause consumers to shy away from in-depth evaluations. The exploratory results further illustrate the situational dependence of heuristic processing and emphasize the importance of contextual factors such as time restrictions and product familiarity in affecting customer behavior.

In summary, brand familiarity influenced participants' cognitive processes but had no significant effect on decision speed in low-time-pressure situations. Nevertheless, participants familiar with brands relied more on heuristic signals such as the Nutri-Score, likely elevated by brand trust, to simplify their decisions, while unfamiliar participants employed more analytical tactics to compensate for their lack of heuristic anchors. The findings challenge the notion that brand familiarity accelerates decision-making in low-pressure scenarios, underscoring its limited influence on consumer processing without time constraints. This contradiction highlights the need for further exploration into how familiar and unfamiliar brands are evaluated, particularly in contexts where rapid decision-making is less critical. Such insights are crucial for addressing growing health concerns related to unhealthy food choices, where understanding consumer decision-making can help in designing more effective nutritional labeling and marketing strategies.

7.2 General Discussion

Overall, this study examined the relationship between brand familiarity and time restrictions in consumer decision-making, with a focus on heuristic and methodical processing methods. The findings emphasize the importance of time limitations in increasing reliance on heuristic signals, as well as the subtle impact of brand familiarity over a wide range of choice circumstances, including contradicting product information.

Under time constraints, heuristic processing took precedence, as consumers emphasized speed and cognitive efficiency. This was especially obvious among participants with little brand awareness, who relied significantly on simpler signals such as the Nutri-Score while undervaluing thorough ratings from the Nutritional Information Table. These findings are consistent with Kahneman's Dual Process Theory (2011), which posits that cognitive restrictions favor intuitive, System 1 processing. While decision speed did not differ significantly among participants with high brand familiarity, the use of heuristic cues suggests that familiar brands act as cognitive anchors, fostering trust and reducing the need for systematic processing (Hoyer and Brown 1990; Velasco Vizcaíno and Velasco 2019). However, the absence of statistically significant effects on decision speeds shows that time constraints, rather than brand familiarity, govern processing processes in constrained contexts.

When time limits were eliminated, consumers, particularly those who were unfamiliar with the brands, were more engaged in System 2 processing. To compensate for the lack of heuristic anchoring, these individuals used systematic assessments, such as reviewing the Nutritional Information Table. Participants with high brand familiarity, on the other hand, chose heuristic shortcuts, demonstrating the trust and cognitive ease associated with well-known brands (Zajonc 1980; Robertson, Andersson, and Lunn 2022). Nevertheless, there were no significant differences in decision speed across familiarity groups, suggesting that brand familiarity does not accelerate decision-making when cognitive resources are available. The presence of contradicting information weakened heuristic reliance, particularly among those unfamiliar with the brand. Under severe time pressure, conflicting information increased decision durations, implying that cognitive load surpassed the ability for heuristic shortcuts, resulting in incomplete analytical processing (Finucane et al. 2000). Under minimal time constraint, individuals acquainted with the brand took considerably longer to make decisions for contradictory items, demonstrating that conflicts challenge the confidence associated with familiar brands and engage System 2 processing to reconcile discrepancies. This contradicts the "shielding effect" of brand familiarity (Velasco Vizcaíno and Velasco 2019; Jo, Nakamoto, and Nelson 2003), since it appears decreased when cognitive resources allow for critical examination, highlighting the need for more study into its conditionality.

Nutritional knowledge further moderated reliance on heuristic versus systematic processing. Among participants unfamiliar with brands, higher nutritional knowledge increased reliance on the Nutritional Information Table and decreased reliance on the Nutri-Score, even under high time pressure. Conversely, less knowledgeable consumers relied more on the Nutri-Score, reflecting its role as a compensatory heuristic tool that simplifies decision-making when cognitive or informational resources are limited (Julia and Hercberg 2017; Li, Wang, and Zhang 2022). Participants who were familiar with brands, on the other hand, showed no significant effect from nutritional information, indicating that brand familiarity may serve as a stabilizing heuristic in addition to detailed or simplified signals.

Finally, the study underlines the importance of time constraint in promoting heuristic processing, as well as brand familiarity's stabilizing effect as a cognitive anchor. While conflicting information disrupted heuristic reliance, prompting partial or full analytical processing, the absence of time constraints allowed unfamiliar consumers to engage more deeply with detailed information. The results highlight the conditional nature of heuristic reliance, shaped by time availability, brand familiarity, and individual factors like nutritional knowledge, while emphasizing the importance of simplified tools such as the Nutri-Score in facilitating efficient decisions under constrained conditions when making healthier consumption choices.

7.2.1 Implications

The findings have important implications for companies, politicians, marketers, and consumers looking to improve decision efficiency and encourage healthier food choices for consumers. Businesses should emphasize intuitive FOPLs to assist time-pressed consumers, particularly those unfamiliar with their products, in selecting healthier alternatives (Julia and Hercberg 2017; Egnell et al. 2018). For well-established brands, consistency between reputation and product quality is critical to maintain consumer trust, as contradictions can erode confidence. For instance, brands like *Nesquik* may face scrutiny if their perceived healthiness conflicts with simplified signals (Velasco Vizcaíno and Velasco 2019).

Marketers must carefully adjust message to their clients' demands. In time-sensitive situations, highlighting positive Nutri-Score evaluations in advertising may influence customers who depend on heuristic signals. For nutritionally motivated clients with greater cognitive skills, marketing that emphasizes product transparency and general health advantages can build trust and long-term commitment (Chandon 2013; Robertson, Andersson, and Lunn 2022). Policy makers should mandate standardized FOPLs to simplify health-related information and guide consumers toward healthier options, particularly taking into account the latest trends toward convenience (Hersey et al. 2013). Combining such policies with nutritional education programs can empower consumers to critically evaluate products. For instance, public campaigns promoting Nutri-Score literacy alongside detailed tables could improve the effectiveness of labeling systems across varying cognitive abilities (Roberto et al. 2012; Freire et al. 2017). Consumers, meanwhile, should strive to balance heuristic tools like brand familiarity and the Nutri-Score with deeper evaluations when time and cognitive resources allow. While simplified signals enable quick decisions, their overreliance risks oversimplification. For example, a food with a high Nutri-Score may nonetheless have high sugar levels (Chandon 2013). Consumers with greater nutritional knowledge demonstrated a preference for the Nutritional Information Table when evaluating products, underscoring the value of nutritional literacy in enabling systematic evaluations. As a consequence, educational efforts should specifically target low-knowledge consumers, promoting deliberate, healthier food choices.

7.2.2 Limitations

The limitations of our study design provide further explanations for why brand familiarity did not have the expected impact on decision speed, which should be addressed to enhance the robustness and generalizability of our findings in future research.

First, the survey was performed online, thus we were unable to account for any distractions or guarantee that participants were completely focused on the study, even though it was meant to isolate factors efficiently. Brand familiarity may not have the same effect as a cognitive shortcut in an online setting as it would in a more controlled context. The study's limited ecological validity may have similarly impacted the results as our experimental online setup does not replicate the complexities of real-world decision-making, often involving multitasking and external distractions that increase cognitive load. Second, the lack of significant variations in decision times across Hypotheses 1 and 2 implies that assessing decision speed alone may not capture nuanced cognitive processes. While brand familiarity affected heuristic reliance, it did not always speed up decision-making. To address this, future research should use sophisticated approaches like as eye-tracking to compare fixation on heuristic cues to systematic signals, or neuroimaging techniques (e.g., EEG) to identify cognitive load and processing styles more objectively. Third, the study's focus on specific brands such as Nesquik and Activia may limit generalizability. Participants' familiarity with these brands could be influenced by cultural or personal exposure, which was not controlled. To address this, future research should incorporate a wider range of brands and product categories, ensuring diversity across cultural and demographic groups to test whether these findings hold universally.

Fourth, the reliance on self-reported processing styles introduces potential bias. Participants' stated reliance on heuristic cues is subjective and prone to social desirability. To provide a more precise understanding of cognitive processing, future studies should include objective behavioral measures such as fixation durations, click behavior, or response mapping during decision-making tasks. Fifth, while this study focused on the influence of contradicting information on breaking heuristic reliance, particularly under time limitations (Hypothesis 4), it did not specifically look into the cognitive cost or emotional strain caused by these conflicts. Future research should look at the role of working memory capacity and stress levels in processing contradictory information in order to better understand how such disruptions impact heuristic vs systematic decision-making. Furthermore, nutritional awareness was identified as a major mediator, particularly among people unfamiliar with the brands. However, baseline nutritional literacy was not thoroughly assessed in this investigation. To further understand its influence, future research should include standardized measures of nutritional knowledge that systematically analyze its relationship with time constraints and choice methods.

Finally, future research might look at the long-term impacts of heuristic reliance in decision making. For example, investigating how recurrent reliance on simplified cues such as the

Nutri-Score affects trust and decision quality over time may give further insight into customer behavior under various settings.

8 Conclusion

Our findings conclude that under time constraints, consumers rely on heuristic tools to simplify decision-making, while low-time-pressure scenarios allow for more analytical engagement, underscoring the context-dependent nature of decision-making processes. Contextual factors such as time constraints and cognitive load affect the usefulness of brand familiarity as a heuristic signal, which may not always be suitable for guiding consumer decisions. This inappropriateness occurs when, due to time pressure and complex depiction of product information, buyers rely too much on familiar brands without properly investigating other product characteristics or newer, potentially superior alternatives. Such dependency may lead to poor choices based on recognition rather than a full analysis of product quality or relevance to the consumer's needs. As a result, while brand familiarity may aid decision-making, it may also influence customer behavior in ways that are not in their best interests or preferences. When cognitive resources are available, like in relaxed circumstances, consumers ten to study information more analytically and consciously, reducing the heuristic benefit of brand familiarity. These findings suggest that marketers should incorporate situational aspects, such as time pressure and distractions, in order to increase decision-making efficiency when implementing brand-familiarity-based tactics that encourage customers to pick healthier products. To further understand how brand familiarity effects consumer behavior, future research should focus on ecologically realistic environments that mimic the pressures and distractions of ordinary life. A future study into these contextual variables can expand on the concepts offered here, allowing us to better understand the effects of brand familiarity in particular.

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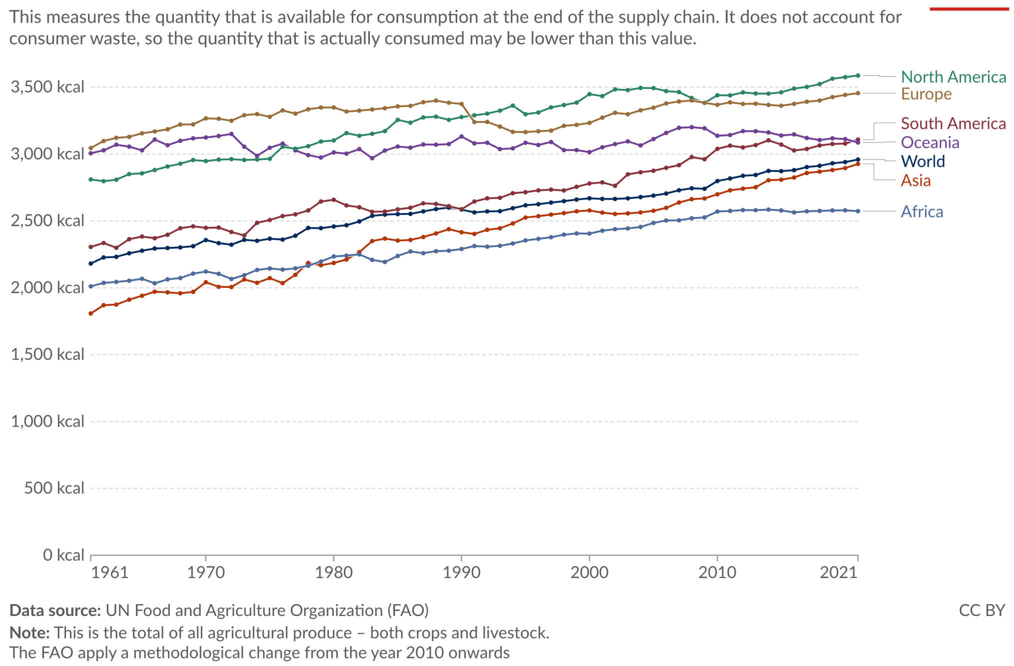
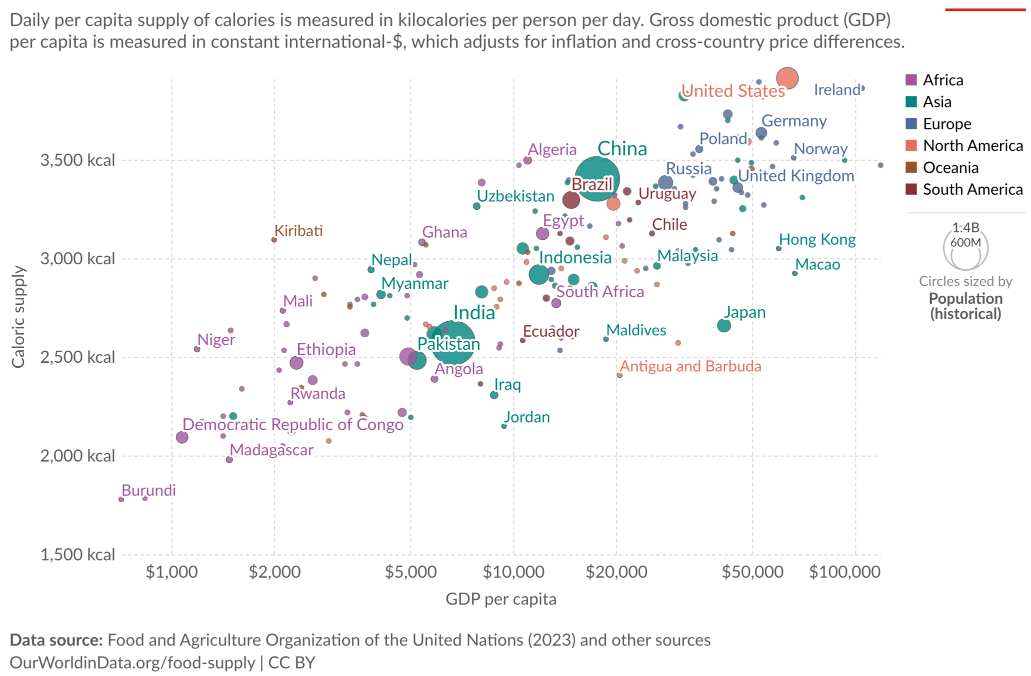
10 Appendix

Appendix 1: Per capita kilocalorie supply from all foods per day, 1961 to 2021



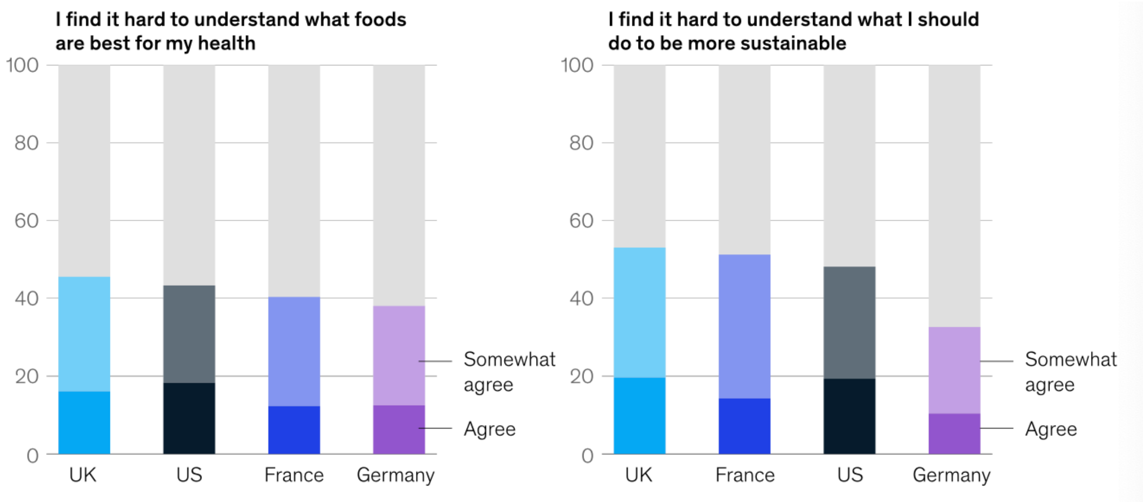
Source: Food Supply (Roser, Ritchie, and Rosado 2023).

Appendix 2: Daily per capita supply of calories vs. GDP per capita, 2021



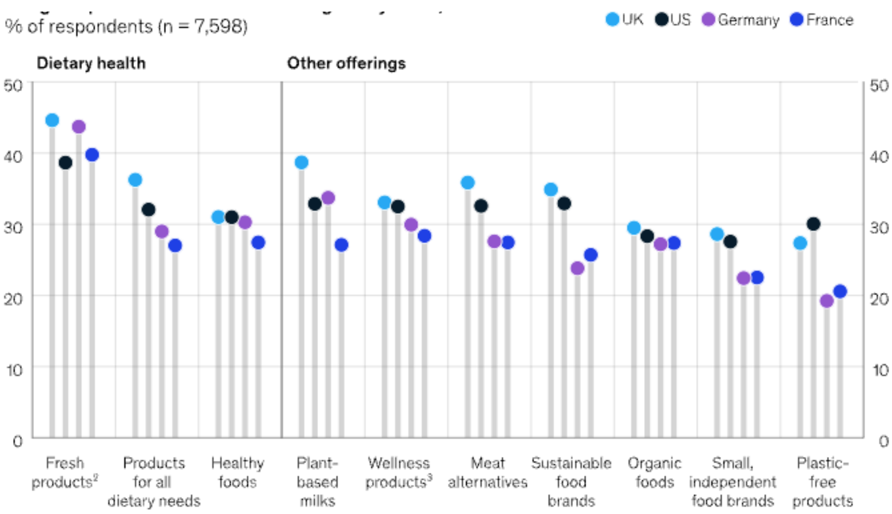
Source: Food Supply (Roser, Ritchie, and Rosado 2023).

Appendix 3: Health and sustainability understanding, by country



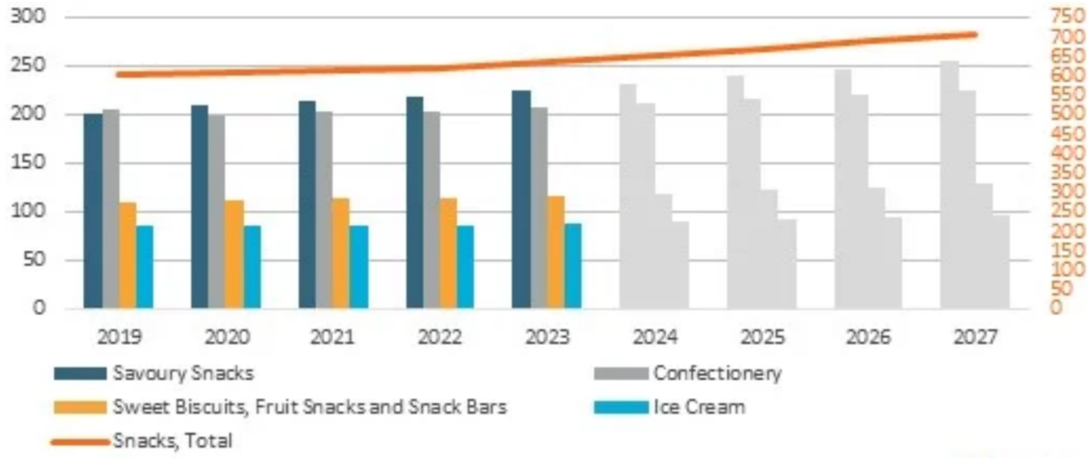
Source: McKinsey Global Future of Food Survey 2022 (Grimmelt et al. 2022).

Appendix 4: Range of products available in main grocery store



Source: McKinsey Global Future of Food Survey 2022 (Grimmelt et al. 2022).

Appendix 5: Global Sales of Snacks 2019-2027 in USD

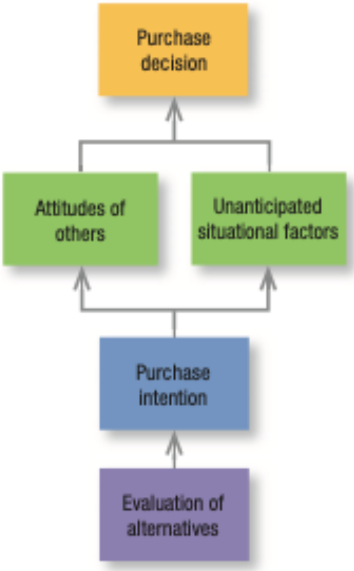


Source: McKinsey Global Future of Food Survey 2022 (Grimmelt et al. 2022).

Appendix 6: The Five-Stage Model of the Consumer Buying Process

Source: Marketing Management 15. Global Edition (Kotler and Keller 2016) page 195

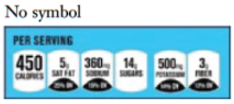
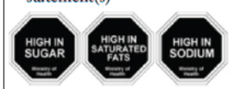
Appendix 7: Steps between Evaluation of Alternatives and a Purchase Decision



Source: Marketing Management 15. Global Edition (Kotler and Keller 2016) page 199.

Appendix 8: Dimensions of front-of-package nutrtion labels and common labeling systems

Table 1 Dimensions of front-of-package nutrition labels and common labeling systems

Dimension	Guideline Daily Amount	Traffic light (United Kingdom)	Nutri-Score (France)	Health Star Rating (Australia)	High in (Chile)
Symbol	No symbol 	Traffic lights 	Letters/colors 	Star system 	Stop sign displaying "high in" statement(s) 
Summary indicator versus nutrient-specific	Nutrient-specific	Nutrient-specific	Summary	Summary	Nutrient-specific
Interpretive versus non-interpretive information provision	Noninterpretive	Interpretive	Interpretive	Interpretive	Interpretive
Nutrient threshold(s) for label display	No threshold	No threshold	No threshold	No threshold	Threshold

Note: Front-of-package labeling systems, such as the traffic-light label and the Health Star Rating, are displayed along with additional information on nutrient amounts.

Source: The Influence of Front-of-Package Nutrition Labeling on Consumer Behavior and Product Reformulation (Roberto et al. 2021).

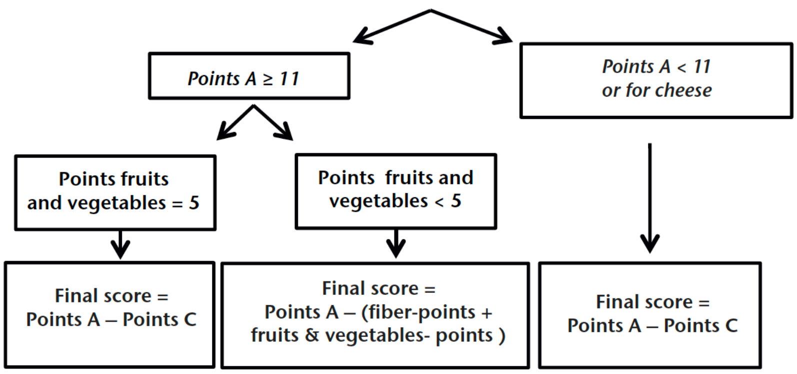
Appendix 9: Attribution of points, based on the content of nutrients and other elements per 100 g of a food/beverage

Points	Energy (kJ)	Sugars (g)	Specific cut-offs: beverages Energy (kJ)	Specific cut-offs: beverages Sugars (g)	Saturated fat (g)	Specific cut-offs: fats Saturated fat/ Lipids (%)	Sodium (mg)
0	≤ 335	≤ 4.5	≤ 0	0	≤ 1	< 10	< 90
1	> 335	> 4.5	≤ 30	≤ 1.5	> 1	< 16	> 90
2	> 670	> 9	≤ 60	≤ 3	> 2	< 22	> 180
3	> 1,005	> 13.5	≤ 90	≤ 4.5	> 3	< 28	> 270
4	> 1,340	> 18	≤ 120	≤ 6	> 4	< 34	> 360
5	> 1,675	> 22.5	≤ 150	≤ 7.5	> 5	< 40	> 450
6	> 2,010	> 27	≤ 180	≤ 9	> 6	< 46	> 540
7	> 2,345	> 31	≤ 210	≤ 10.5	> 7	< 52	> 630
8	> 2,680	> 36	≤ 240	≤ 12	> 8	< 58	> 720
9	> 3,015	> 40	≤ 270	≤ 13.5	> 9	< 64	> 810
10	> 3,350	> 45	≤ 270	> 13.5	> 10	≥ 64	> 900
	0–10 (a)	0–10 (b)	0–10 (a)	0–10 (b)	0–10 (c)	0–10 (c)	0–10 (d)
Total	Points A = (a) + (b) + (c) + (d) [0 – 40]						

Points	Fruits, veg (%)	Specific cut-offs: beverages Fruits, veg (%)	Fiber (g)	Protein (g)
0	≤ 40	≤ 40	≤ 0.7	≤ 1.6
1	< 40		> 0.7	> 1.6
2	> 60	> 40	> 1.4	> 3.2
3	–		> 2.1	> 4.8
4	–	> 60	> 2.8	> 6.4
5	> 80		> 3.5	> 8.0
6				
7				
8				
9				
10		> 80		
	0–5 (a)	0–10 (a)	0–5 (b)	0–5 (c)
Total	Points C = (a) + (b) + (c) [0 – 15]			

Source: *Julia, C., & Hercberg, S. (2017). Nutri-Score: Evidence of the effectiveness of the French front-of-pack nutrition label. Ernährungs Umschau, 64(12), 181-187.*

Appendix10: Final Nutri-Score Calculation



Source: *Julia, C., & Hercberg, S. (2017). Nutri-Score: Evidence of the effectiveness of the French front-of-pack nutrition label. Ernährungs Umschau, 64(12), 181-187.*

Appendix 11: Attribution of colors for the Nutri-Score

Foods (points)	Beverages (points)	Color
min to -1	water	green
0 to 2	min to 1	light green
3 to 10	2–5	yellow
11 to 18	6–9	orange
19 to max	10 to max	dark orange

Green: highest quality

Red: lowest quality

Source: *Julia, C., & Hercberg, S. (2017). Nutri-Score: Evidence of the effectiveness of the French front-of-pack nutrition label. Ernährungs Umschau, 64(12), 181-187.*

Appendix 12: Example from the survey: Nutri-Score calculation of Oreo

1) Nutritional table of Oreo

Nutritional values per 100g	
Energy	1982 kJ/472 kCal
Fat of which saturated fatty acids	19 g 5.4 g
Carbohydrates of which sugar	67 g 35 g
Fiber	2.9 g
Protein	5.6 g
Salt	0.76 g

2) Attribution of points, based on the content of nutrients per 100 g

			Specific cut-offs: beverages			Specific cut-offs: fats	
Points	Energy (kJ)	Sugars (g)	Energy (kJ)	Sugars (g)	Saturated fat (g)	Saturated fat/ Lipids (%)	Sodium (mg)
0	≤ 335	≤ 4.5	≤ 0	0	≤ 1	< 10	< 90
1	> 335	> 4.5	≤ 30	≤ 1.5	> 1	< 16	> 90
2	> 670	> 9	≤ 60	≤ 3	> 2	< 22	> 180
3	> 1,005	> 13.5	≤ 90	≤ 4.5	> 3	< 28	> 270
4	> 1,340	> 18	≤ 120	≤ 6	> 4	< 34	> 360
5	> 1,675	> 22.5	≤ 150	≤ 7.5	> 5	< 40	> 450
6	> 2,010	> 27	≤ 180	≤ 9	> 6	< 46	> 540
7	> 2,345	> 31	≤ 210	≤ 10.5	> 7	< 52	> 630
8	> 2,680	> 36	≤ 240	≤ 12	> 8	< 58	> 720
9	> 3,015	> 40	≤ 270	≤ 13.5	> 9	< 64	> 810
10	> 3,350	> 45	≤ 270	> 13.5	> 10	≥ 64	> 900
	0–10 (a)	0–10 (b)	0–10 (a)	0–10 (b)	0–10 (c)	0–10 (c)	0–10 (d)
Total	Points A = (a) + (b) + (c) + (d) [0 – 40]						

	not listed here	Specific cut-offs: beverages	not listed here	
Points	Fruits, veg (%)	Fruits, veg (%)	Fiber (g)	Protein (g)
0	≤ 40	≤ 40	≤ 0.7	≤ 1.6
1	< 40		> 0.7	> 1.6
2	> 60	> 40	> 1.4	> 3.2
3	–		> 2.1	> 4.8
4	–	> 60	> 2.8	> 6.4
5	> 80		> 3.5	> 8.0
6				
7				
8				
9				
10		> 80		
	0–5 (a)	0–10 (a)	0–5 (b)	0–5 (c)
Total	Points C = (a) + (b) + (c) [0 – 15]			

2 (energy) + 7 (sugars) + 5 (saturated fat) + 8 (sodium) = negative points

2 (protein) = 3 positive points

Final Score = 6 (negative points) - 2 (positive points) = 19

3) Attribution of colors

Foods (points)	Beverages (points)	Color
min to -1	water	green
0 to 2	min to 1	light green
3 to 10	2–5	yellow
11 to 18	6–9	orange
19 to max	10 to max	dark orange

NUTRI-SCORE
A B C D E

Green: highest quality

Red: lowest quality

Source: own exemplified calculation based on *Julia, C., & Hercberg, S. (2017). Nutri-Score: Evidence of the effectiveness of the French front-of-pack nutrition label. Ernährungs Umschau, 64(12), 181-187.*

Appendix 13: Detailed Nutrition Table Displayed in Survey

Nutritional values per 100g	
Energy	364 kJ /87 kCal
Fat of which saturated fatty acids	2.9 g 1.8 g
Carbohydrates of which sugar	11.3 g 10.8 g
Calcium	151 mg
Protein	3.8 g
Salt	0.14 g

Source: Own illustration of our survey

Appendix 14: Stimuli for High-Familiarity Condition Using a Non-Contradicting Product (Chips)

NUTRI-SCORE

A B C D E

Nutritional values per 100g	
Energy	2249 kJ/539 kCal
Fat of which saturated fatty acids	32 g 4.2 g
Carbohydrates of which sugar	53 g 2.9 g
Fiber	4.3 g
Protein	6.4 g
Salt	1.7 g

Source: Own illustration within our survey

Appendix 15: Stimuli for High-Familiarity Condition Using a Non-Contradicting Product (Cookies)

Nutritional values per 100g	
Energy	1982 kJ/472 kCal
Fat of which saturated fatty acids	19 g 5.4 g
Carbohydrates of which sugar	67 g 35 g
Fiber	2.9 g
Protein	5.6 g
Salt	0.76 g

Source: Own illustration within our survey

Appendix 16: Stimuli for High-Familiarity Condition Using a Non-Contradicting Product (Rice Waffles)

Nutritional values per 100g	
Energy	1628 kJ /389 kCal
Fat of which saturated fatty acids	3 g 0.6 g
Carbohydrates of which sugar	81 g 0.9 g
Fiber	3.5 g
Protein	7.9 g
Salt	0.0 g

Source: Own illustration within our survey

Appendix 17: Stimuli for High-Familiarity Condition Using a Contradicting Product (Granola)

NUTRI-SCORE
A B C D E

Nutritional values per 100g	
Energy	1802 kJ /429 kCal
Fat of which saturated fatty acids	13.4 g 1.7 g
Carbohydrates of which sugar	64.9 g 17.9 g
Fiber	7.1 g
Protein	8.7 g
Salt	0.22 g

Source: Own illustration within our survey

Appendix 18: Stimuli for High-Familiarity Condition Using a Contradicting Product (Macadamia Nuts)

NUTRI-SCORE
A B C D E

Nutritional values per 100g	
Energy	2951 kJ/717 kCal
Fat of which saturated fatty acids	72 g 22 g
Carbohydrates of which sugar	4.3 g 3.9 g
Fiber	11 g
Protein	7.4 g
Salt	0.82 g

Source: Own illustration within our survey

Appendix 19: Stimuli for High-Familiarity Condition Using a Contradicting Product (Cornflakes)

NUTRI-SCORE

Nutritional values per 100g	
Energy	1598 kJ /378 kCal
Fat of which saturated fatty acids	3 g 0.7 g
Carbohydrates of which sugar	74.6 g 22.1 g
Fiber	9.3 g
Protein	8.7 g
Salt	0.22 g

Source: Own illustration within our survey

Appendix 20: Stimuli for High-Familiarity Condition Using a Contradicting Product (Nut Bars)

NUTRI-SCORE

Nutritional values per 100g	
Energy	2064 kJ/493 kCal
Fat of which saturated fatty acids	37 g 8.1 g
Carbohydrates of which sugar	40 g 14 g
Fiber	18 g
Protein	14 g
Salt	0.87 g

Source: Own illustration within our survey

Appendix 21: Stimuli for Low-Familiarity Condition Using a Non-Contradicting Product (Chips)

Nutritional values per 100g	
Energy	2249 kJ/539 kCal
Fat of which saturated fatty acids	32 g 4.2 g
Carbohydrates of which sugar	53 g 2.9 g
Fiber	4.3 g
Protein	6.4 g
Salt	1.7 g

Source: Own illustration within our survey

Appendix 22: Stimuli for Low-Familiarity Condition Using a Non-Contradicting Product (Cookies)

Nutritional values per 100g	
Energy	1982 kJ/472 kCal
Fat of which saturated fatty acids	19 g 5.4 g
Carbohydrates of which sugar	67 g 35 g
Fiber	2.9 g
Protein	5.6 g
Salt	0.76 g

Source: Own illustration within our survey

Appendix 23: Stimuli for Low-Familiarity Condition Using a Non-Contradicting Product (Rice Waffles)

NUTRI-SCORE

A B C D E

Nutritional values per 100g	
Energy	1628 kJ /389 kCal
Fat of which saturated fatty acids	3 g 0.6 g
Carbohydrates of which sugar	81 g 0.9 g
Fiber	3.5 g
Protein	7.9 g
Salt	0.0 g

Source: Own illustration within our survey

Appendix 24: Stimuli for Low-Familiarity Condition Using a Contradicting Product (Granola)

NUTRI-SCORE

A B C D E

Nutritional values per 100g	
Energy	1802 kJ /429 kCal
Fat of which saturated fatty acids	13.4 g 1.7 g
Carbohydrates of which sugar	64.9 g 17.9 g
Fiber	7.1 g
Protein	8.7 g
Salt	0.22 g

Source: Own illustration within our survey

Appendix 25: Stimuli for Low-Familiarity Condition Using a Contradicting Product (Macadamia Nuts)

NUTRI-SCORE
A B C D E

Nutritional values per 100g	
Energy	2951 kJ/717 kCal
Fat of which saturated fatty acids	72 g 22 g
Carbohydrates of which sugar	4.3 g 3.9 g
Fiber	11 g
Protein	7.4 g
Salt	0.82 g

Source: Own illustration within our survey

Appendix 26: Stimuli for Low-Familiarity Condition Using a Contradicting Product (Cornflakes)

NUTRI-SCORE
A B C D E

Nutritional values per 100g	
Energy	1598 kJ /378 kCal
Fat of which saturated fatty acids	3 g 0.7 g
Carbohydrates of which sugar	74.6 g 22.1 g
Fiber	9.3 g
Protein	8.7 g
Salt	0.22 g

Source: Own illustration within our survey

Appendix 27: Stimuli for Low-Familiarity Condition Using a Contradicting Product (Nut Bars)

NUTRI-SCORE

A B C D E

Nutritional values per 100g	
Energy	2064 kJ/493 kCal
Fat of which saturated fatty acids	37 g 8.1 g
Carbohydrates of which sugar	40 g 14 g
Fiber	18 g
Protein	14 g
Salt	0.87 g

Source: Own illustration within our survey

Appendix 28: Levene's Test of Equality of Error Variances for Decision Time

		Levene Statistic	df1	df2	p
Timing – Page Submit	Based on Mean	2.345	3	276	.073
	Based on Median	2.277	3	276	.080
	Based on Median and with adjusted df	2.277	3	255.279	.080
	Based on trimmed mean	2.396	3	276	.068
Timing – Page Submit	Based on Mean	3.685	3	276	.013
	Based on Median	2.107	3	276	.100
	Based on Median and with adjusted df	2.107	3	246.791	.100
	Based on trimmed mean	3.008	3	276	.031
Timing – Page Submit	Based on Mean	2.806	3	276	.040
	Based on Median	1.780	3	276	.151
	Based on Median and with adjusted df	1.780	3	198.593	.152
	Based on trimmed mean	2.320	3	276	.076
Timing – Page Submit	Based on Mean	8.964	3	276	<.001
	Based on Median	6.861	3	276	<.001
	Based on Median and with adjusted df	6.861	3	240.105	<.001
	Based on trimmed mean	8.163	3	276	<.001
Timing – Page Submit	Based on Mean	3.339	3	276	.020
	Based on Median	2.453	3	276	.064
	Based on Median and with adjusted df	2.453	3	235.520	.064
	Based on trimmed mean	2.921	3	276	.034
Timing – Page Submit	Based on Mean	6.437	3	276	<.001
	Based on Median	4.633	3	276	.004
	Based on Median and with adjusted df	4.633	3	211.013	.004
	Based on trimmed mean	5.418	3	276	.001
Timing – Page Submit	Based on Mean	7.656	3	276	<.001
	Based on Median	5.093	3	276	.002

	Based on Median and with adjusted df	5.093	3	203.663	.002
	Based on trimmed mean	6.539	3	276	<.001
Timing – Page Submit	Based on Mean	19.686	3	276	<.001
	Based on Median	10.088	3	276	<.001
	Based on Median and with adjusted df	10.088	3	147.394	<.001
	Based on trimmed mean	16.371	3	276	<.001

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

[a]. Design: Intercept + GRP1 + GPR2 + GRP1 * GPR2

Within Subjects Design: Product

Source: SPSS

Appendix 29: Tests of Within-Subjects Effects for Decision Time

Source		Type III Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
Product	Sphericity Assumed	57060.82	7	8151.55	93.48	<.001	.253
	Greenhouse-Geisser	57060.82	5	11417.41	93.48	<.001	.253
	Huynh-Feldt	57060.82	5.16	11066.33	93.48	<.001	.253
	Lower-bound	57060.82	1	57060.82	93.48	<.001	.253
Product * Time Pressure	Sphericity Assumed	3495.28	7	499.33	5.73	<.001	.020
	Greenhouse-Geisser	3495.28	5	699.38	5.73	<.001	.020
	Huynh-Feldt	3495.28	5.16	677.87	5.73	<.001	.020
	Lower-bound	3495.28	1	3495.28	5.73	.017	.020
Product * Brand Familiarity	Sphericity Assumed	985.29	7	140.76	1.61	.127	.006
	Greenhouse-Geisser	985.29	5	197.15	1.61	.153	.006
	Huynh-Feldt	985.29	5.16	191.09	1.61	.151	.006
	Lower-bound	985.29	1	985.29	1.61	.205	.006
Product * Time Pressure * Brand Familiarity	Sphericity Assumed	898.90	7	128.42	1.47	.172	.005
	Greenhouse-Geisser	898.90	5	179.86	1.47	.196	.005
	Huynh-Feldt	898.90	5.16	174.33	1.47	.194	.005
	Lower-bound	898.90	1	898.90	1.47	.226	.005
Error (Product	Sphericity Assumed	168470.89	1932	87.20			
	Greenhouse-Geisser	168470.89	1379.37	122.14			
	Huynh-Feldt	168470.89	1423.13	118.38			
	Lower-bound	168470.89	276	610.40			

Source: SPSS

Appendix for H2:

Appendix 30: Manipulation of Brand Familiarity

Table 1: Estimates

BF vs. NBF	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
BF	5.486	.085	5.319	5.653
NBF	1.600	.090	1.422	1.778

Table 2: Pairwise Comparison

(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p[b]	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
BF	NBF	3.886*	.124	<.001	3.642	4.130
NBF	BF	-3.886*	.124	<.001	-4.130	-3.642

Based on estimates marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni

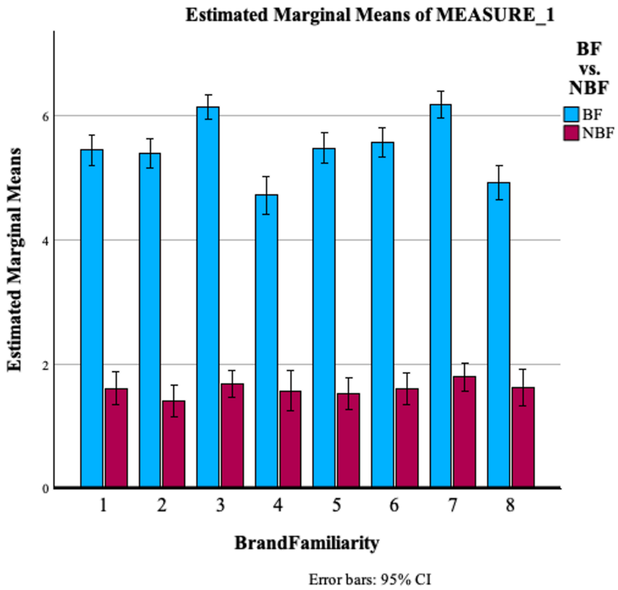
Table 3: Univariate Tests

TP vs. NTP		Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
TP	Contrast	1043.261	1	1043.261	982.051	<.001	.782
	Error	291.078	274	1.062			

The F tests the effect of BF. vs. NBF. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 31: Manipulation of Brand Familiarity per Product (BF vs. NBF * BrandFamiliarity)



Source: SPSS

Appendix 32: Hypothesis Analysis: TP vs. NTP * BF vs. NBF

Table 1: Estimates

				95% Confidence Interval	
TP vs. NTP	BF vs. NBF	Mean	Std. Error	Lower Bound	Upper Bound
TP	BF	19.560	1.004	17.583	21.536
	NBF	21.248	1.075	19.131	23.365
NTP	BF	26.384	1.052	24.312	28.455
	NBF	26.923	1.117	24.724	29.123

Table 2: Pairwise Comparison

						95% Confidence Interval for [a]	
TP vs. NTP	(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p[a]	Lower Bound	Upper Bound
TP	BF	NBF	-1.689	1.471	.252	-4.585	1.208
	NBF	BF	1.689	1.471	.252	-1.208	4.585
NTP	BF	NBF	-.539	1.535	.725	-3.561	2.482
	NBF	BF	.539	1.535	.725	-2.482	3.561

Based on estimates marginal means

*. The mean difference is significant at the .05 level.

a. Adjustment for multiple comparisons: Bonferroni

Table 3: Univariate Tests

TP vs. NTP		Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
TP	Contrast	103.586	1	103.586	1.317	.252	.005
	Error	21703.745	276	78.637			
NTP	Contrast	9.715	1	9.715	.124	.725	.000
	Error	21703.745	276	78.637			

Each F tests the simple effects of TP. vs. NTP within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 33: Assessment Type: TP vs. NTP

Table 1: Estimates

			95% Confidence Interval	
TP vs. NTP	Mean	Std. Error	Lower Bound	Upper Bound
TP	3.028	.138	2.755	3.300
NTP	3.987	.144	3.704	4.270

Table 2: Pairwise Comparison

					95% Confidence Interval	
(I) TP vs. NTP	(J) TP vs. NTP	Mean Difference (I-J)	Std. Error	p[b]	Lower Bound	Upper Bound
TP	NTP	-959*	.200	<.001	-1.352	-.566
NTP	TP	-959*	.200	<.001	.566	1.352

Based on estimates marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni

Table 3: Univariate Tests

	Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
Contrast	63.772	1	63.772	23.081	<.001	.077
Error	759.817	275	2.763			

The F tests the effect of TP. vs. NTP. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 34: Assessment Type: BF vs. NBF

Table 1: Estimates

			95% Confidence Interval	
BF vs. NBF	Mean	Std. Error	Lower Bound	Upper Bound
BF	3.173	.136	2.905	3.441
NBF	3.842	.146	3.555	4.129

Table 2: Pairwise Comparison

					95% Confidence Interval	
(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p[b]	Lower Bound	Upper Bound
BF	NBF	-669*	.200	<.001	-1.062	-.276
NBF	BF	669*	.200	<.001	.276	1.062

Based on estimates marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni

Table 3: Univariate Tests

	Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
Contrast	31.030	1	31.030	11.231	<.001	.039
Error	759.817	275	2.763			

The F tests the effect of BF. vs. NBF. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 35: Assessment Type: TP vs. NTP * BF vs. NBF

Table 1: Estimates

TP vs. NTP	BF vs. NBF	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
TP	BF	2.705	.188	2.335	3.076
	NBF	3.351	.203	2.951	3.751
NTP	BF	3.641	.197	3.252	4.029
	NBF	4.333	.209	3.921	4.746

Table 2: Pairwise Comparison

TP vs. NTP	(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p[b]	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
TP	BF	NBF	-.646	.277	.020	-1.191	-.101
	NBF	BF	.646	.277	.020	.101	1.191
NTP	BF	NBF	-.692	.288	.017	-1.259	-.126
	NBF	BF	.692	.288	.017	.126	1.259

Based on estimates marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni

Table 3: Univariate Tests

TP vs. NTP		Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
TP	Contrast	15.023	1	15.023	5.437	.020	.019
	Error	759.817	275	2.763			
NTP	Contrast	16.007	1	16.007	5.794	.017	.021
	Error	759.817	275	2.763			

Each F tests the simple effects of TP. vs. NTP within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 36: Nutri Score Reliance: TP vs. NTP

Table 1: Estimates

			95% Confidence Interval	
TP vs. NTP	Mean	Std. Error	Lower Bound	Upper Bound
TP	3.898	.152	3.599	4.197
NTP	3.334	.157	3.025	3.643

Table 2: Pairwise Comparison

					95% Confidence Interval	
(I) TP vs. NTP	(J) TP vs. NTP	Mean Difference (I-J)	Std. Error	p[b]	Lower Bound	Upper Bound
TP	NTP	.564*	.218	.010	.135	.994
NTP	TP	-.564*	.218	.010	-.994	-.135

Based on estimates marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni

Table 3: Univariate Tests

	Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
Contrast	22.000	1	22.000	6.689	.010	.024
Error	901.212	274	3.289			

Each F tests the effect of TP vs. NTP. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 37: Nutri Score Reliance: BF vs. NBF

Table 1: Estimates

			95% Confidence Interval	
BF vs. NBF	Mean	Std. Error	Lower Bound	Upper Bound
BF	3.476	.149	3.183	3.769
NBF	3.756	.160	3.441	4.070

Table 2: Pairwise Comparison

					95% Confidence Interval	
(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p[a]	Lower Bound	Upper Bound
BF	NBF	-.280	.218	.201	-.710	.150
NBF	BF	280	.218	.201	-.150	.710

Based on estimates marginal means

[a.] Adjustment for multiple comparisons: Bonferroni

Table 3: Univariate Tests

	Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
Contrast	5.412	1	5.412	1.646	.201	.006
Error	901.212	274	3.289			

The F tests the effect of BF. vs. NBF. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 38: Nutritional Table Reliance: TP vs. NTP * BF vs. NBF

Table 1: Estimates

TP vs. NTP	BF vs. NBF	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
TP	BF	3.604	.222	3.167	4.041
	NBF	4.224	.238	3.755	4.693
NTP	BF	4.303	.231	3.847	4.758
	NBF	5.357	.246	4.874	5.841

Table 2: Pairwise Comparison

TP vs. NTP	(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p[b]	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
TP	BF	NBF	-.620	.326	.058	-1.261	.021
	NBF	BF	.620	.326	.058	-0.21	1.261
NTP	BF	NBF	-1.054*	.337	.002	-1.718	-.390
	NBF	BF	.1.054*	.337	.002	.390	1.718

Based on estimates marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni

Table 3: Univariate Tests

TP vs. NTP		Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
TP	Contrast	13.771	1	13.771	3.625	.058	.013
	Error	1040.764	274	3.798			
NTP	Contrast	37.106	1	37.106	9.769	.001	.034
	Error	1040.764	274	3.798			

Each F tests the simple effects of TP. vs. NTP within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 39: Decision Confidence: BF vs. NBF

Table 1: Estimates

			95% Confidence Interval	
BF vs. NBF	Mean	Std. Error	Lower Bound	Upper Bound
BF	5.801	.082	5.639	5.964
NBF	5.590	.087	5.418	5.762

Table 2: Pairwise Comparison

					95% Confidence Interval	
(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p[a]	Lower Bound	Upper Bound
BF	NBF	.211	.120	.080	-0.25	.448
NBF	BF	-.211	.120	.080	-.448	.025

Based on estimates marginal means

a. Adjustment for multiple comparisons: Bonferroni

Table 3: Univariate Tests

	Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
Contrast	3.090	1	3.090	3.092	.080	.011
Error	273.758	274	.999			

The F tests the effect of BF. vs. NBF. This test is based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 40: Decision Confidene: BF vs. NBF * Confidence

Table 1: Estimates

				95% Confidence Interval	
BF vs. NBF	Confidence	Mean	Std. Error	Lower Bound	Upper Bound
BF	1	5.899	.161	5.583	6.215
	2	5.771	.155	5.465	6.076
	3	5.840	.153	5.539	6.141
	4	5.573	.157	5.263	5.882
	5	5.697	.158	5.387	6.007
	6	5.938	.156	5.632	6.245
	7	6.025	.143	5.744	6.307
	8	5.665	.160	5.350	5.981
NBF	1	5.342	.170	5.007	5.677
	2	5.770	.164	5.447	6.094
	3	5.630	.162	5.311	5.949
	4	5.755	.166	5.427	6.083
	5	5.662	.167	5.334	5.991
	6	5.198	.165	4.873	5.523
	7	5.687	.152	5.388	5.985
	8	5.675	.170	5.341	6.009

Table 2: Pairwise Comparison

						95% Confidence Interval	
Confi-dence	(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p^b	Lower Bound	Upper Bound
1	BF	NBF	.557*	.234	.018	.096	1.018
	NBF	BF	-.557	.234	.018	-1.018	-.096
2	BF	NBF	.000	.226	.999	-.445	-.390
	NBF	BF	.000	.226	.999	-.446	.445
3	BF	NBF	.211	.223	.345	-.228	.649
	NBF	BF	-.211	.223	.345	-.649	.228
4	BF	NBF	-.183	.229	.426	-.633	.268
	NBF	BF	.183	.229	.426	-.268	.633
5	BF	NBF	.035	.229	.880	-.417	.486
	NBF	BF	-.035	.229	.880	-.486	.417
6	BF	NBF	741*	.227	.001	.294	1.188
	NBF	BF	-.741*	.227	.001	-1.188	-.294
7	BF	NBF	.339	.208	.105	-.072	.749
	NBF	BF	-.339	.208	.105	-.749	.072
8	BF	NBF	-.009	.233	.968	-.469	.450
	NBF	BF	.009	.233	.968	-.450	.469

Based on estimates marginal means.

Table 3: Univariate Tests

Confidence		Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
1	Contrast	21.465	1	21.465	5.662	.018	.020
	Error	1038.661	274	3.791			
2	Contrast	1.243E-5	1	1.243E-5	.000	.999	.000
	Error	969.375	274	3.538			
3	Contrast	3.074	1	3.074	.895	.345	.003
	Error	941.057	274	3.435			
4	Contrast	2.306	1	2.306	.636	.426	.002
	Error	993.431	274	3.626			
5	Contrast	.083	1	.083	.023	.880	.000
	Error	998.169	274	3.643			
6	Contrast	37.972	1	37.972	10.647	.001	.037
	Error	977.208	274	3.566			
7	Contrast	7.943	1	7.943	2.643	.105	.010
	Error	823.585	274	3.006			
8	Contrast	.006	1	.006	.002	.968	.000
	Error	1031.645	274	3.765			

Each F tests the simple effects of BF. vs. NBF within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 41: Decision Confidence: TP vs. NTP * Confidence

Table 1: Estimates

				95% Confidence Interval	
TP vs. NTP	Confidence	Mean	Std. Error	Lower Bound	Upper Bound
TP	1	5.625	.162	5.305	5.945
	2	5.947	.157	5.638	6.256
	3	5.835	.155	5.530	6.139
	4	5.755	.159	5.442	6.068
	5	5.754	.159	5.441	6.068
	6	5.584	.158	5.274	5.894
	7	6.087	.145	5.802	6.372
	8	5.647	.162	5.328	5.966
NTP	1	5.616	.168	5.284	5.947
	2	5.595	.163	5.274	5.915
	3	5.635	.160	5.319	5.951
	4	5.573	.165	5.248	5.897
	5	5.605	.165	5.280	5.930
	6	5.552	.163	5.230	5.874
	7	5.625	.150	5.330	5.921
	8	5.693	.168	5.363	6.024

Table 2: Pairwise Comparison

Confi-dence	(I) TP vs. NTP	(J) TP vs. NPT	Mean Difference (I-J)	Std. Error	p^b	95% Confidence Interval Lower Bound	Upper Bound
1	TP	NTP	.010	.234	.967	-.451	.471
	NTP	TP	-0.10	.234	.967	-.471	.451
2	TP	NTP	.352	.226	.121	-.093	.797
	NTP	TP	-.352	.226	.121	-.797	0.93
3	TP	NTP	.200	.223	.371	-.239	.638
	NTP	TP	-.200	.223	.371	-.638	.239
4	TP	NTP	.182	.229	.426	-.268	.633
	NTP	TP	-.182	.229	.426	-.633	.268
5	TP	NTP	.149	.229	.517	-.303	.601
	NTP	TP	-.149	.229	.517	.601	.303
6	TP	NTP	.032	.227	.888	-.415	.479
	NTP	TP	-.032	.227	.888	-.479	.415
7	TP	NTP	.461	.208	.028	.051	.872
	NTP	TP	-.461	.208	.028	.872	-.051
8	TP	NTP	-.046	.233	.843	-.505	.413
	NTP	TP	.046	.233	.843	-.413	. 505

Based on estimates marginal means.

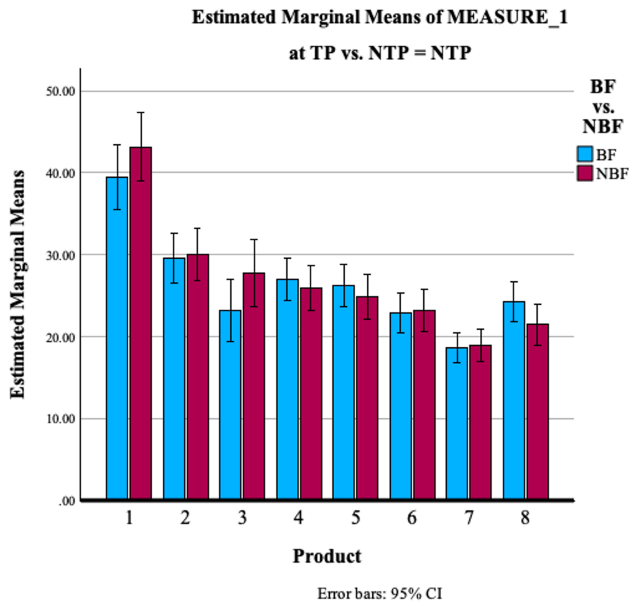
Table 3: Univariate Tests

Confidence		Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
1	Contrast	.007	1	.007	.002	.967	.000
	Error	1038.661	274	3.791			
2	Contrast	8.567	1	8.567	2.422	.121	.009
	Error	969.375	274	3.538			
3	Contrast	2.756	1	2.756	.803	.371	.009
	Error	941.057	274	3.435			
4	Contrast	2.301	1	2.301	.635	.426	.002
	Error	993.431	274	3.626			
5	Contrast	1.535	1	1.535	.421	.517	.002
	Error	998.169	274	3.643			
6	Contrast	.070	1	.070	.020	.888	.000
	Error	977.208	274	3.566			
7	Contrast	14.719	1	14.719	4.897	.028	.018
	Error	823.585	274	3.006			
8	Contrast	.148	1	.148	.039	.843	.000
	Error	1031.645	274	3.765			

Each F tests the simple effects of TP. vs. NTP within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

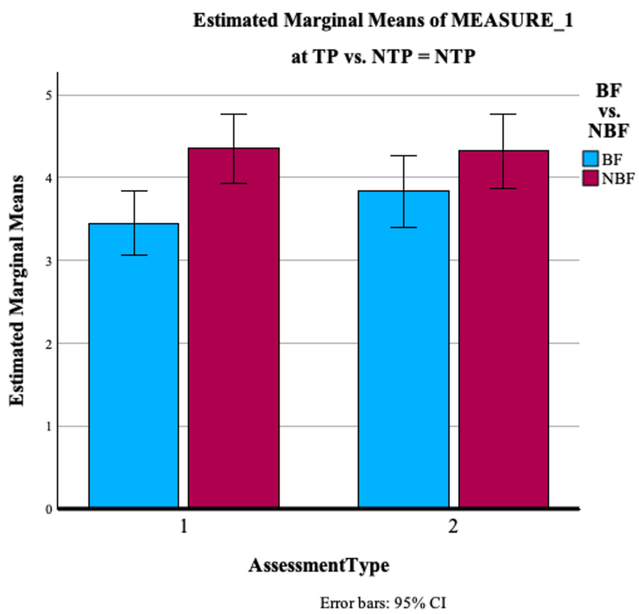
Source: SPSS

Appendix 42: Comparison of Estimated Marginal Means of Decision Time for BF and NBF in NTP-Condition Across Eight Products



Source: SPSS

Appendix 43: Comparison of Estimated Marginal Means of AssessmentType for BF and NBF in NTP-Condition for Non-Contradicting (= 1) and Contradicting (= 2) Products



Source: SPSS

Appendix 44: Decision Confidence: BF vs. NBF * Confidence

Table 1: Estimates

BF vs. NBF	Confidence	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
BF	1	5.899	.161	5.583	6.215
	2	5.771	.155	5.465	6.076
	3	5.840	.153	5.539	6.141
	4	5.573	.157	5.263	5.882
	5	5.697	.158	5.387	6.007
	6	5.938	.156	5.632	6.245
	7	6.025	.143	5.744	6.307
	8	5.665	.160	5.350	5.981
NBF	1	5.342	.170	5.007	5.677
	2	5.770	.164	5.447	6.094
	3	5.630	.162	5.311	5.949
	4	5.755	.166	5.427	6.083
	5	5.662	.167	5.334	5.991
	6	5.198	.165	4.873	5.523
	7	5.687	.152	5.388	5.985
	8	5.675	.170	5.341	6.009

Table 2: Pairwise Comparison

Confi-dence	(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p^b	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	BF	NBF	.557*	.234	.018	.096	1.018
	NBF	BF	-.557*	.234	.018	-1.018	.096
2	BF	NBF	.000	.226	.999	-.445	.446
	NBF	BF	.000	.226	.999	-.446	.445
3	BF	NBF	.211	.223	.345	-.228	.649
	NBF	BF	-.211	.223	.345	-.649	.228
4	BF	NBF	-.183	.229	.426	-.633	.268
	NBF	BF	.183	.229	.426	-.268	.633
5	BF	NBF	.035	.229	.880	-.417	.486
	NBF	BF	-.035	.229	.880	-.486	.417
6	BF	NBF	.741*	.227	.001	.294	1.188
	NBF	BF	-.741*	.227	.001	-1.188	-.294
7	BF	NBF	.339	.208	.105	-.072	.749
	NBF	BF	-.339	.208	.105	-.749	.072
8	BF	NBF	-.009	.233	.968	-.469	.450
	NBF	BF	.009	.233	.968	-.450	. 469

Based on estimates marginal means.

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni

Table 3: Univariate Tests

Confidence		Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
1	Contrast	21.465	1	21.465	5.662	.018	.020
	Error	1038.661	274	3.791			
2	Contrast	1.243E-5	1	1.243E-5	.000	.999	.000
	Error	969.375	274	3.538			
3	Contrast	3.074	1	3.074	.895	.345	.003
	Error	941.057	274	3.435			
4	Contrast	2.306	1	2.306	.636	.426	.002
	Error	993.431	274	3.626			
5	Contrast	.083	1	.083	.023	.880	.000
	Error	998.169	274	3.643			
6	Contrast	37.972	1	37.972	10.647	.001	.037
	Error	977.208	274	3.566			
7	Contrast	7.943	1	7.943	2.643	.105	.010
	Error	823.585	274	3.006			
8	Contrast	.006	1	.006	.002	.968	.000
	Error	1031.645	274	3.765			

Each F tests the simple effects of TP. vs. NTP within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 45: Health Perception: BF vs. NBF * HealthPercept

Table 1: Estimates

BF vs. NBF	HealthPercept	Mean	Std. Error	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
BF	1	4.384	.125	4.138	4.630
	2	3.045	.144	2.761	3.329
	3	2.053	.103	1.850	2.256
	4	4.895	.136	4.627	5.163
	5	4.372	.121	4.133	4.611
	6	3.174	.149	2.881	3.467
	7	1.848	.101	2.649	2.048
	8	5.085	.129	4.831	5.338
NBF	1	4.209	.133	3.947	4.472
	2	2.634	.154	2.331	2.937
	3	1.827	.110	1.610	2.043
	4	4.835	.145	4.550	5.121
	5	4.451	.129	4.196	4.705
	6	3.009	.159	2.697	3.322
	7	1.942	.108	2.155	2.155
	8	4.882	.137	4.611	5.152

Table 2: Pairwise Comparison

Health-Percept	(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p[b]	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
1	BF	NBF	.175	.183	.340	-.185	.534
	NBF	BF	-.175	.183	.340	-.534	.185
2	BF	NBF	.411	.211	.053	-.005	.826
	NBF	BF	-.411	.211	.053	-.826	.005
3	BF	NBF	.227	.151	.133	-.070	.523
	NBF	BF	-.227	.151	.133	-.523	.070
4	BF	NBF	-.060	.199	.764	-.332	.451
	NBF	BF	.060	.199	.764	-.451	.332
5	BF	NBF	-.078	.177	.659	-.427	.271
	NBF	BF	.078	.177	.659	-.271	.427
6	BF	NBF	.164	.218	.451	-.264	.593
	NBF	BF	-.164	.218	.451	-.593	.264
7	BF	NBF	-.094	.148	.527	-.386	.198
	NBF	BF	.094	.148	.527	-.198	.386
8	BF	NBF	.203	.188	.282	-.168	.574
	NBF	BF	-.203	.188	.282	-.574	.168

Based on estimates marginal means.

a. Adjustment for multiple comparisons: Bonferroni.

Table 3: Univariate Tests

HealthPercept		Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
1	Contrast	2.119	1	2.119	.914	.340	.003
	Error	640.119	276	2.319			
2	Contrast	11.729	1	11.729	3.787	.053	.014
	Error	854.763	276	3.097			
3	Contrast	3.573	1	3.573	2.267	.133	.008
	Error	435.145	276	1.577			
4	Contrast	.248	1	.248	.090	.764	.000
	Error	759.580	276	2.572			
5	Contrast	.426	1	.426	.195	.659	.001
	Error	603.550	276	2.187			
6	Contrast	1.878	1	1.878	.570	.451	.002
	Error	909.583	276	3.296			
7	Contrast	.641	1	.614	.402	.527	.001
	Error	421.872	276	1.529			
8	Contrast	2.867	1	2.867	1.160	.282	.004
	Error	681.846	276	2.470			

Each F tests the simple effects of BF. vs. NBF within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 46: Purchase Likelihood: BF vs. NBF * PurchaseIntention

Table 1: Estimates

				95% Confidence Interval	
BF vs. NBF	PurchaseIntention	Mean	Std. Error	Lower Bound	Upper Bound
BF	1	4.015	.152	3.715	4.315
	2	2.759	.153	2.458	3.060
	3	1.742	.100	1.545	1.939
	4	4.842	.148	4.552	5.133
	5	4.077	.142	3.797	4.356
	6	2.912	.152	2.612	3.211
	7	1.595	.097	1.404	1.787
	8	4.914	.146	4.626	5.202
NBF	1	3.846	.162	3.527	4.165
	2	2.507	.163	2.187	2.827
	3	1.602	.106	1.392	1.811
	4	4.636	.157	4.327	4.944
	5	4.291	.151	3.994	4.587
	6	2.634	.162	2.315	2.952
	7	1.836	.104	1.632	2.039
	8	4.759	.156	4.453	5.065

Table 2: Pairwise Comparison

						95% Confidence Interval	
Confi-dence	(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p^b	Lower Bound	Upper Bound
1	BF	NBF	.169	.222	.448	-.269	.607
	NBF	BF	-.169	.222	.448	-.607	.269
2	BF	NBF	.252	.223	.260	-.187	-.691
	NBF	BF	-.252	.223	.260	-.691	.187
3	BF	NBF	.141	.146	.336	-.147	.428
	NBF	BF	-.141	.146	.336	-.428	.147
4	BF	NBF	-.207	.215	.338	-.217	.630
	NBF	BF	.207	.215	.338	-.630	.217
5	BF	NBF	-.214	.207	.302	-.621	.194
	NBF	BF	.214	.207	.302	-.194	.621
6	BF	NBF	.278	.222	.212	-.159	.715
	NBF	BF	-.278	.222	.212	-.715	.159
7	BF	NBF	-.240	.142	.092	-.520	.040
	NBF	BF	.240	.142	.092	-.040	.520
8	BF	NBF	.154	.214	.470	-.266	.575
	NBF	BF	-.154	.214	.470	-.575	.266

Based on estimates marginal means.

a. Adjustment for multiple comparisons: Bonferroni.

Table 3: Univariate Tests

Confidence		Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
1	Contrast	1.963	1	2.963	.577	.448	.002
	Error	928.678	273	3.402			
2	Contrast	4.371	1	4.371	1.275	.260	.005
	Error	935.571	273	3.427			
3	Contrast	1.363	1	1.363	.928	.336	.003
	Error	400.815	273	1.468			
4	Contrast	2.936	1	2.936	.920	.338	.003
	Error	871.242	273	3.191			
5	Contrast	3.151	1	3.151	1.068	.302	.004
	Error	805.215	273	2.950			
6	Contrast	5.317	1	5.317	1.567	.212	.006
	Error	926.020	273	3.392			
7	Contrast	3.971	1	3.971	2.854	.092	.010
	Error	379.782	273	1.391			
8	Contrast	1.641	1	1.641	.523	.470	.002
	Error	856.862	273	3.139			

Each F tests the simple effects of BF. vs. NBF within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

Source: SPSS

Appendix 47: Decision Confidence: TP vs. NTP * BF vs. NBF * Confidence

Table 1: Estimates

					95% Confidence Interval	
TP vs. NTP	BF vs. NBF	Confidence	Mean	Std. Error	Lower Bound	Upper Bound
TP	BF	1	5.868	.223	5.429	6.308
		2	5.908	.216	5.483	6.333
		3	5.934	.213	5.516	6.353
		4	5.539	.218	5.109	5.969
		5	5.803	.219	5.372	6.234
		6	5.947	.217	5.521	6.374
		7	6.276	.199	5.885	6.668
		8	5.500	.223	5.062	5.938
	NBF	1	5.382	.236	4.918	5.847
		2	5.985	.228	5.536	6.434
		3	5.735	.225	5.293	6.178
		4	5.971	.231	5.516	6.425
		5	5.706	.231	5.250	6.162
		6	5.221	.229	4.770	5.671
		7	5.897	.210	5.483	6.311
		8	5.794	.235	5.331	6.257
NTP	BF	1	5.930	.231	5.475	6.384
		2	5.634	.223	5.194	6.073
		3	5.746	.220	5.313	6.179
		4	5.606	.226	5.161	6.051
		5	5.592	.227	5.146	6.037
		6	5.930	.224	5.488	6.371
		7	5.775	.206	5.370	6.180
		8	5.831	.230	5.378	6.284
	NBF	1	5.302	.245	4.819	5.784
		2	5.556	.237	5.089	6.022
		3	5.524	.223	5.064	5.983
		4	5.540	.240	5.067	6.012
		5	5.619	.240	5.146	6.092
		6	5.175	.238	4.706	5.643
		7	5.476	.218	5.046	5.906
		8	5.556	.244	5.074	6.037

Group Part

Table 2: Pairwise Comparison

TP vs. NTP	Confidence	(I) BF vs. NBF	(J) BF vs. NBF	Mean Difference (I-J)	Std. Error	p[b]	95% Confidence Interval Lower Bound	Upper Bound
TP	1	BF	NBF	.486	.325	.136	-.154	1.126
		NBF	BF	-.486	.325	.136	-1.126	.154
	2	BF	NBF	-.077	.314	.805	-.696	.541
		NBF	BF	.077	.314	.805	-.541	.696
	3	BF	NBF	.199	.309	.521	-.410	.808
		NBF	BF	-.199	.309	.521	-.808	.410
	4	BF	NBF	-.431	.318	.176	-1.057	.195
		NBF	BF	.431	.318	.176	-.195	1.057
	5	BF	NBF	.097	.319	.762	-.530	.724
		NBF	BF	-.097	.319	.762	-.724	.530
	6	BF	NBF	.727*	.315	.022	.106	1.347
		NBF	BF	-.727*	.315	.022	-1.347	-.106
	7	BF	NBF	.379	.289	.191	-.190	.949
		NBF	BF	-.379	.289	.191	-.949	.190
	8	BF	NBF	-.294	.324	.365	-.932	.344
		NBF	BF	.294	.324	.365	-.344	.932
NTP	1	BF	NBF	.628	.337	.063	-.035	1.291
		NBF	BF	-.628	.337	.063	-1.291	.035
	2	BF	NBF	.078	.326	.810	-.563	.719
		NBF	BF	-.078	.326	.810	-.719	.563
	3	BF	NBF	.223	.321	.488	-.409	.854
		NBF	BF	-.223	.321	.488	-.854	.409
	4	BF	NBF	.066	.330	.842	-.583	.715
		NBF	BF	-.066	.330	.842	-.715	.583
	5	BF	NBF	-.027	.330	.934	-.678	.623
		NBF	BF	.027	.330	.934	-.623	.678
	6	BF	NBF	.755*	.327	.022	.111	1.398
		NBF	BF	-.755*	.327	.022	-1.398	-.111
	7	BF	NBF	.298	.300	.321	-.292	.889
		NBF	BF	-.298	.300	.321	-.889	.292
	8	BF	NBF	.275	.336	.413	-.386	.937
		NBF	BF	-.275	.336	.413	-.937	.386

Based on estimates marginal means.

*. The mean difference is significant at the .05 level.

[b]. Adjustment for multiple comparisons: Bonferroni.

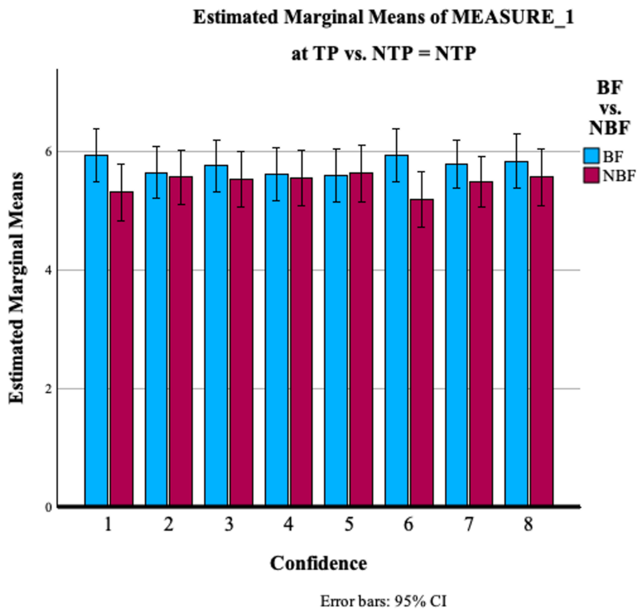
Table 3: Univariate Tests

TP vs. NTP	Confi-dence		Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
TP	1	Contrast	8.479	1	8.479	2.237	.136	.008
		Error	1038.661	274	3.791			
	2	Contrast	.215	1	.215	.061	.805	.002
		Error	969.375	274	3.538			
	3	Contrast	1.420	1	1.420	.413	.521	.007
		Error	941.057	274	3.435			
	4	Contrast	6.670	1	6.670	1.840	.176	.000
		Error	993.431	274	3.626			
	5	Contrast	.336	1	.336	.092	.762	.019
		Error	998.169	274	3.643			
	6	Contrast	18.957	1	18.957	5.315	.022	.006
		Error	977.208	274	3.566			
	7	Contrast	5.162	1	5.162	1,717	.191	.003
		Error	823.585	274	3.006			
	8	Contrast	3.105	1	3.105	.825	.365	.013
		Error	1031.645	274	3.765			
NTP	1	Contrast	13.164	1	13.164	3.473	.063	.013
		Error	1038.661	274	3.791			
	2	Contrast	.204	1	.204	.058	.810	.000
		Error	969.375	274	3.538			
	3	Contrast	1.655	1	1.655	.482	.488	.002
		Error	941.057	274	3.435			
	4	Contrast	.145	1	.145	.040	.842	.000
		Error	993.431	274	3.626			
	5	Contrast	.025	1	.025	.007	.934	.000
		Error	998.169	274	3.643			
	6	Contrast	19.026	1	19.026	5.335	.022	.019
		Error	977.208	274	3.566			
	7	Contrast	2.973	1	2.973	.989	.321	.004
		Error	823.585	274	3.006			
	8	Contrast	2.532	1	2.532	.673	.413	.002
		Error	1031.645	274	3.765			

Each F tests the simple effects of TP. vs. NTP within each level combination of the other effects shown. These tests are based on the linearly independent pairwise comparisons among the estimated marginal means.

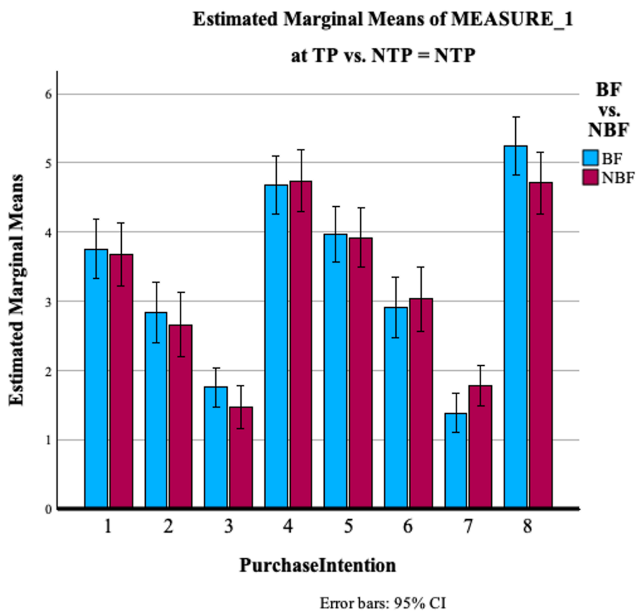
Source: SPSS

Appendix 48: Comparison of Estimated Marginal Means of Judgement Confidence for BF and NBF in NTP-Condition Across Eight Products



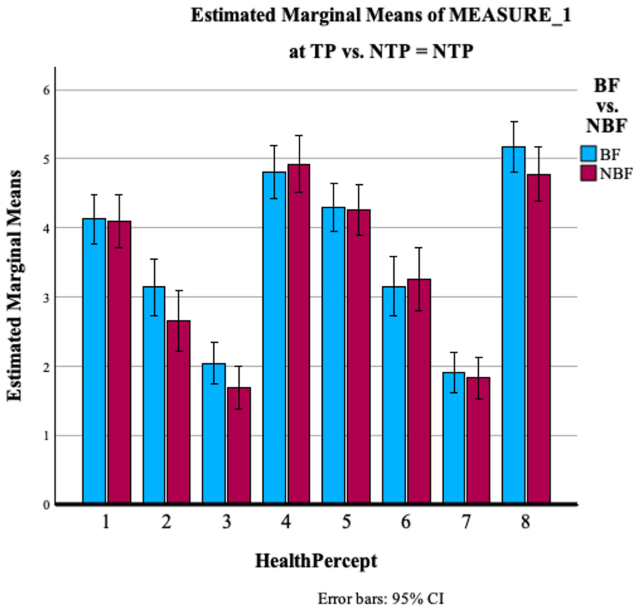
Source: SPSS

Appendix 49: Comparison of Estimated Marginal Means of Purchase Intention for BF and NBF in NTP-Condition Across Eight Products



Source: SPSS

Appendix 50: Comparison of Estimated Marginal Means of Healthiness Perception for BF and NBF in NTP-Condition Across Eight Products



Source: SPSS

Disclaimer: Use of Artificial Intelligence (AI)

In the preparation of this thesis, the AI tool ChatGPT by OpenAI was used to generate product pictures, ensuring the condition of low brand familiarity in our research study. Additionally, ChatGPT by OpenAI was employed to improve the readability and language of this work project. All generated content was carefully reviewed to ensure its accuracy and alignment with academic standards and the Nova SBE guidelines.

The responsibility for the content of this thesis, including the interpretation of results and conclusions, rests entirely with the four authors. The use of AI adhered to the ethical and academic standards of Nova SBE.