Exploring decision processes behind food choices: An eye tracking approach

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The candidate confirms that the work submitted is her own, except where work which has formed part of jointly-authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

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I developed the study concept together with Jacob Lund Orquin. I prepared the experimental stimuli and performed the data collection. I performed the data analysis and interpretation of results under the supervision of Jacob Lund Orquin.

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Abstract

This doctoral dissertation makes a twofold contribution to the understanding of psychological processes behind food choice. First, it explores whether cognitive shortcuts, known as heuristics, based on seemingly irrational beliefs can lead to rational behaviours when applied in the right context. One such heuristic, the *organic = healthful heuristic*, is explored. It is the belief that organic products are more healthful than conventional products. There is no conclusive evidence supporting this belief, also known as the *halo effect*, where positive attitudes towards organic products transfer to beliefs about specific properties such as healthfulness. Here I propose *statistical learning* as an alternative explanation to the halo effect, and test this in three studies. Study 1 shows that food products from healthful food categories are more likely to be organic. Study 2 shows that consumer perceptions of the healthfulness and the number of organic products across food categories are accurate. Study 3 shows that consumers perceive organic products as more healthful when the statistical structure justifies this inference. These findings show that consumers correctly use organic products as a cue for healthfulness because they are, on average, 30% more healthful than conventional products. Second, this doctoral dissertation develops a new information search measure which complements existing measures to better describe consumer search processes. One area, which is currently not covered by existing measures, is when information search consists of equal amounts of attribute- and alternative-wise search sequences. I propose a new measure, *the Systematicity of Search Index* (*SSI*), which explores information search in terms of systematicity or the proportion of non-random search. Study 4 demonstrates the usefulness of the measure and shows that the SSI can shed light on processes not captured by the existing measures for analysing information search.

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Chapter 1

Introduction

1.1 Importance of understanding food choice

The motivation for this doctoral dissertation has been to understand how consumers make food choices so that we can help them to make better decisions. To do this, we first need to have a theoretical understanding of what consumers do when making food choices. The importance of understanding how consumers make food choices is underlined by a range of different social issues. Three issues were central to this thesis: growing obesity rates, growing food waste rates, and issues regarding food safety. In the following paragraphs, I will discuss each of these three issues in more detail, and the reasons why they were central to the thesis.

First, understanding why obesity rates continue to rise is one of the main reasons for studying food choice. Studies predict that one fifth of adults worldwide will be obese by 2025, with the citizens of the United Kingdom (UK) expected to be the most obese population in Europe by the same date (National Health Service, 2016a). It is well known that obesity increases the risks of developing Type 2 diabetes, coronary heart disease, stroke and specific types of cancer such as breast and bowel cancer (National Health Service, 2016b). By understanding how consumers make food choices, we can help them make more healthful choices with regards to the causes of obesity.

Second, growing food waste rates also contribute to the need for better understanding of food choice. Statistics show that approximately one third of the food produced globally, (i.e. 1.3 billion tonnes), on a yearly basis gets wasted which amounts to approximately US$ 680 billion in industrialized and US$ 310 billion in developing countries (Food and Agriculture Organization of the United Nations, 2017). In the UK, the estimated amount of household food waste for 2015 was 7.3 million tonnes, which is an increase of 4.3% on 7.0 million tonnes of food waste produced in 2012. Of these 7.3 million tonnes, the amount of the food waste that could have been avoided, i.e. the food that was edible at some point before it was thrown away, was 4.4 million tonnes, compared to 4.2 million tonnes in 2012, which is an increase of 4.8%. The retail value of the avoidable food waste was around £13 billion, and this was associated with 19 million tonnes of CO_2, which is the same as the emissions produced by one in four cars on UK roads (Waste Resources Action Programme, 2017). It is therefore important to understand how consumers make food choices, to reduce the amount of avoidable food waste and hence reduce these negative effects on the environment.

Third, it is also becoming more important to understand consumer decisions when it comes to food safety. In the last few decades, food safety received more attention due to the emergence of various ‘food scares’ such as bovine spongiform encephalopathy (BSE) in beef, the Belgian dioxin scandal, salmonella outbreaks and the horsemeat scandal, to name just a few. Consequently, every year in the world, almost one in 10 consumers gets ill from eating contaminated food, which results in 420,000 deaths. Furthermore, almost 125,000 children under the age of five, die every year from foodborne diseases which makes this group particularly vulnerable, and amounts to 30% of all deaths (World Health Organization, 2015). In the UK, there are more than 500,000 cases of food poisoning every year, which result in approximately 500 deaths (Food Standards Agency, 2014). These figures are very high, and might be reduced by a better understanding of how consumers make decisions related to food safety, so as to improve education to help people to make better decisions.

In sum, the previously presented issues are mutually intertwined. For instance, inappropriate communication regarding food safety warnings can cause unnecessary anxiety and therefore increase food waste and/or undermine healthful food choices (Bown, Kaptan, & Preston, 2015). On the other hand, changing consumers’ negative perceptions about frozen food, such as frozen vegetables, could have a positive effect on decreasing obesity rates and food waste, as well as improving food safety (Kaptan, Bown, Piper, & Bruine de Bruin, 2016). It is evident that the advancement of understanding of food choice has multiple positive implications for both consumers and the environment. Relevant findings could be implemented through more effective public policies, adaptations in the environments in which we make food choices, such as supermarkets and restaurants, so that we are encouraged to make more healthful and safer choices with minimal food waste. To conclude, enhancing the understanding of food choice should be of special interest for researchers in various domains. However, as I show in the following section, this is not an easy task, because food choice is a very complex matter.

In the remainder of this chapter, I discuss first the factors that contribute to the complexity of food choice. Then, I discuss the idea that consumers deal with this complexity using simple cognitive shortcuts. I continue by focusing more closely on consumer decision processes, with a specific focus on consumer information search. Finally, I give an outline of the doctoral dissertation chapters.

1.2 The complexity of food choice

Food choice is an essential, yet very complex, task. It includes five main types of determinant: namely psychological determinants such as beliefs, habits, values, mood and past experiences with food; social determinants such as family, peers and wider society; economic determinants such as cost and income; biological determinants such as hunger, appetite and taste, and finally, cultural determinants such as the culture in which we are brought up (Bisogni, Connors, Devine, & Sobal, 2002; Rozin, 2006). There are also various decision processes behind each food choice, which could be classified as either general or specific. Broadly speaking, general processes include processes such as what to eat, where, when, why and with whom (Köster, 2009). More specific processes include processes such as whether eating will be done in parallel to another activity such as eating and reading a magazine; goals we want to achieve such as eating more vegetables; current physical condition such as being hungry or tired, and recurrent or habitual events such as morning coffee (Bisogni et al., 2007).

In addition to the matters described above, the abundance of food related information we are faced with today (Schwartz, 2004), contributes to the complexity of an already complex task. Statistics show that between 1975 and 2008 the number of products in the average supermarket increased from approximately 8,950 to almost 47,000. What is more, the number of product varieties has been increasing within each product category and so consumers are nowadays faced with a challenge to choose between a great amount of very similar products (Consumer Reports, 2014). For instance, the UK's largest grocery retailer Tesco (Department for Environment, Food & Rural Affairs, 2015) stocks up to 90,000 products with, for instance, 283 types of coffee, 98 type of rice or 28 types of tomato ketchup (theguardian, 2015). At the same time, there has been an increase in the amount of information legally required on labels as well as an increase in the amount of information voluntarily provided by manufacturers (Food Standards Agency, 2008). This wealth of information and alternatives to choose from has been termed as *the tyranny of choice* (Schwartz, 2000) or *choice overload* (Iyengar & Lepper, 2000) and refers to a decreased motivation to make a choice, weaker preference strength and decreased choice satisfaction, as well as stronger negative emotions, such as disappointment and regret. However, a recent meta-analysis (Scheibehenne, Greifeneder, & Todd, 2010) has shown that the average 'effect size' of choice overload was around zero, with large variance between studies which was not explained by the number of product alternatives participants were presented with. Put differently, consumers seem to be unaffected by the growing number of product alternatives in the supermarkets after all.

In a different study, conducted by Wansink and Sobal (2007), it has been shown that consumers are often unaware of just how complex food choices really are, and this is reflected in their underestimating of the number of food and beverage related decisions made daily. More specifically, Wansink and Sobal found that when asked to estimate how many food and beverage related decisions they make daily, participants gave an estimation of an average of 14.4 decisions. However, when asked several specific questions regarding what they ate, when, where, how much and so on, the number increased to an average of 226.7 decisions. A great difference between these two numbers was attributed to the fact that participants did not label something as a food or beverage related decision unless it was an actual choice. Put differently, they did not classify merely thinking about buying a product as a food and beverage related decision because it did not result in an actual purchase of that product. Nevertheless, when focusing solely on the number of decisions which resulted in an actual purchase, Wansink and Sobal found that participants on average made 59 food and beverage related decisions, which is still four times higher than the initially estimated 14.4 decisions.

In sum, there are probably a few potential explanations why consumers may not be perplexed by the complexity of food choice as a process. Since time is a limited resource, and choice contexts are evidently becoming more complex, one reason could be attributed to the use of cognitive shortcuts to simplify the choice process. This assumption is discussed in more detail in the following section.

1.3 Simple heuristics behind food choices

The dominant assumption in research on food decision making is that consumers are rational decision makers. Specifically, they sample all available information, weight them considering their subjective preferences, and then combine these into an overall evaluation (e.g. Dennison & Shepherd, 1995; Rappoport, Peters, Downey, McCann, & Huff-Corzine, 1993). Yet, another stream of research shows that consumers often respond to complex tasks, such as food choice, using simplifying strategies called *heuristics* (Gigerenzer, Todd, & the ABC Research Group, 1999; Payne, Bettman, & Johnson, 1993; Simon, 1957; Tversky & Kahneman, 1974). Heuristics are defined as cognitive shortcuts that enable people to make decisions based on only a few important pieces of information. Winter Falk, Bisogni and Sobal (1996) identified several such heuristics which can be used in the context of food choice, namely focusing on one attribute such as the healthiest food product; routinization such as eating the same breakfast every day; elimination such as cutting sweets out of diet; limitation such as limiting the intake of coffee per day; substitution such as eating dark bread instead of white bread; addition such as eating a salad with every lunch, and modification such as removing fat from meats.

However, it has also been shown that relying on some heuristics, such as focusing on one attribute when making food choices, can sometimes lead to systematic biases and inferior choices (Tversky & Kahneman, 1974). In the context of food choice, this has been especially studied in the case of various food labels, such as low-fat, organic, fair trade and so on, which have been perceived as having better nutritional content and therefore lead to the increased intake of food products that bear these labels (Chandon & Wansink, 2007; Lee, Shimizu, Kniffin, & Wansink, 2013; Schuldt, Muller, & Schwarz, 2012; Wansink & Chandon, 2006). These effects have so far been explained with a cognitive bias called *halo effect* (Thorndike, 1920). The halo effect in the food context refers to a belief that global evaluations of a food product may alter evaluations of specific food product attributes when there is sufficient information for an independent assessment. This happens, for instance, when an individual can assess the nutritional content of a food product by assessing the nutritional table on the back of the product, but instead, relies on a food label on the front of the package and makes an assessment based on this single piece of information.

Even though the previously mentioned studies suggest that consumers may be misled by a halo effect, I speculate that there could be more to these beliefs than motivated reasoning. More specifically, if one considers the environment in which these beliefs about food products occur, these inferences could be justified if the environment is structured in such a way that encourages the formation of these beliefs. This notion has been termed as *ecological rationality* and refers to the match between the mind and the environment (Todd & Gigerenzer, 2007; Todd, Gigerenzer, & the ABC Research Group, 2012). Accordingly, the first research question I aim to address in this doctoral dissertation is: *can irrational beliefs sometimes lead to rational behaviours when making food choices?*

This research question is studied in the context of organic food products, i.e. products produced with a minimal use of pesticides, fertilizers, soil conditioners etc. (EUR-Lex, 2007). There are two reasons why I chose these specific products. First, the Research Institute of Organic Agriculture (FiBL) and International Federation of Organic Agricultural Movements' (IFOAM) report shows a continuous growth in the global market for organic food products which should continue in the following years (Willer & Lernoud, 2017). This suggests there is a growing interest in organic food products.

Second, there is an ongoing debate regarding the advantages of organic versus conventional food production which has ramifications for nature, agriculture, business, and consumers alike. More specifically, research shows that organic food production is likely more environmentally sustainable (Bahlai, Xue, McCreary, Schaafsma, & Hallett, 2010; Crowder, Northfield, Strand, & Snyder, 2010) but, as previously shown, many consumers also believe that organic food products are more healthful than their conventional counterparts (Lee et al., 2013). Superior health attributes would be an important argument for organic production, but, so far, evidence supporting this claim is mixed, at best (Barański et al., 2014; Dangour et al., 2009; Smith-Spangler et al., 2012). It is beyond the scope of this doctoral dissertation to determine whether there are nutritional composition differences between organic and conventional food products in favour of organic food products. However, the aim is to explore whether organic food products could be in some way more healthful than conventional food products, by being more prevalent in less processed food product categories. If this would be so, then this currently irrational belief, i.e. organic food products being more healthful, would no longer be irrational and therefore could result in rational behaviour, i.e. buying more organic food products. I explore these speculations in three studies, the findings of which are reported in Chapter 3.

1.4 Information search processes behind food choices

Traditional economic approach to decision making focuses on what decisions are made, rather than how they are made (Payne & Venkatraman, 2011). However, it has been repeatedly pointed out that human decision making cannot be understood by merely observing final outcomes (Berg & Gigerenzer, 2010; Einhorn & Hogarth, 1981; Payne & Venkatraman, 2011; Svenson, 1979). Payne and Venkatraman (2011) have nicely summarised the previous findings from decision research revealing why this is so, i.e. why it is advantageous to focus also on the processes and not just the outcomes.

First, decisions are extremely susceptible to apparently small changes to decision tasks and contexts. For instance, numerous studies have found that increasing task complexity induces the use of strategies that employ less information (Payne, 1976; Swait & Adamowicz, 2001); that the format of information presentation strongly influences how we search for information (Bettman & Kakkar, 1977); and that, in general, people use various decision strategies in different situations as an adaptive response to the demands of the task (Payne, Bettman, & Johnson, 1993).

Second, it is clear by now that there are differences between individuals in how they make decisions when presented with the same decision task. There are therefore many measures used to study these differences. Appelt, Milch, Handgraaf and Weber (2011) have proposed the following classification of measures used to study individual differences in decision research: decision-making measures, risk attitude measures, cognitive ability measures, motivation measures, personality inventories, personality construct measures, and miscellaneous measures. However, Payne and Venkatraman (2011) argue that to better understand these differences between individuals, one should focus not only on the outcomes, but the processes as well. Including processes into the models has the potential to enhance the prediction of individual differences in decision making.

Third, better understanding of how decisions are made is correlated with improving decisions. This suggests that focusing on studying the processes behind choices can, for instance, help with creating environments which could encourage better decisions (e.g. Thaler & Sunstein, 2008).

In the previous section, I showed that consumers often rely on heuristics when making food choices. However, research exploring the actual decision processes behind food choices is still limited. Therefore, it is not clear whether these heuristics are the result of long or short decision processes. As heuristics are cognitive shortcuts, they should simplify the decision process; however, food choices based on only one attribute could, in theory, also be the result of an extensive search process. For instance, a person choosing a food product with an organic label as the most healthful food product may have performed a quick, but to some extent extensive, search of the available products and concluded that the one bearing the organic label is the most healthful one. However, if we focus only on the outcomes, i.e. the choice of a product with an organic label as the most healthful food product, we may say that this person is biased. A fundamental issue is, if we do not explore the processes behind food choices, we cannot be sure that a choice is a result of heuristic thinking.

One way to better understand decision processes, is to look at how consumers search for information. There have been several measures proposed to differentiate between different search patterns. The most commonly used one has been *the Search Index* (*SI*, Payne, 1976). This index differentiates between the two search patterns, namely, the information search that can be characterised as within attributes (alternative-wise) or across attributes (attribute-wise) search. An alternative-wise search is a search based on looking at a specific set of at least two attributes such as price and organic label across at least two different alternatives. An alternative-wise search is usually associated with compensatory strategies, i.e. decision strategies where a good value on one attribute can compensate for a poor value on another attribute. On the other hand, an attribute-wise search is a search based on looking at one attribute, e.g. organic label, across at least two different alternatives. An attribute-wise search is usually associated with non-compensatory strategies, i.e. decision strategies where a good value on one attribute cannot compensate for a poor value on another attribute (Payne et al., 1993).

However, several important criticisms regarding the characteristics of the SI have been identified. First, the analysis of an information search is restricted to single-step transitions in the information search sequence and therefore not all available information is used. This criticism has been addressed by Ball (1997) who proposes focusing on multiple-step transitions.

Second, there is a lack of chance correction, i.e. the mean SI is zero only when a decision task consists of the same number of alternatives and attributes. When this is not the case, the SI points either to an alternative-wise information search when the number of attributes is higher than the number of alternatives, or an attribute-wise information search when the number of alternatives is higher than the number of attributes. This criticism has been addressed by Böckenholt and Hynan (1994) who proposed using a different measure called Strategy Measure (SM).

Third, it is unclear how to classify search strategies that include approximately the same number of both alternative and attribute-wise transitions and, therefore, cannot be associated with either compensatory or non-compensatory strategies (Ball, 1997). This criticism has not yet been addressed.

There is therefore an additional research question which I aim to address in this doctoral dissertation: *what measure can complement the Search Index (SI) to better describe information search?* To answer this question, I propose a new measure, *the Systematicity of Search Index* (*SSI*), for exploring information search behaviour. The SSI explores information search in terms of systematicity or the proportion of non-random search. I explore this in more detail in Chapter 4 where I introduce the proposed measure and test it in a specifically designed study.

1.5 Tracking processes behind food choices

It is clear by now that to better understand how food choices arise, it is very important to focus not only on the outcomes, that is, food choices, but also on the processes that precede the choices. The *information processing* approach, which stems from human problem solving research (Newell & Simon, 1972), has been particularly useful for trying to understand which decision processes precede which responses. Therefore, to uncover these decision processes, more emphasis has been put on the *process tracing* methodology (Payne, Braunstein, & Carroll, 1978). The process tracing methodology consists of many different methods; however, to understand how consumers search for food related information, a group of methods for tracing information acquisition, i.e. information boards, eye tracking and active information search, has been of special importance.

To address the research questions in this doctoral dissertation, I need to apply a nonobtrusive and effortless method for tracing information acquisition, such as eye tracking. Eye tracking is a process tracing method used for measuring eye movements. It has significantly developed over the last couple of decades. The equipment has become more accessible in terms of price, the reliability of the obtained data has improved and there are minimal restrictions imposed on the natural behaviour of decision makers (Glaholt & Reingold, 2011).

The experimental design of the studies in this doctoral dissertation is such that using any other method for tracing information acquisition apart from eye tracking, would be both time consuming and could affect the experimental manipulation. More specifically, by posing these specific research questions, I try to shed light on the decision processes behind the outcomes. I expect participants to search for information in a natural way as they would search for information if they were in a natural setting such as at the supermarket. Put differently, the method used for tracking their search should not influence the way participants search for information. Previous literature suggests that eye tracking is a promising method for studying both automatic and deliberate decision processes, i.e. it does not hinder the application of one or the other type of processes such as mouse tracking (Franco-Watkins & Johnson, 2011; Glöckner

& Herbold, 2011; Horstmann, Ahlgrimm, & Glöckner, 2009; Norman & Schulte-Mecklenbeck, 2009). Therefore, using eye tracking seems to be a logical choice of the methodology for answering the research questions.

1.6 Outline of the dissertation

This doctoral dissertation is organised as follows. The following chapter, Chapter 2, is a literature review consisting of three sections. In the first section, I look more closely into the cognitive approach to explore food choice behaviour. More specifically, I discuss the three distinct accounts: decision analysis, heuristics and biases and fast and frugal heuristics, and put them in the context of food choice. In the following section, I introduce methodological approaches to studying decision processes: I discuss the importance of a process tracing approach in decision making; a specific group of process tracing methods relevant for this doctoral dissertation; strengths and weaknesses of each of these methods, and finally, the metrics used within this group of methods. In the final section, I provide a literature review of the eye tracking studies exploring the decision processes behind food choices.

Chapter 3 is the first empirical chapter, in which I answer the first research question by exploring how sometimes consumers' irrational beliefs can lead to rational behaviours. To answer the question, I combine field, online, and laboratory studies to show that consumers learn structures in the environment, that is, in supermarkets, and use them to guide their decisions. This chapter consists of five sections. In the first section, I introduce the topic. In the following three sections, I report the methods and results from the three studies. In the final section, I combine the results from all three studies and discuss the findings.

Chapter 4 is the second empirical chapter, in which I answer the second research question by developing a new measure, the Systematicity of Search Index (SSI), for analysing consumer search processes. The SSI explores consumer search in terms of systematicity or the proportion of non-random search, and, addresses the questions overlooked by existing measures for analysing information acquisition. This chapter consists of four sections. In the first section, I introduce the topic. In the following section, I report the methods and results of the experiment. In the third section, I apply the SSI to the data from the Study 3 described in Chapter 3. In the final section, I discuss the findings.

Chapter 5 is the final chapter of this doctoral dissertation and it consists of three sections. In the first section, I provide a general discussion of the findings from Chapters 3 and 4, including the limitations of the research and suggestions for further research. In the following section, I outline and discuss the theoretical, methodological and practical implications. In the final section, I provide some concluding remarks.

Chapter 2

Literature review

In this chapter, I review the literature which has motivated my research questions; the literature about the methodology used to answer those questions, and the studies which on a broader level explored similar research problems using the same methodology. This chapter consists of three sections. In the first section, I look more closely into the cognitive approach which I use to enhance understanding of how consumers make food choices. In the following section, I introduce methodological approaches for exploring decision processes, with a special emphasis on the *process tracing* approach. In the final section, I provide a review of the studies exploring decision processes behind food choices using eye tracking.

2.1 A cognitive approach to exploring food choice behaviour

Different disciplines offer a range of distinct approaches for exploring food choice behaviour. For instance, the biological approach focuses on how genetic predispositions influence food choices (e.g. Birch, 1992, 1999); the cultural approach focuses on what should be eaten in different cultures, how food should be prepared and so on (e.g. Schutz, 1994); the contextual approach focuses on how environment influences food choices (for a review see Meiselman, 2006); the economic approach focuses on the monetary aspects of food choice such as diet costs (e.g. Drewnowski & Darmon, 2005; Drewnowski & Specter, 2004); the sensory approach focuses on how liking and wanting food shape food preferences and consequently food choices (for a review see de Graaf, 2006); the sociological approach focuses on how underlying social relations influence food choices (e.g. Mennell, Murcott, & van Otterloo, 1993); the cognitive approach focuses on how human thought, reasoning, intelligence and memory influence food choices (for a review see Shepherd & Raats, 2006).

Each of these approaches focuses on specific aspects of food choice, and therefore each contributes to the better understanding of food choice in its own way. In this doctoral dissertation, I focus exclusively on the cognitive approach to food choice. More specifically, I explore consumer decision processes related to food choices. However, even within the cognitive approach, perspectives are not homogeneous, i.e. there are different theories which are grouped around different, but in some ways intertwined, accounts. There are three prominent accounts: *decision analysis*, *heuristics and biases* and *fast and frugal heuristics*. In the following sections, I introduce and discuss these three accounts and place them in the context of food choice.

2.1.1 Decision analysis

The first account of human decision making, *decision analysis*, comes from the fields of economics, statistics and mathematics. In its simplest form, decision analysis can be broken down into three steps: formulating a problem, listing the possible scenarios and systematically assessing each scenario (Fox, 2015). The prominent concept here is the term *expected utility* which was first introduced by Bernoulli in 1738 (1954) and later developed by von Neumann and Morgenstern (1944) and Savage (1954). Expected utility refers to calculating the utility of each scenario as the sum of the utility of every possible outcome, each multiplied by the probability of its occurrence. An optimal decision would then be the one that maximises the expected utility. This became the basis of the expected utility theory which suggests that the decision maker chooses between the two uncertain options, based on the comparison of their expected utility values.

To determine optimal decisions and policies, the expected utility theory has been used as a normative theory, i.e. what people *should* do if they want to be rational decision makers, within a decision analysis account. However, to explain various phenomena, in some fields such as economics, the expected utility theory has also been used as a descriptive theory, i.e. what people *actually* do and how they do it (Tversky, 1975). Classical economics therefore considers people as rational decision makers. Furthermore, it is assumed that people possess complete, or at least clear and extensive, knowledge of the relevant aspects of their environment; well-organised and stable system of preferences, and computation skills for maximising behaviour (Becker, 1976). This implies that they sample all available information, weight them based on their subjective preferences, and then combine into an overall evaluation.

From the perspective of today's shopper, utility theory suggests sampling all available information about each food product in a supermarket such as sensory appeal, price, nutritional information and so on; weighting them based on the preferences, e.g. price most important, followed by sensory appeal and then nutritional information; assigning a score to each product, and then choosing the one with the highest score. In so doing, the shoppers maximise their utility, that is satisfaction. In a situation where a typical modern supermarket stocks thousands of food products (Rozin, 2006), this does not seem a feasible approach.

Nonetheless, theories such as the expectancy-value theory (Fishbein, 1967), the theory of reasoned action (TRA, Ajzen & Fishbein, 1980; Fishbein & Ajzen, 1975) and the theory of planned behaviour (TPB, Ajzen, 1985, 1988, 1991), which assume that individual's behaviour and choices are controlled by rational considerations, are perhaps some of the theories most frequently used to explain food choices (Conner & Armitage, 2006; Köster, 2009). The key factor in these theories is the individual's *intention* to perform a given behaviour, and it is generally considered that the strength of the intention to engage in a behaviour specifies the probability of its performance. The TPB extends the framework by introducing the concept of perceived behavioural control, which refers to decision maker's confidence in their ability to perform a given behaviour (Ajzen, 1991).

Even though some research has shown that TRA and TPB could be useful predictors of food choice intentions (Armitage & Conner, 1999; Sparks & Shepherd, 1992), these theories in combination with the methodologies used have been extensively criticised. For instance, Bentler and Speckart (1979) argue that Fishbein and Ajzen's (1975) account is incomplete because they do not distinguish between, on the one hand, predicting future behaviour based on attitudes and past behaviour, and on the other hand, predicting future behaviour based on intentions. Put differently, TRA restricts itself to volitional behaviours due to a proposition that intentions alone control behaviour (Conner & Armitage, 1998). These limitations were recognized by Ajzen (1988, 1991) as well, which is why TPB was introduced in the first place, to attempt to predict non-volitional behaviours.

On the other hand, Köster and Mojet (2007) criticise the methodology used, and argue that often there are no observations of actual food choice behaviour to validate the results. Instead, consumer attitudes, beliefs and intentions are measured using self-reports, which often results in a weak connection between intentions and actual behaviour. Furthermore, these theories are completely based on correlational measures and the correlations are usually low, which affects the credibility of the findings (Köster, 2009). Finally, Sutton (1997) suggests that these theories seem to be best suited for studying occasional behaviours (e.g. Askelson et al., 2010) rather than often repeated behaviours (e.g. McDermott et al., 2015). Thus, these theories may not be the most appropriate tools for understanding how consumers make food choices.

In sum, decision analysis suggests that to be a rational decision maker, an individual should calculate the expected utility of different scenarios and use these values for maximising behaviour. However, some disciplines such as classical economics argue that this, in fact, is how people make decisions. This view has been heavily criticised by scientists from other fields, particularly psychologists, and some of these criticisms are discussed in the following section.

2.1.2 Heuristics and biases

One of the most prominent critics of the economists' view of a decision maker was Herbert A. Simon (1955, 1990, 1997) who argued that decision makers should be viewed as boundedly rational instead of utility maximisers. More specifically, Simon proposed that human behaviour is "shaped by a scissors whose two blades are the structure of task environments and the computational capabilities of the actor" (1990, p.7). Put differently, he introduced the term *bounded rationality* for rational choices that consider cognitive limitations of decision makers, in terms of knowledge and computational capacity. Simon argued it is unrealistic to expect that decision makers can always maximise their utility and therefore, to describe their behaviour, he introduced the term *satisficing*, a combination of *satisfy* and *suffice*, which is a form of bounded rationality that suggests satisfaction of all the needs at some specified level (1956). Put differently, satisficing suggests willingness to settle for a good enough alternative which does not necessarily have to be the best one. Simon's intention was therefore to describe these cognitive shortcuts or rules of thumb, known as *heuristics*, as a useful tool for making decisions in the world, where time, knowledge and cognitive capacities are limited.

Other prominent critics of the decision analysis account were Daniel Kahneman and Amos Tversky. They conducted a series of experiments showing the presence of fundamental differences between the economists' view of human decision making and how decision makers actually assess probabilities and make decisions. In their seminal papers (1979, 1986, 1992) Kahneman and Tversky criticised the expected utility theory for its wide application as a normative and a descriptive model of human behaviour, by presenting decision-making tasks in which preferences systematically violate the axioms of the expected utility theory.

Instead, to describe how decision makers actually make decisions, they proposed prospect theory (1979) and later cumulative prospect theory (1992). Prospect theory describes how decision makers decide between two risky alternatives. The theory has two key elements. First, it suggests that decision makers base their decisions on the values of potential losses or gains rather than final outcomes. More specifically, decision makers' value function is commonly concave for gains, which implies risk aversion; convex for losses which implies risk seeking; and is generally steeper for losses than for gains, which implies that decision makers are generally loss-averse. Second, decision makers commonly overweight small probabilities and underweight moderate to high probabilities.

To explain why decision makers' behaviours deviate from the ones described by the normative theory described above, Tversky and Kahneman (1974) used the concept of *heuristics*. They argued that heuristics in general can be quite useful, but sometimes lead to systematic errors called *biases*. This often happens when judgments and choices are made intuitively. Therefore, Kahneman and Tversky argued that human reasoning can be divided into two common forms; a natural, intuitive mode and a logical, rational mode, and that decision makers show great affinity for intuitive reasoning (Tversky & Kahneman, 1983).

To demonstrate, one such heuristic is the representativeness heuristic, where probabilities of two events are evaluated by the degree to which one event resembles the other. However, if decision makers evaluate probabilities based on the representativeness heuristic, they may neglect prior probabilities and therefore commit the base rate bias, i.e. overly focus on the specific information compared to the general information provided, when this is not justified. Tversky and Kahneman's (1974) famous example of an individual whose description encourages decision makers to conclude that he is engaged in a less probable occupation, such as a librarian, rather than a farmer, demonstrates the use of the representativeness heuristic which results in the base rate bias. Put differently, using the representativeness heuristic, the description of an individual is matched with a mental image of a librarian. In so doing, decision makers ignore the prior probabilities that there are many more farmers than librarians in the population, which results in the base rate bias.

In the context of food choice, relying on heuristic cues, such as a specific food product attribute or diverse symbols and signs on the food product packaging, can sometimes result in biases and inferior choices. For instance, Chandon and Wansink (2007) and Wansink and Chandon (2006) showed that specific nutrient claims, such as low-fat, can promote calorie underestimation and therefore increase food intake. Furthermore, Lee, Shimizu, Kniffin, and Wansink (2013), Schuldt and Schwarz (2010) and Sörqvist and colleagues (2015) all found that the organic label, i.e. an ethical claim related to the production of food products, distorts the overall image of a product. More specifically, products that bear the organic label are judged as being lower in calories, with better nutritional content, and they therefore elicit greater willingness to pay. Since there is currently no conclusive evidence to support these beliefs about organic food products (Barański et al., 2014; Dangour et al., 2009; Smith-Spangler et al., 2012), it is generally considered that decision makers are biased towards thinking that organic food products are more healthful than conventional food products. Therefore, in both examples, i.e. low-fat claim and organic label, decision makers' behaviour is described as influenced by a specific heuristic, namely the *health halo effect*. Put differently, the health halo effect creates false beliefs regarding the healthfulness of food products based on a single claim such as low-fat, organic and so on.

Another example of the detrimental effect of heuristics comes from the literature exploring how the structure of the environment influences food choices. More specifically, it has been shown that in a restaurant setting, the design of menus, portion sizes, food variety, music, visual displays, waitress behaviour and health rating systems (e.g. hygiene) influence what consumers choose to eat and in which quantities (Cohen & Babey, 2012). Furthermore, in a supermarket setting, consumers' food choices are influenced by the location and placement of food products, product packaging, product labelling, sales promotions, product sampling, product variety, in-store media and atmosphere (Cohen & Babey, 2012). Such choices, made by the retailer in such settings could potentially lead to growing obesity rates. For instance, bigger portion sizes increase the amount of energy consumed and therefore contribute to weight gain (Young & Nestle, 2002); similarly, food options positioned at the beginning or the end of a menu can be up to twice as popular compared to food options positioned in the centre of the menu (Dayan & Bar-Hillel, 2011).

To help consumers make better decisions, Thaler and Sunstein (2008) proposed organising the context in which consumers make choices and, by doing so, guiding them to make better decisions, which they termed as *libertarian paternalism*. For instance, they proposed rearranging school cafeterias in such a way that more healthful food alternatives become more accessible, whereas less healthful food alternatives become less accessible. In this way, one could increase or decrease the consumption of many food alternatives. In their experiment, Rozin and colleagues (2011) supported this idea by showing that, indeed, one could reduce intake of specific food alternatives by 8 – 16% by making a food alternative slightly more difficult to reach (by varying its proximity by about 10 inches) or just simply changing the serving utensil (spoon or tongs). In another experiment, Hanks, Just and Wansink (2013) tested whether low- and no-cost environmental changes in school cafeterias could lead children to take and eat more healthful food alternatives, by making fruits and vegetables more attractive and convenient. This was done, for instance, by placing fresh fruit next to cash registers, keeping 100% fruit juice boxes next to ice cream in freezer or by displaying fresh fruit in nice bowls. They found that 13% of children were more likely to take fruits and 23% were more likely to take vegetables, whereas the actual consumption increased by 18% for fruits and by 25% for vegetables. These findings have important implications because they show how small structural changes in the environment could potentially lead to developing and adopting more healthful behaviours, and therefore help to reduce growing obesity rates.

2.1.3 Fast and frugal heuristics

The third account of human decision making builds on Simon's idea of bounded rationality presented above, and represents heuristics as useful aids for making a decision. The main claim behind this account is that the heuristics consumers use to make decisions are not necessarily inferior to the utility maximisation account provided by decision analysis (Fox, 2015). More specifically, following Simon's idea of bounded rationality, Gigerenzer and Goldstein (1996) have proposed a class of models: fast-and-frugal algorithms, which are based on a simple psychological mechanism called one-reason decision making. One-reason decision making refers to making choices based solely on a single cue (reason) which differs from decision to decision.

To test the performance of these algorithms, Gigerenzer and Goldstein tested one such algorithm, the *take-the-best* algorithm, with "rational" algorithms such as multiple regression. The results showed that fast-and-frugal algorithms, in this case the take-the-best algorithm, do not have to trade accuracy for simplicity. That is to say, simple psychological mechanisms can yield about as many, or even more, correct inferences in less time than standard statistical linear models. Fast-and-frugal heuristics, i.e. algorithms, became a part of the so called *adaptive toolbox* which is a collection of heuristics that are fast, frugal, computationally cheap and adapted to specific environments (Gigerenzer et al., 1999).

The fast-and-frugal heuristics account has three goals: *descriptive*, *normative* and *engineering* (Gigerenzer, Hertwig, & Pachur, 2011). *The descriptive goal* is to analyse heuristics, their building blocks, i.e. search rules, stopping rules and decision rules, and the learned core capacities such as recognition memory, frequency monitoring, on which heuristics operate.

The normative goal is to determine in which environmental structures a given heuristic will succeed or fail, which has been termed as ecological rationality, i.e. the match between mind end environment (Todd & Gigerenzer, 2007; Todd et al., 2012). This goal heavily relies on Simon's idea that human behaviour is shaped by the two blades of scissors, i.e. the structure of task environments and the computational capacities. Put differently, it is impossible to understand why a heuristic succeeds or fails by focusing solely on the heuristic. Instead, one should study heuristics in different environments to find out in which environments specific heuristic predicts faster, more accurately or by requiring less information.

The engineering goal is to combine the results from the descriptive and normative goals, to design heuristics and environments which will encourage making better decisions. To accomplish these three goals, Gigerenzer and colleagues (2011) propose relying on *process* models instead of *as-if* models, i.e. models that "explain behaviour on an aggregate level by explicitly ignoring the underlying cognitive processes" (Volz & Gigerenzer, 2014, p.575). Put differently, they argue for understanding actual decision processes and not only the outcomes. In addition, they propose focusing on computational models such as recognition heuristic, rather than vague one-word labels such as availability, because these models enable studying the heuristics in specific environments which in turn leads to novel predictions.

Apart from Simon, the development of the fast-and-frugal heuristics program was also influenced by the work of some other eminent scholars such as John W. Payne, James R. Bettman and Eric J. Johnson. For instance, Payne, Bettman and Johnson (1993) introduced the concept of the *adaptive decision maker* to explain how an individual uses a repertoire of various strategies in making a decision, dependent upon different factors such as the display of information and the complexity of the problem. They have built on the work of Ebbesen and Konečni (1980) who explored the differences between real world and simulated decision tasks and found that various features of decision tasks impact the decisions individuals make, such as the context in which the decision problem is presented, the salience of alternatives, the number of cues, and so on.

Furthermore, Einhorn and Hogarth (1981) have argued that judgment and choice are strongly dependent on minor changes in task. Payne and colleagues (1993) therefore suggested that decision makers continuously shift their strategies in accordance with the demands of the task, rather than being affected by various cognitive limitations and biases. More specifically, they made a summary of characteristics that describe choice behaviour, such as the level of compensatoriness, i.e. the degree to which the trade-off between attributes is made; selectivity in processing, i.e. the degree to which the amount of processing is consistent or selective across alternatives or attributes; alternative-based versus attribute-based processing, and so on. In addition, based on these characteristics, they provided an overview of some of the most common decision strategies, used such as the weighted additive (WADD) rule, which examines the values of all the relevant attributes for each alternative, as well as the importance of each attribute for a decision maker; the equal weight (EQW) heuristic which examines all the alternatives, as well as all the attribute values, but ignores the relative importance of each attribute; the satisficing (SAT) heuristic which examines the alternatives based on all the attributes and chooses the first one that meets the previously set threshold for all the attributes; the lexicographic (LEX) heuristic which examines all the alternatives based on the value of the most important attribute and chooses the one with the best value; the elimination-by-aspects (EBA) heuristic which orders attributes based on their importance, assigns threshold levels to each and then eliminates all the alternatives below these threshold levels accordingly; the majority of confirming dimensions (MCD) heuristic which examines pairs of alternatives on all the attributes, keeps the one with the majority of better attributes and continues the process of pairwise comparison until there is only one alternative left; to name just a few.

In the context of food choice, Scheibehenne, Miesler and Todd (2007) explored whether a simple heuristic, such as a non-compensatory lexicographic rule, is able to account for individual food choices compared to a compensatory weighted additive model. Therefore, they asked participants to choose a dish from each of 20 pairs of lunch dishes and to indicate their importance weights, together with evaluation ratings of each dish, on nine different factors. They found that the simple lexicographic heuristic is as good at predicting participants' food choices (72%) as a weighted additive model (73%) and concluded that food choices may be based on simple heuristics. Similarly, Schulte-Mecklenbeck, Sohn, de Bellis, Martin and Hertwig (2013) investigated whether decision makers do indeed search for as much information they can, or if they simply rely on simple decision strategies when making food choices by employing a process-tracing technique called MouselabWEB, i.e. a process-tracing tool used to monitor the information acquisition process (explained in more detail in section 2.2.1.1). They tested eight different decision strategies in an experiment where participants were asked to make a choice in a series of choices between two lunch dishes. They found that non-compensatory decision strategies described their participants' choices much better than compensatory strategies did. Interestingly, no choices were classified as being based on the weighted additive rule. On the contrary, 20-30% of choices were classified as being based on the lexicographic strategy.

In sum, the fast-and-frugal heuristics program shares some basic features with the heuristics and biases program, such as that both programs strive to provide more psychologically realistic theories of rational behaviour as opposed to the account provided by decision analysts. However, Gigerenzer and colleagues (2011) highlighted three important differences between these two programs. First, the heuristics in the heuristics and biases program have not been developed into computational models. Second, the definition of rationality is not based on Simon’s scissors, that is the mind-environment interaction, and therefore it is logical instead of ecological. Third, the heuristics and biases program assumes that heuristics are less effortful and therefore can never be more accurate than more complex strategies.

Nevertheless, the main difference could be summarised as follows: the fast-and-frugal program does not perceive an individual as cognitively inferior because of cognitive limitations. Instead, cognitive limitations encourage decision makers to rely on heuristics, which are perceived as useful strategies for making reasonable decisions, so that focus is placed on ways and settings where heuristics lead to accurate inferences. On the contrary, heuristics and biases program looks at heuristics as unreliable aids, so it seeks out settings where they can be accused of poor reasoning (Gigerenzer et al., 1999).

2.2 Methodological approaches to studying decision processes

The cognitive processes underlying individual decision making have been an important focus of research for several decades. Two methodologically distinct approaches have been used to study these processes: a *structural approach* and an *information processing* approach (Abelson & Levi, 1985; Ford, Schmitt, Schechtman, Hults, & Doherty, 1989; Newell & Simon, 1972; Payne et al., 1978; Westenberg & Koele, 1994). The structural approach is based on statistical models that describe the relationship between information stimuli (input) and decision responses (outcomes) (Abelson & Levi, 1985). For instance, the parameters in multiple linear regression analysis are regarded as representing important aspects of decision makers' decision strategies. More specifically, if a specific attribute receives a high weight, it is generally considered that this attribute is very important for the decision maker (Reisen, Hoffrage, & Mast, 2008). However, this approach has been extensively criticized for focusing solely on the final stage of decision behaviour and therefore neglecting the processes that lead to a decision (Payne et al., 1978; Svenson, 1979).

The information processing approach, on the other hand, stems from human problem solving research (Newell & Simon, 1972) and tries to understand which cognitive processes precede a response (Payne et al., 1978). Since this approach investigates cognitive processes more directly, it often produces more detailed explanatory models of the decision-making behaviour that leads to a specific choice (Harte, Westenberg, & van Someren, 1994; Payne et al., 1978; Payne, 1976). However, this approach has been criticized for its theoretical background. For instance, the crude classification of decision-making behaviour as compensatory and non-compensatory is not deemed to be specific enough, and it is in direct contrast to the amount of detail provided by this approach. In addition, a criticism has also been directed at the frequent practice of trying to explain cognitive processes by aggregating the vast amount of gathered data into some simple statistics (Bröder, 2000).

Overall, it has been argued that both the information processing and structural approach have contributed to explaining decision making behaviour by shedding light on different aspects of the behaviour, and that researchers should continue using them in a complementary way (Costa-Gomes, Crawford, & Broseta, 2001; Einhorn &

Hogarth, 1981; Einhorn, Kleinmuntz, & Kleinmuntz, 1979; Riedl, Brandstätter, & Roithmayr, 2008). However, it has also been argued that sometimes these two approaches lead to contrasting conclusions and therefore cannot always be used in a complementary way. Instead, one should choose the appropriate method based on the theory behind a research question (Bröder, 2000). Since both research questions, in a broader or narrower sense, explore how decision makers search for information, the information processing approach has been deemed as more appropriate. Therefore, in the following section, I will more closely reflect on the methodology associated with the information processing approach.

2.2.1 Process tracing in decision making

The methodology derived from the information processing approach, often referred to as process tracing, has been used to uncover the cognitive processes preceding the decision maker's response (Payne et al., 1978). There are several process-tracing methods that have been applied in decision-making research. According to Schulte-Mecklenbeck, Kühberger and Ranyard (2011), they can loosely be classified into three groups: a) methods for tracing information acquisition (e.g. information boards, eye tracking and active information search); b) methods for tracing information integration and evaluation (e.g. thinking aloud and structured response elicitation), and c) methods for tracing physiological, neurological, and other accompanying cognitive processes (e.g. measurement of reaction time, galvanic skin conductance, pupil dilation and neuronal techniques of location). As one of the aims of this doctoral dissertation is to explore information search behaviour that precedes a final choice, in the next section, I focus on explaining the methods for tracing information acquisition.

2.2.1.1 Information boards

This is a process-tracing technique where participants acquire information by opening envelopes from a matrix of envelopes attached to a sheet of cardboard. Each envelope contains a card with some text on it. To acquire a specific piece of information, the participant has to take a card out of the appropriate envelope, turn it around, read it, and place it back into the envelope (Payne, 1976; Wilkins, 1967).

This technique provides data regarding what information the decision maker seeks, the sequence of information acquired, and how much information is acquired (Kühberger, Schulte-Mecklenbeck, & Ranyard, 2011). In the late 1970s, information boards became more sophisticated due to the introduction of computer-based information acquisition systems. Information boards were therefore no longer the only type of presentation devices. Instead, computer monitors were introduced for the presentation purposes and keypresses were used to indicate which cells should be opened (Payne & Braunstein, 1978). Ten years later, the introduction of a computer mouse has led to the further development and introduction of the Mouselab system which is, as the name suggests, a system that uses a mouse to perform various decision experiments (Bettman, Johnson, & Payne, 1990; Johnson, Payne, Schkade, & Bettman, 1989). More specifically, this system could have been used to present the experiment instructions as well as a decision problem using one of five possible types of screen layout (e.g. matrix, gamble, decision-tree). In addition, it could have automatically recorded the content of the acquired information, the duration of each acquisition and search order, and choice (Johnson et al., 1989), which was a significant improvement compared to its ancestor, simple information boards. Currently, there are various more advanced (and freely available) online or offline versions of Mouselab system such as MouselabWEB (Willemsen & Johnson, 2008) or MouseTracker (Freeman & Ambady, 2010).

2.2.1.2 Eye tracking

Eye tracking refers to a process-tracing technique where participants' information acquisition behaviour is traced by recording their eye movements.

Recording eye movements has been used for over a hundred years and has becoming increasingly popular over the last couple of decades (Kühberger et al., 2011). There are two main assumptions which closely connect eye movements to cognitive processes, namely the *immediacy* and the *eye-mind* assumption (Just & Carpenter, 1980). The immediacy assumption suggests that the mind follows the eye, i.e. information is interpreted as soon as it is encountered, at the expense of possible false initial interpretations. The eye-mind assumption suggests that the eye follows the mind, i.e. the eye remains fixated on an object as long as this object is being processed.

In a way similar to Mouselab, computer screens are used to present information in experiments when recording eye movements. However, instead of using a computer mouse to choose pieces of information, decision makers simply look at the information presented on the screen. The information acquisition process therefore resembles a more natural situation (Reisen et al., 2008). The eye tracking equipment records saccadic, i.e. rapid, voluntary movements from one object to another, and non-saccadic eye movements, i.e. focusing on a single point or object of interest (Russo, 2011). Parameters of specific interest for decision researchers are saccadic movements and fixations. Therefore, to draw inferences about cognitive processes, one can explore the tempo, amplitude, duration or latency of saccadic movements and the duration, frequency and scanning path of fixations (Kühberger et al., 2011).

Generally, eye tracking techniques can be divided into two groups: a group focusing on measuring the position of the eye relative to the head and a group focusing on measuring the orientation of the eye in space, or the so called *point of regard* (i.e. gaze point). There are four categories of eye movement measurement methodologies used to estimate the point of regard. These involve the measurement of: electro-oculography, i.e. measuring the position of the eye by placing skin electrodes around the eye and recording potential differences; scleral contact lens/search coil, i.e.

attaching a mechanical or optical reference object mounted on a contact lens and then positioning it directly on the eye; photo-oculography or video-oculography, i.e. measuring the distinct characteristics of the eyes under rotation/translation, and video-based combined pupil/corneal reflection, i.e. measuring the point of regard by either keeping the head position fixed or by measuring features such as corneal reflection and the pupil centre (Duchowski, 2007; Young & Sheena, 1975). The last category, video-based combined pupil/corneal reflection, is the prevailing method for estimating the point of regard, and has made eye tracking more convenient to use and therefore applicable in a broad range of research topics.

Further advancements in the field have led to the development of the two distinct groups of eye trackers: remote eye trackers (i.e. desktop eye trackers) and mobile eye trackers. The leading manufacturers in this field are SR Research with the EyeLink system, SensoMotoric Instruments (SMI) and Applied Systems Laboratory (ASL) with Tobii Technology (Holmqvist et al., 2011). Recently, eye tracking has been receiving growing interest from the field that develops virtual reality. Therefore, there are already several available solutions on the market. This combination of methodologies has great potential to make research in “natural” environments more accessible, and therefore enhance the external validity of experiments.

2.2.1.3 Active information search

Active information search (AIS) refers to a process-tracing technique where participants only receive a basic description of the decision task. Therefore, to receive additional information, a participant needs to ask questions (Kühberger et al., 2011). This method was first introduced by Engländer and Tyszka (1980) and later developed by Huber, Wider and Huber (1997) who wanted to develop a method which would require less reactive information presentation or, put differently, participants would not be required to use a specific, already predetermined, piece of information.

As previously mentioned, the basic idea behind AIS is to first present the participant with only a necessary description of the decision task. To minimize the danger of influencing the participant, the description should be as short as possible. However, the description also needs to be rich enough to enable the participant to formulate questions. Next, to obtain more information about the task from the experimenter, the participant needs to ask questions. The participant can ask any type and as many questions as she wants, as well as repeat already asked questions. To avoid situations where the experimenter answers the questions and therefore potentially influences the participant, the questions are recorded, and answers are given on small cards from a list of already prepared answers. Therefore, for each decision task, pilot studies are used to optimize the short description of the task and to find as many questions as possible, which allows preparing the list of answers. However, if the participant asks a question which was not encountered during the pilot study, the experimenter needs to answer it during the experiment by improvising. The probability of new questions asked should therefore be small.

This method was further developed by Huber, Beutter, Montoya and Huber (2001) who introduced a structured version of the AIS. More specifically, instead of leaving the formulation of questions completely to the participant, in this version, she can choose a question from a list of questions and ask them to the experimenter one at the time. Questions are structured based on different types of questions identified in Huber et al. (1997). Some of the examples are questions concerning the probability of an event, questions dealing with the participant’s control over the external event or negative consequences, questions requiring information regarding what can be done in case of a negative event, questions regarding certain or uncertain consequences of a specific alternative and so on. In the standard version of AIS method, the type, frequency and sequence of the collected information are recorded, whereas in the computerized version (e.g. WebDiP system – Web Decision Processes), one can also record the reading time (Kühberger et al., 2011).

2.2.2 Strengths and weaknesses of methods for tracing information acquisition

Each of the process-tracing methods for tracing information acquisition presented in the previous section has its strengths and weaknesses which may affect the choice of the method. A summary of these characteristics is presented in Table 2.1 (based on Huber et al., 2001; Reisen et al., 2008).

Table 2.1 Strengths and weaknesses of methods for tracing information acquisition

Strengths	Weaknesses
Information boards (including computerized versions)	
Relatively easy to set up and use	Time and effort required to acquire a piece of information
Requires no calibration procedure and therefore it works with almost every participant	Almost exclusively relies on written information
Quite convenient for participants because they are presented with a relatively well-structured decision task in which all the available information is clearly presented	Requires some type of information restructuring
Many participants can be run at the same time and even over the Internet (e.g. MouselabWEB)	Too structured; participants may be influenced regarding what information to use or to consider important
Easier interpretation of the data compared to eye tracking	
Eye tracking	
A large amount of data; data regarding which pieces of information are acquired, how many, the sequence and time spent on information acquisition	Calibration procedure can sometimes be difficult to perform and therefore on some occasions no reliable calibration can be achieved

Table 2.1 Continued

Strengths	Weaknesses
Very fast and effortless information acquisition	Special equipment which can be expensive
No constraints in the choice of the stimuli	Noise in the information acquisition process (e.g. fixations we are not aware of)
Reduces the reactivity concern (changing the behaviour due to being observed)	Too structured; participants may be influenced regarding what information to use or to consider important
Eye tracking	
Accurate and precise data	One can track only one participant at a time
Flexibility in terms of data collection location (e.g. mobile eye tracking in supermarkets)	Possible constraints on participants (e.g. head position stabilized using a chin rest)
Active information Search (AIS)	
One can gain, in a non-reactive approach, information about the decision task and the alternatives the participant is actually interested in	Less exact monitoring of the information acquisition processes than with the other two techniques
Avoids restructuring of the decision task by the experimenter	Procedural issues (e.g. question related) that can emerge during the data collection process

The final choice of the process-tracing method should, apart from pragmatic reasons, depend on the research goals (Lohse & Johnson, 1996). For instance, it has been shown that each process-tracing technique requires different levels of information acquisition effort. For instance, experiments applying the Mouselab method require significantly more time to complete the tasks compared to eye tracking, with the time needed being correlated to the complexity of the task (Card, Moran, & Newell, 1983;

Lohse & Johnson, 1996; Russo, 1978). In addition, Mouselab can yield more alternative-wise search patterns than eye tracking. This may be so because this technique promotes a serial mode of information acquisition and therefore restricts the possibility of making quick comparisons between multiple pieces of information, as well as detecting specific patterns (Glöckner & Betsch, 2008). Also, participants tend to re-examine more information using eye tracking compared to when using Mouselab, as well as exhibiting greater variability in the proportion of information acquisition. In sum, the complexity of the task, in terms of amount of information to process, is positively correlated to the difference between eye tracking and mouse tracking techniques (Lohse & Johnson, 1996).

2.2.3 Metrics for exploring information acquisition behaviour

Increased interest regarding uncovering the decision processes behind decision makers' choices has brought a lot of attention to the judgment and decision-making field. Therefore, different researchers have proposed several metrics to explore information acquisition behaviour and to draw conclusions about decision makers' cognitive strategies in decision situations. Table 2.2 shows the summary of the proposed metrics (adapted from Riedl, Brandstätter, & Roithmayr, 2008).

Table 2.2 Metrics for exploring information acquisition behaviour

Author	Metric
(Hogarth, 1975; Pollay, 1970)	Decision time
(Payne, 1976)	Proportion of information searched; search index; variability in the amount of information searched per alternative
(Jacoby, Chestnut, Weigl, & Fisher, 1976)	Reacquisition rate
(Van Raaij, 1977)	Comparing the number of times alternative- and attribute-wise transitions occur in the first versus the second part of the search process
(Klayman, 1982)	Variability in the amount of information searched per attribute; contingency measures
(Payne et al., 1993)	Total amount of processing; total amount of time spent on the information in the boxes; average time spent per item of information acquired
(Böckenholt & Hynan, 1994)	Strategy measure
(Koele & Westenberg, 1995)	Compensation index (i.e. combination of the variability of search with the depth of search)
(Ball, 1997)	Multiple-step transition types

2.3 A review of eye tracking studies exploring decision processes behind food choices

This review includes peer-reviewed studies on decision processes and food choices using eye tracking. I searched the databases Web of Science and Google Scholar using the following key words: decision process AND food AND eye track*, which generated four papers that matched the requirements. I used a review by Orquin and Mueller Loose (2013) on eye movements and decision making to identify two additional papers. Finally, I identified the last four papers using either backward or forward citation search of the previously identified papers, which generated a further nine papers which I included in the review. I classified the papers into three groups depending on their approach to studying decision processes. The first group explores different stages of the decision process (five papers), the second group explores different cognitive thinking styles (two papers) and the third group explores the use of specific decision strategies (two papers). An overview of the papers is shown in Table 2.3.

Table 2.3 Summary of papers included in the review

Study	Approach	Finding
Clement (2007)		In-store purchase decision processes explained by the five-stage model, which consists of: pre-attention stage, succeeded attention stage, the tipping point, semantic information process stage and the post-purchase stage.
Gidlöf, Wallin, Dewhurst, & Holmqvist (2013)		Used the three-stage model proposed by Russo and Leclerc and supplemented this with the Natural Decision Segmentation Model (NDSM) to identify decision making in a real-world supermarket environment.
Reutskaja, Nagel, Camerer, & Rangel (2011)	Stages of the decision process	Tested three models which assume two-stage decision process (screening and evaluation) to find out: what computational processes decision makers use during the search and decision processes and to what extent they correspond to standard economic search models; how the complexity of a choice affects these processes, and whether computational processes exhibit systematic biases.
Russo & Leclerc (1994)		Three-stage model of decision process: orientation, evaluation and verification.
Schaffer, Kawashima, & Matsuyama (2016)		Consumer decision process in multi-alternative choice situations described by the two-stage model (exploration and evaluation); introduced the probabilistic gaze model to understand search stages.

Table 2.3 Continued

Study	Approach	Finding
Ares, Mawad, Giménez, & Maiche (2014)	Cognitive thinking styles	Rational decision makers engage in deeper and longer information search for making their choices than intuitive decision makers as well as appreciating more complex information; rational decision makers also engage in more thoughtful analysis of the labels and nutritional information compared to intuitive decision makers.
Mawad, Trías, Giménez, Maiche, & Ares (2015)		Field dependent decision makers tend to engage in less thoughtful information processing than field independent decision makers, and they make fewer fixations on traditional nutritional information.
Stüttgen, Boatwright, & Monroe (2012)	Decision strategies	A choice model based on Simon's satisficing choice rule (1955) which consists of the two interrelated parts: search and evaluation; decision makers seem to follow the satisficing choice rule; it is possible to estimate choice models that adapt more closely to the actual decision process.
Wästlund, Otterbring, Gustafsson, & Shams (2015)		Decision makers who chose a low-cost product of their preference directed less of their visual attention towards the task-relevant stimulus compared with consumers who chose a specific, predetermined product within the same product category. The findings are explained by suggesting that decision makers in the task non-specific group were most likely affected by the satisficing heuristic and therefore performed shorter search.

2.3.1 Stages of the decision process

Studies have shown that decision processes in more complex (multi-alternative) decision tasks can be segmented into two stages: a *screening* stage in which some of the alternatives are eliminated, and an *evaluation* stage in which a few remaining alternatives are more closely inspected (Lussier & Olshavsky, 1979; Payne, 1976; Wright & Barbour, 1977). Studies conducted in the context of food choice have reached a similar conclusion. For instance, Reutskaja, Nagel, Camerer and Rangel (2011, p.900) have tested three models, i.e. an optimal search model with zero search costs, a satisficing search model and a hybrid search model, to answer the three questions: a) What are the computational processes deployed by consumers during the search and decision processes, and to what extent are they compatible with standard economic search models? b) How do the processes, and their performance, change with the number of options? c) Do the computational processes exhibit systematic biases that can be exploited by sellers to manipulate their choices?

All three tested models described above assume that the decision process has two stages, i.e. an initial search stage and a final decision stage. More specifically, these models assume that decision makers begin the decision process by searching through the set of alternatives using distinct fixation sequences. After the initial search stage ends at a certain time, the decision process enters the next and final stage. There are two main differences between these models: namely, how the initial search stage stops and how the final decision is made. The optimal search model with zero costs assumes that during the initial search stage decision makers look at as many alternatives as possible, depending on the time available. The satisficing search model assumes that during the initial search stage decision makers search until either the time runs out, or the decision maker finds an alternative that meets her threshold.

The hybrid search model includes elements of both models. Model differences regarding how the final decision is made are reflected in the use of a decision rule. Reutskaja and colleagues assume that when decision makers reach the final decision stage, they use the probabilistic decision rule, i.e. all alternatives are assigned a probability of choice proportionally to their utility values. However, this does not apply to the case of the satisficing search model where an alternative which meets the threshold is found during the initial search stage.

Reutskaja and colleagues found that the hybrid search model, in which decision makers search for a random amount of time depending on the number of alternatives available, and then choose the alternative that meets their threshold, best describes how decision makers might search and decide in complex situations such as making food choices. They also found that decision makers search and choice processes changed with the increased number of alternatives, which was reflected in their eye fixations. More specifically, decision makers were making shorter eye fixations and searching for longer in total; therefore, sampling more alternatives before making a choice. Finally, they found that decision makers show a bias towards looking first and more often at the alternatives that are placed in the centre of the display, which they also in the end choose more often.

Schaffer, Kawashima and Matsuyama (2016) tested the assumption that the consumer decision process in multi-alternative choice situations can be described by the two decision stages, namely, *exploration* and *evaluation*. They defined exploration as a decision stage where decision makers aim to gather broad information about alternatives by examining them. On the other hand, they defined evaluation as a decision stage where decision makers aim to gather detailed information about a set of specific alternatives. To understand search stages in a multi-alternative choice situation, they proposed the probabilistic approach to modelling search behaviour, i.e. a probabilistic gaze model. This model is based on a few simple assumptions regarding how often the chosen alternative is looked at to identify search stages. For instance, they suggested that the probability of a *dwell* on the chosen alternative, where a dwell is a set of successive eye fixations on an alternative, should be higher in the evaluation stage compared to the exploration stage, and this was confirmed. They also observed that decision processes differed between different decision makers, where some decision makers frequently changed search stages, whilst others just shifted their stage from the exploration to the evaluation stage. The proposed model was successful at accounting for these differences in search behaviour.

Russo and Leclerc (1994) also explored the presence and characteristics of decision stages in consumer decision processes. However, they studied this in a more naturalistic decision task, where decision makers made choices between real food products presented on a shelf in the laboratory. They proposed that the decision process consists of three stages, namely, *orientation*, *evaluation*, and *verification*. Each stage was identified based on one pattern of eye fixations, i.e. a sequence of eye fixations without re-fixating a previously observed alternative.

The orientation stage is defined as the stage that occurs before the first re-fixation, and might represent one of two different processes: screening or orientation. Screening corresponds to the first stage of the standard two-stage theory and serves as an initial consideration of the available alternatives, which should not require more than one fixation per alternative. Similarly, orientation corresponds to acquiring information about available alternatives to restrict following processing to a set of alternatives. The difference between screening and orientation is reflected in the number and length of fixations; specifically, screening requires more and longer fixations, whereas orientation requires fewer and shorter fixations. The evaluation stage occurs between the first and last re-fixation. In this stage, the alternatives that are considered more seriously are more thoroughly evaluated. The verification stage could be divided into two stages: the first verification stage occurs after the last re-fixation and lasts until the announcement of a choice, whereas the second verification stage occurs after the announcement of a choice, and could be interpreted as an additional verification.

These findings were explained by providing two possible explanations. First, the methodology used to trace processes might have been responsible for observing differing numbers of stages, i.e. eye tracking provides more detailed data compared to other process-tracing techniques. Second, decision tasks usually used were represented with alternative-attribute matrices, whereas in this case a laboratory simulation of supermarket shelving was used.

More recently, Gidlöf, Wallin, Dewhurst and Holmqvist (2013) used the three stage model proposed by Russo and Leclerc to identify decision making in a real-world supermarket environment. However, due to difficulties in differentiating between the orientation and the evaluation stages, based solely on a first re-fixation, they introduced the Natural Decision Segmentation Model (NDSM). In the NDSM, these two stages differ, based on the time the chosen alternative is first re-fixated. More specifically, after the first re-fixation on the chosen alternative, the initial screening stage ends and the evaluation stage begins. Gidlöf and colleagues argued that the introduction of the NDSM would better capture the differences between these three stages and therefore this model would be better able to differentiate between the search and decision processes.

Gidlöf and colleagues found that the NDSM better captures the more extensive processing of the alternatives in the evaluation stage, which is reflected in dwell times which are significantly longer compared to Russo and Leclerc's findings. Also, they argued that only with the NDSM model can one observe a difference between the search and the decision processes, which is reflected in the number of re-fixations in the evaluation and the verification stages. In addition, they emphasized the importance of re-fixations, not only in the evaluation stage but in other stages as well, because they can serve as a measure of search and task difficulty. Lastly, they concluded that supermarkets are very complex environments which require more difficult search for an alternative than laboratory settings, and therefore require more visual processing, which is confirmed by their findings.

Finally, Clement (2007) proposed the use of the self-organising criticality system to explain in-store purchase decision processes. This model consists of five stages: a) the build-up stage, b) the critical stage, c) the re-organising stage, d) the focal activity stage and e) the dormancy stage. These stages could be compared to the purchase decision process, which starts with a *pre-attention stage* (corresponds to the build-up stage), where the decision makers' attention is attracted by the packaging of various alternatives. The next stage is the *succeeded attention stage* (corresponds to the critical stage) where the visual influence from packaging design accumulates in the decision makers' mind. Next comes *the tipping point* (corresponds to the re-organising stage) where decision makers reach out for an alternative and then enter *the physical action stage*, which, if it results in a purchase, shifts the decision process into the *semantic information process stage* (corresponds to the focal activity stage). The final stage is *the post-purchase stage* which corresponds to the dormancy stage in the self-organising criticality system.

In his experiment, Clement found that gaze times followed his speculations about stages of a decision process in an in-store purchase setting. More specifically, the gaze time was short in the first two stages. Afterwards, it significantly increased during the stage where an alternative was in the decision maker's hand, and finally, it shortened again in the last, post-purchase stage.

In sum, the previously presented studies have three things in common. First, the authors agree that studying the decision process in the context of a food choice is a complex task, especially if the experiments are conducted in a natural environment, such as a supermarket. Second, all studies employ eye tracking, which is considered as advantageous compared to other process-tracing techniques, in terms of the amount of data it generates. Finally, they all divide the decision process into several stages, with a clear difference between the studies conducted in the laboratory setting, which find two stages (Reutskaja et al., 2011; Schaffer et al., 2016) versus studies performed in a more natural environment, which find three (Gidlöf et al., 2013; Russo & Leclerc, 1994) or even five stages (Clement, 2007).

2.3.2 Cognitive thinking styles

Cognitive thinking style refers to the way decision makers think and process information. One of the most prominent theoretical accounts in the understanding of human decision making has certainly been the dual-process framework, i.e. the models that classify cognitive processes into two main categories: intuition and reason. This framework has initially been applied to understand biases in judgments under uncertainty (e.g. Chaiken, 1980; Epstein, Pacini, Denes-Raj, & Heier, 1996; Tversky & Kahneman, 1974); however, later it has been extended to be applied in the food choice domain as well. Nonetheless, research applying the dual-process framework for explaining consumer food choices using process-tracing methodology is still very limited.

Some studies have shown that different thinking styles, i.e. rational versus intuitive, do indeed impact decision processes and food related decisions. For instance, Ares, Mawad, Giménez and Maiche (2014) tested consumer processes and choices when evaluating yogurt labels using eye tracking. They expected that rational decision makers would engage in deeper information search for making their choices than intuitive decision makers, and that the former would prefer more complex information, e.g. nutritional information, to the graphic designs of the labels. They also expected differences regarding the extent to which the nutritional information would be processed. To identify decision maker groups with similar thinking style, Ares and colleagues performed a latent class cluster analysis which resulted in two clusters. Decision makers in Cluster 1 were classified as rational, and the decision makers in Cluster 2 were classified as intuitive.

Eye tracking analysis showed that decision makers in Cluster 2 overall made significantly fewer and shorter fixations on the choice sets than decision makers in Cluster 1, which points to more superficial information processing. Furthermore, decision makers in Cluster 2 made fewer and shorter visits to the individual labels in the choice set. Additionally, the percentage of decision makers who fixated their gaze on nutritional information was significantly lower for Cluster 2 compared to Cluster 1. Also, decision makers in Cluster 2 tended to fixate their gaze on nutritional information and traffic light system earlier than decision makers in Cluster 2. The findings also showed that decision makers in Cluster 2 extracted less information to complete the task than decision makers in Cluster 1 which was confirmed by fewer visits and fixations on the central image and nutritional information. To conclude, even though the findings of Ares and colleagues (2014) are limited by a non-representative sample, they provide preliminary evidence that thinking style could affect decision processes and choices when evaluating food product labels.

In a similar study, Mawad, Trías, Giménez, Maiche and Ares (2015) explored whether different cognitive styles influenced consumer information processing and yoghurt choices. However, the cognitive styles explored were one of the earliest styles studied, namely *field dependence* and *field independence* (Witkin, Moore, Goodenough, & Cox, 1977). Decision makers using a field independent style tend to separate details from the surrounding context, whereas decision makers using a field dependent style are relatively unable to distinguish detail from the other information around it. To distinguish between the field independent and field dependent decision makers, the Group Embedded Figures Test (GEFT; Witkin, Oltman, Raskin, & Karp, 1971) was used. Two groups emerged: Group 1, which consisted of field dependent decision makers, and Group 2, which consisted of field independent decision makers.

Eye tracking analysis showed that decision makers with different cognitive styles differed in how they visually processed the information in the task. Decision makers in Group 1 made significantly fewer and shorter fixations on the choice sets than decision makers in Group 2. Furthermore, field independent decision makers performed a more thorough analysis of the yogurt labels. More specifically, field independent decision makers fixated more often on the four areas of interest (i.e. central image, brand, nutritional information and traffic light system) than field dependent decision makers. Also, field independent decision makers made more fixations on traditional nutritional information than field dependent decision makers.

In sum, different cognitive styles seem to provide a good explanation for some of the observed differences in the decision process. Mawad and colleagues argue that the importance of studying the influence of different cognitive styles on food choice could potentially contribute to the development of successful communication strategies aiming at changing the eating patterns.

2.3.3 Decision strategies

Decision strategies that decision makers may apply to make decisions have been classified into two groups of strategies: compensatory, i.e. a good value on one attribute can compensate for a poor value on another, and non-compensatory strategies, i.e. a good value on one attribute cannot compensate for a poor value on another (Payne et al., 1993). Each of these two groups of decision strategies includes quite different search processes (Pachur, Hertwig, Gigerenzer, & Brandstätter, 2013). For instance, the compensatory weighted additive (WADD) rule considers the values of each alternative on all the relevant attributes as well as the weight of each relevant attribute (Payne et al., 1993). In contrast, the non-compensatory LEX heuristic (Fishburn, 1974), instead of weighting and adding, orders attributes and relies on the first attribute that allows for a decision.

However, research exploring the use of different decision strategies in the context of food choice using eye tracking is still very limited. Thus, I only managed to two identify two papers that matched these criteria. The first paper is the one by Stüttgen and colleagues (2012) who proposed a choice model based on Simon's satisficing heuristic (1955), i.e. choosing any option that meets the threshold level. They tested the model in an incentive compatible task which required making a choice of instant noodles. The proposed model consists of the two interrelated parts, namely search and evaluation. More specifically, during search, a decision maker constantly acquires more information, but also constantly updates her evaluations of the alternatives. These evaluations can end up in one of the three groups: satisfactory products, unsatisfactory products and undetermined products, i.e. alternatives for which she still does not have enough information to form a judgment. What is essential about this model is that it allows for these evaluations to influence the continued search, as well as the final decision, once a decision maker proceeds to the termination stage.

Stüttgen and colleagues found that, overall, the decision makers seem to follow the satisficing heuristic, because more than 70% of participants had on average less than two satisfactory options across choice sets before terminating their search. This suggests that most decision makers were satisfied with finding one good enough alternative which led to terminating their search very soon after. Stüttgen and colleagues also evaluated the predictive ability of the satisficing model compared to a standard multinomial logit model and found that that the proposed model out-predicts the multinomial logit model. In sum, their findings show that it is possible to estimate choice models that adhere more closely to the actual decision process.

The second paper is the one by Wästlund and colleagues (2015), who tested whether consumers more often rely on the previously mentioned satisficing heuristic rather than on the take-the-best heuristic, i.e. choosing an option based on the first cue that discriminates between them, where the cues are ordered from the highest to the lowest (Gigerenzer & Goldstein, 1996), when asked to buy a relatively cheap product. They used a 2 (task specificity: specific versus non-specific) × 2 (choice task: first versus second) mixed design. The task-specificity was a between-subjects factor and the choice task was a within-subjects factor. The goal of the first task was to choose a package of coffee. The participants were instructed either to find a specific type of coffee (task specific group), or to choose a package of coffee they preferred (task non-specific group). The goal of the second task was to go to the pastry department and choose any type of pastry they preferred.

Wästlund and colleagues found that participants in the task non-specific group observed a significantly smaller number of AOIs than participants in the task specific group. This suggests that consumers who choose a low-cost product of their preference direct less of their visual attention towards the task-relevant stimulus compared with consumers who choose a specific, predetermined product within the same product category. The authors explained these findings by suggesting that consumers in the task non-specific group were most likely affected by the satisficing heuristic and therefore performed shorter search.

In sum, research exploring decision processes in the context of food choice using eye tracking is still scarce. However, as emphasised in the introduction of this doctoral dissertation, understanding how consumers make food choices is becoming increasingly important for the three main societal reasons outlined already, i.e. growing obesity rates, food waste rates and concerns regarding food safety. Therefore, to enhance understanding of food choice, one needs to consider its complexity, and, as has been repeatedly pointed out, focus also on the processes that precede a choice, and not just the final choice. Eye tracking, as a process-tracing technique, has great potential to bring valuable insights into decision processes behind food choices.

In the following chapters I contribute to the literature described above by exploring consumer decision processes behind food choices, using eye tracking. More specifically, I propose a different explanation as to why consumers may behave in a specific way, and this explanation sheds more light on decision processes which leads to a specific choice. I then focus more closely on how consumers acquire information, which is the beginning stage of every decision process, by proposing methodological improvements to the existing measures for analysing information search.

Chapter 3

Irrational beliefs can lead to rational behaviours

In this chapter, I explore my first research question: *can irrational beliefs sometimes lead to rational behaviours when making food choices?* I explore this research question in the context of organic food products. It was motivated by the currently dominant belief that organic food products are more healthful than conventional food products, even though there is still no conclusive scientific evidence for this belief. In this chapter, I first consider a current explanation in the literature as to why this may be so, which is that consumers may be influenced by a *halo effect*. Then, I propose a different explanation, which explores the *organic = healthful heuristic* by placing it in the right context. This explanation consists of the three hypotheses which I test in the three studies and the findings of which I report separately. I finish this chapter with a general discussion of all the findings in the light of the research question asked.

3.1 Introduction

The *halo effect* was first coined by Thorndike (1920) who set out to explore how commanding officers evaluate their soldiers in terms of physical qualities, intelligence, leadership, personal qualities and general value to the service. He found unusually high and equal correlations between the tested traits. For instance, a soldier rated as intelligent also tended to get high marks on physical qualities such as physique, energy and endurance, and the other way around. Thorndike therefore concluded that a positive or negative halo of general merit influenced the ratings of the special abilities. Half a century later, Nisbett and Wilson (1977) experimentally reproduced the halo effect in a seminal paper. They divided their participants into two groups and asked them to watch a video and rate a college instructor who spoke English with a Belgian accent on his likability, physical appearance, mannerism and accent. In both videos the instructor answered the same questions; however, in one video he was warm and friendly, and in the other he was cold and distant. Interestingly, the 'warm' version of the instructor influenced participants to rate his appearance, mannerism and accent as appealing, whereas the 'cold' version had the opposite effect. Nisbett and Wilson therefore concluded that global evaluations of a person can alter evaluations of the person's attributes about which the individual has sufficient information for an independent assessment. Another 20 years later, Roe, Levy and Derby (1999) discovered the halo effect in the area of food choice. They found that consumers tend to overgeneralize specific health claims believing that a product is more healthful than it really is, which implies that the claim creates a halo effect. There has been a vast amount of research on the perception of health claims since then, but it remains an open question whether health claims actually lead to halo effects (Orquin & Scholderer, 2015).

A similar line of research has found that organic food products seem to have a robust halo effect with regards to health perceptions. Specifically, it has been shown that organic food products are perceived as being more healthful (Hughner, McDonagh, Prothero, Shultz, & Stanton, 2007; Lee et al., 2013; Orquin & Scholderer, 2015; Schuldt & Hannahan, 2013; Schuldt & Schwarz, 2010; Sörqvist et al., 2015), safer (Michaelidou & Hassan, 2008) and of better quality (Lockie, Lyons, Lawrence, & Mummery, 2002). Since there is currently no conclusive evidence that organic food products are indeed more healthful than conventional alternatives (Barański et al., 2014; Dangour et al., 2009; Smith-Spangler et al., 2012), it is often concluded that decision makers have an irrational bias in favour of organic food products (EUFIC review, 2013).

Even though it seems that decision makers are in fact biased by the halo effect, there may be other explanations for the *organic = healthful heuristic*. One counterhypothesis is that the heuristic is not a bias at all, but rather a clever adaptation to a specific environment. This idea is often termed as ecological rationality (see section 2.1.3) (Gigerenzer et al., 1999; Todd et al., 2012) and refers to the application of simple heuristics in appropriate environments. More specifically, when taken out of its environment a heuristic may seem irrational, but with the right application, it can sometimes lead to better outcomes than other procedurally more complicated processes (Gigerenzer & Goldstein, 1996).

Therefore, here I propose that the *organic = healthful heuristic* may be ecologically rational if the environment is structured such that organic food products are in some way more healthful than conventional food products. While currently there is no evidence for such a claim, I speculate that organic food products are more prevalent in less processed, as opposed to processed, food product categories due to various restrictions regarding organic production; that is to say that unprocessed or less processed food products, such as vegetables, fruit, milk, meat, eggs and so on, are more likely to be organic than more processed food products, such as frozen pizzas, candy, chips, prepackaged meals and so on. If this is true, then the *organic = healthful heuristic* would be ecologically rational; a person primarily buying organic food products would have a higher likelihood of buying from healthful (less processed) food product categories.

If such a statistical structure exists in the environment, would consumers be able to learn it? Research shows that people are undoubtedly sensitive to statistical regularities observed in the world. According to Reber (1989) this type of learning, sometimes referred to as statistical or implicit learning (Conway & Christiansen, 2006; Perruchet & Pacton, 2006), evolves without conscious attempts to pick up the rule-governed complexities of the environment. Such unsupervised learning allows us to infer distributional properties, correlations, and transition probabilities in the environment (Thiessen, Kronstein, & Hufnagle, 2013) and the learning happens fast (Saffran, Newport, Aslin, Tunick, & Barrueco, 1997), across sensory modalities (Conway & Christiansen, 2005), and in different domains (Brady & Oliva, 2008; Kushnir, Xu, & Wellman, 2010; Xu & Garcia, 2008). While statistical learning is mainly concerned with language and visual learning, it could provide an opportunity to understand ecological rationality in decision making. When combining this line of thought with the finding that decision makers are typically very categorical in thinking about food healthfulness (Orquin, 2014; Rozin, Ashmore, & Markwith, 1996), it seems plausible that consumers may observe a natural correlation between organic food products, and less processed food product categories, and form the sensible conclusion that organic food products are in fact more healthful than conventional food products. This suggests that in the case of the organic food products, the putative halo effect may not be a halo effect after all, but rather a heuristic based on statistical learning.

Based on the previously introduced idea that the *organic = healthful heuristic* is a matter of statistical learning rather than a halo effect, I derive the following hypotheses. First, I hypothesise that *there is a correlation between organic and more healthful food products in the natural environment*, i.e. food product categories which are less processed have a higher prevalence of organic food products. Second, I hypothesise that *consumers observe this statistical structure* and, therefore, perceive organic food products to be more prevalent across more healthful food product categories. Third, I hypothesise that *it is also possible to experimentally reproduce statistical learning in the lab by manipulating the correlation between organic and health cues*. As an objective health cue, I use the Nordic Keyhole label which indicates healthful alternatives within a product category (Ministry of Food, Agriculture and Fisheries, 2013). I expect that a positive correlation between organic and the Keyhole label will increase attention to, and use of, organic cues when estimating food healthfulness. Put simply, consumers will be more likely to look at and choose food products with organic cues when these cues are a valid predictor for food healthfulness.

I tested these hypotheses in three studies. Study 1 is a field study from six Danish supermarkets in which I tested the first hypothesis by obtaining the true correlation between organic food prevalence and the healthfulness of food product categories. In Study 2, I tested the second hypothesis in an online consumer study where participants provided estimates of the healthfulness and prevalence of organic food products for the food product categories identified in Study 1. In Study 3, I tested the third hypothesis in an eye tracking experiment by manipulating the correlation between organic and health cues in a health judgment task.

3.2 Study 1

In Study 1, I investigated the assumption that there is a correlation between the likelihood of a product being organic, and the likelihood of that product being healthful. I obtained the true percentages of organic food products across food product categories in six Danish supermarkets as well as the estimates of food healthfulness from a panel of food and nutrition experts. I expected to find a positive correlation between organic food prevalence and food healthfulness.

3.2.1 Methods

3.2.1.1 Design and procedure

To obtain estimates of organic product prevalence, I manually counted the total number of products within various food categories as well as the number of organic food products within the same food categories. The counting took place in six supermarkets in Aarhus, Denmark; of these, three would be considered small, one medium, and two large. The coding scheme was developed over three rounds by adding new categories as new products were encountered. The inclusion criterion was whether a food product could be consumed independently of other products or ingredients. For that reason, I decided that raw ingredient sub-components, such as flour, salt, sugar and so on, would not be taken into consideration. Thus, 54 food product categories emerged and were used as a basis for developing a coding scheme. The initial coding scheme consisted of 17 super-ordinate categories and 54 sub-ordinate categories. The coding scheme was revised two more times, in the second and the fourth supermarket respectively. The final coding scheme consisted of 17 super-ordinate and 59 sub-ordinate categories. Organic food products within those 59 food product categories were detected by inspecting the presence of a Danish organic label or the EU organic label (see Figure 3.1). To ensure that the counting performed was unbiased, an independent coder, blind to the study hypotheses, was used in one supermarket. The coders assessed 53 food product categories. I calculated the inter-coder reliability separately for total food product counts and organic food product counts obtained from each coder. To do that, I compared the frequencies of all food products per food category and frequencies of organic food products per food category for two coders. The inter-coder reliability (Krippendorff's alpha; Krippendorff, 2011) was high for both total food product counts, $\alpha = .93$, and organic food product counts, $\alpha = .88$.

a b

Figure 3.1 An image of (a) Danish organic label and (b) EU organic label.

To obtain objective estimates of the healthfulness of the 59 food product categories, 15 nutrition and food scientists were asked to complete a short survey, indicating the healthfulness of each category on a 7-point Likert scale ranging from 'extremely unhealthful' to 'extremely healthful'. Ten participants completed the survey. One expert provided the same score for all 59 food product categories and was excluded from further analysis, resulting in a final sample of nine experts. A copy of the survey used can be found in Appendix A.

3.2.2 Results

The field data show that organic food products are more prevalent in food product categories that require less processing. For instance, food product categories such as whole-grain pasta, brown rice, milk, eggs etc. have a higher prevalence of organic food products compared to categories such as prepackaged meals, candy, chips and canned meat. An overview of the average number of food products, percentage of organic food products, and corresponding expert estimates can be found in Table 3.1 (columns two to four). An overview of all counting scores from the six supermarkets can be found in Appendix B.

Table 3.1 Average number of food products, percentage of organic food products, and expert and consumer estimates of healthfulness

Category	Totals	% Organic	Expert	Consumer
Whole-grain pasta	17.33	84.39	5.38	5.06
Non-dairy milk	9.17	78.94	4.5	4.61
Brown rice	3.83	64.58	5	5.27
Milk	15.33	53.47	5.5	5.09
Unprocessed breakfast cereals	28.17	50.89	5.88	5.21
Eggs	9	36.82	6.38	5.22
Oil	30.33	31.46	4.88	4.16
Plain yoghurt products	19.5	30.67	6.13	4.99
Syrups	32.17	29.67	1.88	2.94
Crispbread and rice crackers	37	27.15	4.75	4.35
Dried fruits, nuts and seeds	100.33	25.97	5.25	4.84
Vegetables	136.33	25.45	6.63	6.16
Butter	14.67	24.46	2.75	3.34
White rice	15.83	22.92	3.5	3.57
Fruit	39.50	20.61	6.13	5.80
Honey	8.5	20.4	3.38	4.36
Juices	57.83	19.39	3.63	4.02
Processed meat	25.17	18.79	2.38	2.87
Marmalade	51.17	16.37	2.88	3.15
Chocolate spreads	14	16.26	2	2.74
Crackers	11.17	15.48	2.5	3.09

Table 3.1 Continued

Category	Totals	% Organic	Expert	Consumer
Fruit yoghurts	42	14.86	3	4.07
Frozen meat	13.33	14.35	4.5	4.49
Fresh meat	62.17	13.08	5	4.96
Whole-grain bread	25.33	12.37	6.25	5.52
Canned vegetables	91.5	12.23	4.88	4.5
Cream	12.33	11.42	2.63	3.04
Frozen fruit	6.5	11.21	5.38	4.82
Frozen bread	19.67	10.78	4.13	3.67
Cheese	153.67	10.56	4.5	4.57
Frozen vegetables	33.33	9.9	6.25	5.27
Canned fruit	15.83	9.89	3.5	3.96
Sauces (tomato, pesto)	42.83	9.58	4.63	4.05
Cold cuts	123	9.29	3.5	4.02
Refined wheat flour pasta	36	8.21	2.75	3.2
Ice cream	39.5	7.49	2.25	2.68
Dressings	76.5	6.38	3.38	2.86
Cakes and cookies	80.67	5.49	2.13	2.24
Muesli and protein bars	16	5.28	4	4.09
Frozen prepackaged meals	64.67	5.11	2.5	3.22
Processed breakfast cereals	25.33	4.71	1.75	2.66
Refined wheat flour bread	42	4.19	2.88	2.77
White wine	44.83	4.18	4	3.36
Sodas	109.5	3.51	1.5	2.06
Alcoholic beers and shakers	131.33	3.32	3	2.45
Mayonnaise-based salads	36.83	3.03	3	3.09
Chips	56.33	2.67	1.5	1.92
Red wine	121.17	2.59	4.38	3.69

Table 3.1 Continued

Category	Totals	% Organic	Expert	Consumer
Candy	382.83	2.19	1.38	1.92
Soups	12.83	1.31	4	3.97
Frozen fish	15.17	1.04	6	5.21
Dry prepackaged meals	17.33	0.83	2.88	3.16
Processed fish (refrigerated)	49.17	0.76	5.25	4.99
Prepackaged meals: sauces	38	0.29	2.13	2.95
Take-out meals	4.67	0	3	3.18
Canned fish	35.5	0	5.63	4.63
Canned meat	5.83	0	3.25	3.56
Fresh fish	5.17	0	6.63	5.99
Refrigerated prepackaged meals	11.17	0	2.75	3.27

The results show a medium-sized, positive correlation between the true percentages of organic food products and healthfulness estimates by experts, $r = .35$, $CI_{95} = [.1, .56]$ (see Fig. 3.2a).

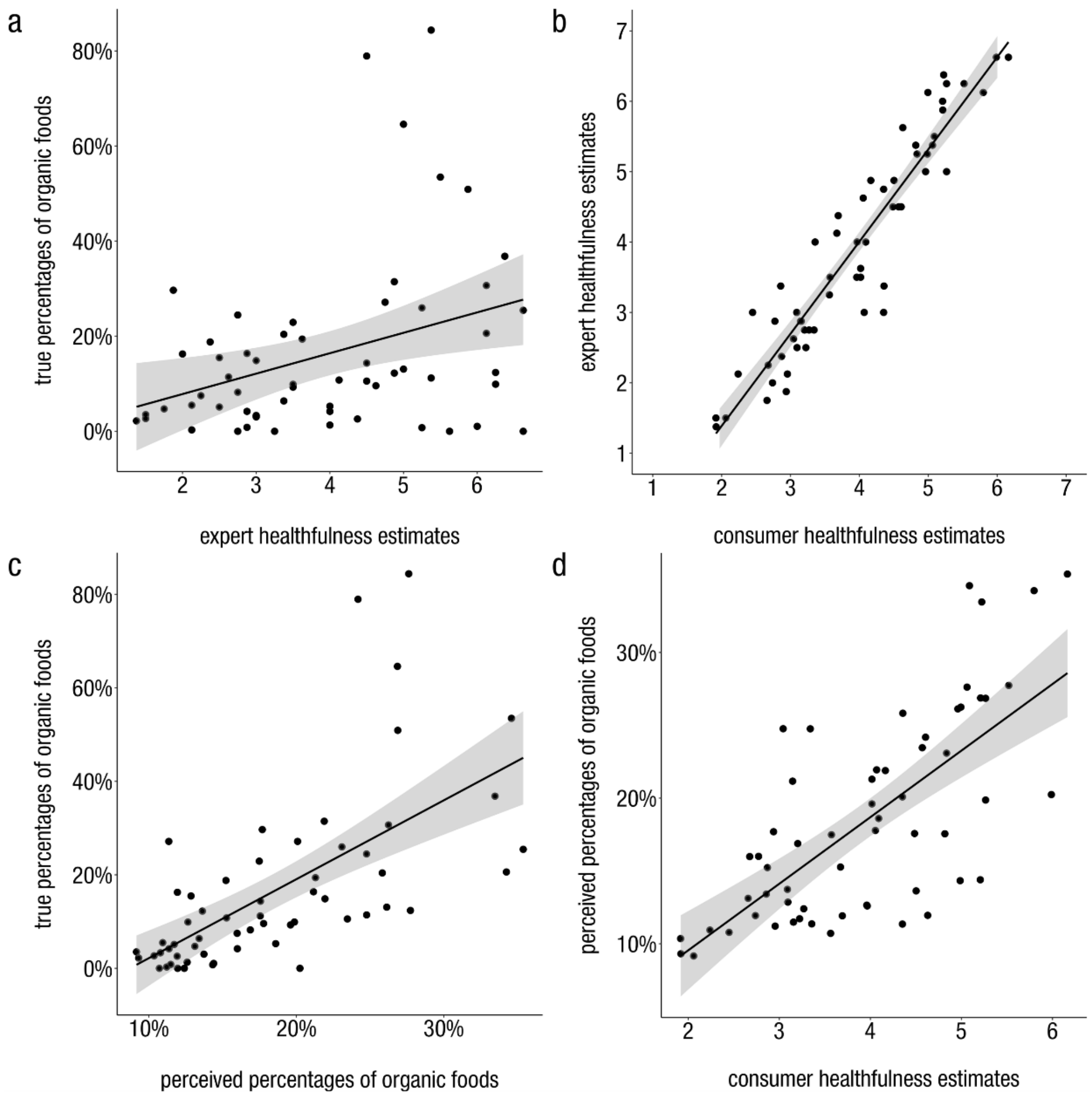


Figure 3.2 Scatter plot of (a) the true percentages of organic food products and expert healthfulness estimates, (b) healthfulness estimates by experts and consumers, (c) the true and perceived percentages of organic food products and (d) the perceived percentages of organic food products and healthfulness estimates by consumers. The trend lines in all plots represent the best-fitting, linear regression line and its 95% confidence interval.

Next, I calculated the expected healthfulness of organic and conventional food products using the following equation:

$$M = \sum_{i=1}^{n} p_i x_i$$

where p_i denotes the probability of a product being in category i and x_i denotes the expert healthfulness rating for that category. I applied the calculation separately for organic and conventional food products. The results show that organic food products, $M = 4.47$, $SD = 1.48$, are, on average, 30% more healthful than conventional food products, $M = 3.44$, $SD = 1.59$, $d = .67$.

3.3 Study 2

The findings from Study 1 show a correlation in the environment between the likelihood of a product being organic and the likelihood of that product being healthful. According to my previous assumption, consumers have learned this statistical structure which should be reflected in their ability to accurately estimate the percentage of organic food products across food product categories. Therefore, in Study 2, I conducted an online survey to test this assumption. Given that consumers learn about the statistical nature of the environment, I expected to find a strong correlation between their perceptions and the true state of the environment.

3.3.1 Methods

3.3.1.1 Participants

Seven hundred and seventy-three participants representative of the Danish population were recruited through a consumer panel provider. Six hundred and thirty-seven participants completed the study which gives a response rate of 82.4%. The participants ranged in age from 17 to 81 ($M = 42.95$, $SD = 16.09$) with an approximately even distribution of male and female participants (315 women). The sample captured a broad spectrum of the population with regards to age, gender, education and shopping behaviour as well as psychographic dimensions. For a full description of the sample, see Figure D1-D3 in the Appendix D. Each participant received approximately €1 for completing the study. The sample size was determined by maximising within budget constraints. A post-hoc power analysis was conducted using the 'pwr' package in R (Champely, 2017) which revealed that the power to detect a small-sized effect (d = .2; see Cohen, 1988) with the sample size of 637 and the alpha level .05 is .99. The study received ethical approval from the University of Leeds.

3.3.1.2 Materials and procedure

Participants were recruited online and all gave informed consent before commencing the study. Participants were asked to estimate the percentage of organic food products for the 59 food product categories identified in Study 1. Subsequently, participants were asked to estimate the healthfulness of each food category on a 7-point Likert scale ranging from 'extremely unhealthful' to 'extremely healthful'. Besides the main variables, demographic and psychographic information about the sample was collected as well as information about organic purchasing behaviour. Organic purchasing behaviour was measured with two items. The first item measured the frequency of purchasing organic food products using a 7-point unipolar scale ranging from 'never' to 'always' (Magnusson, Arvola, Hursti, Åberg, & Sjödén, 2001). The second item measured the percentage of organic food products purchased with a visual analogue scale ranging from 0 to 100. The organic purchasing attitudes were measured by asking participants to indicate how 'good', 'important' and 'wise' they think it is to purchase organic food products. To do that, 7-point bipolar scales from Magnusson and colleagues (2001) was used ranging from 'very bad' to 'very good', 'very unimportant' to 'very important', and 'very foolish' to 'very wise'.

Beliefs about organic food products were measured by asking participants to rate on a 7-point Likert scale whether they think organic food products are 'healthier', 'tastier', 'have less calories', 'better quality', 'fresher', and 'safer' than conventional food products. A copy of the survey used can be found in Appendix C.

3.3.2 Results

The results from Study 1 and Study 2 combined show a positive correlation between the true and perceived percentages of organic food products across food product categories, $r = .65$, $CI_{95} = [.45, .77]$, suggesting that participants have accurately learned the prevalence of organic food products across food product categories. The results also show a strong, positive correlation between expert and consumer healthfulness estimates, $r = .95$, $CI_{95} = [.91, .97]$, suggesting that participants make very accurate healthfulness estimates. Finally, the results show a strong positive correlation between consumer perceptions of organic food products prevalence and food healthfulness, $r = .72$, $CI_{95} = [.55, .81]$. An overview of the consumer estimates can be found in Table 1 (column five). Figure 3.2b, 3.2c and 3.2d show scatterplots of the observed data.

The results from Study 2 also show that participants in general hold positive attitudes towards organic food products, $M = 4.82$, $CI_{95} = [4.81, 4.84]$. However, the results indicate the absence of an overall spread of attitudes. Specifically, there is no relationship between attitudes and the calories attribute, $r = .05$, $CI_{95} = [.04, .06]$. On the other hand, there is a strong positive correlation between attitudes and the health attribute, $r = .64$, $CI_{95} = [.63, .64]$. What is more, the results also show a moderate to strong correlation for other tested attributes, namely the taste, quality, freshness, and safety attributes (see Table 3.2).

Table 3.2 Correlations with 95% confidence intervals between participants' attitudes towards organic food products and specific attributes

Attribute	Correlation	95% Confidence Interval
Health	.64	[.63, .64]
Taste	.54	[.53, .55]
Calories	.05	[.04, .06]
Quality	.61	[.60, .61]
Freshness	.44	[.43, .45]
Safety	.61	[.60, .61]

The mean responses from the attribute scales support previous results showing that responses for all attributes, besides the calories attribute, are above the middle value, indicating neither agreement nor disagreement. While interpreting scales' mean in absolute terms can be unjustified, it can be noticed that the health attribute has the highest mean response, $M = 4.78$, $CI_{95} = [4.77, 4.80]$, suggesting that participants on average agree that organic food products are more healthful than conventional food products. The calories attribute has the lowest mean response, $M = 2.98$, $CI_{95} = [2.96, 3]$, suggesting that participants on average disagree that organic food products have less calories than conventional food products. The remaining attributes indicate that participants on average find that organic food products taste better, are of a higher quality, fresher and safer than conventional food products. An overview of the mean attribute values, standard deviations and confidence intervals can be found in Table 3.3.

Table 3.3 Means, standard deviations and 95% confidence intervals of consumer beliefs about organic compared to conventional food product attributes

Attribute	Mean	Standard Deviation	95% Confidence Interval
Health	4.78	1.49	[4.77, 4.80]
Taste	4.26	1.51	[4.24, 4.27]
Calories	2.98	1.53	[2.96, 3.00]
Quality	4.55	1.51	[4.53, 4.56]
Freshness	4.04	1.48	[4.03, 4.06]
Safety	4.56	1.55	[4.55, 4.58]

3.4 Study 3

While Study 1 and Study 2 have provided evidence in support of the statistical learning hypothesis, the studies are correlational in nature. The question of whether consumers can learn a statistical structure where organic food products are correlated with more healthful food product categories remains to be answered. Therefore, in Study 3, I conducted a lab-based, eye tracking study, manipulating the correlation between organic cues and cues about the healthfulness of food products. The task for participants was to choose, in their opinion, the most healthful of eight food product alternatives. As an objective health cue, I used the Nordic Keyhole label which indicates healthful food product alternatives within a food product category (Ministry of Food, Agriculture and Fisheries, 2013).

However, as the Keyhole is present only on some healthful products (Orquin, 2014), it is useful to rely on other cues as well, when judging product healthfulness. More specifically, the Keyhole label is a 100% valid cue for a healthful product (Orquin, 2014), but the Keyhole is only available on 39% of healthful products. In contrast, the organic label is available on 100% of organic food products (Orquin, 2014). Consequently, when cue availability varies, it is an advantage to know many cues because it reduces the number of times we must choose at random (Berretty, Todd, & Martignon, 1999). I therefore expect that participants would be more likely to look at and choose organic food products when organic cues are positively correlated with health cues, compared to situations with zero or negative correlation between the two.

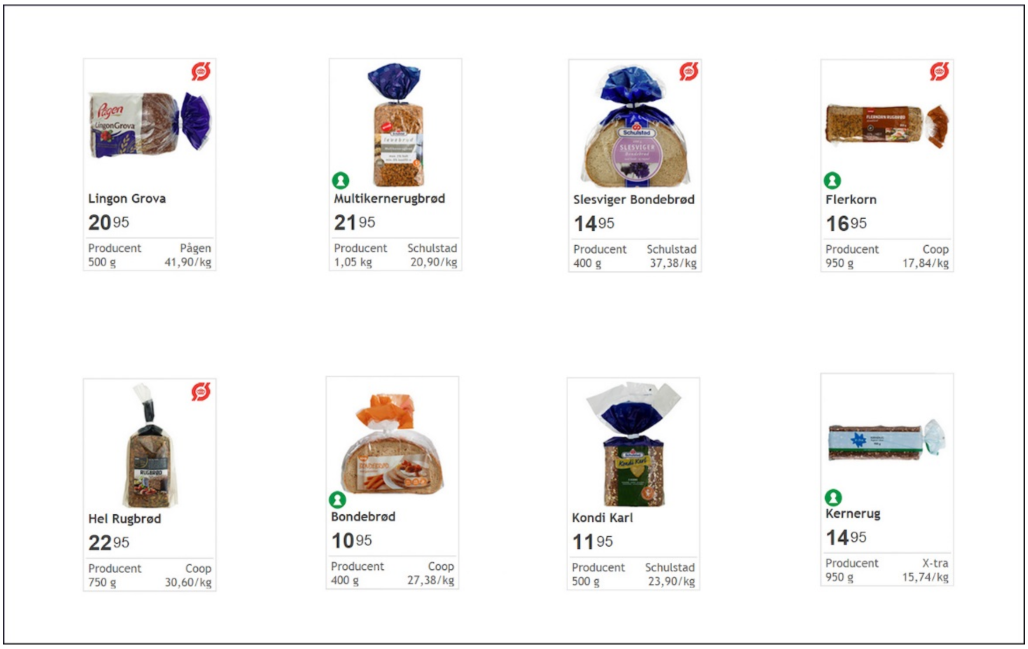
3.4.1 Methods

3.4.1.1 Participants

Seventy-eight Danish participants were recruited through a consumer panel provider. Seven participants were excluded after the experiment due to insufficient data quality, resulting in a total sample of 71 participants. The participants ranged in age from 18 to 74 years (*M* = 45.73, *SD* = 15.12) with more male than female participants (19 women). The data was collected from participants with normal, or corrected-to-normal, and full colour vision only. Each participant received a gift card of approximately €34 for completing the study. All participants gave informed consent. The sample size was determined by maximising within budget constraints, which gave at least 20 participants per cell thereby exceeding the threshold suggested by Simmons, Nelson, & Simonsohn (2011). The study received ethical approval from the University of Leeds.

3.4.1.2 Stimuli and apparatus

The experimental stimuli consisted of 50 trials of processed food products, each with eight alternatives positioned in a 4x2 array with a separation of 5.1° horizontal and 10.3° of vertical visual angle. Each alternative contained several features, i.e. product picture, name, brand, price, weight, and two manipulated features – a Keyhole label and an organic label. The degree of overlap between the Keyhole and organic labels varied across three conditions (25%, 50% and 75% overlap). More specifically, the number of Keyhole and organic labels was constant across conditions (four Keyhole and four organic labels). Therefore, 25% overlap between labels implies that only one product bore both labels, $r = -0.5$, 50% of overlap implies that two products bore both labels, $r = 0$, and 75% overlap implies that three products bore both labels, $r = 0.5$. An example of the experimental stimulus from each condition is shown in Figure 3.3. The labels were randomly distributed across alternatives in each trial, and the presentation order of the trials was randomised across participants.



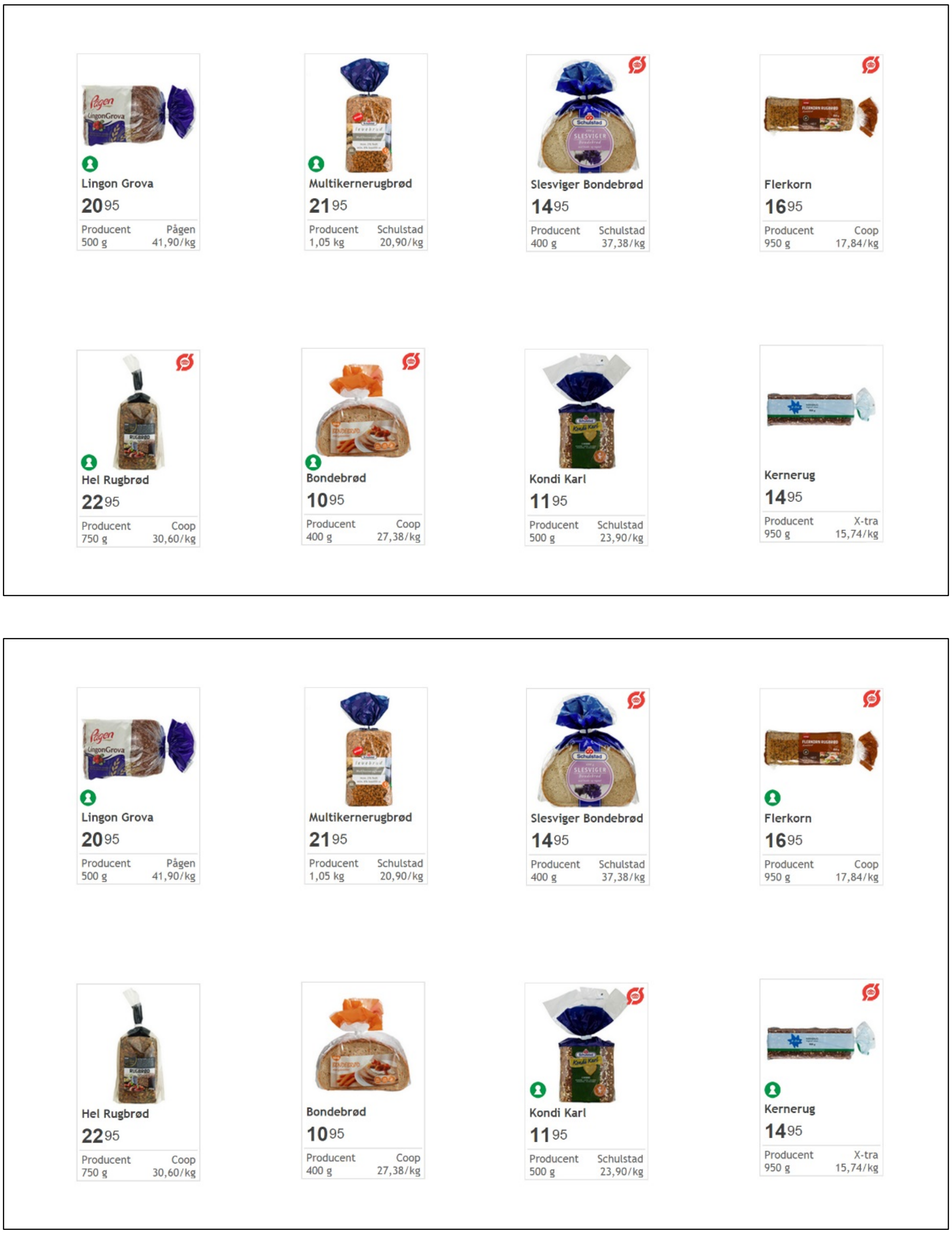


Figure 3.3 Example of a trial with 25% overlap (-0.5 condition) between the Keyhole and organic labels (top), 50% overlap (0 condition) between the Keyhole and organic labels (middle), 75% overlap (0.5 condition) between the Keyhole and organic labels (bottom).

Eye movements were recorded using a Tobii T60 XL eye tracker with a temporal resolution of 60 Hz and a screen resolution of 1920 × 1200 pixels. Average viewing distance was 60 cm from the screen and a chin rest was used to stabilize head position. I determined areas of interest (AOIs) by defining the pixel positions of the manipulated labels in each trial (16 possible positions). Fixations were identified using a velocity based algorithm (I-VT algorithm) with default settings (Salvucci & Goldberg, 2000). Specifically, the maximum length of the gap between fixations was set to 75 ms. A noise reduction function was not applied, and averaged data from both eyes were used. The velocity threshold was set to 30°/s. Fixations with a duration less than 60 ms were discarded. Margins of the AOIs were set to approximately 0.15° larger than the actual labels, to consider the inaccuracy in recording of fixation locations. There have been several attempts to define the most suitable AOI margins. More specifically, I tested the margins 0°, 0.15° and 0.5° of visual angle for a random sample of three participants and six trials per condition with a total number of 432 hand-coded AOIs. The hand-coded fixation count was used as criterion and compared with the fixation count for each AOI margin size, by counting the number of false negatives and false positives[1]. I found that different AOI margin sizes influenced the results with respect to the number of false negatives and false positives registered. The AOI margin size of 0.15° of visual angle had the most acceptable rates of false negatives and false positives. The results are presented in Table 3.4 and are in accordance with the findings of Orquin, Ashby and Clarke (2016) which indicate that using maximal AOI sizes may, as suggested by Holmqvist

[1] False negatives occur when margins of the AOIs are too narrow so they do not capture the eye fixations belonging to the specific AOI whereas false positives occur when margins of the AOIs are too wide so eye fixations belonging to the objects close by are captured as if they belong to the AOI we are interested in.

and colleagues (2011), not always be a good idea. Specifically, in a situation when fixation distributions overlap due to shorter object distances, smaller AOI sizes are expected to yield a better ratio of true to false positives which was confirmed in this situation.

Table 3.4 The influence of AOI margin sizes on the number of false negatives and positives

AOI	Condition	False Negatives (%)	False Positives (%)
0°	-0.5	3.7	0
0°	0	2.78	0
0°	0.5	5.09	0
0.15°	-0.5	3.01	0
0.15°	0	1.39	.46
0.15°	0.5	3.01	0
0.5°	-0.5	.23	5.56
0.5°	0	0	5.79
0.5°	0.5	.93	6.25

3.4.1.3 Procedure

The study was conducted in a light-controlled, laboratory environment. Upon arrival, participants were greeted, and seated in front of the eye tracker. The height of the chin rest was adjusted for each participant and calibration was performed using the Tobii Studio 9-point calibration procedure. After calibration, each participant was randomly assigned to one of the three conditions. The experiment started with instructions to choose the most healthful alternative among eight food products and to indicate the choice with a mouse click. A fixation cross lasting 1000 ms appeared before each trial. Participants were given as much time as needed to make their choices.

3.4.2 Results

3.4.2.1 Eye movement analysis

To test whether participants fixate more on the organic label when there is a high degree of overlap between the organic and Keyhole label, I analysed the eye tracking data by means of a generalized linear mixed model. The model was fitted using the ‘lme4’ package in R (Bates, Mächler, Bolker, & Walker, 2015). I used fixation selection (AOI-fixated or not) as a dependent variable, and condition and label type as independent variables. The best-fitting model was identified using a step-up procedure and had a binomial response distribution, a logit link function, two random intercepts grouped by participant and trial and a random slope of label type grouped by participant. Summary statistics for the best fitting model are reported in Table 3.6.

Table 3.6 Summary statistics for the best fitting model

Parameter	Value	Standard error	95% CI
Intercept	-2.39	0.20	[-2.79, 2.00]
Condition 0	0.02	0.28	[-0.53, 0.56]
Condition .5	-0.20	0.30	[-0.78, 0.39]
Label type organic	-.077	0.23	[-1.22, -0.32]
Condition 0 × label type organic	0.47	0.31	[-0.14, 1.09]
Condition .5 × label type organic	0.63	0.33	[-0.02, 1.28]
AIC	16484.1		
BIC	16566.6		
Log Likelihood	-8232.1		
Number of observations	28400		
Number of groups: Participant	71		
Number of groups: Trial	50		
Variance: Participant (Intercept)	0.90		
Variance: Participant (Label type organic)	1.01		
Variance: Trial (Intercept)	0.03		

To interpret the direction of the interaction effect, I plotted the fixation likelihood across condition and label type (see Fig. 3.3). Figure 3.4 shows that participants fixate on the organic label more frequently at the expense of the Keyhole label as the degree of overlap between the two labels increases.

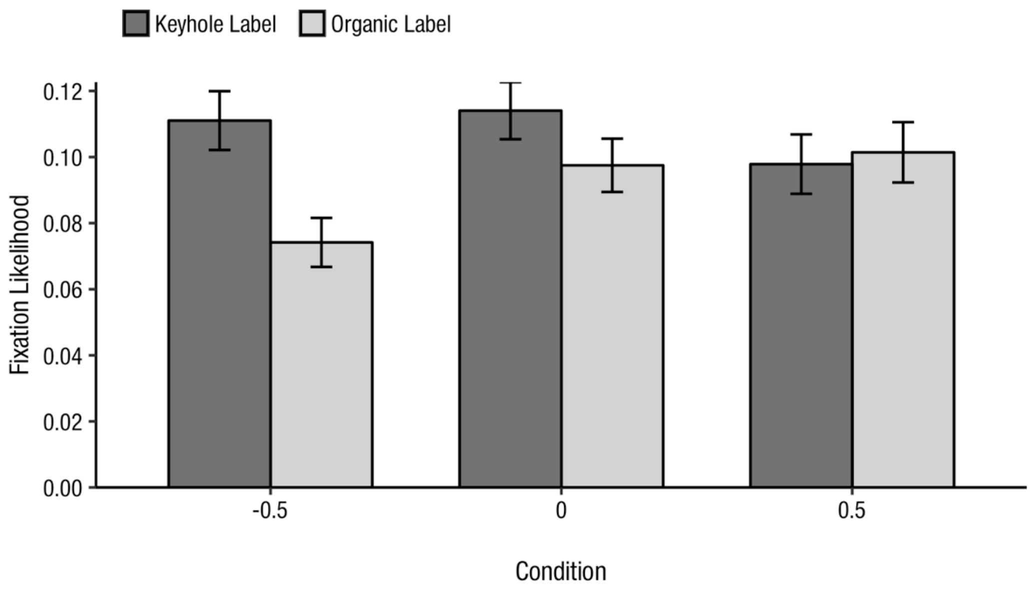


Figure 3.4 Fixation likelihood for the Keyhole and organic labels across conditions. Error bars represent 95% confidence intervals.

3.4.2.2 Follow up analysis

One potential problem with the fixation likelihood analysis is that fixations to the organic label in the 0.5 condition could be an artefact. Specifically, the pattern in Figure 3.4 could occur if participants searched for the Keyhole label and then fixated on the remaining information on Keyhole labelled food products. If this was the case, I would expect the Keyhole to drive fixations to the food product, i.e. participants should be faster to fixate on the Keyhole label than the organic label. To exclude this possibility, I inspected the cases where participants fixated on both labels. As can be seen in Table 3.7 below, participants who fixated on both labels on a food product were equally likely to fixate on the Keyhole label or the organic label first. I take this to imply that the Keyhole label did not drive fixations and hence that the results of the fixation likelihood analysis are not artefactual.

Table 3.7 Number of cases where the Keyhole or the organic label was fixated first given that both labels were fixated on a product

Condition	Keyhole first	Organic first
-0.5	18	15
0	29	31
0.5	42	44

3.4.2.3 Choice analysis

To examine the effect of the condition on participants' choice of organic food products, I fitted participants by means of multinomial logit models using the 'mlogit' package in R (Croissant, 2013). Each participant was fitted with a null model, including only intercepts for the eight food product alternatives, and a full model including a term for product type, i.e. whether the alternative had a Keyhole label, organic label, both labels, or none of the labels. I calculated the AIC difference as $AIC_{full} - AIC_{null}$. Out of 71 participants, 42 participants were identified as label users ($AIC_{diff} > 0$) and 29 as non-label users ($AIC_{diff} \leq 0$). I then calculated the standardized mean difference between the choice likelihood in the 0.5 and -0.5 conditions for the food products with an organic label and food products with both labels correcting for chance level:

$$SMD = \frac{(M_{0.5} - M_{-0.5}) - (M_{0.5\,chance} - M_{-0.5\,chance})}{SD_{pooled}}$$

For label users, I found a medium increase in the likelihood of choosing food products with an organic label in the 0.5 condition, SMD = .42, and a large increase in the likelihood of choosing food products with both labels, SMD = .83, relative to the -0.5 condition. For non-label users, I found that choices are close to chance level for products with an organic label, SMD = -.08, and food products with both labels, SMD = .06. Figure 3.5 shows the choice likelihood across conditions for food products carrying organic, Keyhole, both, or neither of the labels.

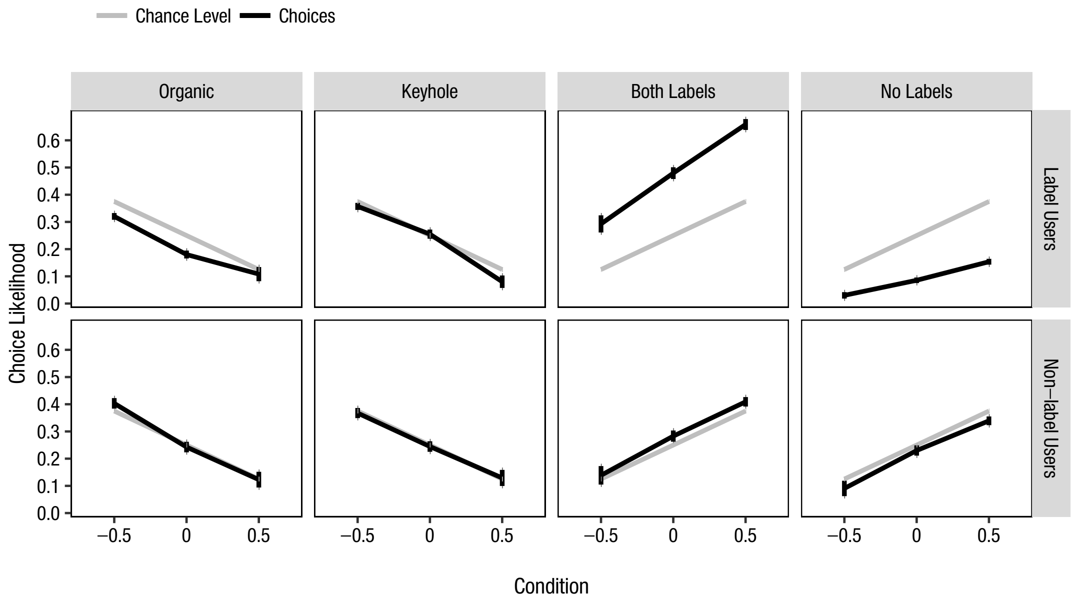


Figure 3.5 Likelihood of choosing products per label type and statistical condition for label users and non-label users. The black line represents observed choice likelihood, the grey line represents chance level choice, and error bars represent 95% confidence intervals.

3.5 Discussion

This chapter explored whether irrational beliefs can sometimes lead to rational behaviours when making food choices. I explored this in the context of organic food products. A motivating question was why consumers perceive organic food products as more healthful than conventional food products, when in fact there is no conclusive scientific evidence for this belief (Barański et al., 2014; Dangour et al., 2009; Smith-Spangler et al., 2012)? This belief can therefore be considered as irrational. So far the only explanation as to why this may be so, is the idea of a halo effect which implies that general positive attitudes towards an object spread to all associated attributes (Nisbett & Wilson, 1977; Thorndike, 1920). In the context of organic food products, this implies that a general positive attitude towards organic food products spreads to specific attributes such as health perceptions (Lee et al., 2013).

Taken out of context, this *organic = healthful heuristic* may seem irrational, but what if the same heuristic is applied in an appropriate environment? More specifically, if one assumes that: a) the level of food processing is related to food healthfulness, b) organic food products are more prevalent in less processed food product categories, c) consumers observe this statistical structure in the environment and d) consumers can learn statistical structures from their environment and apply them correctly, then the *organic = healthful heuristic* would actually be meaningful and could lead to rational behaviour. Considering these assumptions, I hypothesised that organic food products are more prevalent in less processed food product categories. Furthermore, I hypothesised that consumers observe this statistical structure in the supermarkets. Finally, I hypothesised that consumers can learn the statistical structure of a natural environment and apply it correctly in a form of a decision heuristic. These hypotheses were tested in three studies, the findings of which are discussed in the following paragraphs.

The findings from Study 1 support the hypothesis that less processed and therefore more healthful food product categories have a higher prevalence of organic food products. More specifically, the findings from a field study show that food product categories such as vegetables, fruit, milk, meat, eggs, and so on have a higher prevalence of organic food products. There are two possible explanations for this finding. First, it seems that it is more difficult to produce processed organic food products since each of the ingredients must be organic, meaning that highly processed food products with many ingredients are rarely organic. These highly processed food product categories such as prepackaged meals, candy, and chips tend to be unhealthful food products. Second, it appears that organic producers target health-conscious consumers, which leads to an overrepresentation of organic food products in more healthful sub-categories. For example, whole-grain pasta is more likely to be organic than pasta made with refined wheat flour.

The findings from Study 2 support the hypothesis that consumers observe the statistical structure of their environment regarding the distribution of organic food products across food product categories. More specifically, the findings from an online consumer survey show that consumers accurately estimate the prevalence of organic food products across food product categories. Furthermore, their estimates of healthfulness of food product categories are consistent with the ones made by food and nutrition experts. Interestingly, there is a stronger correlation between consumer perceptions of organic prevalence and their healthfulness estimates, $r = .72$, than between the true prevalence of organic food products and expert healthfulness estimates, $r = .35$. This could be due to the *organic = healthful heuristic* influencing either the consumer perception of organic food prevalence or the healthfulness of food product categories.

Finally, the findings from Study 3 support the hypothesis that consumers can learn the statistical structure of a natural environment and apply it correctly in the form of a decision heuristic. More specifically, the findings from an eye tracking experiment show that participants respond to the statistical structure, that is the correlation between organic and health cues in a health judgment task, both in their eye movements and their choices. When there is a positive correlation between organic and health cues, participants are more likely to look at organic labels compared to a negative or zero correlation between the cues. This gaze bias suggests that participants in this statistical condition consider the organic label as relevant to the health judgment task (Orquin & Mueller Loose, 2013). The findings also show that most participants include labels in their judgments, and these participants are more likely to choose food products with organic labels when there is a positive correlation. In addition, the findings show that participants choose food products with both labels more often than would be expected by chance in all three conditions (see Figure 3.5). This means that participants generally prefer food products with both labels to food products with either label or no label. The preference for having both labels increases under a positive correlation. Overall, these findings support the hypothesis that consumers are, without explicit instructions, capable of learning the statistical structure of the environment and are able to apply the learned correlation correctly in the form of a decision heuristic, such as the *organic = healthful heuristic*.

In sum, the previously presented findings provide strong support for the idea that the *organic = healthful* belief is a consequence of statistical learning rather than the halo effect. However, I do not claim that the halo effect is hereby falsified. In fact, the halo effect and the statistical learning hypothesis are not mutually exclusive - both mechanisms could, in theory, contribute to explaining the *organic = healthful* belief. Whether statistical learning and halo effects co-exist remains an open question, but it should be clear that one should be careful before labelling something as a halo effect and, in general, before labelling beliefs as irrational. Beliefs and behaviours that seem irrational at first glance may, in fact, lead to ecologically rational behaviours when applied in the right environment. Hence, I propose that the *organic = healthful* belief is meaningful when applied in the right context.

Consumers who hold this belief and purchase organic food products for this reason will ultimately purchase food products that are, on average, 30% more healthful.

In the next chapter, I focus more closely on the consumer decision processes. More specifically, I am most interested in the first stage of the decision process, i.e. information acquisition (Einhorn & Hogarth, 1981). Common practice suggests analysing search strategies by looking at whether the search could be characterised as predominantly alternative or attribute-wise. However, when the search includes approximately equal amounts of both search patterns, it is not clear how to classify it. The existing measures do not provide an answer to this issue. Therefore, in the next chapter, I discuss the limitations of the existing measures and propose a new measure which addresses those limitations. I use the new measure to reanalyse the data from Study 3 and therefore shed more light on consumer search processes.

Chapter 4

Systematicity of Search Index: A new measure for exploring information search patterns

In Chapter 3, I showed that consumer beliefs that at first seem irrational can, in fact, lead to rational behaviour. However, when looking more closely at consumer decision processes and how consumers search for information, I noticed that in some situations the existing measures for exploring the pattern of information search are not informative enough. Therefore, in this chapter, I explore my second research question: *what measure can complement the Search Index (SI) to better describe information search?* I begin this chapter with a discussion of the existing measures and their criticisms. Then, I present a new measure, *the Systematicity of Search Index (SSI)*, to address these criticisms. Next, I test the SSI in an experiment and on the data of Study 3. I finish the chapter with a general discussion of the findings in the light of the research question asked.

4.1 Introduction

Cognitive processes behind judgment and decision making can be broken down into several sub-processes such as information acquisition, evaluation, action, and feedback/learning (Einhorn & Hogarth, 1981). Information acquisition concerns the processes of information search and storage, and has received much attention over the last 40 years. Therefore, several measures have been developed to explore information acquisition processes such as the depth of search, the pattern of information search, the variability of search, the compensation index, the latency of search and the content of search, to name just a few (Harte & Koele, 2001; Riedl, Brandstätter, & Roithmayr, 2008). Of all the measures on information acquisition, measures for exploring the pattern of information search have received the most attention so far, mainly due to Payne's seminal paper (1976) where he proposed a simple measure for detecting the pattern of information search. Hence, in the sections to follow, I focus exclusively on the measures for exploring the pattern of information search.

4.1.1 Pattern of information search

Focusing on the pattern of information search when studying cognitive processes has also been labelled as "analysis of transitions" because it considers the change from one acquired piece of information to the next (Jacoby et al., 1976). Four types of transitions can be distinguished with respect to whether the sequence of information searched consists of transitions belonging to a different or the same alternative, and a different or the same attribute (see Fig. 4.1). Type II transitions, i.e. transitions occurring within the same alternative but different attributes, and type III transitions, i.e. transitions occurring within the same attribute but different alternatives, are most often analysed in decision-making studies (Norman & Schulte-Mecklenbeck, 2009).

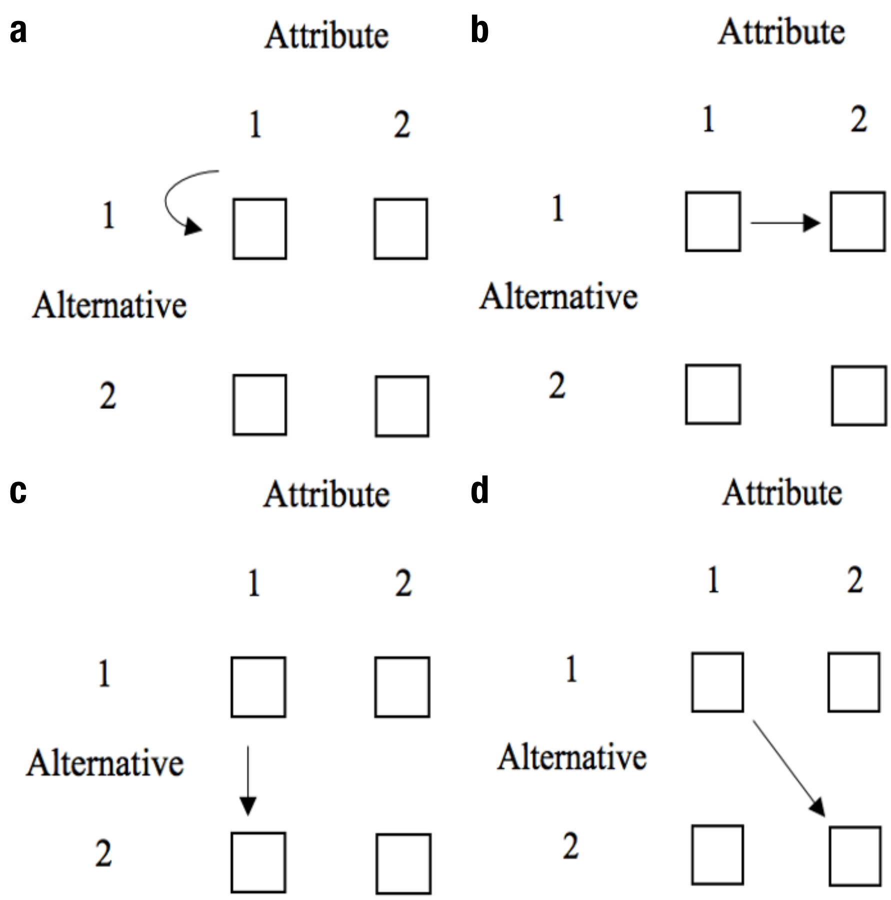


Figure 4.1 Types of single-step transitions during information search (a) type I (reassessing the same attribute within the same alternative), (b) type II (assessing different attributes within the same alternative), (c) type III (assessing same attributes within different alternatives) and (d) type IV (assessing different attributes within different alternatives).

Based on these four types of transitions, several measures have been proposed for analysing the pattern of information search in process-tracing studies. Since these four types of transitions include the analysis of single-step transitions, they have been labelled as single-step transition measures (Ball, 1997). The number of citations suggests[2] that the most commonly used measure is the Search Index (SI) proposed by Payne (1976) which shows the proportion of alternative-wise (type II) and attribute-wise (type III) search. The index is a ratio of the number of alternative-wise transitions minus the number of attribute-wise transitions over the sum of those two numbers:

$$\mathrm{SI} = \frac{N_{type\ 2} - N_{type\ 3}}{N_{type\ 2} + N_{type\ 3}}$$

It ranges from -1 to 1, -1 being a fully attribute-wise search and 1 being a fully alternative-wise search. In case there is an equal number of alternative- and attribute-wise transitions, the SI equals to zero. An alternative-wise search allows trade-offs between attributes, i.e. a high value on one attribute can compensate for a low value on another, so it often relates to the use of *compensatory* strategies, whereas an attribute-wise search does not allow such trade-offs so it relates to the use of *non-compensatory* strategies (Ford et al., 1989; Payne, Bettman, & Johnson, 1993). The overall simplicity of the measure could potentially explain its wide application.

However, there has been much criticism of the SI. For instance, Böckenholt and Hynan (1994) suggested that for an accurate categorization of information-acquisition strategies, one needs to consider characteristics of the decision environment, such as the number of presented alternatives and attributes. Specifically, when the number of attributes is higher than the number of alternatives, the SI points to an alternative-wise information search and when the number of

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[2] The number of citations of Payne's paper *Task complexity and contingent processing in decision making: An information search and protocol analysis* was 2161 on 25 August 2017 (obtained using Google Scholar).

alternatives is higher than the number of attributes, the SI points to an attribute-wise information search. The SI may, therefore, lead to misleading classifications of information search behaviour because it ignores these characteristics of the decision environment. Moreover, the index mean varies not only as a function of the number of alternatives and attributes, but also the number of transitions. Therefore, the values of the SI observed in different sized matrices as well as different numbers of transitions could not be compared directly (Bettman & Jacoby, 1976; Böckenholt & Hynan, 1994). In addition, extreme SI values have a higher probability of occurrence than intermediate values (Böckenholt & Hynan, 1994). Böckenholt and Hynan, therefore, proposed a new index, the Strategy Measure (SM), which describes information search strategies as standardized deviations from random search patterns:

$$\mathrm{SM} = \frac{\sqrt{N}((AD/N)(r_a - r_d) - (D - A))}{\sqrt{A^2(D-1) + D^2(A-1)}}$$

where *N* represents the total number of transitions, *A* represents the number of alternatives and *D* the number of attributes (dimensions) in an information matrix, r_a represents the frequency of alternative-wise transitions and r_d the frequency of attribute-wise transitions. However, Payne and Bettman (1994) have argued that the limitation of the SM lies in its inability to provide consistent results when decision makers make only one type of transition (e.g. alternative- or attribute-wise). On the other hand, the SM delivers identical results when it should not, for instance, in a case of a search pattern consisting of only attribute-wise transitions versus a pattern consisting of a mixture of alternative- and attribute-wise transitions. Ball (1997) suggests that the distribution of SM values still varies with changes in the number of alternatives and attributes in a matrix as well as the total number of transitions made.

Furthermore, comparing the mean SM values for the same search strategy applied in different sized matrices yields mixed results, as the calculation of the mean is sensitive to extreme values.

A different line of thought has led Van Raaij (1977) to propose a measure which is based on the same input as the SI but compares the number of times alternative- and attribute-wise transitions occur in the first versus the second part of the search process. More specifically, the information search patterns may change over time due to the application of different decision strategies during different stages of a decision process. The analysis is, therefore, sometimes divided into a few equal parts which are analysed separately (Svenson, 1979). The Van Raaij index can be calculated using:

$$\frac{[N(type\ j)_1 - N(type\ j)_2]}{M-1}$$

where *N* represents the number of observations for a particular type of transition, *j* represents the type of transition (type II or type III), the subscripts 1 and 2 represent the first and second half of the decision process respectively and *M* represents the total number of information items searched for. This measure has been shown to be more sensitive in detecting strategies used in the first versus the second phase of the decision process than the SI (Stokmans, 1992). Furthermore, the index is independent of the number of alternative- and attribute-wise transitions and the expected value of it is zero.

Overall, Ball (1997) nicely summarizes the three main limitations of measures that include the analysis of single-step transitions. First, since the analysis is restricted to single steps in the information search sequence, not all available information is used. Second, one does not actually learn about the search strategies used because the measures often restrict comparisons of search strategies to strict compensatory (e.g. weighted additive strategy) and non-compensatory strategies (e.g. lexicographic strategy). Specifically, Ball argues that it is not clear how to classify strategies that include both types of transitions and, therefore, fall between these two extremes. This is a direct criticism of the SI and particularly noticeable in the example of strategies that include an equal amount of both types of transitions so the SI concentrates around zero. This issue has also been addressed by other scholars (e.g. Harte & Koele, 2001). Finally, the distributions of such measures seem to be dependent on the number of dimensions, i.e. alternatives and attributes, of a matrix.

Ball, therefore, proposes the use of multiple-step transitions, which overcomes these limitations by focusing on a more complex and complete range of transitions. More specifically, he proposes pairwise comparison (type V) and multi-attribute comparisons (type VI; type *k*, where *k* = number of attributes + 4). Pairwise comparison is described as a comparison of the same two alternatives on more than one attribute in succession whereas multi-attribute comparison refers to a comparison of two or more alternatives on two or more attributes that are examined in the same order for each alternative. The maximum number of multi-attribute comparison transitions is a function of the number of attributes representing the different alternatives. For instance, in a situation where each alternative consists of four attributes, a decision maker can assess alternatives by focusing on two attributes (type VI), three attributes (type VII) or all four attributes (type VIII). Figure 4.2 shows examples of type V to type VII transitions. In his paper, Ball also provided specific examples of how to detect different search strategies by focusing on multiple-step transitions. For instance, type V transitions can be indicative of a majority of confirming dimensions (MCD) strategy, whereas type VII transitions can be indicative of weighted additive (WADD) and equal weight (EQW) strategies. Conversely, he pointed out how single-step measures can sometimes be misleading when the search process consists of type II (60%) and type III transitions (40%), which results in the SI being zero, and is indicative of a satisficing strategy which is usually considered to be a non-compensatory strategy.

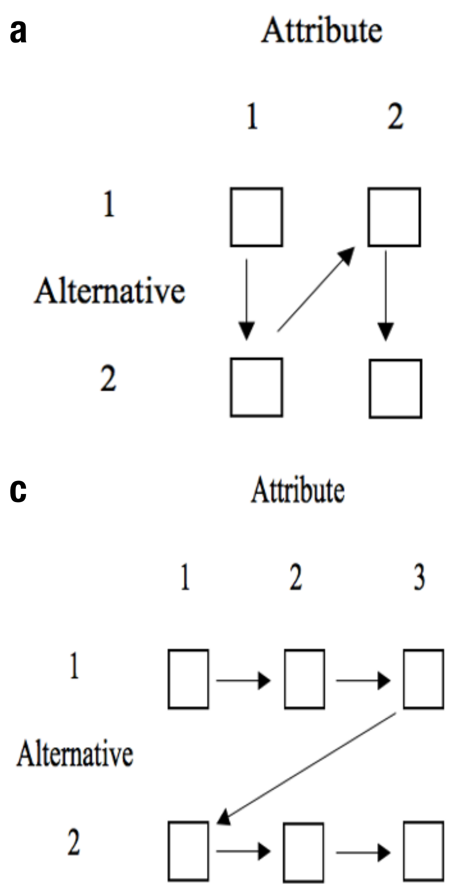

Figure 4.2 Types of multiple-step transitions during information search (a) type V (pairwise comparison), (b) type VI (two-attribute comparison) and (c) type VII (three-attribute comparison).

Here I focus more closely on Ball's previously introduced remarks. I am particularly interested in shedding light on how to categorise information search when the SI equals to zero. Put differently, when it equals to zero, all that the SI conveys is that a decision maker made approximately the same number of alternative- and attribute-wise transitions. However, does this mean that a decision maker's information search should, therefore, be described as random, or is it possible that this similar number of both types of transitions did not happen by chance?

To address this issue and answer my research question about *what measure can complement the Search Index (SI) to better describe information search*, I propose a new measure, *the Systematicity of Search Index* (*SSI*). The SSI explains the pattern of information search in terms of systematicity or the proportion of non-random search, i.e. a search that is alternative- or attribute-wise, corrected for chance. In addition, the SSI is a measure based on multiple-step transitions. As I show later, this measure has the potential to complement existing measures for exploring the pattern of information search, most specifically the SI. In the next section, I briefly outline how the SSI was developed (a detailed account is presented in the results section). I then discuss the hypotheses and report an experiment in which I test the usefulness of the SSI. Finally, I test the SSI on the data of Study 3 and discuss all the findings.

4.1.2 Development of Systematicity of Search Index

I developed the SSI by proposing the three alterations to the SI. First, rather than focusing on simple single-step transitions, I propose focusing on alternative- and attribute-wise patterns, i.e. sequences of either alternative- or attribute-wise transitions of specific length. The reasoning behind this alteration is an attempt to set the threshold higher in terms of what can be accepted as an indication of alternative- or attribute-wise processing. Second, I propose assessing whether the obtained patterns occur by chance by estimating the probability of a pattern occurring using a Monte Carlo simulation. Third, to get the proportion of systematic search, I propose that the SSI should be a ratio of alternative- and attribute-wise patterns corrected for chance over all transitions made. The SSI ranges from zero to one, zero representing a random or unsystematic search and one representing a non-random or systematic search. The SSI can, therefore, be calculated using the following equation:

$$\mathrm{SSI} = \frac{\sum_{i=1}^{n} l_i \, N_i \; (1 - p_i)}{l_{total}}$$

where l_i is the length of a pattern i, N_i is the frequency of a pattern i, p_i is the probability of a pattern *i* occurring by chance and l_{total} is the length of a total sequence of all transitions, i.e. string length.

I hypothesise that *the SSI is a more informative measure than the SI in situations where decision makers make approximately the same amount of alternative- and attribute-wise transitions (SI ≈ 0)*. More specifically, I expect that the SSI will show whether these alternative- and attribute-wise transitions did or did not occur by chance. I also hypothesise that *the SSI is higher when information presentation is visually organised compared to when it is visually disorganised*, because the visual organisation of information should encourage the level of systematic search. I test these hypotheses in an experiment reported below.

4.2 Study 4

I tested the previous hypotheses in a discrete choice experiment using eye tracking. I used four *within-subjects* conditions in which information was presented in an organised or disorganised way to encourage either systematic or unsystematic search, respectively. More specifically, as illustrated in the stimuli section below, in the conditions encouraging systematic search, the pieces of information were presented by either grouping alternatives (alternative array condition), grouping similar attributes (attribute array condition) or by presenting alternatives vertically in a matrix (matrix condition). In contrast, in the condition which encourages unsystematic search, all pieces of information belonging to each alternative were presented randomly in a matrix. As explained in the introduction of this chapter, the expected SI score for a random information search is zero only in the case of a symmetrical matrix. Therefore, to answer my research question about *what measure can complement the Search Index (SI) to better describe information search*, I was particularly interested in the conditions with matrix visual grouping.

4.2.1 Method

4.2.1.1 Participants

Thirty-five Danish participants were recruited through a consumer panel provider. Three participants were excluded from further analyses due to insufficient data quality, resulting in a total sample of 32 participants. An *a priori* power analysis performed through a simulation in R indicated that to have 95.6% power for detecting a small-sized effect (d = .2; see Cohen, 1988) with an alpha level of .05 for a within-subjects design with four conditions and 100 trials per participant, a sample size of 28 participants is required. The participants ranged in age from 23 to 50 years (M = 29.59, SD = 6.36) with more female than male participants (18 women). The data was collected from participants with normal and full colour vision only. Each participant received approximately €10 for completing the study. All participants gave informed consent. The study received ethical approval from the University of Leeds.

4.2.1.2 Design

In this discrete choice experiment, participants were instructed to choose the most healthful alternative out of four. Four within-subjects conditions were used, i.e. alternative array, attribute array, matrix and random matrix, in which information was presented differently. Each condition had 25 trials resulting in a total of 100 trials per participant. Each trial had four alternatives named A, B, C and D. Each alternative had four attributes: brand, percentage of fat, grams of protein and grams of sugar. The attributes had four levels (see Table 4.1) all of which were presented in each trial. In every trial participants were, therefore, presented with 16 pieces of information. Each trial was generated by randomly combining attribute levels without replacement, meaning that when one attribute was sampled, this attribute could no longer be chosen again in that trial. The order of conditions was randomised across participants.

Table 4.1 Attributes and attribute levels

Attribute			
Brand	Fat (%)	Protein (g)	Sugar (g)
Alpro	0.2	3	4
Cultura	1	6	8
Thise	1.5	9	12
Yoggi	3	12	16

4.2.1.3 Stimuli

The sixteen pieces of information in each trial were presented with 32 Gabor patches (i.e. sinusoidal gratings typically with a Gaussian envelope) paired in the following way: each Gabor patch pair had a target Gabor and a distractor Gabor.

Distractor Gabors had a rectangular envelope (5 cycles/deg, 3˚ x 3˚) and target Gabors had a circular envelope (5 cycles/deg, diameter 1˚). The distractor Gabors were oriented horizontally. The target Gabors were tilted either 20˚, 70˚, 110˚ or 160˚ clockwise from vertical. Each orientation of the target Gabor represented a different alternative. The Gabors tilted 20˚, 70˚, 110˚ and 160˚ belonged to alternatives A, B, C and D respectively. A grey rectangle (2˚ x 0.7˚) was positioned in the centre of each target Gabor. An attribute level (text height = 0.5˚) was positioned within each rectangle.

Each condition had its own unique visual presentation. In the alternative array condition, all attributes belonging to an alternative were presented together in a group (see Fig. 4.3a). The spacing between Gabor pairs within groups was 1˚ and between groups 3˚. The centres of the Gabor pair groups were located at the following coordinates: {(-5,5), (5,5), (-5,-5), (5,-5)}. The locations of target Gabors were randomised within groups across all trials. The attributes were randomly assigned to the four group locations. Additionally, the locations of attribute levels within groups were randomised. In the attribute array condition, similar attributes were presented together in groups, i.e. brand with brand, fat percentage with fat percentage and so on (see Fig. 4.3b). The spacing and the location of Gabor pairs were the same as in the alternative array condition. The locations of target Gabors were randomised between groups across all trials. The attributes were randomly assigned to the four group locations. Additionally, the locations of attribute levels within groups were randomised. In the matrix condition, alternatives and attributes were presented in a matrix, i.e. alternatives were presented vertically and attributes horizontally (see Fig. 4.3c). The spacing between Gabor pairs was 1˚. The locations of target Gabors and attribute levels were randomised column-wise and row-wise, respectively, across all trials. In the random matrix condition, alternatives and attributes were presented in a matrix as in the matrix condition; however, all pieces of information were presented independently (see Fig. 4.3d). The locations of target Gabors and attribute levels were randomised across all trials.

Figure 4.3 Visual array of (a) alternative array condition: alternatives presented together (note the orientation of the lines in the circular Gabor Patch), (b) attribute array condition: attribute levels belonging to the same attribute presented together, (c) matrix condition: alternatives presented vertically and attributes horizontally and (d) random matrix condition: all pieces of information presented independently.

4.2.1.4 Apparatus

The stimuli were created and presented using PsychoPy 1.84.2 (Peirce, 2007, 2009). Eye movements were recorded using a desk-mounted EyeLink 1000 eye tracker with a monocular sampling rate of 1000 Hz and a screen resolution of 1920x1200 pixels. The screen subtended a visual angle of 46.5˚ horizontally and 30.1˚ vertically. Average viewing distance was 60 cm from the screen. A chin rest was used to stabilize head position. Fixations were detected using a velocity, acceleration and motion-based algorithm with velocity, acceleration, and motion thresholds of 30˚/sec, 8,000 $˚/sec^2$, and 0.15˚, respectively (Holmqvist et al., 2011; SR Research, 2008). To consider the inaccuracy in recording of eye fixation locations, an area of interest (AOI) was drawn around every distractor Gabor (Orquin et al., 2016).

4.2.1.5 Procedure

The study was conducted in a light-controlled laboratory environment. Upon their arrival to the laboratory, participants were greeted and asked to read the study information sheet and fill in the consent form. This was followed immediately by an explanation of the procedure, task and visual design of the experiment. Specifically, participants were presented with four possible Gabor pairs and informed that each Gabor orientation represented a specific alternative throughout the experiment. They were also shown a screenshot of each condition and asked to locate alternatives in each. After determining the dominant eye, participants were calibrated using a 9-point calibration procedure followed by a 9-point drift validation test. A calibration offset < 1.0° was considered as acceptable. After the calibration, participants were introduced to the experiment layout and instructions on the screen. To test whether participants had memorized the target Gabors, they practiced recognizing in up to 48 practice trials. Each target Gabor was presented randomly 12 times. Feedback was given after each practice trial. Participants proceeded to the next practice trial only by providing the correct answer. In case of 10 correct answers in a row, suggesting mastery of recognition, participants immediately proceeded to the experiment. Participants were instructed to choose the most healthful among four alternatives by indicating their choice through a key press (A, B, C or D). They were given as much time as needed to make their choices. No feedback was given between trials. To control the location of the first fixation, a fixation cross lasting 1000 ms appeared in the centre of the screen preceding each trial. Participants completed 25 trials per condition, resulting in a total of 100 trials. The experiment lasted 45 minutes on average.

4.2.2 Results

4.2.2.1 Analysis of practice trials

The analysis of practice trials showed that participants on average completed 20 practice trials (M = 20.09, SD = 13.01, C_{95} = [24.78, 15.4]) before they proceeded to the experiment. However, three out of the 32 participants completed the maximum of 48 trials before they proceeded to the experiment, which suggests they may have not mastered recognizing the alternatives. Without considering the results for these participants, the rest of the participants on average completed 17 practice trials before proceeding to the experiment (M = 17.21, SD = 9.76, C_{95} = [20.92, 13.49]). Bearing in mind that participants needed to have 10 correct answers in a row to be able to proceed to the experiment, this result suggests that, overall, they did not have issues with mastering recognizing which alternative is represented by each target Gabor. Table 4.2 shows an overview of how many practice trials participants completed before they proceeded to the experiment.

Table 4.2 The number of participants within four practice trial intervals

Number of Practice Trials	Number of Participants
10 – 20	22
20 – 30	5
30 – 40	0
40 – 50	5

4.2.2.2 Calculating the Systematicity of Search Index

The analysis of participants' information search behaviour was divided into seven steps (see Table 4.3). First, I determined which attributes participants fixated on and in which order. I therefore coded eye fixations considering 16 possible combinations of four alternatives and four attribute levels (see Table 4.4) which resulted in a string length of 154,355 elements for all participants. Table 4.5 shows an overview of the first ten rows of the data set after coding the AOIs. Since I was only interested in whether participants fixated on an attribute at least once, subsequent fixations, i.e. two or more fixations in a row to the same attribute within an alternative were deleted from the string which resulted in a total string length of 96,029 elements.

Table 4.3 An overview of the seven-step procedure to calculate the SSI

Step Number	Step Name
1	Data preparation
2	Identifying alternative-wise patterns
3	Identifying attribute-wise patterns
4	Assessing whether the obtained patterns occurred by chance (Monte Carlo simulation)
5	Calculating probabilities of occurrence for each pattern
6	Calculating probability complements
7	Applying the SSI equation

Table 4.4 Recoding of eye fixations depending on attribute-alternative combination

		Alternative			
		(1) 20°	(2) 70°	(3) 110°	(4) 160°
Attribute	Brand (b)	1b	2b	3b	4b
	Fat (f)	1f	2f	3f	4f
	Protein (p)	1p	2p	3p	4p
	Sugar (s)	1s	2s	3s	4s

Table 4.5 An overview of the first ten rows of the data set after coding the AOIs

Participant	Condition	Trial	Alternative	Attribute
1	Alternative array	1	3	b
1	Alternative array	1	1	s
1	Alternative array	1	1	s
1	Alternative array	1	1	f
1	Alternative array	1	1	f
1	Alternative array	1	1	f
1	Alternative array	1	1	f
1	Alternative array	1	1	f
1	Alternative array	1	1	b
1	Alternative array	1	1	b

Next, I determined alternative- and attribute-wise patterns in the string. The patterns were created for every participant on a trial level. I started by identifying alternative-wise patterns by searching for the substrings where at least two subsequent fixations belonged to different attributes within the same alternative. Then, I focused on the order and frequency of the elements within each substring. Specifically, in each substring, I ordered the elements alphabetically and deleted every repeating instance of an element. In other words, if a participant inspected three attributes within an alternative and then focused on the same three attributes, but in a different order in the next alternative, the attributes were coded as if they had been inspected in the same order. For example, a sequence sugar-protein-fat which is equal to fat-protein-sugar and protein-sugar-fat and so on, was then coded as fat-protein-sugar, i.e. ‘fps’. Additionally, if a participant fixated on an attribute within an alternative several times, the additional fixations were deleted. For example, if a participant made a sequence sugar-protein-sugar-protein-sugar within an alternative, I coded it as protein-sugar, i.e. 'ps'.

After identifying and recoding all substrings, I concatenated the identical subsequent substrings which belonged to different alternatives. For example, if a participant fixated on protein and sugar levels twice in a row across two different alternatives, a pattern named 'psps' was produced. To be classified as an alternative-wise pattern, the same substring of a minimal length of two had to appear at least twice in a row. For this reason, a pattern length of 'four' was the shortest possible alternative-wise pattern length. An example of the 10 alternative-wise patterns obtained can be found in Table 4.6 (column three). The maximum pattern length in this example is 12 (trial three).

I then proceeded to identify attribute-wise patterns by searching for the substrings where at least four subsequent fixations belonged to the same attribute, but different alternatives within a trial. For example, if a participant fixated on a sugar level four times in a row across four different alternatives, an attribute-wise pattern named 'ssss' was produced. Since the shortest possible alternative-wise pattern was of length 'four', I considered only the attribute-wise patterns of length 'four' or greater. An example of the 10 attribute-wise patterns obtained can be found in Table 4.7 (column three). The maximum pattern length in this example is eight (trial 26). I then determined the frequency for every alternative- and attribute-wise pattern (see column four in Table 4.6 and Table 4.7).

After identifying patterns and their frequencies, I assessed whether the obtained patterns occurred by chance. To do this, I, used a Monte Carlo simulation and simulated 10,000 random observations for each participant, with the string length being equal to the one in the original data set. An observation consisted of an alternative number (1 to 4) and an attribute initial (b, f, p and s). I analysed the random data sets in the same way as I analysed the original data set in terms of identifying alternative- and attribute-wise patterns and calculating their frequencies. I then compared all the patterns and their frequencies from the original data set with the patterns and the associated frequencies (see column five in Table 4.6 and Table 4.7) in 10,000 random data sets. Specifically, I looked at how frequently a pattern from the original data set occurred in that amount or more in 10,000 random data sets. For example, if I observed that a pattern ‘ssss’ occurred four times in a trial in the attribute array condition, I looked at how many times this pattern occurred at least four times or more in a trial in the attribute array condition in 10,000 random data sets.

I then calculated the probabilities by dividing these pattern frequencies by the total number of simulations (10,000) (see column six in Table 4.6 and Table 4.7). To preserve the data, instead of deleting the patterns that occurred below a specific threshold level (.05), i.e. by chance, I used the probability complements. Specifically, I multiplied each pattern from the original data set with its probability complement (see column seven in Table 4.6 and Table 4.7).

Table 4.6 First 10 alternative-wise patterns identified for one participant on a trial level

Condition	Trial	Pattern	Pattern Frequency	Pattern Frequency (Simulation)	Probability	Probability Complement
Alternative array	1	fpsfps	1	33	.0033	. 9967
Alternative array	2	bfsbfs	1	4	.0004	.9996
Alternative array	3	bfpsbfpsbfps	1	0	0	1
Alternative array	4	fpsfps	1	31	.0031	.9969
Alternative array	5	bfpsbfps	2	0	0	1
Alternative array	6	bfpsbfps	1	4	.0004	.9996
Alternative array	6	bsbsbs	1	19	.0019	.9981
Alternative array	6	fpsfps	1	38	.0038	.9962
Alternative array	6	psps	1	621	.0621	.9379
Alternative array	10	bfpsbfps	1	0	0	1

Note. Attributes: b: brand, f: fat, p: protein and s: sugar.

Table 4.7 First 10 attribute-wise patterns identified for one participant on a trial level

Condition	Trial	Pattern	Pattern Frequency	Pattern Frequency (Simulation)	Probability	Probability Complement
Alternative array	7	ssss	1	324	.0324	.9676
Alternative array	8	sssssss	1	2	.0002	.9998
Alternative array	9	ssss	1	925	.0925	.9075
Alternative array	11	sssss	1	64	.0064	.9936
Alternative array	12	ssss	1	214	.0214	.9786
Alternative array	17	ssss	1	529	.0529	.9471
Alternative array	18	sssss	1	66	.0066	.9934
Alternative array	21	ssss	1	645	.0645	.9355
Attribute array	26	bbbbbb	1	29	.0029	.9971
Attribute array	26	ffffffff	1	3	.0003	.9997

Note. Attributes: b: brand, f: fat, p: protein and s: sugar.

Finally, I applied the following, previously introduced equation, to calculate the systematicity of participants' information search within each condition on a trial level:

$$\text{SSI} = \frac{\sum_{i=1}^{n} l_i \, N_i \, (1 - p_i)}{l_{total}}$$

where l_i is the length of a pattern i, N_i is the frequency of a pattern i, p_i is the probability of a pattern i occurring by chance and l_{total} is the length of a total sequence of all transitions (i.e. string length). I also calculated the direction of participants' information search within each condition and for each trial by calculating the SI using:

$$\text{SI} = \frac{N_{type\,2} - N_{type\,3}}{N_{type\,2} + N_{type\,3}}$$

where type II are transitions occurring within the same alternative but different attributes, and type III are transitions occurring within the same attribute but different alternatives. I present these results in the following section. The full R code used to generate the previously described steps can be found in Appendix E.

4.2.2.3 Eye movement analysis

To test whether participants are being more systematic in the three visually organised conditions compared to a disorganised one, i.e. alternative array, attribute array, matrix and random matrix condition, respectively, the data was analysed by means of linear mixed-effects model. The model was fitted using the 'lme' function from 'nlme' package in R (Pinheiro, Bates, DebRoy, Sarkar, & R Core Team, 2017). I used the SSI as a dependent variable, condition as an independent variable and participant variable as a random effect. The analysis revealed that adding the fixed effect of condition to the model significantly improved the fit compared to the baseline model, $\chi^2(3) = 113.13$, $p < .001$. A Tukey *post hoc* test revealed that the SSI was significantly different in the alternative array compared to the random matrix condition (b = - .15, $p < .001$, d = -.96), the attribute array compared to the random matrix condition (b = - .30, $p < .001$, d = -1.56), the matrix compared to the random matrix condition (b = - .27, $p < .001$, d = -1.38), the alternative array compared to the attribute array condition (b = .15, $p < .001$, d = .63) and the alternative array compared to the matrix condition (b = .12, $p < .001$, d = .51). However, there was no significant difference between the attribute array compared to the matrix condition (b = - .03, p = .69, d = -.10).

To test the direction of participants' information search across four conditions, again I applied linear mixed-effects model using the 'lme' function from 'nlme' package in R. I used the SI as an outcome variable, condition as a predictor variable and participant variable as a random effect. Again, the analysis revealed that adding the fixed effect of condition to the model significantly improved the fit compared to the baseline model, $\chi^2(3) = 193.31$, $p < .001$. A Tukey *post hoc* test revealed that the direction of information search was significantly different between all conditions. Specifically, there was a significant difference between the alternative array compared to the attribute array condition (b = - 1.09, $p < .001$, d = -3.12), the alternative array compared to the matrix condition (b = - .62, $p < .001$, d = -1.52), the alternative array compared to the random matrix condition (b = - .40, $p < .001$, d = -.99), the attribute array compared to the matrix condition (b = .48, $p < .001$, d = 1.18), the attribute array compared to the random matrix condition (b = .70, $p < .001$, d = 1.76) and the matrix compared to the random matrix condition (b = .22, $p < .001$, d = .49).

To better understand the relationship between the two indices, I plotted the SSI against SI across conditions (see Fig. 4.4). Figure 4.4 shows that participants scored higher on the SSI in the alternative array condition, attribute array condition, and matrix condition compared to the random matrix condition. The SI, on the other hand, shows that participants on average made more alternative-wise transitions in the alternative array condition and more attribute-wise transitions in the attribute array condition. In the matrix condition, participants on average made approximately an equal amount of alternative- and attribute-wise transitions, while in the random matrix condition they on average made slightly more alternative- than attribute-wise transitions. Table 4.8 shows an overview of means, standard deviations and 95% confidence intervals for the SSI and SI across conditions.

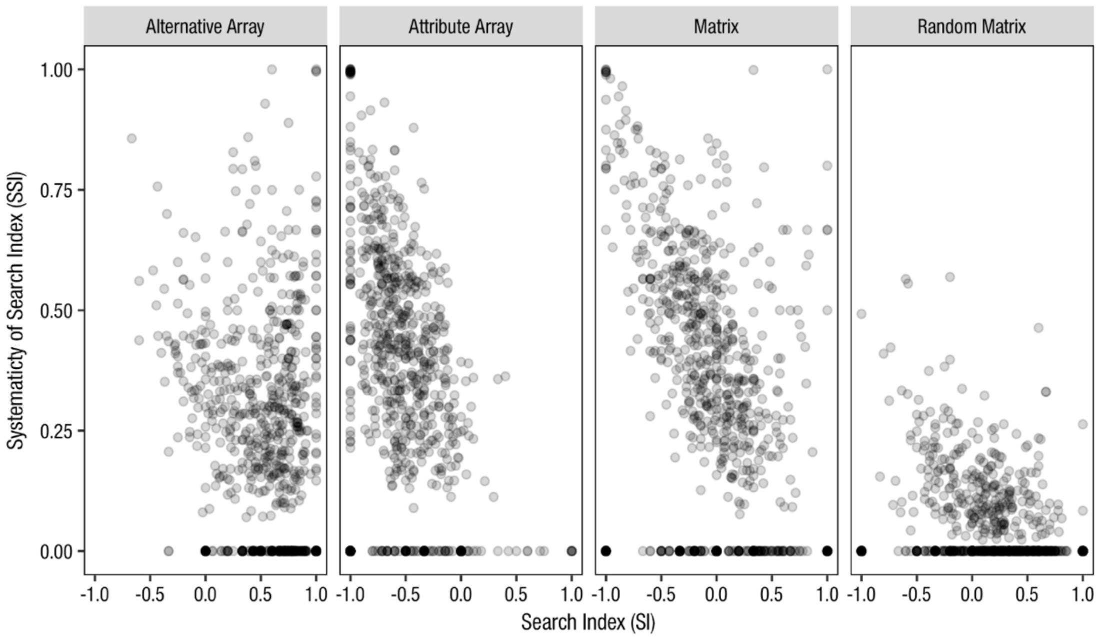

Figure 4.4 Systematicity of Search Index (SSI) and Search Index (SI) across conditions on a trial level.

Table 4.8 Means, standard deviations and 95% confidence intervals for the Systematicity of Search Index (SSI) and Search Index (SI) across conditions

	SSI			SI		
Condition	*M*	*SD*	95%CI	*M*	*SD*	95%CI
Alternative array	.21	.22	[.19, .22]	.55	.35	[.53, .58]
Attribute array	.35	.26	[.34, .37]	-.54	.35	[-.57, -.52]
Matrix	.33	.27	[.31, .35]	-.07	.45	[-.10, -.03]
Random matrix	.05	.09	[.05, .06]	.16	.44	[.12, .19]

4.2.2.4 Choice analysis

To examine the effect of the relative attribute importance on participants' choices of the most healthful food product, I fitted participants by means of a multinomial logit model (MNL) using the 'mlogit' package in R (Croissant, 2013). Each participant was fitted with a null model including intercepts for the four product alternatives and a full model including a term for each attribute, i.e. brand, fat, protein and sugar. I analysed the choices based on random utility theory (McFadden, 1974; Thurstone, 1927), which assumes that a) choice is a discrete event, b) utility towards an alternative varies across individuals as a random variable and c) individuals choose the alternative that maximises their subjective utility. Utility is defined as (Louviere, Hensher, & Swait, 2000):

$$U_{iq} = V_{iq} + \varepsilon_{iq}$$

where U_{iq} is the utility of the ith alternative for the qth individual, V_{iq} is a matrix component or 'representative utility' and ε_{iq} is a random component which reflects all possible unobserved influences on decisions. The matrix component is further defined as:

$$V_{iq} = \sum_{k=1}^{K} \beta_{ik} X_{ikq}$$

where X_{ikq} is the value of alternative i for individual q with attributes k (k = 1, ..., 4), and β_{ik} is a part-worth utility estimated for each attribute and each individual. If I assume that the random error terms ε_{iq} are independent across alternatives and are identically distributed, the probability of individual q choosing alternative i follows the closed-form expression of the MNL model:

$$P(iq) = \frac{\exp(V_{iq})}{\sum_{j=1}^{J} \exp(V_{jq})}$$

Parameters of the MNL model are estimated with maximum likelihood where likelihood is defined as:

$$L = \prod_{q=1}^{Q} \prod_{j=1}^{J} P_{jq}^{f_{jq}}$$

where Q is a random sample of individuals, f_{jq} is a dummy variable such that $f_{jq} = 1$ if alternative j is chosen and $f_{jq} = 0$ otherwise. The log likelihood function L^* can be then written as:

$$L^* = \sum_{q=1}^{Q} \sum_{j=1}^{J} f_{jq} \ln P_{jq}$$

To investigate the explanatory power of each attribute for each participant, I calculated the relative attribute importance as the partial log-likelihood, i.e. how much each attribute contributes to the overall log-likelihood of a choice model, assuming a linear integration of the four attributes (Crouch & Louviere, 2004; Lancsar, Louviere, & Flynn, 2007) using:

$$\frac{\Delta L^{*}{}_{k}}{\sum_{k=1}^{K} \Delta \square^{*}{}_{k}}$$

where $\Delta L^{*}{}_{k}$, the delta log-likelihood for attribute *k*, is the log-likelihood difference between the full model and the full model excluding attribute *k*:

$$\Delta L^{*}{}_{k} = L^{*}{}_{full} \text{ - } L^{*}{}_{full(-k)}.$$

After fitting the model and estimating the relative importance of each attribute, I evaluated the model by employing a *Prediction Success Index* (*PSI*, McFadden, 1977), which is one of the general goodness-of-fit measures for discrete choice models. To do that, I obtained the probabilities of choice for each individual on a trial level using the predict function from the 'mlogit' package in R. I then compared the choice probabilities generated by the model with the observed choices and calculated the PSI for each individual in each condition using the following equation:

$$\sigma_i = \frac{N_{ii}}{N_{.i}} - \frac{N_{.i}}{N_{..}}$$

where $N_{ii}/N_{.i}$ is the proportion of individuals expected to choose an alternative who indeed chose that alternative and $N_{.i}/N_{..}$ is the proportion which would be successfully predicted if the choice probabilities for each individual were assumed to equal the observed aggregate shares. I then calculated an overall PSI for each condition as well as each participant within each condition using the following equation:

$$\sigma = \sum_{i=1}^{J} \left(\frac{N_{ii}}{N_{.i}} - \frac{N_{.i}}{N_{..}} \right)^2$$

The index is generally non-negative with a maximum value occurring when the model predicts perfectly. The index can also be normalized to have a maximum value of one with values closer to one showing greater predictive capability of the model. The results show that the overall PSI for alternative array, attribute array, matrix and random matrix condition was .43, .38, .42 and .33 respectively, suggesting that the systematicity of participants' choices was the lowest in the random matrix condition. An overview of the full prediction success tables for each condition can be found in Appendix F.

To inspect whether there is a relationship between the highest relative attribute importance and the PSI for each participant within each condition, I looked at the correlations between the two. I found medium to large positive correlations in all conditions (see Table 4.9) between attributes with the highest relative importance and the PSI.

Table 4.9 Correlations with the 95% confidence intervals between attributes with the highest relative importance and Prediction Success Index (PSI) across conditions

Condition	Correlation	95% Confidence Interval
Alternative array	.74	[.54, .87]
Attribute array	.68	[.43, .83]
Matrix	.46	[.14, .70]
Random Matrix	.54	[.23, .75]

Put differently, the more participants relied on one attribute when making choices, the higher their PSI. Figure 4.5 shows a scatterplot of the highest relative attribute importance and PSI across conditions. I also calculated the proportion of the sample predominantly relying on one attribute when making choices, and it appears that 80% of the sample had a relative attribute importance greater than 50% for one of the four attributes. This implies that participants predominantly relied on one attribute when making choices regardless of condition. Further analysis showed that participants who predominantly relied on one attribute when choosing the most healthful product, mostly relied on the sugar attribute (70% of the sample).

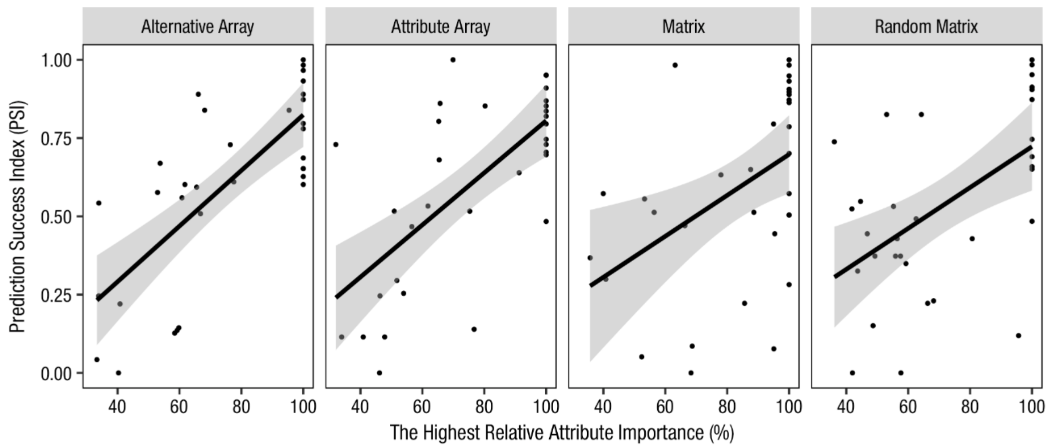

Figure 4.5 Scatter plot of the highest relative attribute importance and Prediction Success Index (PSI).

To test whether there is a relationship between the SSI and the PSI across conditions, I calculated the correlations between the two. I found a small positive correlation between the SSI and the PSI in the alternative array and attribute array conditions and a small to medium negative correlation in the matrix and random matrix condition (see Table 4.10). Figure 4.6 shows a scatterplot of the SSI and PSI across conditions.

Table 4.10 Correlations with the 95% confidence intervals between the Systematicity of Search Index (SSI) and Prediction Success Index (PSI) across conditions

Condition	Correlation	95% Confidence Interval
Alternative array	.25	[-.11, .55]
Attribute array	.11	[-.24, .45]
Matrix	-.21	[-.52, .14]
Random Matrix	-.30	[-.59, .06]

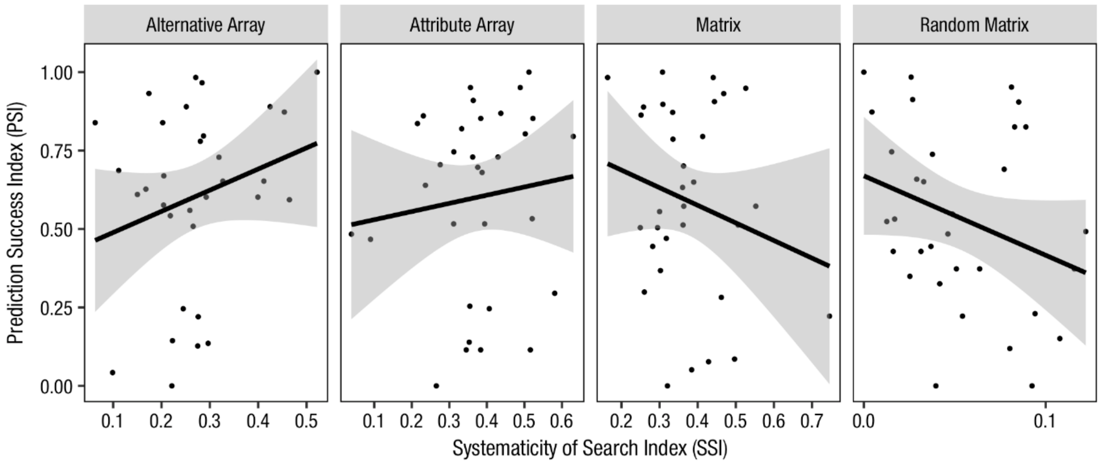

Figure 4.6 Scatter plot of the Systematicity of Search Index (SSI) and Prediction Success Index (PSI).

4.3 Applying the SSI and SI measures to the eye movement data from Study 3

To explore how the SSI performs in a different eye tracking study, I tested how participants searched for information in Study 3. The methods for Study 3 are explained in more detail in section 3.4.1. To calculate the SSI and SI, I followed the steps from one to seven described in section 4.2.2.2. The results of the analysis are reported in Table 4.11. More specifically, Table 4.11 shows an overview of means, standard deviations and 95% confidence intervals for the SSI and SI across conditions.

Table 4.11 Means, standard deviations and 95% confidence intervals for the Systematicity of Search Index (SSI) and Search Index (SI) across conditions

	SSI			SI		
Condition	*M*	*SD*	95%CI	*M*	*SD*	95%CI
-0.5	.36	.26	[.34, .37]	.03	.41	[0, .05]
0	.32	.24	[.31, .33]	.10	.39	[.08, .12]
0.5	.31	.23	[.30, .32]	.15	.36	[.13, .17]

To better understand the relationship between the two indices, I plotted the SSI against SI across conditions (see Fig. 4.7). Figure 4.7 shows what the mean values of the indices indicate, i.e. that participants performed a relatively systematic search in all three conditions. The SI, on the other hand, shows that participants' search was mostly grouped around zero, which suggests that participants in all three conditions overall made approximately the same number of alternative and attribute-wise transitions.

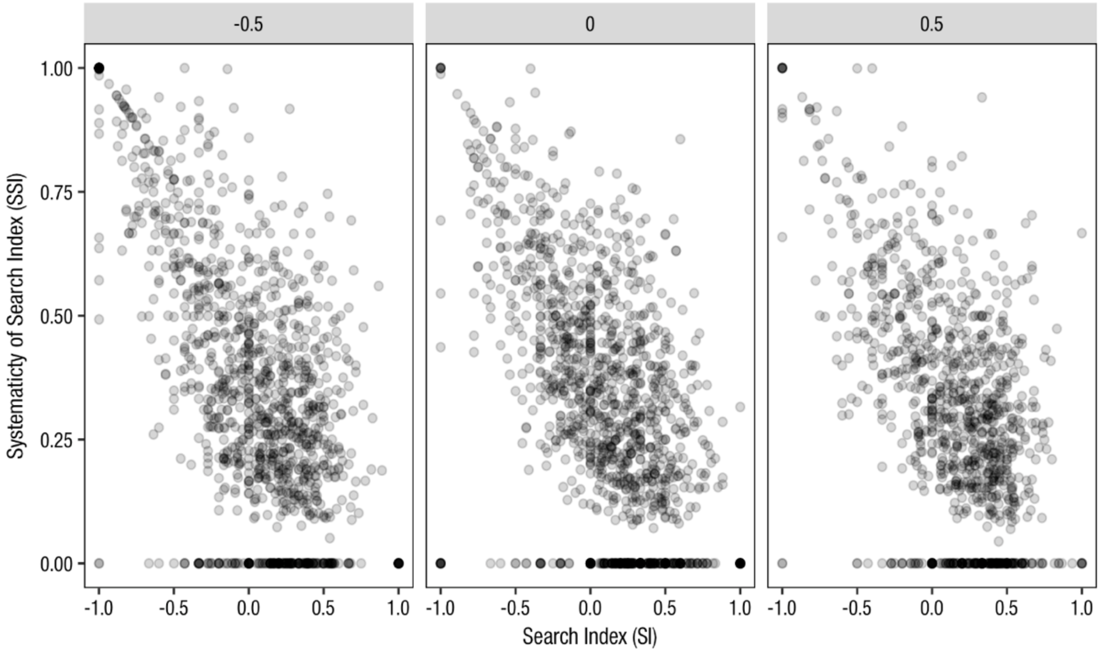

Figure 4.7 Systematicity of Search Index (SSI) and Search Index (SI) across conditions on a trial level.

4.4 Discussion

To answer the research question posed in this chapter: *what measure can complement the Search Index (SI) to better describe information search,* I proposed a new measure, *the Systematicity of Search Index* (*SSI*), as an additional measure for exploring information search behaviour. More specifically, I developed a measure for exploring how systematic decision makers are when searching for information, by determining the proportion of non-random search, i.e. a search that is alternative- or attribute-wise, corrected for chance.

I hypothesised that *the SSI is a more informative measure than the SI in situations where decision makers make approximately the same amount of alternative- and attribute-wise transitions (SI ≈ 0)*. I also hypothesised that *the SSI is higher when information presentation is visually organised compared to when it is* *visually disorganised*. I therefore tested the usefulness of this index in a discrete choice experiment with four within-subjects conditions (alternative array, attribute array, matrix and random matrix) using eye tracking. In each condition, I used different visual presentation to create either organised or disorganised information presentation format.

The findings show there is a difference between the SSI in conditions with an organised (alternative array, attribute array and matrix) versus disorganised (random matrix) information presentation format, with the largest difference being between the attribute array compared to the random matrix condition, d = -1.56. I also observed a large difference between the alternative array and random matrix conditions, as well as the matrix and random matrix conditions, d = -.96 and d = -1.38 respectively. Furthermore, the SSI was, on average, higher in the alternative array, the attribute array, and the matrix condition compared to the random matrix condition (see Table 4.8) which supports my hypothesis that the SSI will be higher in conditions where information was visually organised compared to the condition where it was disorganised.

When comparing the SI in the conditions with an organised and disorganised information presentation format, I observed the largest difference between the attribute array and the random matrix condition, d = 1.76. I also observed a large difference between the alternative array compared to the random matrix condition, d = -.99, and a medium difference between the matrix compared to the random matrix conditions, d = .49. As expected, participants on average made more alternative-wise search transitions in the alternative array condition and more attribute-wise transitions in the attribute array condition. In the matrix condition, participants on average made approximately an equal amount of alternative- and attribute-wise transitions, while in the random matrix condition they on average made slightly more alternative- than attribute-wise transitions (see Table 4.8).

These findings, therefore, support my hypothesis that the SSI is a more informative measure than the SI, when the SI is close to zero. Specifically, the SI suggests that participants, on average, made an equal amount of alternative- and attribute-wise transitions in the matrix condition (SI = -.07), whereas the SSI suggests that although this may be the case, it did not happen by chance (SSI = .33). In addition, the SI in the random matrix condition suggests that participants, on average, produce slightly more alternative-wise transitions (SI = .16), whereas the SSI suggests that this most likely happened by chance (SSI = .05).

Finally, a follow-up choice analysis showed a small positive correlation between the SSI and the PSI in the alternative array and attribute array conditions, and a small to medium negative correlation in the matrix and random matrix conditions. I take this to imply that the information presentation format may influence the relationship between the systematicity of the eye movements and choices. However, I do not want to draw any specific conclusions since the confidence intervals are wide. This finding supports previous research suggesting that presentation format strongly influences decision makers' information processing (Bettman & Kakkar, 1977). Furthermore, the analysis of participants' highest relative attribute importance and their PSI revealed a medium to strong correlation between the two in all conditions. This suggests that the more participants relied on one attribute when making choices, the higher was their PSI. Furthermore, the findings show that 80% of the sample had a relative attribute importance that was greater than 50% for one of the four attributes. These findings, therefore, imply that participants who predominantly relied on one attribute made more systematic choices.

After applying the SSI to the eye movement data from Study 3, I found that the SSI proved to be useful as a complementary measure to the SI. More specifically, the mean SI values showed that in all three conditions participants made approximately the same number of alternative- and attribute-wise transitions, whereas the mean SSI values showed that this equal amount of transitions did not happen by chance (see Table 4.11).

In sum, the previously presented findings contribute to the existing knowledge on information search by providing a new measure for exploring the pattern of search. Generally speaking, the SSI is useful as an additional measure for exploring the pattern of information search; however, it has been shown that it is particularly useful in situations when the SI is close to zero. The experiment confirmed the usefulness of the new measure by showing that decision makers' systematicity of information search depends to a great extent on the visual format of an environment. Hence, the SSI can be used for calculating the systematicity of information search in process-tracing studies and, therefore, serve as a complementary measure to existing measures for exploring the pattern of information search.

Chapter 5

General discussion and conclusion

The preceding chapters of this doctoral dissertation have dealt with exploring decision processes behind food choices. More specifically, in Chapter 3, I addressed the first research question: *can irrational beliefs sometimes lead to rational behaviours when making food choices?* In this chapter, I explored a novel hypothesis that consumers may not be biased when concluding that organic food products are, in general, more healthful than conventional food products. Instead, I proposed that consumers use this *organic = healthful heuristic* because in the environment, i.e. supermarkets, organic food products are more prevalent in more healthful food product categories which consumers have observed. This was tested in three studies, i.e. a combination of field, online and lab studies.

In Chapter 4, I addressed the second research question: *what measure can complement the Search Index (SI) to better describe information search?* To answer this research question, I focused on analysing the measures for exploring the pattern of information search, which, of all the measures on information acquisition, have received the most attention so far. In particular, one of the measures for exploring the pattern of information search, i.e. the Search Index (SI), has received a lot of attention. Although applied in various contexts, this index also received several important criticisms. To address these criticisms, I proposed a new measure, *the Systematicity of Search Index (SSI)*, which sheds light on processes not captured by the SI and therefore complements it. I tested the SSI in an experiment in the lab. Afterwards, I also used it to reanalyse the data from Study 3.

This final chapter consists of three sections. In the first section, I discuss the findings from the empirical chapters in more detail. I also reflect on the possible limitations and discuss potential future research ideas. Next, I outline and discuss theoretical, methodological and practical implications of the findings. In the final section, I provide some concluding remarks.

5.1 General discussion

The first research question I aimed to address in this doctoral dissertation was whether irrational beliefs can sometimes lead to rational behaviours when making food choices. This research question was driven by the previous findings that consumers perceive organic food products as more healthful than conventional food products (Lee et al., 2013; Schuldt & Schwarz, 2010; Sörqvist et al., 2015) when in fact there is currently no conclusive scientific evidence for this belief (Barański et al., 2014; Dangour et al., 2009; Smith-Spangler et al., 2012). It has been argued that consumers draw such conclusions because they are influenced by a *halo effect*. As discussed in more detail in section 3.1, the halo effect is a cognitive bias in which general positive attitudes towards an object spread to all associated attributes (Nisbett & Wilson, 1977; Thorndike, 1920). In the context of organic food products, that would mean that a general positive attitude regarding organic food products is assumed to spread to all other more specific attributes such as health, quality or safety perceptions.

I proposed a different explanation as to why this may be so. More specifically, taken out of context, this *organic = healthful heuristic* may seem irrational. However, if the same heuristic is applied in an appropriate context, it could actually lead to a meaningful conclusion, and therefore be considered as rational behaviour. This assumption is grounded in the literature that studies *ecological rationality*, i.e. the match between the mind and the environment (Todd &

Gigerenzer, 2007; Todd et al., 2012). In particular, it has been argued that the right application of a heuristic can sometimes lead to better outcomes than other procedurally more complicated processes (Gigerenzer & Goldstein, 1996).

However, there were several prerequisites for the previous assumption to hold. First, organic food products had to be, in some way, more healthful than conventional food products. As there is currently no conclusive scientific evidence to support this, I hypothesised that organic food products may be more prevalent in less processed, and therefore more healthful, food product categories, simply because it is easier to make a product with fewer organic ingredients. In that case, it would be meaningful to conclude that organic food products are in general more healthful than conventional food products. I tested this hypothesis in a field study (Study 1) by visiting six supermarkets and counting organic food products within 59 food product categories (see section 3.2).

Second, considering that organic food products are indeed more prevalent in more healthful food product categories, I hypothesised that consumers have observed this in the environment, that is, in supermarkets, and learned it. I tested this hypothesis in an online consumer survey (Study 2) where consumers were asked to assess the healthfulness of the 59 food product categories identified in the field study, and to estimate the prevalence of organic food products within these categories (see section 3.3).

Finally, I hypothesised that consumers can learn, in an unsupervised manner, that some cues are correlated, and use these cues in a heuristic way. More specifically, I hypothesised that consumers can learn a correlation between organic and health cues and use this correlation as a heuristic when choosing the most healthful food products. This hypothesis has a background in the literature that studies statistical learning (Conway & Christiansen, 2006; Perruchet & Pacton, 2006) which is a type of learning that evolves without conscious attempts to learn distributional properties, correlations, and transition probabilities in the environment (Thiessen et al., 2013). I tested this hypothesis in an eye tracking experiment (Study 3) with the three conditions (positive correlation, no correlation and negative correlation condition) which differed in the size of a correlation between organic and health cues (see section 3.4).

The findings from Study 1 support the first hypothesis that organic food products are more prevalent in more healthful food product categories. More specifically, organic food products are more prevalent in less processed food product categories, such as fruit, vegetables, eggs and so on, possibly because fewer organic ingredients are required. This implies that highly processed food products such as prepackaged meals, candy, crisps and so on, are rarely organic, which is supported by the findings from Study 1. The findings also show that organic food products are also more prevalent in less processed variants of specific food products. For instance, whole-grain pasta is more likely to be organic compared to pasta made with refined wheat flour. In addition, a calculation of the expected healthfulness of organic and conventional food showed that organic food products are, on average, 30% more healthful than conventional food products.

The findings from Study 2 support the second hypothesis that consumers have observed and learned the statistical structure of the environment where organic food products are more prevalent in more healthful food product categories. More specifically, consumers gave accurate estimates of the prevalence of organic food products across different food product categories. In addition, consumer estimates of food product categories' healthfulness matched the ones provided by food and nutrition experts, suggesting that consumers can distinguish more healthful from less healthful food products on a category level. This is in line with the previous findings arguing that consumers are typically very categorical in thinking about food healthfulness (Orquin, 2014; Rozin, Ashmore, & Markwith, 1996).

The findings from Study 3 support the third hypothesis that consumers can learn the statistical structure of a natural environment and apply the learned cue in their decision making. The findings show that participants are more likely to look at organic labels when there is a positive correlation between organic and health cues. This gaze bias suggests that participants in this condition consider the organic label as relevant to the health judgment task (Orquin & Mueller Loose, 2013). The findings also show that participants who include labels in their judgments are more likely to choose food products with organic labels when there is a positive correlation between the two labels. However, they are even more likely to choose products with both labels when there is a positive correlation between the two. This suggests that participants generally preferred products with both labels, but also relied on organic labels if this cue was easier to retrieve.

In sum, the findings from these three studies show that one ought to be careful before labelling something as a bias and, in general, before labelling beliefs as irrational. Beliefs and behaviours that seem irrational at a glance may, in fact, lead to rational outcomes in the right context. It is, therefore, important to focus not only on the outcomes, i.e. in this case irrational beliefs about organic food products, but also on the processes which lead to their emergence.

Each decision process consists of several sub-processes and generally starts with information acquisition (Einhorn & Hogarth, 1981). There are different measures proposed to explore information acquisition, the most applied of which, based on the number of citations, is without a doubt the *Search Index* (*SI*, Payne, 1976). However, there have been several criticisms raised so far regarding specific characteristics of the SI, such as a lack of chance correction or analysis of search behaviour restricted to single-step transitions and so on (Ball, 1997; Böckenholt & Hynan, 1994). One of the criticisms is directed towards the ambiguity of the SI in specific situations, i.e. when the SI is close to zero (Ball, 1997). This criticism has not been addressed yet and so it has motivated the second research question. Therefore, the second research question I aimed to answer in this doctoral dissertation was whether there is a measure which can complement the SI to better describe information search.

To answer this question, I proposed a new measure, the *Systematicity of Search Index* (*SSI*), as an additional measure for exploring information search behaviour. I developed the SSI by addressing the criticisms directed towards the SI. The SSI therefore describes how systematic information search is, which is expressed as the proportion of non-random search, i.e. search that is alternative- or attribute-wise corrected for chance. I hypothesised that the SSI is a more informative measure than the SI in situations where decision makers make approximately the same amount of alternative- and attribute-wise transitions (SI $\approx$ 0). I also hypothesised that the SSI is higher when information presentation is visually organised compared to when it is visually disorganised.

I tested these hypotheses in an experiment (Study 4) with four within-subjects conditions using eye tracking. In each condition, I used different visual presentation to create either organised or disorganised information presentation format, which resulted in three conditions with organised information presentation (alternative array, attribute array and matrix) and one condition with disorganised information presentation (random matrix).

Two of the conditions (matrix and random matrix) were especially important for testing the hypothesis that the SSI is a more informative measure than the SI when decision makers make approximately the same amount of alternative- and attribute-wise transitions (SI $\approx$ 0). More specifically, the mean SI is zero only in case of a matrix with the same number of alternatives and attributes. Otherwise, the SI points to an alternative-wise information search when the number of attributes is higher than the number of alternatives or to an attribute-wise information search, when the number of alternatives is higher than the number of attributes. Even though in this case the number of alternatives and attributes was equal in all conditions, alternative and attribute array conditions applied different visual groupings which were expected to nudge the SI to alternative- or attribute-wise search respectively. To test the hypothesis that the SSI is higher when information presentation is visually organised compared to environments when information presentation is visually disorganised, all four conditions were equally important (see section 4.2).

The findings from Study 4 support the two hypotheses. More specifically, the findings show that the SSI is informative when the SI is close to zero. This is noticeable in both matrix conditions where the SI is relatively close to zero; however, the SSI shows that information search was systematic in the matrix condition and unsystematic in the random matrix condition, suggesting that in this condition it most likely happened by chance. In addition, the findings show that the SSI appears to be a useful measure for exploring information search, which is reflected in higher SSI scores in conditions with an organised information presentation format compared to the condition with a disorganised format.

Additionally, I tested the performance of the SSI on the data from Study 3. The findings support the earlier hypothesis, i.e. that the SSI is a more informative measure than the SI when the SI is close to zero. More specifically, in all three conditions the SI was close to zero, suggesting that participants made approximately equal amounts of alternative- and attribute-wise transitions. However, the SSI indicated that these search patterns did not happen by chance (see section 4.3).

The findings from the choice analysis showed that participants who predominantly relied on one attribute when making choices ended up making more systematic choices. However, when inspecting the relationship between the systematicity of participants' eye movements and their choices, the findings were not that clear. Systematicity of eye movements and choices were positively correlated in the alternative and attribute array conditions, whereas the two were negatively correlated in the matrix and random matrix conditions. This suggests that presentation format has a strong influence on information processing, which is supported by the previous findings in the literature (e.g. Bettman & Kakkar, 1977). However, I cannot draw more specific conclusions because these findings were accompanied by wide confidence intervals (see section 4.2.2.4).

In sum, the SSI has the merit of calculating the systematicity of information search by taking into consideration the probability of a search sequence being due to chance. Furthermore, the SSI is a measure based on multiple-step transitions and, therefore, addresses the limitations of single-step transition measures summarized by Ball (1997). It can, therefore, shed light on processes not captured by the SI. More specifically, when the SI is close to zero, all we know is that information search consists of approximately equal amounts of alternative- and attribute-wise transitions. Therefore, extra information on whether information search did or did not occur by chance in this situation, which is provided by the SSI, is beneficial. Considering the findings from Study 4, which suggest that the SSI is a useful measure, it can be concluded that the SSI can be used as a complementary measure to the SI to better understand information search behaviour.

5.1.1 Limitations

As with all studies, there are some potential limitations of the studies reported in this doctoral dissertation. In the following paragraphs, I therefore discuss potential limitations of the four studies.

One limitation of Study 1 is that I only included the numbers of organic food products per each of 59 assessed food product categories in the supermarkets. In other words, I did not include the numbers of products that bear only the Keyhole label, nor the numbers of products that bear both labels, i.e. the Keyhole and organic label, per each food category. Therefore, it is not clear which of the conditions in Study 3 best represents the true state of the environment, because I could not calculate a correlation between the Keyhole and organic labels. However, this limitation should not affect the overall findings. Instead of the Keyhole label, to check whether there is a correlation between organic and more healthful food products in the environment, I used food healthfulness estimates provided by food and nutrition experts.

One possible limitation of Study 2 is that I did not control for numeracy skills. More specifically, numeracy refers to mathematical proficiency and includes "basic logic and quantitative reasoning skills, knowing when and how to perform multistep operations, and an understanding of ratio concepts, notably fractions, proportions, percentages, and probabilities" (Reyna & Brainerd, 2008; Reyna, Nelson, Han, & Dieckmann, 2009, p.5). Since one of the questions for participants in the survey was to estimate the percentages of organic food products in different food product categories in their local supermarket, testing numeracy would have made sense. However, it seems that this did not affect the findings from Study 2 because participants gave quite accurate estimates of organic food product prevalence in different food product categories.

One limitation of Study 3 lies in the experimental stimuli. In this study, I used screenshots of the actual food products from an online supermarket to make the stimuli as realistic as possible. Therefore, the distances of the Keyhole and organic labels from other product features such as product image or name were sometimes too small. To address this limitation, I tested different AOI margins, i.e. 0°, 0.15° and 0.5° of visual angle, to find the most suitable margin considering the numbers of false positives and false negatives (see section 3.4.1.2).

Another limitation of the naturalistic stimuli used in Study 3 is the difference in sizes, positions and salience of food products. Since I did not control for these differences, it is possible that the findings are confounded by them. However, it has been argued that this would have been a problem, if the experiment consisted of one trial only. To address this issue, Orquin and Holmqvist (2017) recommend having at least 16 trials in the experiment. Since each condition in Study 3 had 50 trials, some of these differences should have been randomised away.

One limitation of Study 4 is also related to the experimental stimuli. More specifically, experimental manipulation required that objects in the experimental stimuli should be positioned differently in each condition. Therefore, some of the objects had a higher likelihood to be looked at. However, I did not take this into consideration when creating random data sets used for comparing whether identified patterns occurred by chance. Instead, I created randomised data sets by sampling equally from specific sets of numbers and letters suggesting that every object had an equal chance to be looked at. In addition, some of the elements varied in size such as attribute names. I addressed this limitation by creating more than one trial per condition, which were generated by randomly combining all object elements. I therefore argue that, as in Study 3, these differences have randomised away.

One possible limitation of the SSI measure proposed in Study 4 could be that there the SSI is used to explore the information search by testing it for the strict compensatory and non-compensatory strategies only. Therefore, I neglected the entire repertoire of strategies that an individual could use dependent on the decision maker's characteristics, decision task and decision environment (Payne et al., 1993). However, I deem this was an appropriate approach to start out with when developing a new measure for exploring information search, which serves as a complementary measure to the SI.

Additionally, the SSI is a measure for exploring information search behaviour, which shows whether the search performed was systematic or it happened by chance. It has been shown previously that the SSI is specifically useful when the SI is close to zero. However, the SSI by itself is not very informative, i.e. it does not tell us anything about the search strategies used. Therefore, it should be used together with the SI, which could show the direction of systematic search, i.e. whether the information search was predominantly alternative or attribute-wise.

Finally, another limitation of Study 4 is that in comparison to the SI measure, the SSI could be perceived as a slightly more complex measure, which may deter some decision researchers from using it. Hence, to simplify the use of the SSI, I plan to develop an R package. Consequently, there would be no further potential restrictions in implementing the SSI for analysing the pattern of information search.

In the meantime, one can use a script with the R code which can be found in Appendix E. Alternatively, the script can be accessed at the following link: https://github.com/sonjaPerkovic.

5.1.2 Future research

There are several suggestions for future research based on the findings, limitations or methods used in this doctoral dissertation. First, using the combination of methods employed to study the halo effect bias in the context of organic food products, i.e. a combination of field, online and lab studies, I could also study other heuristics and cognitive biases. For instance, *social proof* or *bandwagon effect* (Cialdini, 1993) could also be studied in the context of organic food products. Social proof is a phenomenon where people tend to adopt specific beliefs or ideas after observing other people doing so. Social proof becomes more effective if people who adopt specific beliefs are perceived as knowledgeable about a situation or if there is a greater number of people adopting this behaviour.

This theory could also be tested in the context of organic food products. More specifically, the fact that consumers perceive organic food products as more healthful than conventional food products could be attributed to the social proof phenomenon. Put differently, consumers may observe other consumers, who are perceived as being on a healthful diet, buying organic food products and therefore conclude that these products must be healthful. At first, this seems to be irrational; however, it is possible that if studied in the right context, this heuristic could be ecologically rational.

To test the meaningfulness of the social proof heuristic in the context of organic food products, I propose a combination of three studies, i.e. field, online and lab studies. The first study, a field study, would aim to assess whether consumers who buy more healthful food products also buy more organic food products. To assess the healthfulness of consumer shopping baskets and the percentages of organic food products bought, I would require getting access to the purchase data from a supermarket. The healthfulness of a shopping basket could be calculated by assessing the ratio of processed vs unprocessed food products bought. Then, I could calculate the percentage of organic foods in all food products bought and assess the correlation between the two. This would ideally show that the more healthful a consumer shopping basket is, based on the ratio of processed vs unprocessed food products bought, the more organic food products consumers tend to buy.

In the second study, an online consumer survey, I would explore whether consumers observe this phenomenon, that is that eating organic food products is a part of a healthful diet, by asking them to provide evaluations regarding behaviours of two different types of consumers. More specifically, I would provide participants with two scenarios. In the first scenario, they would assess on a scale from one (extremely unlikely) to five (extremely likely) how likely it is that an individual on a healthful diet consumes specific food products. The set of food products would consist of various food products including both organic and non-organic alternatives. In the second scenario, they would do the same but for an individual on an unhealthful diet. This would ideally show that consumers perceive that individuals on a healthful diet consume more organic food products.

In the third study, a lab study, I would explore whether consumers can learn this connection between a healthful diet and organic food products by observing other individuals. I would ask participants to come to the lab where they would be presented with, for instance, four food product alternatives from one food product category which is not obviously healthful nor unhealthful such as breakfast cereals.

Their task would be to choose the most healthful food product alternative among these four food product samples. At the same time, there would be a confederate in the lab also sampling food products. The confederate would always choose a different, randomly assigned, food product. In one condition the confederate would be an individual who gives an impression of a person on a healthful diet whereas in the other condition that would be an individual who gives an impression of a person on an unhealthful diet. Afterwards, I would assess whether participants' choices were influenced by the confederate's choices. More precisely, I would assess whether participants were influenced by the confederate on a healthful diet by more often choosing the same food product as the most healthful food product.

If the findings from all three studies confirmed the expectations, it would be meaningful to conclude that beliefs that at first seemed to be irrational could result in ecologically rational conclusions. More specifically, if the findings from the field study showed that consumers who generally consume healthful food products also consume more organic food products, this would suggest that organic food products are correlated with healthfulness. If the findings from the online survey and lab study showed that consumers observed this correlation and that they can learn it, then this would be yet another example of a belief that at first seems to be irrational but can lead to an ecologically rational conclusion when studied in the right context.

The second idea for future research is related to tackling the limitation regarding the SSI being restricted to detecting strict compensatory and non-compensatory strategies only. I therefore propose that the SSI could be adjusted so that it captures various search strategies, preferably in different decision environments with different decision tasks. For instance, the SSI could capture type V to type VII transitions proposed by Ball (1997) (see section 4.1.1). This could be done by adjusting the existing code so that it analyses participants' information search strings by searching for these specific types of transitions. In this way, the SSI would gain more power to discriminate between specific decision strategies such as weighted additive, equal weight or majority of confirming dimensions.

The final idea for future research would be to test the SSI against the Strategy Measure (SM) proposed by Böckenholt and Hynan (1994) (see section 4.1.1). Since the SM is a measure for exploring information search behaviour that, as the SI, focuses on single-step transitions, it is also susceptible to the criticisms of this type of measure provided by Ball (1997). Testing the SSI against the SM would therefore show whether there are situations in which the SSI could complement the SM. I would approach this by re-analysing the existing data set used for assessing the performance of the SI to see how the SM performs in that setting. Based on the findings, I would design a new experiment which would be suited to studying the specific situations in which the SM perhaps gives ambiguous results. This would ideally result in providing specific recommendations for when the SM should be complemented with the SSI to obtain a more informative assessment of the information search process.

5.2 Theoretical, methodological and practical implications

This doctoral dissertation has several very important implications for theory, methodology and practice. On a theoretical level, there are three important implications. First, this doctoral dissertation contributes to a better understanding of ecological rationality. More precisely, it has been shown that ecologically rational behaviour can be a result of statistical learning processes. This process can be broken down into two steps. First, statistical learning processes lead to a development of specific beliefs about statistical properties of the environment. Second, these beliefs may then translate into decision rules that match the environment and therefore produce ecologically rational behaviours. Another theoretical implication is the finding that irrational beliefs can sometimes lead to rational behaviours. More specifically, a belief which at first appears to be irrational, could be rational if studied in an appropriate context. Finally, this doctoral dissertation also contributes to the theory by showing that systematic search for information is not always necessarily a result of using heuristics, but can also be a result of systematicity in the presentation format. Put differently, visual grouping of relevant pieces of information can enhance the systematicity of processing that information without an explicit need for simplifying the information and therefore use of heuristics.

On a methodological level, there are two important implications. The first methodological implication is the novel combination of different methods to study one phenomenon. This doctoral dissertation used a combination of three different approaches, i.e. a field study, an online survey and an eye tracking experiment to explore the first research question. To avoid limitations associated with any particular method and to obtain more robust results, tackling a research question using different methods has been endorsed many times, by different scholars (e.g. Davis, Golicic, & Boerstler, 2011; Stewart, 2009). Therefore, it has been argued that a multi-method approach to decision research should always be applied when possible (Payne et al., 1978). The second methodological implication is the new method proposed, that is the Systematicity of Search Index (SSI), for exploring information search behaviour. This measure addresses the questions overlooked by existing measures for exploring information search behaviour and therefore serves as a good complementary measure to those measures. Study 4 confirmed the usefulness of the measure, which suggests that this measure can be used for exploring information search behaviour.

On a practical level, this doctoral dissertation contributes with the finding that, overall, organic food products are 30% more healthful than conventional food products. This finding can be used as a heuristic when trying to find more healthful food products. More specifically, since there is a correlation between organic food products and less processed food products in the supermarkets, consumers who want to buy more healthful food products could search for food product categories that have a higher prevalence of organic food products. Consuming food products from these food product categories would imply consuming less processed and therefore more healthful food products. This is especially useful for anybody who is struggling with obtaining a healthful diet and is unsure about the healthfulness of specific food product categories. Considering the continuous rise in obesity rates, and the fact that consumers are overwhelmed by conflicting information about what to eat or avoid (International Food Information Council Foundation, 2017; Nagler, 2014), it seems that this heuristic could be useful for many consumers. In addition, on a broader level, this heuristic could also be useful for food practitioners and public policymakers for enhancing policies, organising interventions, and guiding consumer behaviour towards more healthful food alternatives.

As a heuristic for identifying more healthful food product categories, this practical implication could have a direct influence on tackling growing obesity rates, one of the three societal reasons for studying food choice discussed at the beginning of this doctoral dissertation (see section 1.1). On the indirect level, this practical implication could potentially address growing food waste rates and issues around food safety, the two other societal reasons for studying food choice. For instance, as previously mentioned, the use of the *organic = healthful heuristic* provides consumers with a clear guideline towards more healthful food products, and therefore should have a positive impact on their diet. This would then reduce the need for purchase of various diet products and ultimately reduce the number of such products on the market, and consequently reduce food waste rates. Furthermore, the use of the *organic = healthful heuristic* could also be beneficial for dealing with the issues around food safety. For instance, the findings show that food categories with frozen food products (see Table 3.1) contain more organic food products compared to many other food product categories. Hence, following the *organic = healthful heuristic*, consumers should eventually acquire more positive attitudes towards frozen food products which could have positive impacts on both food safety and food waste (see section 1.1).

Finally, marketers could also have an important role in helping consumers to apply the *organic = healthful heuristic*. This could be used in different areas of marketing, such as supermarket layout, product packaging and promotion strategies, to name just a few. For instance, one recommendation would be to make organic food products more salient both regarding their packaging and their positioning on the shelves, which would help consumers to more easily detect organic food products. Alternatively, organic food products could be positioned in a special supermarket section. This would correspond to the attribute-wise condition in Chapter 4 which would make it easier for consumers to apply non-compensatory decision strategies. By making it easier to apply the *organic = healthful heuristic*, supermarkets would ideally encourage consumers to follow this heuristic. Marketers could also use the *organic = healthful heuristic* to promote more healthful food product categories. This would greatly benefit consumers because the higher the number of sources presenting this heuristic, the sooner consumers can start using it to improve their food choices.

5.3 Concluding remarks

Food choice is a complex task which often occurs in multi-dimensional environments. The findings from this doctoral dissertation suggest that, even though environments are complex, consumers can learn the structures of these environments and use them to form simple heuristics. Furthermore, when the environments are visually extremely complex, consumers still seem to use heuristics by identifying the most relevant pieces of information which are then used for making choices. Therefore, one should be careful before labelling something as a bias, and in general, before labelling beliefs as irrational, because, in some situations, consumer food choice behaviour seems to be guided by sophisticated underlying mechanisms.

This doctoral dissertation shows that there is significant potential for a better understanding of food choice by studying the decision processes behind them. A process tracing approach has been shown to be particularly useful for this. However, there is still more work needed in developing appropriate measures for analysing these processes. Researchers should strive to constantly work on developing better measures based on the limitations of the existing ones. This doctoral dissertation has made an attempt in this direction.

Finally, the findings from this doctoral dissertation also provide clear implications about how to improve consumer food choices. Particularly, this refers to a simple heuristic, the *organic = healthful heuristic*, which can help consumers to detect more healthful food product categories. This heuristic is simple enough to be used by consumers; however, it could also be used as a basis for organizing nutrition related interventions.

In sum, even though consumer food choices cannot generally be described as irrational, there are still many situations where their decision making could be improved. Tackling this problem from different theoretical viewpoints, and combining different methods to solve it, appears to be necessary for answering a seemingly simple, yet complex question about how food choice is made. In this way, we increase the chances of developing clear implications and guidelines for both theory and practice. The clearer the implications, the greater the chance that consumers will include them in their everyday decision making. Consequently, this would then lead to much needed behaviour change, and therefore address the main existing drivers for studying food choice.

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Appendix A

Study 1 survey

1. What is your gender:
    - Female
    - Male
2. What is your age?
3. What is your education?
4. What is your current job?

5. In your opinion, how healthy are the following food products (tick the appropriate box)?

	Extremely unhealthy	Very unhealthy	Slightly unhealthy	Neither healthy nor unhealthy	Slightly healthy	Very healthy	Extremely healthy
Crispbread and rice crackers	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Whole-grain bread	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Refined wheat flour bread	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen bread	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Vegetables	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Fruit	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen vegetables	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen fruit	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Canned vegetables	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Canned fruit	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Dried fruits, nuts, and seeds	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Butter	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Cream	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

Milk	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Plain yoghurt products	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Fruit yoghurt	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Cheese	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Non-dairy milk	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Eggs	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Fresh meat	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Cold cuts	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Processed meat	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen meat	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Canned meat	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Canned fish	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Fresh fish	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen fish	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Processed fish (fridge)	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Oil	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Brown rice	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

White rice	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Refined wheat flour pasta	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Whole-grain pasta	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Sauces (tomato, pesto)	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Prepackaged meals: sauces	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Dressings (salad dressings, mayo, ketchup, mustard)	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Juices	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Syrups	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Sodas	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
White wine	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Red wine	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Alcoholic beers and shakers	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Chips	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Savoury biscuits	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Muesli and protein bars	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Cakes and cookies	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

Candy	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Ice cream	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Honey	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Processed breakfast cereals	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Unprocessed breakfast cereals	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Marmalade	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Chocolate spreads	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Mayonnaise-based salads	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Soups	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Refrigerated prepackaged meals	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen prepackaged meals	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Dry prepackaged meals	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Takeaway meal	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

Appendix B

Study 1 results

		Total count of all food products (T) and organic food products (O) per six supermarkets												Total count of all and organic food products (additional coder)	
Category	Product name	T1	O1	T2	O2	T3	O3	T4	O4	T5	O5	T6	O6	T6	O6
Bread	Crispbread and rice crackers	26	4	18	4	19	3	66	25	81	31	12	4	11	3
Bread	Whole-grain bread	19	1	31	2	13	4	38	3	25	5	26	1	39	1
Bread	Refined wheat flour bread	41	0	42	2	17	1	70	1	46	6	36	0	28	0
Bread	Frozen bread	17	4	25	4	9	1	23	1	31	3	13	0	14	0
Fruit & veg	Vegetables	94	20	140	41	76	16	187	53	228	59	93	25	89	32
Fruit & veg	Fruit	31	6	35	8	23	4	52	11	62	12	34	8	33	8
Fruit & veg	Frozen vegetables	30	2	44	5	15	0	34	7	57	9	20	1	19	1

Fruit & veg	Frozen fruit	5	0	3	0	5	0	10	2	11	3	5	1	5	1
Fruit & veg	Canned vegetables	57	2	58	2	48	7	184	25	151	43	51	5	30	6
Fruit & veg	Canned fruit	14	0	14	0	3	0	34	6	24	10	6	0	6	0
Fruit & veg	Dried fruits, nuts, and seeds	58	14	58	16	28	7	188	54	215	81	55	7	53	10
Dairy	Butter	13	2	14	2	12	3	18	3	19	8	12	4	11	3
Dairy	Cream	12	1	16	3	7	1	13	2	17	2	9	0	12	1
Dairy	Milk	11	4	14	8	14	6	20	14	18	11	15	8	13	6
Dairy	Plain yoghurt products	25	4	17	3	14	5	21	7	26	10	14	6	18	7
Dairy	Fruit yoghurt	22	1	43	4	36	6	50	7	61	12	40	10	34	10
Dairy	Cheese	106	8	104	11	85	13	263	27	233	28	131	10	126	9
Dairy	Non-dairy milk	6	1	5	5	3	3	9	7	24	23	7	5	7	6
Eggs	Eggs	7	2	8	2	6	2	13	6	11	6	9	3	10	3
Meat	Fresh meat	49	5	65	12	29	3	97	14	80	14	53	4	59	3
Meat	Cold cuts	104	6	124	9	66	9	175	15	159	21	110	8	98	6

Meat	Processed meat	28	0	19	0	15	0	51	2	4	4	34	3	56	2
Meat	Frozen meat	8	0	5	3	4	0	27	3	20	3	16	0	18	0
Meat	Canned meat	7	0	4	0	2	0	16	0	4	0	2	0	1	0
Fish	Canned fish	24	0	21	0	16	0	86	0	50	0	16	0	17	0
Fish	Fresh fish	2	0	10	0	3	0	6	0	3	0	7	0	4	0
Fish	Frozen fish	7	0	17	0	6	0	22	0	16	1	23	0	22	0
Fish	Processed fish (fridge)	25	0	32	0	21	0	103	1	66	1	48	1	63	1
Oil	Oil	16	3	11	2	13	4	53	20	80	40	9	3	8	3
Rice	Brown rice	2	1	2	1	1	1	8	6	8	5	2	1	2	1
Rice	White rice	17	3	8	2	13	2	21	2	29	12	7	2	7	2
Pasta	Refined wheat flour pasta	19	1	16	2	14	1	84	5	68	8	15	1	11	1
Pasta	Whole-grain pasta	6	6	8	6	9	7	40	26	35	31	6	6	8	6
Sauces & dressings	Sauces (tomato, pesto)	32	2	15	1	9	1	103	11	79	18	19	0	24	4

Sauces & dressings	Prepackaged meals: sauces	26	0	15	0	11	0	100	0	58	1	18	0	19	0
Sauces & dressings	Salad dressings, mayo, ketchup, mustard)	39	2	45	1	46	3	149	19	154	12	26	1	28	1
Soft drinks	Juices	26	2	38	5	19	3	109	22	102	53	53	4	23	2
Soft drinks	Syrups	32	7	13	6	11	4	75	13	44	15	18	4	10	2
Soft drinks	Sodas	64	0	95	0	51	3	233	15	160	14	54	0	36	0
Alcoholic drinks	White wine	53	0	53	1	31	1	25	4	67	1	40	1	48	1
Alcoholic drinks	Red wine	63	1	50	1	56	1	291	5	178	11	89	2	86	2
Alcoholic drinks	Alcoholic beers and shakers	34	0	84	3	66	1	299	15	248	20	57	1	62	1
Snacks	Chips	57	0	37	0	29	1	91	2	77	8	47	0	42	0
Snacks	Savoury biscuits	10	2	10	1	4	1	28	5	10	0	5	1	-	-

Snacks	Muesli and protein bars	12	0	14	2	3	0	22	1	39	5	6	0	-	-
Sweets	Cakes and cookies	65	0	59	1	46	1	174	8	94	23	46	0	-	-
Sweets	Candy	342	0	253	6	214	3	854	6	487	29	147	4	-	-
Sweets	Ice cream	24	3	23	1	37	2	59	5	65	7	29	1	29	1
Sweets	Honey	4	1	5	1	5	0	21	4	12	4	4	1	4	1
Cereals	Processed breakfast cereals	27	0	18	0	14	1	45	2	36	6	12	0	12	0
Cereals	Unprocessed breakfast cereals	13	8	13	6	17	8	54	29	50	28	22	9	21	9
Spreads	Marmalade	23	4	26	3	20	6	147	24	74	17	17	0	20	2
Spreads	Chocolate spreads	10	2	15	1	8	0	25	4	19	5	7	2	-	-
Spreads	Mayonnaise-based salads	30	0	26	0	12	0	65	0	66	12	22	0	24	0

Prepackaged meals	Soups	4	0	5	0	3	0	25	1	26	1	14	0	7	0
Prepackaged meals	Refrigerated prepackaged meals	5	0	10	0	6	0	21	0	8	0	17	0	14	0
Prepackaged meals	Frozen prepackaged meals	55	1	60	0	43	1	93	6	106	11	31	3	55	3
Prepackaged meals	Dry prepackaged meals	7	0	9	0	5	0	37	0	40	2	6	0	5	0
Prepackaged meals	Takeaway meal	0	0	0	0	0	0	25	0	3	0	0	0	0	0

Appendix C

Study 2 survey

6. What is your gender:
    - Female
    - Male
7. What is your age?
8. What is your education? (Your longest completed education)
    - Primary school
    - Secondary school
    - Store clerk
    - Craftsman
    - Short higher education (up to 2 years)
    - Medium higher education (up to 3 years)
    - Long higher education (up to 5 years)

- Other education

9. Which supermarket do you usually use for your grocery shopping?

    - Fotex
    - Bilka
    - Netto
    - Rema 1000
    - Kiwi
    - Spar
    - Lidl
    - Aldi
    - Super Brugsen
    - Kvickly
    - Irma
    - Brugsen
    - Fakta

- ○ Lovbjerg
- ○ Menu
- ○ Another supermarket

10. In your opinion, what percentage of food products in your local supermarket are organic?

	0% = no products are organic					100% = all products are organic				
Crispbread and rice crackers	0	10	20	30	40	50	60	70	80	90	100
Whole-grain bread	0	10	20	30	40	50	60	70	80	90	100
Refined wheat flour bread	0	10	20	30	40	50	60	70	80	90	100
Frozen bread	0	10	20	30	40	50	60	70	80	90	100
Vegetables	0	10	20	30	40	50	60	70	80	90	100
Fruit	0	10	20	30	40	50	60	70	80	90	100
Frozen vegetables	0	10	20	30	40	50	60	70	80	90	100
Frozen fruit	0	10	20	30	40	50	60	70	80	90	100
Canned vegetables	0	10	20	30	40	50	60	70	80	90	100
Canned fruit	0	10	20	30	40	50	60	70	80	90	100
Dried fruits, nuts, and seeds	0	10	20	30	40	50	60	70	80	90	100

Butter	0	10	20	30	40	50	60	70	80	90	100
Cream	0	10	20	30	40	50	60	70	80	90	100
Milk	0	10	20	30	40	50	60	70	80	90	100
Plain yoghurt products	0	10	20	30	40	50	60	70	80	90	100
Fruit yoghurt	0	10	20	30	40	50	60	70	80	90	100
Cheese	0	10	20	30	40	50	60	70	80	90	100
Non-dairy milk	0	10	20	30	40	50	60	70	80	90	100
Eggs	0	10	20	30	40	50	60	70	80	90	100
Fresh meat	0	10	20	30	40	50	60	70	80	90	100
Cold cuts	0	10	20	30	40	50	60	70	80	90	100
Processed meat	0	10	20	30	40	50	60	70	80	90	100
Frozen meat	0	10	20	30	40	50	60	70	80	90	100
Canned meat	0	10	20	30	40	50	60	70	80	90	100
Canned fish	0	10	20	30	40	50	60	70	80	90	100
Fresh fish	0	10	20	30	40	50	60	70	80	90	100
Frozen fish	0	10	20	30	40	50	60	70	80	90	100
Processed fish (fridge)	0	10	20	30	40	50	60	70	80	90	100

Oil	0	10	20	30	40	50	60	70	80	90	100
Brown rice	0	10	20	30	40	50	60	70	80	90	100
White rice	0	10	20	30	40	50	60	70	80	90	100
Refined wheat flour pasta	0	10	20	30	40	50	60	70	80	90	100
Whole-grain pasta	0	10	20	30	40	50	60	70	80	90	100
Sauces (tomato, pesto)	0	10	20	30	40	50	60	70	80	90	100
Prepackaged meals: sauces	0	10	20	30	40	50	60	70	80	90	100
Dressings	0	10	20	30	40	50	60	70	80	90	100
Juices	0	10	20	30	40	50	60	70	80	90	100
Syrups	0	10	20	30	40	50	60	70	80	90	100
Sodas	0	10	20	30	40	50	60	70	80	90	100
White wine	0	10	20	30	40	50	60	70	80	90	100
Red wine	0	10	20	30	40	50	60	70	80	90	100
Alcoholic beers/shakers	0	10	20	30	40	50	60	70	80	90	100
Chips	0	10	20	30	40	50	60	70	80	90	100
Savoury biscuits	0	10	20	30	40	50	60	70	80	90	100
Muesli and protein bars	0	10	20	30	40	50	60	70	80	90	100

Cakes and cookies	0	10	20	30	40	50	60	70	80	90	100
Candy	0	10	20	30	40	50	60	70	80	90	100
Ice cream	0	10	20	30	40	50	60	70	80	90	100
Honey	0	10	20	30	40	50	60	70	80	90	100
Processed breakfast cereals	0	10	20	30	40	50	60	70	80	90	100
Unprocessed breakfast cereals	0	10	20	30	40	50	60	70	80	90	100
Marmalade	0	10	20	30	40	50	60	70	80	90	100
Chocolate spreads	0	10	20	30	40	50	60	70	80	90	100
Mayonnaise-based salads	0	10	20	30	40	50	60	70	80	90	100
Soups	0	10	20	30	40	50	60	70	80	90	100
Refrigerated prepackaged meals	0	10	20	30	40	50	60	70	80	90	100
Frozen prepackaged meals	0	10	20	30	40	50	60	70	80	90	100
Dry prepackaged meals	0	10	20	30	40	50	60	70	80	90	100
Takeaway meal	0	10	20	30	40	50	60	70	80	90	100

11. In your opinion, how healthy are the following food products (tick the appropriate box)?

	Extremely unhealthy	Very unhealthy	Slightly unhealthy	Neither healthy nor unhealthy	Slightly healthy	Very healthy	Extremely healthy
Crispbread and rice crackers	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Whole-grain bread	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Refined wheat flour bread	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen bread	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Vegetables	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Fruit	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen vegetables	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen fruit	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Canned vegetables	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Canned fruit	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Dried fruits, nuts, and seeds	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Butter	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Cream	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

Milk	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Plain yoghurt products	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Fruit yoghurt	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Cheese	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Non-dairy milk	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Eggs	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Fresh meat	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Cold cuts	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Processed meat	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen meat	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Canned meat	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Canned fish	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Fresh fish	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen fish	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Processed fish (fridge)	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Oil	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Brown rice	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

White rice	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Refined wheat flour pasta	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Whole-grain pasta	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Sauces (tomato, pesto)	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Prepackaged meals: sauces	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Dressings	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Juices	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Syrups	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Sodas	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
White wine	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Red wine	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Alcoholic beers and shakers	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Chips	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Savoury biscuits	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Muesli and protein bars	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Cakes and cookies	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Candy	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

Ice cream	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Honey	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Processed breakfast cereals	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Unprocessed breakfast cereals	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Marmalade	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Chocolate spreads	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Mayonnaise-based salads	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Soups	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Refrigerated prepackaged meals	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Frozen prepackaged meals	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Dry prepackaged meals	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]
Takeaway meal	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]	[ ]

12. How often do you purchase organic food products?

- Never
- Very rarely
- Rarely
- Sometimes
- Often
- Very often
- Always

13. On average, what percentage of your shopping basket belongs to organic food products?

% Organic food products purchased	0	10	20	30	40	50	60	70	80	90	100

14. How good/bad do you think it is to buy organic food products?

Very bad (1)	(2)	(3)	(4)	(5)	(6)	Very good (7)

15. How important/unimportant do you think it is to buy organic food products?

Very unimportant (1)	(2)	(3)	(4)	(5)	(6)	Very important (7)

16. How wise/foolish do you think it is to buy organic food products?

Very foolish (1)	(2)	(3)	(4)	(5)	(6)	Very wise (7)

17. Indicate how much you agree or disagree with the following statements:

	Totally disagree	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree	Totally agree	Do not know
Organic foods are healthier than conventional foods.	1	2	3	4	5	6	7	[ ]
Organic foods are tastier than conventional foods.	1	2	3	4	5	6	7	[ ]
Organic foods contain fewer calories than conventional foods.	1	2	3	4	5	6	7	[ ]
Organic foods are of higher quality than conventional foods.	1	2	3	4	5	6	7	[ ]

Organic foods are fresher than conventional foods.	1	2	3	4	5	6	7	[ ]
Organic foods are safer than conventional foods.	1	2	3	4	5	6	7	[ ]

Appendix D

Demographic and psychographic information about Study 2 sample

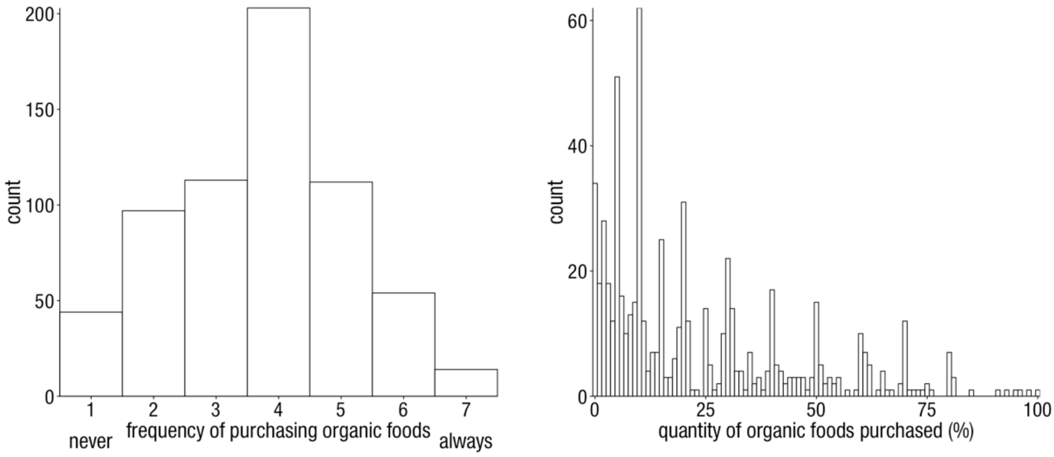

Figure D1 Histogram representing (a) frequency of purchasing organic food products and (b) quantity of organic food products purchased when performing grocery shopping.

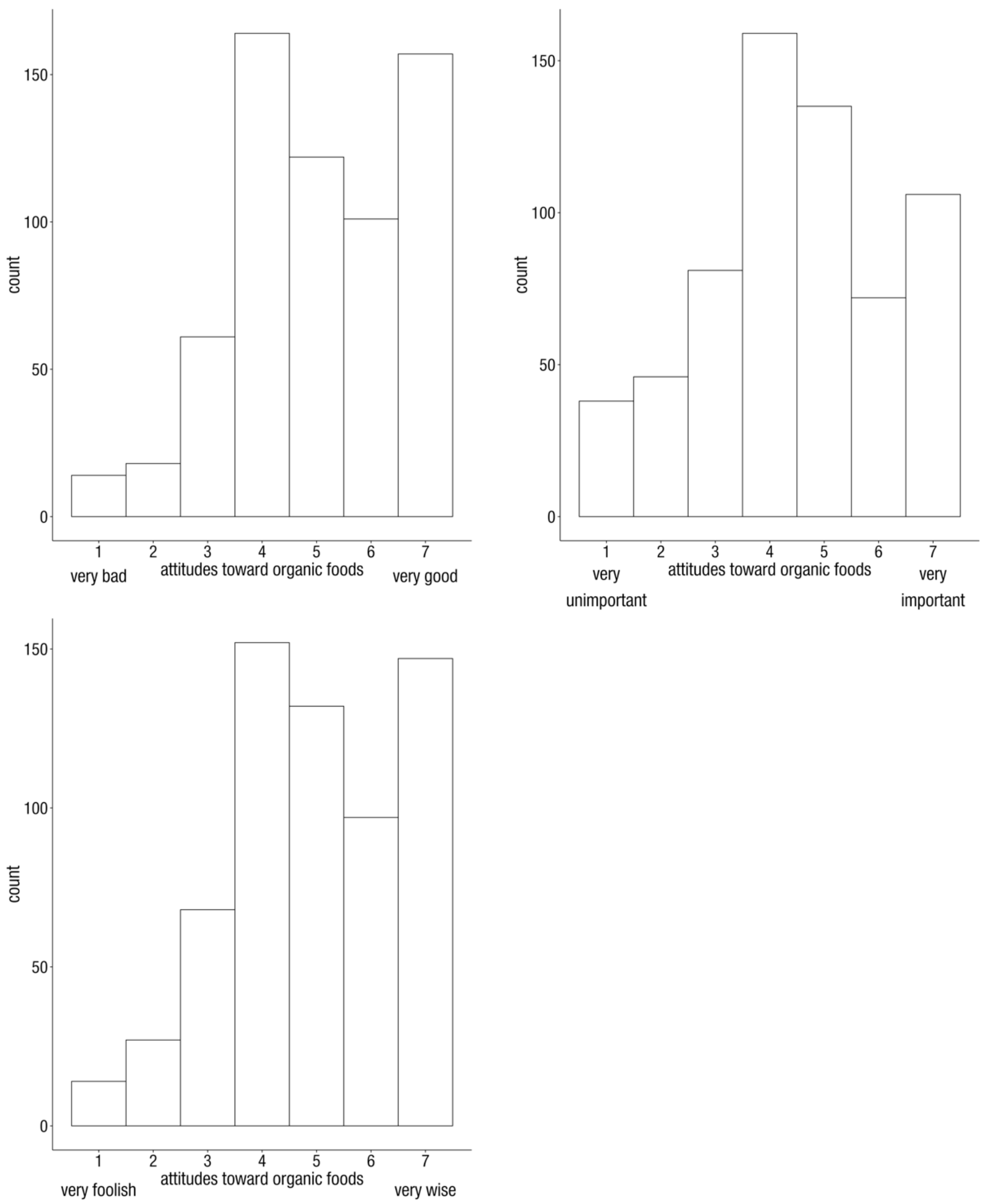

Figure D2 Histogram representing attitudes towards purchasing organic food products (a) good, (b) important and (c) wise.

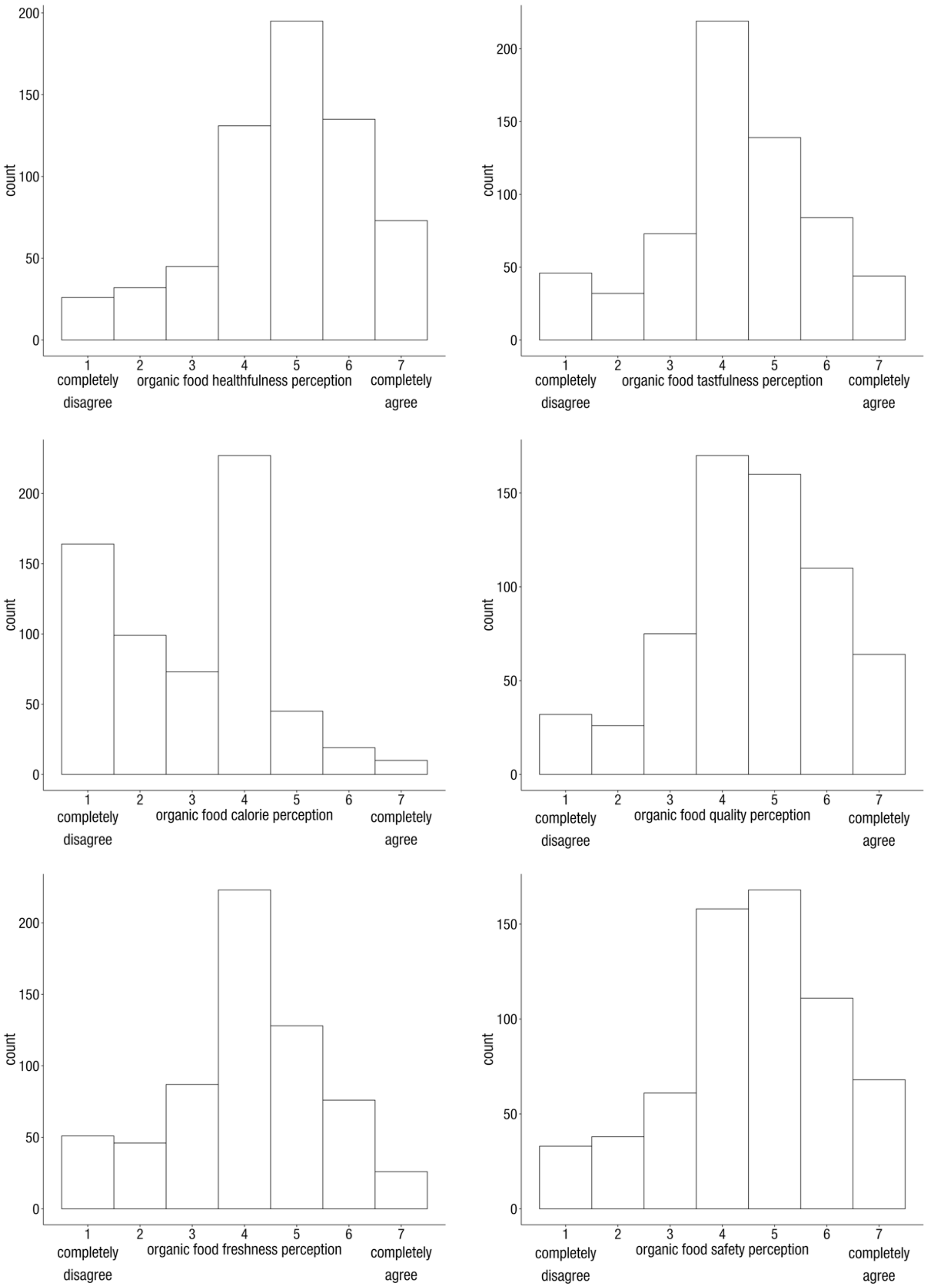

Figure D3 Histogram representing perceptions of organic food (a) healthfulness, (b) tastefulness, (c) calories, (d) quality, (e) freshness and (f) safety.

Appendix E

R code for calculating SSI

```
#import libraries
library(data.table)
library(plyr)
library(dplyr)
library(ggplot2)

#set working directory
setwd("/Users/userName/folderName")

#read in the file
infoSearch <- as.data.table(read.csv("fileName.csv", header = T, sep = ";")) #the
original file consists of five columns: participant, environment, trial, alternative and
attribute column

#preparing the data ####

#identify subsequent eye fixations to an attribute within the same alternative
infoSearch$attributeClean <- ifelse(infoSearch$attribute == shift(infoSearch$attribu
te, 1L) & infoSearch$alternative == shift(infoSearch$alternative, 1L), 1, 0)

#delete subsequent eye fixations to an attribute, i.e. keep only the  first eye fixation
infoSearch <- infoSearch[infoSearch$attributeClean != 1 | is.na(infoSearch$attribute
Clean)]

#delete unnecessary column
infoSearch[, "attributeClean" := NULL]

#create and count alternative-wise transitions (needed for calculating Search Index)
infoSearch$transAlt <- ifelse(infoSearch$attribute != lag(infoSearch$attribute, n = 1
L) & infoSearch$alternative == lag(infoSearch$alternative, n = 1L) & infoSearch$tr
ial == lag(infoSearch$trial, n = 1L) & infoSearch$participant == lag(infoSearch$par
ticipant, n = 1L), 1, 0)

infoSearch[is.na(infoSearch)] <- 0

#new file with alternative-wise transitions for each participant within each
environment and for each trial
altTrans <- ddply(infoSearch,.(participant, environment, trial), summarize, transAlt
= sum(transAlt))

#create and count attribute-wise transitions (needed for calculating  Search Index)
infoSearch$transAtt <- ifelse(infoSearch$attribute == lag(infoSearch$attribute, n =
1L) & infoSearch$alternative != lag(infoSearch$alternative, n = 1L) & infoSearch$t
rial == lag(infoSearch$trial, n = 1L) & infoSearch$participant == lag(infoSearch$pa
```

```
rticipant, n = 1L), 1, 0)

infoSearch[is.na(infoSearch)] <- 0

#new file with attribute-wise transitions for each participant within each
environment and for each trial
attTrans <- ddply(infoSearch,.(participant, environment, trial), summarize, transAtt
= sum(transAtt))

#combine two data sets by columns and calculate Search Index
searchIndex <- as.data.table(cbind(attTrans, altTrans))

searchIndex$searchIndex <- (searchIndex$transAlt - searchIndex$transAtt) / (search
Index$transAlt + searchIndex$transAtt)

#delete unnecessary columns
searchIndex[, c("participant", "environment", "trial") := NULL]

#set order of columns
setcolorder(searchIndex, c("participant", "environment", "trial", "transAlt", "transAt
t", "searchIndex"))

#calculate the length of total string of eye fixations per participant per trial (needed
for calculating the denominator of Systematicity of Search Index)
stringLength <- ddply(infoSearch, .(participant, environment, trial), function(infoSe
arch) length(infoSearch$attribute))

#rename column
setnames(stringLength, "V1", "N")

#create counter variable for alternative-wise search (focusing on a set of attributes
when inspecting different alternatives)
infoSearch <- setDT(infoSearch)[, counterAltwise:= rleid(environment, trial, altern
ative)] #assigning the same number to the eye  fixations  to the attributes within the
same alternatives (e.g. if a participant   first fixated on sugar and fat levels within on
e   alternative and then  sugar and protein levels within another alternative, values
1,1,2,2 would have been assigned to the counter variable)

#create counter variable for attribute-wise search (focusing on the same attribute
when inspecting different alternatives)
infoSearch <- setDT(infoSearch)[, counterAttwise:= rleid(environment, trial, attribu
te)] #since additional eye fixations have been deleted, when there is a fixation on the
same attribute, it must belong to a different alternative

#identify alternative-wise patterns ####

#create alternative-wise strings (i.e. sequences of letters) based on counter variable
altwiseStrings <- infoSearch[,list(string <- paste(attribute, collapse = ""), participant
= unique(participant), environment = unique(environment), trial = unique(trial)), b
y = counterAltwise] #collapsing all attributes within the same alternative into a
```

```
string of letters; in the above example we would and up with two strings of  length
two: 'fs' and 'ps' (i.e. 'fat and sugar' and 'protein and   sugar')

#delete counter variable
altwiseStrings[, "counterAltwise" := NULL]

#rename column
setnames(altwiseStrings, "V1", "string")

#define a function that keeps the unique elements in a string and  sorts them
alphabetically
relaxedFreqOrder <- function(i){
  paste0(unique(sort(unlist(strsplit(i, "")))), collapse = "")
}

#apply the function to the column with previously created alternative-wise strings
altwiseStrings$formattedString <- lapply(altwiseStrings$string, relaxedFreqOrder)

#delete string variable
altwiseStrings[, "string" := NULL]

#rename column
setnames(altwiseStrings, "formattedString", "string")

#change the class of a variable into character
altwiseStrings$string <- as.character(altwiseStrings$string)

#create a counter variable based on string variable within each trial (i.e. assign a
new number for every unique string within each trial)
altwiseStrings <- setDT(altwiseStrings)[, counter:= rleid(string, trial)]

#create a variable that assigns 1 to equal subsequent counter variable values
altwiseStrings$equalCounter <- ifelse(altwiseStrings$counter == lag(altwiseStrings
$counter, n = 1L) | altwiseStrings$counter == lead(altwiseStrings$counter, n = 1L),
1, 0)

#extract equal subsequent counters (equalCounter = 1)
altwiseStrings <- altwiseStrings[altwiseStrings$equalCounter != 0]

#delete strings of length one
altwiseStrings <- subset(altwiseStrings, nchar(as.character(string)) >= 2)

#combine strings into alternative-wise patterns using the counter variable (i.e. all
the strings with the same count should be collapsed into a pattern)
altwisePatterns <- altwiseStrings[,list(string <- paste(string, collapse = ""), participa
nt = unique(participant), environment = unique(environment), trial = unique(trial)),
by = counter]

#delete counter variable
altwisePatterns[, "counter" := NULL]
```

```
#rename column
setnames(altwisePatterns, "V1", "pattern")

#calculate the frequency of occurrence for each pattern within each trial,
environment and for every participant
altwisePatternsCount <- as.data.table(with(altwisePatterns, table(pattern, trial, envi
ronment, participant)))
altwisePatternsCount <- altwisePatternsCount[altwisePatternsCount$N != 0]

#rename column
setnames(altwisePatternsCount, "N", "pattFreq")

#assess whether obtained patterns occurred by chance by making a random data set
to which we will compare the patterns from the original data set ####

altwiseSim <- function() { #create a function which will contain the random version
of the data set

#read in the data file (the original file)
infoSearch <- as.data.table(read.csv("fileName.csv", header = T, sep    = ";"))

#delete unnecessary columns
infoSearch[, c("alternative", "attribute") := NULL]

#randomize data
sim <- 154355 #the number of rows corresponding to the number of eye fixations
made in the original data set

infoSearch$alternative <- sample(1:4, sim, T) #sample the numbers  from 1 to 4
154355 times

infoSearch$attribute <- sample(c("b", "f", "p", "s"), sim, T) #sample the letters b, f,
p and s 154355 times

#identify subsequent eye fixations to an attribute within the same alternative
infoSearch$attributeClean <- ifelse(infoSearch$attribute == shift(infoSearch$attribu
te, 1L) & infoSearch$alternative == shift(infoSearch$alternative, 1L), 1, 0)

#delete subsequent eye fixations to an attribute i.e. keep only the  first eye fixation
infoSearch <- infoSearch[infoSearch$attributeClean != 1 | is.na(infoSearch$attribute
Clean)]

#delete unnecessary column
infoSearch[, "attributeClean" := NULL]

#create counter variable for alternative-wise search (focusing on a set of attributes
when inspecting different alternatives)
infoSearch <- setDT(infoSearch)[, counter:= rleid(environment, trial, alternative)]
```

```
#create alternative-wise strings (i.e. sequences of letters) based on counter variable
altwiseStrings <- infoSearch[,list(string <- paste(attribute, collapse = ""), participant
= unique(participant), environment = unique(environment), trial = unique(trial)), b
y = counter]

#delete counter variable
altwiseStrings[, "counter" := NULL]

#rename column
setnames(altwiseStrings, "V1", "string")

#apply the 'relaxedFreqOrder' function to the column with previously created
alternative-wise strings
altwiseStrings$formattedString <- lapply(altwiseStrings$string, relaxedFreqOrder)

#delete string variable
altwiseStrings[, "string" := NULL]

#rename column
setnames(altwiseStrings, "formattedString", "string")

#change the class of a variable into character
altwiseStrings$string <- as.character(altwiseStrings$string)

#create a counter variable based on string variable within each trial (i.e. assign a
new number for every unique string within each trial)
altwiseStrings <- setDT(altwiseStrings)[, counter:= rleid(string, trial)]

#create a variable that assigns 1 to equal subsequent counter variable values
altwiseStrings$equalCounter <- ifelse(altwiseStrings$counter == lag(altwiseStrings
$counter, n = 1L) | altwiseStrings$counter == lead(altwiseStrings$counter, n = 1L),
1, 0)

#extract equal subsequent counters (equalCounter = 1)
altwiseStrings <- altwiseStrings[altwiseStrings$equalCounter != 0]

#delete strings of length one
altwiseStrings <- subset(altwiseStrings, nchar(as.character(string)) >= 2)

#combine strings into alternative-wise patterns using the counter variable (i.e. all
the strings with the same count should be collapsed into a pattern)
altwisePatterns <- altwiseStrings[,list(string <- paste(string, collapse = ""), participa
nt = unique(participant), environment = unique(environment), trial = unique(trial)),
by = counter]

#delete counter variable
altwisePatterns[, "counter" := NULL]

#rename column
```

```
setnames(altwisePatterns, "V1", "pattern")

#calculate the frequency of occurrence for each pattern within each trial,
environment and for every participant
altwisePatternsCountRan <- as.data.table(with(altwisePatterns, table(pattern, trial,
environment, participant)))
altwisePatternsCountRan <- altwisePatternsCountRan[altwisePatternsCountRan$N !
= 0]

return(altwisePatternsCountRan)
}

#replicate the 'altwiseSim' function 10000 times ####
altwiseSimRep <- do.call(rbind, replicate(10000, altwiseSim(), simplify=FALSE))

#calculate the probabilities and probability complements ####

#write a function which compares the pattern frequencies in original and simulated
data sets for each participant, environment and trial
altwiseProb <- function(i){
sum(altwiseSimRep$pattern == altwisePatternsCount$pattern[i] & altwiseSimRep$
participant == altwisePatternsCount$participant[i] & altwiseSimRep$environment =
= altwisePatternsCount$environment[i] & altwiseSimRep$trial == altwisePatternsC
ount$trial[i] & altwiseSimRep$N >= altwisePatternsCount$pattFreq[i])
}

#apply the 'altwiseProb' function
altwisePatternsCount$pattFreqSim <- sapply(1:nrow(altwisePatternsCount), altwise
Prob)

#calculate the probabilities
altwisePatternsCount$probability <- altwisePatternsCount$pattFreqSim / 10000

#calculate the probability complements (1 - probability)
altwisePatternsCount$prob_complement <- 1 - altwisePatternsCount$probability

#calculate the pattern length
altwisePatternsCount$pattLength <- nchar(altwisePatternsCount$pattern)

#save the table
write.csv(file="fileName.csv", x=altwisePatternsCount) #in case we want to
perform some data analysis without doing the simulation again

#identify attribute-wise patterns ####

#create attribute-wise strings (i.e. sequences of letters) based on counter variable
attwiseStrings <- infoSearch[,list(string <- paste(attribute, collapse = ""), participant
= unique(participant), environment = unique(environment), trial = unique(trial)), b
y = counterAttwise] #collapsing all   attributes between different alternative into a
string of letters; for instance, if a participant inspected sugar attribute between four
```

```
different alternatives, we would end up with a string 'ssss'

#delete strings of length three or less
attwiseStrings <- subset(attwiseStrings, nchar(as.character(V1)) >= 4)

#delete counter variable
attwiseStrings[, "counterAttwise" := NULL]

#rename column
setnames(attwiseStrings, "V1", "pattern")

#calculate the frequency of occurrence for each pattern within each trial,
environment and for every participant
attwisePatternsCount <- as.data.table(with(attwiseStrings, table(pattern, trial, envir
onment, participant)))
attwisePatternsCount <- attwisePatternsCount[attwisePatternsCount$N != 0]

#rename the frequency column
setnames(attwisePatternsCount, "N", "pattFreq")

#assess whether obtained patterns occurred by chance by making a random data set
to which we will compare the patterns from the original data set ####

attwiseSim <- function() { #creating a function which will contain the random
version of the data set

#reading in the data file (the original file)
infoSearch <- as.data.table(read.csv("fileName.csv", header = T, sep = ";"))

#delete unnecessary columns
infoSearch[, c("alternative", "attribute") := NULL]

#randomizing data
sim <- 154355 #the number of rows corresponding to the number of eye fixations
made in the original data set
infoSearch$alternative <- sample(1:4, sim, T) #sample the numbers  from 1 to 4
154355 times

infoSearch$attribute <- sample(c("b", "f", "p", "s"), sim, T) #sample the letters b, f,
p and s 154355 times

#identify subsequent eye fixations to an attribute within the same alternative
infoSearch$attributeClean <- ifelse(infoSearch$attribute == shift(infoSearch$attribu
te, 1L) & infoSearch$alternative == shift(infoSearch$alternative, 1L), 1, 0)

#delete subsequent eye fixations to an attribute i.e. keep only the  first eye fixation
infoSearch <- infoSearch[infoSearch$attributeClean != 1 | is.na(infoSearch$attribute
Clean)]

#delete unnecessary column
```

```
infoSearch[, "attributeClean" := NULL]

#create counter variable for attribute-wise search (focusing on the same attribute
when inspecting different alternatives)
infoSearch <- setDT(infoSearch)[, counter:= rleid(environment, trial, attribute)] #si
nce additional eye fixations have been deleted, when there is an eye fixation on the
same attribute, it must belong to a different alternative

#create attribute-wise patterns (i.e. sequences of letters) based  on counter variable
attwiseStrings <- infoSearch[,list(string <- paste(attribute, collapse = ""), participant
= unique(participant), environment = unique(environment), trial = unique(trial)), b
y = counter]

#delete patterns of length three or less
attwiseStrings <- subset(attwiseStrings, nchar(as.character(V1)) >= 4)

#delete counter variable
attwiseStrings[, "counter" := NULL]

#rename column
setnames(attwiseStrings, "V1", "pattern")

#calculate the frequency of occurrence for each pattern within each trial,
environment and for every participant
attwisePatternsCountRan <- as.data.table(with(attwiseStrings, table(pattern, trial, e
nvironment, participant)))

attwisePatternsCountRan <- attwisePatternsCountRan[attwisePatternsCountRan$N !
= 0]

return(attwisePatternsCountRan)
}

#replicate the 'attwiseSim' function 10000 times ####

attwiseSimRep <- do.call("rbind", replicate(10000, attwiseSim(), simplify=FALSE
))

#calculate the probabilities and probability complements ####

#write a function which compares the pattern frequencies in original and simulated
data sets for each participant, environment and trial
attwiseProb <- function(i){
sum(attwiseSimRep$pattern == attwisePatternsCount$pattern[i] & attwiseSimRep$
participant == attwisePatternsCount$participant[i] & attwiseSimRep$environment =
= attwisePatternsCount$environment[i] & attwiseSimRep$trial == attwisePatternsC
ount$trial[i] & attwiseSimRep$N >= attwisePatternsCount$pattFreq[i])
}

#apply the 'attwiseProb' function
```

```
attwisePatternsCount$pattFreqSim <- sapply(1:nrow(attwisePatternsCount), attwise
Prob)

attwisePatternsCount$probability <- attwisePatternsCount$pattFreqSim / 10000

#calculate the probability complement
attwisePatternsCount$prob_complement <- 1 - attwisePatternsCount$probability

#calculate the pattern length
attwisePatternsCount$pattLength <- nchar(attwisePatternsCount$pattern)

#save the table
write.csv(file="fileName.csv", x=attwisePatternsCount) #in case we want to
perform some data analysis without doing the simulation again

#calculate numerator for Systematicity of Search Index for alternative-wise patterns
(numerator = length of each unique pattern *  frequency of each unique pattern *
probability complement)
altwisePatternsCount$numerator <- altwisePatternsCount$pattFreq * altwisePatterns
Count$pattLength * altwisePatternsCount$prob_complement
sysAltwise <- ddply(altwisePatternsCount,.(participant, environment, trial), summar
ize, altwiseSum = sum(numerator))

#format the data
sysAltwise <- as.data.table(sysAltwise)
sysAltwise$participant <- as.numeric(sysAltwise$participant)
sysAltwise$trial <- as.numeric(sysAltwise$trial)
sysAltwise <- sysAltwise[order(participant, environment, trial),]

#merge in the string length (eye fixations of the entire sample)
sysAltwise <- merge(sysAltwise, stringLength, by = c("participant", "environment",
"trial"), all = T)
sysAltwise[is.na(sysAltwise)] <- 0

#calculate numerator for Systematicity of Search Index for attribute-wise patterns
(numerator = length of each unique pattern * frequency of each unique pattern *
probability complement)
attwisePatternsCount$numerator <- attwisePatternsCount$pattFreq * attwisePatterns
Count$pattLength * attwisePatternsCount$prob_complement
sysAttwise <- ddply(attwisePatternsCount,.(participant, environment, trial), summar
ize, attwiseSum = sum(numerator))

#format the data
sysAttwise <- as.data.table(sysAttwise)
sysAttwise$participant <- as.numeric(sysAttwise$participant)
sysAttwise$trial <- as.numeric(sysAttwise$trial)
sysAttwise <- sysAttwise[order(participant, environment, trial),]

#merge in the string length (eye fixations of the entire sample)
sysAttwise <- merge(sysAttwise, stringLength, by = c("participant", "environment",
```

```
"trial"), all = T)
sysAttwise[is.na(sysAttwise)] <- 0

#calculate Systematicity of Search Index ####
sysIndex <- merge(sysAltwise, sysAttwise, by = c("participant", "environment", "tri
al"), all = T)
sysIndex$N.x <- NULL #delete unnecessary column
setnames(sysIndex, "N.y", "stringLength") #rename column
sysIndex$sysIndex <- (sysIndex$altwiseSum + sysIndex$attwiseSum) / sysIndex$st
ringLength
```

Appendix F

Overview of prediction success tables per conditions

Table F1 Prediction success table for alternative array condition

	Predicted Alternatives				Row Total (N_i)	Observed Share % $(N_{i.}/N_{..})*100$
Actual Alternatives	(1)	(2)	(3)	(4)		
(1) A	64	7	4	10	85	24.15
(2) B	15	58	12	11	96	27.27
(3) C	8	7	64	8	87	24.72
(4) D	6	20	5	53	84	23.86
Column Total ($N_{.i}$)	93	92	85	82	352	100
Predicted Share (%) $(N_{.i}/N_{..})*100$	26.42	26.14	24.15	23.3	100	
Proportion successfully predicted (%) $(N_{ii}/N_{.i})*100$	68.82	63.04	75.29	64.63		
Success index	42.40	36.91	51.15	41.34		
Percent error in predicted share $100*(N_{i}. - N_{i}.)/N_{..}$	-2.27	1.14	0.57	0.57		
Overall PSI (predicted share * success index)	0.43					

Table F2 Prediction success table for attribute array condition

	Predicted Alternatives				Row Total (N_i)	Observed Share % $(N_{i.}/N_{..})$*100
Actual Alternatives	(1)	(2)	(3)	(4)		
(1) A	53	13	10	17	93	26.42
(2) B	9	67	12	11	99	28.13
(3) C	5	7	46	11	69	19.60
(4) D	9	10	15	57	91	25.85
Column Total ($N_{.i}$)	76	97	83	96	352	100
Predicted Share (%) $(N_{.i}/N_{..})$*100	21.59	27.56	23.60	27.27	100	
Proportion successfully predicted (%) $(N_{ii}/N_{.i})$*100	69.74	69.07	55.42	59.38		
Success index	48.15	41.52	31.84	32.10		
Percent error in predicted share 100*$(N_{i\cdot} - N_{i\cdot})/N_{..}$	4.83	0.57	-3.98	-1.42		
Overall PSI (predicted share * success index)	0.38					

Table F3 Prediction success table for matrix condition

	Predicted Alternatives				Row Total (N_i)	Observed Share % $(N_{i.}/N_{..})$*100
Actual Alternatives	(1)	(2)	(3)	(4)		
(1) A	49	10	2	15	76	21.59
(2) B	8	69	9	8	94	26.70
(3) C	6	15	47	9	77	21.88
(4) D	14	8	8	75	105	29.83
Column Total ($N_{.i}$)	77	102	66	107	352	100
Predicted Share (%) $(N_{.i}/N_{..})$*100	21.88	28.98	18.75	30.40	100	
Proportion successfully predicted (%) $(N_{ii}/N_{.i})$*100	63.64	67.68	71.21	70.09		
Success index	41.76	38.67	52.46	39.70		
Percent error in predicted share 100*$(N_{i\cdot} - N_{i\cdot})/N_{..}$	-0.28	-2.27	3.13	-0.57		
Overall PSI (predicted share * success index)	0.42					

Table F4 Prediction success table for random matrix condition

	Predicted Alternatives				Row Total (N_i)	Observed Share % ($N_{i.}/N_{..}$)*100
Actual Alternatives	(1)	(2)	(3)	(4)		
(1) A	48	11	13	16	88	25
(2) B	15	52	14	12	93	26.42
(3) C	12	9	46	12	79	22.44
(4) D	11	14	9	58	92	26.14
Column Total ($N_{.i}$)	86	86	82	98	352	100
Predicted Share (%) ($N_{.i}/N_{..}$)*100	24.43	24.43	23.3	27.84	100	
Proportion successfully predicted (%) ($N_{ii}/N_{.i}$)*100	55.81	60.47	56.10	59.18		
Success index	31.38	36.03	32.80	31.34		
Percent error in predicted share 100*($N_{i\cdot} - N_{i\cdot}$)/$N_{..}$	0.57	1.99	-0.85	-1.7		
Overall PSI (predicted share * success index)	0.33					