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Nutritional food choices: Decision strategies for upgraded food items

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"In any moment of decision, the best thing you can do is the right thing, the next best thing is the wrong thing, and the worst thing you can do is nothing."

Theodore Roosevelt

Abstract

For the modern eater, it can sometimes seem as if, for every new food trend that emerge, a new food component is to be vilified. Be it sugar, fat or gluten, a new menace always appears. In response to these trends, a growing number of food items are now created in an *upgraded* version, similar to original ones in aspect and taste but differing in nutritional values. The existing literature on decision making regarding classic food choices shows that most of these decisions are not made according to rational behavior, by weighting every available piece of information into a holistic judgment but rather through simple heuristics. The intended benefits of *upgraded* food items being abstract and long-term compared to their original version, this study examines the nature of the decision strategies used in choosing between such pairs. Using *upgraded* food items created by the French Center for Culinary Innovation, a computerized process-tracing experiment was implemented to monitor the acquisition of nutritional information by participants (N = 120). While, in accordance with previous findings, the results show a prevalence of heuristics limiting search and using disproportionally weighted attributes, they highlight inadequacies of preferred strategies with current nutritional information displays. Additionally, an exploration of the nature of nutritional difference between two versions of a food item suggest an impact of the quantitative value of an *upgrade* on the ease of decision and on the preference towards *upgraded* items.

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Foreword

This thesis is written as completion of the joint Master's in Culinary Leadership and Innovation between the Institut Paul Bocuse in France; Haaga-Helia University of Applied Sciences in Finland and the University of Stavanger in Norway.

The present work aims at a better understanding of the cognitive processes involved in the decision between classic food items and an upgraded version of the same item.

Given the scope of this master's as a cross-disciplinary program with an emphasis on understanding consumers' behavior and perception of current and future food trends, I believe this topic to be particularly aligned with the other parts of the curriculum.

This project could not have been done without the collaboration of Raphael Haumont and the French Center of Culinary Innovation which creations were at the core of this study.

I would like to thank my advisor Marit Engeset, the program director of the master's Martine Ferry, our academic director at Institut Paul Bocuse Jeffrey Catrett, as well as all the teaching staff in the three universities I was lucky to attend during the past two years.

Introduction

If koalas had achieved sentience, the field of food behavior research would probably be a far cry from what it is today. While these hyper-specialized eaters focus their eating habits on merely 5% of existing eucalyptus species (Martin, 2001), we humans are lucky to be provided with a far more diverse range of choices.

The existence of the omnivore's dilemma was made famous to the public by Michael Pollan (2006). In his eponymous book, he describes the balancing act made by humans and other omnivorous species to determine which food can – or should – be added to their diet.

While the blessing of an omnivorous species resides in its increased resilience and adaptability to multiple environments by finding alternate food sources, its curse remains the never-ending challenge of assessing the lethality thereof.

Answering that dilemma has been an ubiquitous task for the first millennia of human existence, however, in a developed civilization, it is resolved mostly by our shared cultural knowledge and by the high degree of normalization of food products. Hence the rarity for modern humans of encountering true omnivore's dilemma.

Nevertheless, not encountering true omnivore dilemmas does not equate with not encountering numerous food decisions. As shown by Wansink and Sobal (2007), humans can typically have to make 200 food choices per day.

Although our brains are capable of processing enormous amounts of information (Marois & Ivanoff, 2005) regarding food items, ever since the contributions of Kahneman and Tversky (1974) to the field of decision-making, we know that humans are far from being purely rational beings.

Most humans' decisions are made through the use of heuristics and mental shortcuts, and food is no exception. On that topic, recent studies (Scheibehenne, 2007; Schulte-Mecklenbeck, 2013) seem to indicate that most food decisions are made through simple heuristics, instead of complex assessments balancing every available piece of information, as could be expected by an agent aiming to optimize their choices.

Meanwhile, the 20th century saw the development of the processed food industry, and with it, an explosion of the food offering; for the past 15 years, between 15,000 and 20,000 new food and beverage products have been introduced each year (Martinez, 2017) to the US market. That diversity in options, according to Wansink (2007) is linked to the prevalence of mindless eating and of reduced cognitive effort toward food choices.

However, more recently came the trend of the *upgraded* food items, heralded by the 0% fat yogurt. That new trend seems to lie not in the creation of more diverse new food items but in keeping the identity of existing products and in keeping their main characteristics (such as visual aspect and taste). These core characteristics are maintained while manipulating "invisible" intrinsic characteristics, mainly nutritional ones, to improve nutritional properties or ingredient composition. Hence the current proliferation of low-carb, gluten-free or fat-free products.

Given that most of the primary characteristics of these *upgraded* products are similar to their classic versions, one may be inclined to believe that consumers would choose such new products on more than those basic attributes.

Indeed, one could argue that one of the goals of consuming these products is to provide more long-terms benefits than their *classic* version, aiming at future health rather than immediate satisfaction. In which case, the literature (Nederkoorn, 2009) states that food decisions made for short-term benefits (eg to sate hunger) and those made for long-term benefits are quite different.

In a similar fashion to that used by Schulte-Mecklenbeck (2013) in their descriptive research of food decision strategies used to choose between cafeteria lunches, the following thesis will review the current theory on decision strategies before observing information acquisition by participants in a situation of choice between food items in their *classic* and *upgraded* versions.

This information acquisition will be monitored through a process-tracing online experiment, which data on accessed attribute information will be used to determine which types of decision strategies are the most used in these situations.

Literature review

Food information

As underlined by Rozin (1976), the complexity of the food decisions made by omnivorous species (as opposed to the simplicity of the feeding of specialist eater species) is highly connected to brain development. The *omnivore dilemma*, having to assess the pertinence of every food item, is both a critical problem to solve – pertaining to the very short-term survival of a species, as well as a complex one, such an evaluation being hungry for cognitive resources.

The strength of the relationship between brains and alimentation should not be underestimated. Of course, among the many decisions that humans must take, food-related ones have a paramount importance. Additionally, researchers correlate the development of the human brain to the growth of the complexity of the human diet (Martin, 1983).

While the nature of the causal link between omnivorous behavior and complex brains remain in question, the magnitude of that link is indubitably strong.

However, while our alimentation has changed since the paleolithic era, our current physiologies are still equipped with the cognitive tools which evolved to tackle such dilemmas (Pollan, 2006), and therefore still use millennia-old heuristics to process most of our food decisions.

Which is to say that all available information regarding a food item is not processed by the human brain in a rational fashion. For example, as shown by Wansink, Painter & North (2005), the visual aspect of food enjoys a disproportionate weight compared to other information such as nutritional ones.

On the other hand, living in an era of omnipresent nutritional labels, contemporary humans *can* access virtually all desirable information regarding the food they consume. And according to Bender (1992), with consumers being more and more health conscious, the reading of nutrition labels is a rising trend.

Not only are these pieces of information more and more accessed by humans, but they are proved useful. As shown by Neuhouser et al (1999), a strong correlation exists between the time spent reading nutrition labels and the health of a consumer.

It would therefore seem that relevant and useful information about food is available to be accessed, but that it suffers from not being processed as easily as more natural cues.

Inspired by the works of Thaler and Sunstein and their *Nudge Theory* (2008), policy makers are trying to find alternative ways to present nutritional information, such as the project presented in France by the health minister Marisol Touraine, relying on more visual cues than numerical information.

Figure 1: Propositions for simplified nutrition labels in France

The recent studies made regarding the impact of nutrition labels on health has been often using eye tracking devices used to compare the time spent looking at information (Graham et al (2017); Higgins et al (2016), however, among these studies, very few really focus on the cognitive process of these information.

Information processing

Given the potential impact of our food decisions, one would hope that humans could be able to take these decisions in the best possible fashion. Unfortunately, according to Simon (1979), when faced with a problem, being able to determine a perfect solution would necessitate possessing the absolute knowledge of all possible alternative options as well as the absolute knowledge of their consequences.

Universes in which such conditions are met are called by Savage (1954) “small worlds”. Unsurprisingly, we seldom met such universes in our daily lives, being rather confined their alternative, “large worlds”.

Accepting the – practical – impossibility of finding perfect solutions, and therefore admitting that each practical alternative will take place on a spectrum forces humans to use decisions heuristics to optimize the quality of their choices. And indeed, for most of our decisions, opting out is not an option.

The entire spectrum of decision heuristics, however, is quite large, from complex tools such as Bayesian statistics (Savage, 1954) to simple ones such as random choices, our heuristics toolbox can be quite full.

Nevertheless, one should not forget the purpose of these tools: effort reduction. Indeed, Shah & Oppenheimer (2008) argued that the purpose of decision heuristics was the reduction of the cognitive effort, for example by examining fewer cues, reducing the effort of retrieving cue values, simplifying the weighting of cues, integrating less information, or examining fewer alternatives.

Most of these cognitive stop signs, however, are raised without our explicit approval. Kahneman (2011) famously proposed the idea of the human brain having two cognitive modes: the system 1 (fast, automatic and subconscious) and the system 2 (slow, logical and conscious). That dual process theory still enjoys a lasting prevalence. Hence one accepted classification between groups of heuristics is a qualitative one; heuristics either belonging to the group of simple ones, stemming from system 1, or belonging to the group of complex ones, stemming from system 2.

Decision strategies

While dual process theory can be instinctively easy to understand to the layman, analyzing in depth the way humans make decisions necessitates a greater understanding of decision strategies.

Riedl (2008, p 797) defines a decision strategy as “a sequence of operations used to transform an initial stage of knowledge into a final goal state of knowledge in which the decision maker feels that the decision problem is solved.”. This process being highly subjective and internal, researchers are presented with a challenge to find out the nature thereof.

As specified by Riedl (2008), the first methods used in the field of investigating decision making were mostly *structural approaches*, which is to say, only acknowledging the inputs of the process (the stimuli) and its outputs (the decisions). Inferring strategies from such methods was evidently an arduous process, which is why these methods were replaced by *process-tracing techniques* which, in addition to the inputs and outputs of a decision, also monitor the fashion in which the information inputs are accessed.

Among quantitative process-tracing techniques, two notable ones are the tracking of eye movements (Just and Carpenter, 1976) and computerized process-tracing (Payne et al, 1993). Starting from these techniques, a number of metrics have been developed to help inferring subjects' cognitive strategies, such as the total decision time; the time per attribute; the rate of reacquisition or the search index.

Although these metrics, used in conjunction, can never identify decision strategies with perfect accuracy (Ford et al, 1989), they can allow a classification into broad types of strategies.

Logically, each new metric added to the classification process subdivides the existing categories into ever more refined ones. Each study must therefore choose an appropriate set of metrics that will fit the available information.

Food decision strategies

Like any type of decision, food decisions can be solved using any number of heuristics, consciously or not. However, given the high number of food decisions that we encounter on any given day (Wansink and Sobal, 2007), one could expect food decisions to mainly be solved by use of simple heuristics. That assumption was confirmed by Connors et al. (2001), as well as by Schulte-Mecklenbeck et al. (2013).

However, since the beginnings of behavioral economics, a dominating paradigm was that of the inferiority of simple heuristics in the quality of their outcomes (not accounting for processing speed), when compared to rationality-based heuristics (Tversky and Kahneman, 1974), particularly for decisions involving little immediate feedback or unfamiliar items.

The unavoidable dilemma in matters of decisions therefore seemed to be one of sacrificing outcome quality for cognitive ease, in the manner of a cognitive zero-sum game.

To test that paradigm, Scheibehenne et al. (2007), investigated the predictive power of simple heuristics compared to complex ones for food decisions and found that the two categories performed similarly, despite the commonly held belief.

It is worthy of note, however, that the setting of the experiment included food items with which the participants were a priori quite familiar and that were sufficiently different so that participants would have a pre-existing understanding thereof.

The use of simple heuristics therefore seems to be both prevalent and legitimate regarding the case of simple food choices. One can wonder, however, whether that pattern is maintained in the case of less familiar food decisions. Indeed, as Thaler and Sunstein mention in their best-seller Nudge (2008): "[People] do less well in contexts in which they are inexperienced and poorly informed, and in which feedback is slow or infrequent."

That definition seems fitting to the challenge of choosing between food items which differ along non-obvious attributes, for which the feedback, whether physical or psychological is hard to anticipate and delayed such as our *upgraded* items. In that case, the legitimacy of simple heuristics to produce quality outcomes would be challenged for these unfamiliar foods.

Upgraded food items

In an experiment in which they altered the legibility of the font of a written test, Alter et al. (2007) demonstrated that decreasing the fluency of participants toward a task tended to activate the use of their system 2 and to decrease the use of simple heuristics. In other words, it seems possible to “push” participants out of their using system 1 by increasing the cognitive strain from the environment. One could therefore wonder whether a similar effect can be achieved regarding food decisions. In such a setting, the prevalence of simple heuristics could disappear for food decisions involving unfamiliar foods.

A critical point of this study is therefore the elaboration of a sample of *upgraded* food items that will be both unfamiliar and differentiable from their *classic* version solely through nutritional attributes.

The French Center of Culinary Innovation

In order to find a proper sample of *upgraded* items, I developed a partnership with a culinary innovation research lab, the French Center of Culinary Innovation (Centre Français d'Innovation Culinaire – CFIC).

Figure 2: Centre Français d'Innovation Culinaire

The CFIC is French research institution created in 2013 from a partnership between Raphael Haumont, researcher in materials physico-chemistry, and Thierry Marx, Michelin two-star chef.

Hosted by the University of Paris-Saclay, it specializes in research and innovation on topics connected to the future of food, including ecologically sustainable cooking, healthier eating and space food design.

Figure 3: Raphael Haumont, Thierry Marx, and one of their experiments for the European Space Agency in Zero-G

Among the projects done on the topic of healthier eating, the CFIC is working on revisiting traditional food product, by optimizing the culinary transformation that are necessary in the basic recipe. That optimization stems from a physico-chemical understanding of said transformation, and an assessment of the ones providing true added value to the item.

An example of this process is the revisited version of a chocolate mousse:

From a physico-chemical perspective, a chocolate mousse is a colloid, more specifically a gaseous dispersed phase of air within an emulsion of fats and water. Which is why most of the ingredients typically used in a traditional chocolate mousse recipe contribute to that colloidal state (eg eggs contain lecithin, which serves as a surfactant).

Understanding the recipe on a microscopic level enables one to recreate its chemical structure in an optimized fashion. In this case, dark chocolate is already a source of enough fats and surfactant to sustain an emulsion, therefore, a mix of dark chocolate and water with pressurized air is sufficient to replicate the colloidal structure of a chocolate mousse, additionally leaving a more predominant part to the chocolate in the taste profile.

Figure 4: Low pressure chocolate-water emulsion (Credit CFIC)

Such products can arguably be seen as intrinsically superior to their classic version insofar as all nutritional values for a revisited mousse of this type are lower than their classic counterparts.

This type of food *upgrade* can appear unusual since, in the processed food industry, revised versions of food products often rely on tradeoffs between their macronutrients, typically the tradeoff between fats and carbohydrates, or rely on the decrease of one specific macronutrient (eg fat in the case of skimmed milk compared to whole milk).

	Unit	Plain yogurt	Plain low-fat yogurt
Water	g	87.90	85.07
Energy	kcal	61	63
Proteins	g	3.47	5.25
Lipids	g	3.25	1.55
Carbohydrates	g	4.66	7.04

Figure 5: Nutritional values of plain yogurt vs. plain low-fat yogurt (United States Department of Agriculture National Nutrient Database)

Additionally, being borne from applied research, the food items created at the CFIC have never been released to the public, they are therefore *a priori* neutral in regard to public perception.

Research question

The essence of this thesis is therefore to observe the type of decision strategies that are made prevalent by food choices involving a food item in its *classic* version and its *revisited* version.

Several hypotheses are made regarding the type of strategies that are likely to be used in these situations:

1. Completeness hypothesis: given the unfamiliar nature of at least one of the items of each pair and the absence of visual cues susceptible to supersede other attribute, I speculate that most decisions with be forced to rely on strategies involving a complete search of all attributes.

2. Search hypothesis: given the *classic/upgraded* nature of the food items between which choices are made, and their nutritional difference, I presume that most searches will be done as a comparison of attributes between options rather than an in-option evaluation of all attributes.

3. Attribute weight hypothesis: given the "superiority" across all nutritional dimensions of *revisited* items, I speculate that strategies relying on equal weighting of attributes are more likely to result in choosing items from the *revisited* category.

Additionally, the effect of the differences between the various food items pairs will be observed:

4. Time hypothesis: a high difference in nutritional attributes between the two versions of a pair being representative of a "higher" level of *upgrade,* I speculate that those highly different pairs would decrease the total time necessary for participants to take the decision.

5. Novelty hypothesis: given the known risk aversion (Kahneman, 2011) of humans in decision making, I speculate that in the case of two nutritionally close items of a pair, the *classic* version of the item will be more likely to be chosen than in the case of two nutritionally distant items.

Method

Design

Food stimuli

The *upgraded* food stimuli were sampled from a list of 12 food items created by the research team at the CFIC laboratory. Among those 12 items, 6 were selected for their proximity to existent classic food items, and for their differentiation with their classic counterpart being measurable in terms of intrinsic nutritional values. Accordingly, items which innovate mainly in their visual aspect or in their flavor profile were not kept.

The available data for those dishes consists of their nutritional information regarding calories content, the three macronutrients contents (carbohydrates, fats and proteins) and the list of ingredients.

The data regarding the *classic* versions of items were extracted from the USDA Food Composition Database and their nutritional information were likewise integrated into the data pool.

The selected food item pairs are as follows:

Pair #	Revisited	Classic
1	Chocolate mousse	
2	Orange marmalade	
3	Chips	
4	Chocolate cake	
5	Tzatziki	
6	Strawberry sherbet	

Figure 6: 12 dishes presented to the participants

The 12 selected dishes range in calories from 15 kcal to 547 kcal per 100 g, in carbohydrates contents from 4 g to 80 g per 100 g, in fats contents from 0 g to 38 g per 100 g and in protein contents from 0 g to 7 g per 100 g (cf Appendix A for a detailed description of each item).

Control group

The goal of this thesis is to make a descriptive study of the strategy decisions used in the particular context of *upgraded* foods, not to compare the effect of distinct types of food decisions on used strategies.

Indeed, it is very likely that different types of food decisions are met with different types of strategies. However, according to Kahneman (2011), one of the characteristics of activating system 1 or system 2 for decision making is that each activation of a system holds an inertia which persists on following decision.

Studying in parallel different setting susceptible to activate very different types of strategies seems very likely to generate of lot of noise by interference, for that reason, the entirety of participants are observed as a unique group.

Selected attributes

Since the object of this study is the way intrinsic attributes of food items are processed in the realistic fashion, the attributes included as information available to the participants are a fair replica of those available on most nutrition labels for items in grocery stores.

Price was voluntarily not included in the attributes given the importance of its impact on the holistic perceived value, whatever the other intrinsic attributes (Zeithaml, 1988).

Similarly, no visual cue was provided, given the nature of *upgraded* items, food items are virtually similar in their aspect, all existing differences stemming from brand presentation and packaging.

Nutritional distance

One admitted weakness of such *upgrade* pairing is the subjective nature of the upgrade in terms of appreciation.

In order to introduce a quantitative qualifier to each food item pair, each was described by the nutritional distance between the two items of each pair.

That distance is a Euclidean distance measured between the nutritional values across each nutritional dimension:

$$Nutritional\ distance(Classic, Revisited) = \sqrt{\sum_{i=1}^{4} (C_i - R_i)^2}$$

With C_i and R_i being the value of attribute *i*, for the *classic* and *revisited* version of a food item.

The resulting distances are as follows:

Pair #	Revisited	Classic	Nutritional Distance
1	Chocolate mousse		29.24
2	Orange marmalade		235.02
3	Chips		202.98
4	Chocolate cake		93.37
5	Tzatziki		95.40
6	Strawberry sherbet		114.16

Figure 7: Nutritional distance between items of each pair

It is worthy of note that, even though a Euclidean distance is obviously always positive, in this particular instance, there exists a total order between the *revisited* nutritional vector and the *classic* nutritional vector, each *revisited* coordinate being shorter across every dimension than the *classic* one.

Sample

Participants

Participants to this study were recruited among a population of American food enthusiasts through an online query. The original sample of respondent was of 175 participants, however, after removing incomplete questionnaires entries or personal information entries, the final sample was of 120 participants (mean age = 34.5 years old, standard deviation = 11.4 years).

That sample was composed of 91 female participants (mean age = 35.7 years old, standard deviation = 12.0 years) and 29 males (mean age = 30.6 years old, standard deviation = 8.3 years).

Data collection

Behavior tracking

While research on decision strategies traditionally uses self-reported information regarding participants habits and preferences in order to build some of the classification metrics (particularly regarding the weighting of attributes), according to Grunert et al (2010), people self-reported measures of nutritional information uses were significantly different from their actual behavior. For that reason, all metrics were based on observed participants behaviors.

Eye-tracking technology (Duchowski, 2007) has been a commonly used tool in studies regarding information acquisition from nutritional labels (Goldberg, 1999; Graham, 2011) that avoids issues of social conformism in self-reported answers. However, such an apparatus is costly and presents limits in the number of simultaneously active participants.

The following therefore describe the substitute to traditional eye-tracking methods that was used in this study

Stimuli presentation

The setup of this experiment was an online interactive questionnaire created using the open source program MouselabWeb (Willemsen & Johnson, 2011).

This software enables one to create interactive web pages than that display all relevant information to items in a matrix form. That type of display voluntarily resembles that of traditional nutrition labels. The interactive aspect of this program lies in the ability to make the content of the tables hidden or displayed through actions made by participants.

In order to simulate the abilities of an eye-tracking device, the experimental setup starts with all cells containing item information concealed at first, which would then reveal their contents to the participant when they hover a mouse pointer above each cell.

Each page contains a choice between two version of the same item, with information about the name, ingredients, calories, and macronutrients contents for each version.

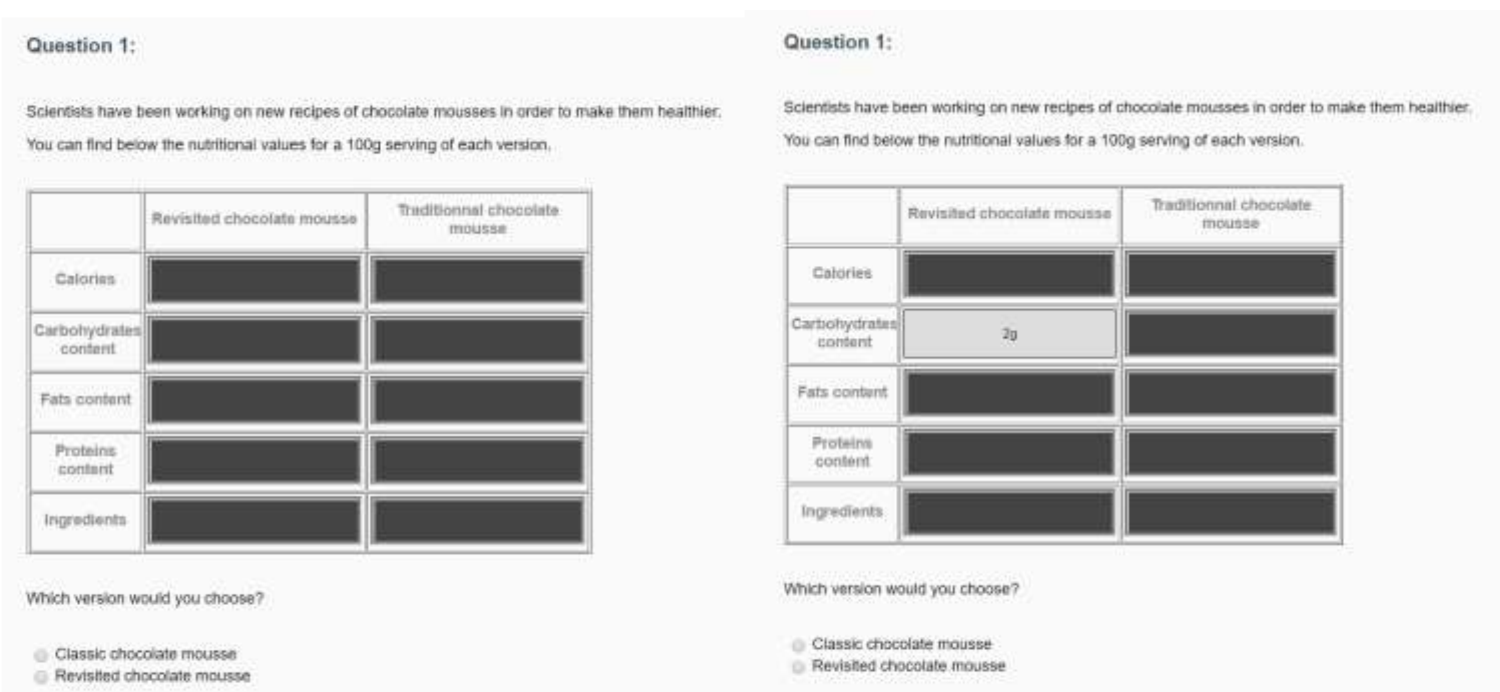

Figure 8: Question display before interacting vs when hovering a mouse pointer above a cell

In a similar fashion to that used by Schulte-Mecklenbeck et al. (2013), the tracing system is able reveal how much time each cell was exposed and therefore accessed by the participant.

The amount of information accessed by participants, the order in which each cell is accessed, as well as the timing thereof for each instance is gathered and transferred through a php script to a dedicated online database.

19	Question1	John Doe	::1	1		2017-05-10 14:46:53	onload	body	body	24	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	subject	header	1	32	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	order	col	0_2_1	32	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	order	row	0_1_2_3_4_5	32	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	events	open_close	0_0	32	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	mouseover	Calories Revisited	62kcal	2862	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	mouseout	Calories Revisited		5669	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	mouseover	Carbs Revisited	2g	5683	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	mouseout	Carbs Revisited		7008	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	mouseover	Carbs Classic	15g	7018	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	mouseout	Carbs Classic		9434	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	mouseover	Fats Classic	8g	9445	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	mouseout	Fats Classic		9518	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	mouseover	Proteins Classic	7g	9535	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	mouseout	Proteins Classic		11471	Classic
19	Question1	John Doe	::1	1		2017-05-10 14:46:53	submit	submit	submit	15227	Classic

Figure 9: Raw data as transferred to the database

While the raw data is usable directly from the database table, another php script enables me to replay the participant behavior on the page for a particular instance in the case of outlier behaviors requiring further understanding.

To ensure the understanding of the questionnaire mechanism, the first page of the questionnaire is designed as a mock question to allow experimenting from the subjects. Additionally, this question is used as a test of good faith from the participants, to avoid mindless submissions.

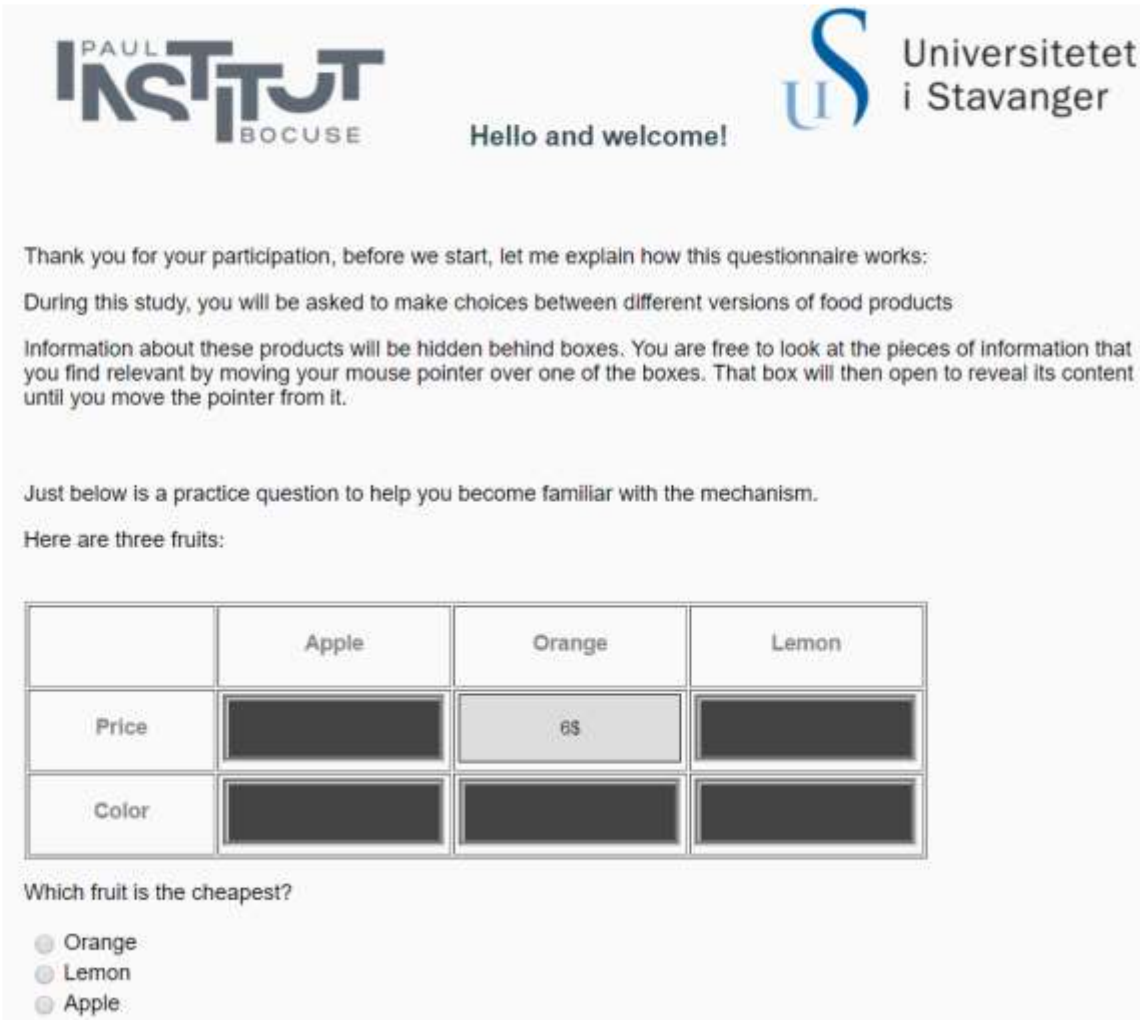

Figure 10: Welcome page with practice question

Bias resiliency

Fitts's Law (Fitts, 1954) predicts that in human-computer interaction, the time necessary for a subject to move their attention from target to target is partially a function of time. Additionally, the order bias (Feenberg, 2017) is well known to emphasize the importance of element ordering of information.

To mitigate those effects, another php script was included in the starting page for each participant to generates a random number corresponding to a different condition for the experiment.

For each experiment condition, the tables for the following questions randomly change the display order of the attribute rows and of the product columns (the first row and the first column are obviously not affected). The experiment can therefore be run through 5! × 2! = 240 conditions.

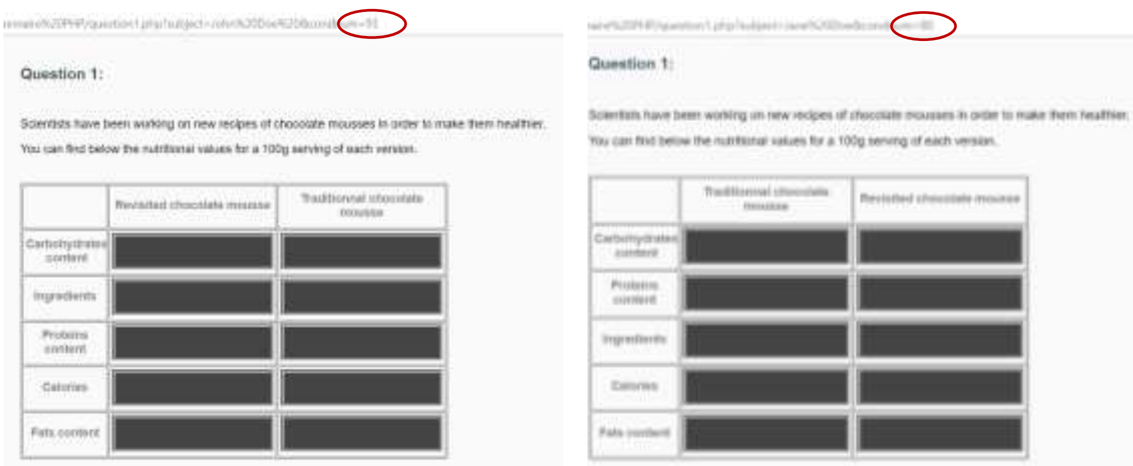

Figure 11: Different experiment conditions

In order to assess whether a cell activation is due to a deliberate act or to the journey of the mouse between to attention point, after some pilot testing, any interaction shorter than t=400ms is considered as an artefact and therefore any interaction shorter than that cutoff was removed from the resulting data.

Measurements

Decision strategies metrics

Once the information acquisition behavior of each participant for each question is established (in 120 × 6 = 720 different instances), that information needs to be translated into decision strategies.

Riedl et al (2008), on the topic of general decision strategies, suggest the use of different metrics to sort behaviors into different classes of strategies, as well as a classification for those strategies.

The two behavioral metrics used by Schulte-Mecklenbeck (2013) are that of *completeness* (ie the propensity for a participant to acquire every piece of information available before making a choice) and the *search index* metric, which establishes whether information is accessed to evaluate attributes within each option or to compare options within each attribute.

Another metric used in food decisions (Scheibehenne, 2007 and Schulte-Mecklenbeck, 2013) is the weighting of each attribute by participants in terms of personal importance. In the two cited studies, the metric of *attribute weight* is determined through separated questions in a declarative form from the participants. Acknowledging the premise from Zagorin (1977) of the discrepancy between declared behavior and preferences and actual behavior, a new metric for *attribute weight* was created, based on the time spent on an attribute and on the number of occurrences of reacquisition of that attribute (ie the number of times a cell corresponding to an attribute was re-opened after the first acquisition).

Completeness metric

Every instance in which participants accessed each of the 10 information cells is defined as *complete* while other instances are defined as *limited*.

This metric is therefore a binary result, able to divide strategies into two class of search complexity.

Search metric

The first metric of classification defined by Riedl et al (2008) studies the transitions between two cells of the information table. The two types of transitions which are studied are (a) the transition from one attribute pertaining to one food option to a different attribute pertaining to the same option (ie staying in the same column) and (b) the transition from one attribute relevant to one food option to the same attribute relevant to the other food option (ie staying in the same row).

The former is defined as *within option* search and the latter as *between option* search. Other types of transitions are considered as necessary artefacts and therefore not included in the metric.

One metric to evaluate the ratio of within to between transition is calculated as such (Böckenholt & Hynan, 1994):

$$Within\ to\ Between\ ratio = \frac{\sqrt{N}\ (\left(\frac{A \times O}{N}\right)(WO - BO) - (O - A))}{\sqrt{A^2\ (O-1) + O^2\ (A-1)}}$$

In which

O	Number of options (= 2)
A	Number of attributes (= 5)
N	Total number of transitions
WO	Number of within option transitions
BO	Number of between option transitions

This metric returns a score which is above 0 when the search is primarily done within each option and below 0 when the search is primarily done within each attribute, which divide strategies into two class of information access.

Weighting metric

The aim of that metric is to determine whether the various attributes are granted equal consideration by participants.

The two behavioral measures of the importance accorded by participants to each attribute are (a) the total time spent accessing an attribute and (b) the number of occurrences of opening cells pertaining to that attribute.

For each instance, the time spent on an attribute is converted to the percentage of time spent on that attribute relative to the total time spent on all attributes in that instance.

Additionally, the number of occurrences of access to attribute cells is transformed into an attribute reacquisition value, corresponding to the sum of accesses to that attribute after the first access for each cell of each option.

Hence the *attribute weight* metric:

$$Attribute\ Weight = (AP \times 10)^{1+\frac{AR}{10}}$$

In which

AP	Percentage of time spent on attribute (in %)
AR	Number of reacquisitions of attribute

This metric aims to allow more weight to highly reacquired attribute even when accessed for relatively shorter proportional times:

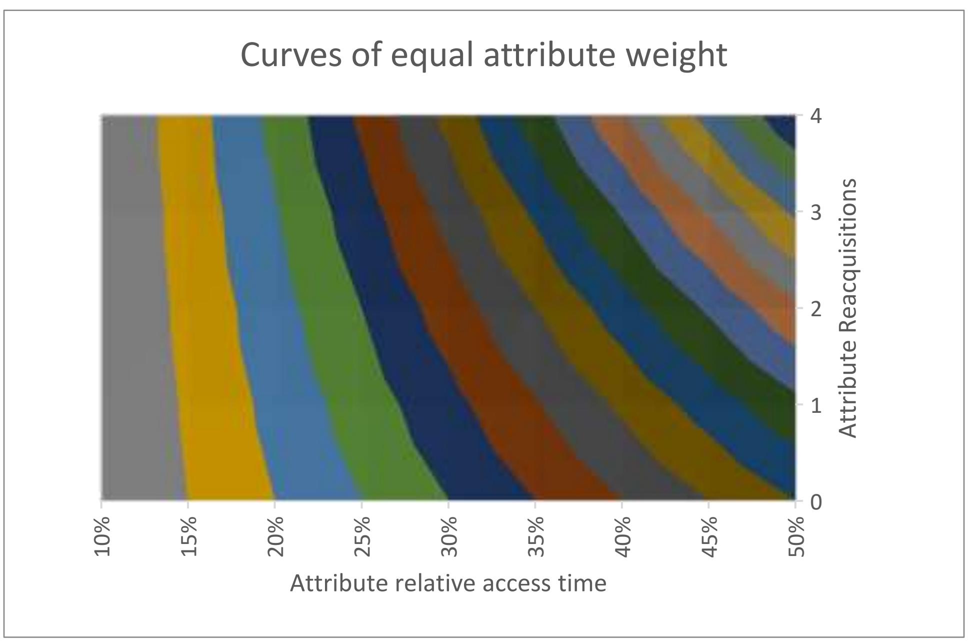

Figure 12: Equal attribute weights by time and reacquisition

This metric always returns a score greater than 0, each instance is therefore described by 5 weighting scores corresponding to the 5 attributes. In order to establish a distinguishing criterion, for each instance the mean and standard deviation of these 5 weighting scores was measured. An attribute is then considered unequally weighted when its score lies more than 1.5 standard deviations above the mean of the 5 scores.

That process is demonstrated in the following example:

	Ingredients Reacquisition	Calories Reacquisition	Carbohydrates Reacquisition	Fats Reacquisition	Proteins Reacquisition
Instance 1	0	0	0	0	0
Instance 2	3	0	0	0	0

	Ingredients Relative Time	Calories Relative Time	Carbohydrates Relative Time	Fats Relative Time	Proteins Relative Time
Instance 1	20%	20%	20%	20%	20%
Instance 2	60%	10%	10%	10%	10%

	Ingredients Weighting Score	Calories Weighting Score	Carbohydrates Weighting Score	Fats Weighting Score	Proteins Weighting Score	Equal Weight
Instance 1	2	2	2	2	2	Yes
Instance 2	10.27061916	1	1	1	1	No

Figure 13: Example of the equal weight criterion

Data analysis

Strategy classification

The three binary metrics defined *supra* logically separate all encountered decision strategies into 8 strategies (2^3 strategies). The strategies selected here are inspired by the existing literature (Payne, 1993; Riedl, 2008 and Schulte-Mecklenbeck, 2013).

The used strategies classification is defined as follows:

Metric								
Completeness	Complete Search				Limited Search			
Search	Within Option		Between Option		Within Option		Between Option	
Weighting	Equal	Unequal	Equal	Unequal	Equal	Unequal	Equal	Unequal
Heuristic	EQW	WADD	MCD	DOM	F-EQW	F-WADD	MIN	LEX

Figure 14: Strategy classification from the metrics

In which:

EQW - Equal Weights Strategy

For each food item, each attribute is accessed equally one after another. After each attribute has been evaluated, an aggregate score is created for that item. The process is repeated for the other item and the best option is chosen.

WADD – Weighted Additive Strategy

For each food item, each attribute is accessed but some of them are given disproportionate consideration. After each attribute has been evaluated, an aggregate score is created for that item. The process is repeated for the other item and the best option is chosen.

MCD – Majority of Confirming Dimensions Strategy

Each attribute is accessed equally. For each attribute, its values for the two items are compared and the most attractive option is noted. After each attribute pair has been evaluated, the item which has the most attractive attributes is selected.

DOM – Dominance Strategy

For each attribute, its values for the two items are compared and the most attractive option is noted. However, some attributes are given disproportionate consideration. After each attribute pair has been evaluated, the item which has the most attractive attributes – weighted by the given attribute consideration – is selected.

F-EQW – Frugal Equal Weights Strategy

For each food item, a subset of all available attributes is selected for consideration, and all of these selected attributes are accessed equally. After each selected attribute has been evaluated, an aggregate score is created for that item. The process is repeated for the other item and the best option is chosen.

F-WADD – Frugal Weighted Additive Strategy

For each food item, a subset of all available attributes is selected for consideration, however some of these selected attributes are given disproportionate consideration. After each selected attribute has been evaluated, an aggregate score is created for that item. The process is repeated for the other item and the best option is chosen.

MIN – Minimalistic Strategy

A subset of all available attributes is selected for consideration, and all of these selected attributes are accessed equally. For each attribute, its values for the two items are compared and the most attractive option is noted. After each selected attribute pair has been evaluated, the item with the most attractive attributes is selected.

LEX – Lexicographic Strategy

A subset of all available attributes is selected for consideration, however, among these selected attributes some are given disproportionate consideration. For each attribute, its values for the two items are compared and the most attractive option is noted. After each selected attribute pair has been evaluated, the item with the most attractive attributes – weighted by the given attribute consideration -is selected. In particular, all decisions made on the basis of judging only one attribute belong in that category.

Food choices and decision time

Finally, as global measures for each decision instance, the decision made by the participant between each food item pair and the total time necessary to achieve that decision are also recorded. The former either falls into the *revisited* or *classic* category while the latter is a numerical score.

Results

Decision strategies

General decision strategies

The data set resulting from the running of the experiment combines the information processing of 120 participants, each of them making 6 unique decisions. That set therefore comprises 720 different decision instances, for which a total of 8 640 pieces of information have been acquired.

The repartition of decision strategies used for the 720 choices according to the previously detailed classification is as follows:

Metric								
Completeness	Complete Search				Limited Search			
Search	Within Option		Between Option		Within Option		Between Option	
Weighting	Equal	Unequal	Equal	Unequal	Equal	Unequal	Equal	Unequal
Heuristic	EQW	WADD	MCD	DOM	F-EQW	F-WADD	MIN	LEX
Frequency	29	42	112	123	73	117	69	155
Percent	4%	6%	16%	17%	10%	16%	10%	22%

Figure 15: Repartition of all decision strategies used

It is noteworthy that every decision that was made by participants was made after acquiring information on at least one attribute, no choice was made purely randomly.

Participant dominant strategy

Looking at the decision strategies used by participants in the course of the study, it appears that making use of a favorite strategy across multiple questions was a common behavior. Even though using solely one strategy for each of the six questions was a marginal phenomenon (only 5 participants out of 120), 77% of participants were seen as having a favorite strategy (existence of a unique mode among strategies used in the course of the 6 questions).

Participants were classified as having no dominant strategy when using systematically different strategies or when having multiple equal modes.

Metric									
Completeness	Complete Search				Limited Search				
Search	Within Option		Between Optio		Within Option		Between Optio		
Weighting	Equal	Unequal	Equa	Unequal	Equal	Unequal	Equal	Unequal	
Heuristic	EQW	WADD	MCD	DOM	F-EQW	F-WADD	MIN	LEX	No Dominant
Frequency	3	0	15	18	7	19	8	22	28
Percent	3%	0%	13%	15%	6%	16%	7%	18%	23%

Figure 16: Repartition of dominant strategies par participant

Completeness of strategies

Based on that strategy repartition, it appears that participants made use of strategies involving limited searches in 57.5% of all cases (414 instances), regardless of the type of search index and attribute weighting used (F-WADD, F-EQW, LEX, MIN), which is significantly different than chance ($p < 0.01$).

Meanwhile, when looking at strategies that are used as participants' favorites, strategies that involve the use of limited searches amount to 60.6% of participants who make use of a dominant strategy.

Search index of strategies

Looking back at the general strategy repartition, participants made use of strategies involving a between options type of search index in 63.8% of all cases (459 instances), regardless of the completeness and attribute weighting of these strategies (MCD, DOM, MIN, LEX), which is significantly different than chance ($p < 0.01$).

Meanwhile, looking at participants' favorites strategies, strategies making use of a between options search index were used by 68.2% of participants who make use of a dominant strategy.

Attribute weight of strategies

Unequal attribute weighting prevalence

Regarding the attribute weighting in general decision strategies, it appears that the available attributes were given unequal weights in 60.7% of all cases (437 instances), regardless of the completeness and search index used by these strategies (WADD, DOM, F-WADD, LEX), which is again significantly different than chance ($p < 0.01$).

Among participants who made use of a favorite strategy, 64.0% of these participants made use of one involving unequal attribute weighting.

Choices by attribute weighting

Due to the superiority – by design of the creation process at the CFIC - of the nutritional attributes of *revisited* items, it seems interesting to observe the relationship between the weight given to attributes in decision strategies and the final choice.

A comparison of the repartition of choices between strategies relying on equally weighted attributes and unequally weighted attributes shows a non-negligible positive relationship ($p < 0.1$) between the use of strategies with equally weighted attribute and the likelihood of choosing *revisited* items.

		Classic	Revisited	Total
Equally Weighted	Count	80	203	283
	Expected Count	95.9	187.1	283.0
Unequally Weighted	Count	164	273	437
	Expected Count	148.1	288.9	437.0
Total	Count	244	476	720

Figure 17: Repartition of choices per weighted attribute strategies

To confirm the singularity of the attribute weight metric, a similar chi-square analysis finds no significant impact of the completeness metric and of the search index metric on the chosen item.

Choices by preferred attribute

Since it appears that using unequally weighted attributes strategies has an impact on the chosen product, we can look deeper on the effect of each attribute when used as the primarily weighted one.

Looking at strategies using *ingredients* as their most weighted attribute, there appears to be a significant positive relationship ($p < 0.05$) between the use of *ingredients* as the most weighted attributes and the likelihood of choosing a *classic* item.

In an opposite way, there is a significant positive relationship ($p < 0.06$) between strategies using *fat* as their most weighted attribute and the likelihood of choosing a *revisited* item.

However, strategies using any other attribute as their most weighted do not seem to have any significant impact on the result of a food choice.

Food item pairs

Decision times

During the study, the range of completion times necessary for participants to make one choice spans from 5.4s to 74.3s, and averages at 13.6s (standard deviation = 9.0s).

Food choices

Since every food item pair was containing one *classic* item and one *revisited* item, the class of item selected by participants in each decision can be agglomerated across all questions. Across all decision made during this study, 66.1% of these decision (476 instances) selected a *revisited* item ($p < 0.01$).

Nutritional distance classification

However, while these numbers give a global picture of completion time and participants' choices, a visual examination of the repartition of those two metrics across question (Figure 18 and Figure 19) suggest the existence of differences in their behavior.

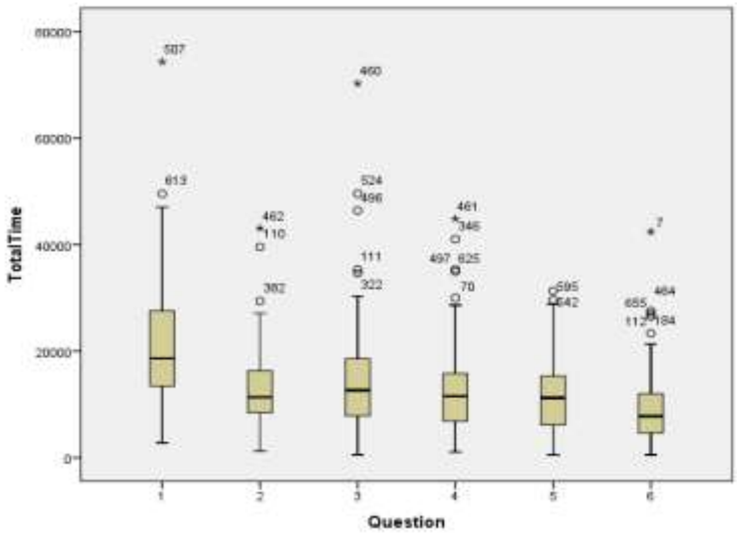

Figure 18: Completion time repartition across questions

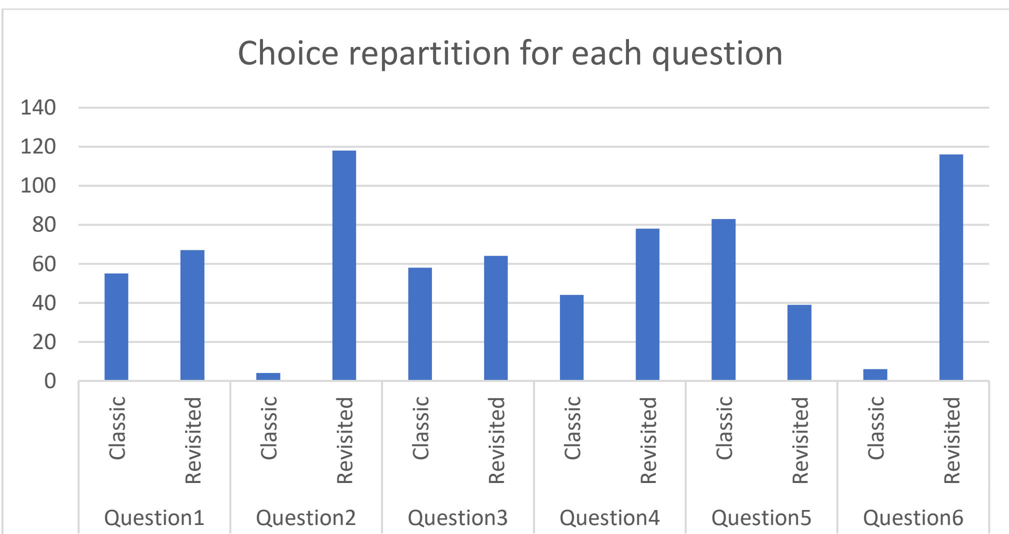

Figure 19: Repartition of classic/revisited choices across questions

Given the values of nutritional distances for the 6 pairs of food items, these pair can easily be split into three groups: a Low Distance group of pairs below 30, a Medium Distance group of pairs between 90 and 120 and a High Distance group of pairs above 200.

Pair #	Revisited Classic	Distance	Nutritional Group
1	Chocolate mousse	29.24	Low Distance
2	Orange marmalade	235.02	High Distance
3	Chips	202.98	High Distance
4	Chocolate cake	93.37	Medium Distance
5	Tzatziki	95.40	Medium Distance
6	Strawberry sherbet	114.16	Medium Distance

Figure 20: Food item pairs per nutritional group

Decision time

Time by nutritional distance group

A comparison of the mean decision times reveals that Low Distance pairs choices are solved in 20.9s (SD = 10.7s), Medium Distance pairs choices are solved in 11.1s (SD = 7.2s) and High Distance pairs choices are solved in 13.7s (SD = 8.5s).

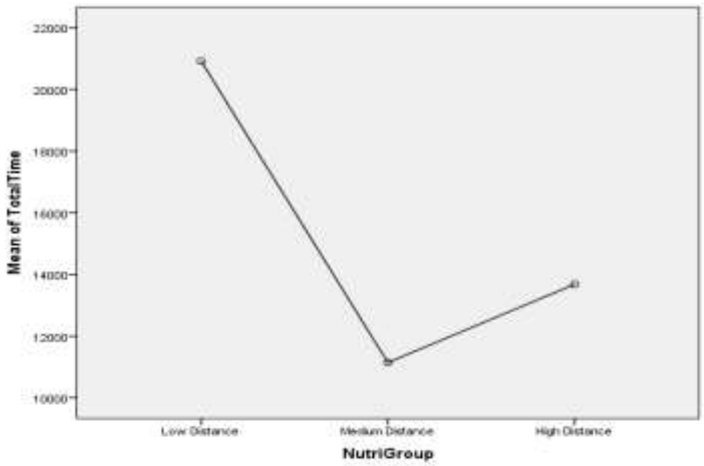

Figure 21: Mean decision times per nutritional group

These decision times differ by a statistically significant amount ($p < 0.01$ for each of the three comparisons).

Food choices

When looking at the relation between nutritional distance and the chosen version of an item pair, *classic* choices were associated to an average nutritional distance of 108.1 (SD = 61.6) while *revisited* choices were associated to an average nutritional distance of 139.5 (SD = 71.3). That difference in nutritional distance is statistically significant ($p < 0.01$).

Reusing the nutritional group classification, the Low Distance and Medium Distance group appear to be more likely to be associated with a *classic* choice, while the High Distance group is more likely to be associated with a *revisited* choice.

		Classic	Revisited	Total
Low Distance	Count	53	64	117
	Expected Count	39.7	77.4	117.0
Medium Distance	Count	131	231	362
	Expected Count	122.7	239.3	362.0
High Distance	Count	60	181	241
	Expected Count	81.7	159.3	241.0
Total	Count	244	476	720

Figure 22: Choice repartition per nutritional distance group

Once again, these difference between groups are found to be statistically significant ($p < 0.01$). That analysis of nominal nutritional distance groups is consistent with the previous analysis using nutritional distance as a numerical score.

Sensitivity analysis

Among the binary metrics, the one regarding weighting is indubitably the more complicated for which to define a cutoff value.

Defining an unequal weight by any attribute with a score more than 1.5 times the standard deviation of attribute scores resulted in 60.7% of all cases using unequal weighting. However, the value of 1.5 times the standard deviation was voluntarily chosen as a high cutoff value for weighting score inequality, in order to strongly ensure the confirmation of the hypothesis.

By changing the cutoff value for unequal weight to 1 standard deviation above the mean, the repartition switches to 96.1% of all cases using unequal weighting.

While that difference with the previous cutoff value is important, the fact is that the domination of unequally weighted attribute strategies unarguably remains.

Expanded to the repartition of all strategies, that change of cutoff value only shifts some points from each strategy to their neighboring one (from EQW to WADD, from MIN to LEX, from MCD to DOM, from F-EQW to F-WADD).

The general repartition of strategies remains unchanged, only the degree to which unequal weight dominates equal weight is.

Discussion

The information structure of the experiment used in this thesis is fairly similar to that available for customers while shopping in a grocery store, nutritional information being as readily available and no taste feedback nor true visual feedback being available.

It therefore seems likely that, in a situation of choice between two version of a same food items, consumers would make use of the same types of decision strategies than those observed here and that the characteristics of the two versions would have the same influence on the final choice than what has been observed in this study.

Acknowledging these findings through the lens of the nudge theory (Thaler, 2008) would enable one to redesign the information architecture available for food choices in grocery stores, whether for marketing purposes, or in the context of government-sponsored dietary nudges, in order to better fit the actual decision strategies used.

Decision strategies

Facilitating limited searches

The first hypothesis of this study was that by presenting participants with difficult choices in the experimental design, through removal of visual cues, introduction of unfamiliar items and the closeness of the items composing each pair, they would find it necessary to use complete decision strategies, acquiring every available piece of information before taking an informed decision.

However, the domination of limited searches strategies was found to be indisputable. While that result goes against the initial hypothesis, it stays consistent with the propensity for frugal information found in general decisions (Gigerenzer, 2011) or in more typical food decisions (Schulte-Mecklenbeck, 2013).

For an actual food choice, that tendency toward limited information access is an argument in favor of simplified nutritional information displays on food packaging. Revised nutritional displays that pre-process the total amount of nutritional information into a color-coded label would therefore probably ensure a greater access to that information than purely numerical displays.

The practical difficulties of between options searches

While it may seem intuitive, this study confirms the second hypothesis that in a situation of choice between different versions of a food item, most decision strategies make use of a *between options* search index.

However, looking at the information structure in a grocery store setting, the presence of nutrition labels on the back of each item packaging *de facto* forces customers to use *within option* searches and to compare options on a holistic appreciation.

The way the real-life structure forces consumers to switch to another class of decision strategies than the one that would be preferred is most likely a handicap towards optimizing food decision, especially when driven by health concerns.

An improved display could therefore be designed by putting nutritional information of various items in a more equally accessible fashion, similarly to that in which prices are displayed in a store, allowing for direct comparisons at a glance.

Leveraging favorite attributes

Consistent with the fact that most strategies used in this study are limited search ones, the third hypothesis is also verified in that most participants made use of strategies relying on unequally weighted attributes.

This mechanism appears as a facilitator of decisions based of frugal information, as was established by Scheibehenne (2007) and Schulte-Mecklenbeck (2013).
Additionally, in this experiment, given the health-wise superiority of *revisited* items on all quantitative attributes (not including the *ingredient* attribute), there appears to be a consistency between making use of a more "rational" decision strategy (ie weighting equally all attributes) and making a choice consistent with the quantitative result of this strategy (ie choosing *revisited* items against *classic* ones).

However, as previously said, the majority of participants take decisions according to a few attributes only. It was therefore interesting to notice that among all attributes, only two of them seemed to have an impact on the final choice when used as the most weighted attribute, namely weighting *ingredients* more heavily is correlated with choosing *classic* items and weighting *fats* more heavily is correlated with choosing *revisited* items.

It is noteworthy that more than 40 years after the dietary goals made for the United States by the American congress (Cockburn, 1977) and the general global movement against fat-rich foods that ensued, fat is still today the macronutrient most likely to influence one's decision.

It would therefore appear that any institutional body aiming to nudge consumers towards eating overall healthier food items would be well advised to put some emphasis on communicating the reduced fats contents, regardless of whether that macronutrient content is the most improved compared to other nutritional values.

On the other hand, the behavior of participants weighting *ingredients* content more heavily than other attributes could let one presume that, regardless of the declared nutritional values and alleged health benefits of a product, there exists an aversion towards unfamiliar ingredients combinations or a preference for familiar ingredients combinations.

Once again, any institution aiming at nudging consumers towards new, *upgraded* products would be well advised to ensure that the ingredient composition appears as "natural" as that of a traditional product, or, if need be, to try and educate about the pettiness of the difference.

Food item pairs

While creating *upgraded* food items most of the time is done with the goal of obtaining healthier items, it seems logical that the nature of the upgrade will vary from one to the next. Hence the difficulty of analyzing *upgraded* foods as a whole.

Although this study was not designed to observe in depth variations within the class of *classic/upgraded* food pairs, the introduced nutritional distance classification can produce some inklings towards directions to extend future research.

Making quick decisions

It has been apparent during this study that one of the most important reasons for enacting decision strategies is to alleviate the mental burdens involved, both in complexity and in time.

Based on the average time necessary for completion, the fourth hypothesis is partially confirmed in that it appears that the one item pair with the lowest nutritional distance demanded by far the longest time to complete, compared to other groups. While this sample is admittedly reduced, it seems intuitive that *upgraded* items would be hard to differentiate from their *classic* version when the improvement is non-obvious.

While both Medium Distance and High Distance choices were made in shorter time, a surprising result is the greater completion time associated with High Distance compared to Medium Distance choices.

A possible explanation could lie in the alien or “too good to be true” nature of an *upgraded* item so far removed from its *classic* version.

Nevertheless, these rough results could warrant a further investigation in the treatment of food items pairs across the existing differences between such pairs.

Specifically, since the nutritional distance is but a crude metric for item pairs difference, food items could be artificially designed to test the impact of other kinds of metrics. For example, item pairs with the same overall nutritional distance but across various nutritional dimensions or nutritional distances calculated as a percentage of the *classic* item nutritional score, measuring the relative added value of the *upgrade*.

A worthy upgrade

Regardless of the ease with which a decision is made, when aiming to nudge a consumer in a particular direction, what matters most is the final choice.
According to the results, the fifth hypothesis is confirmed in that the higher the nutritional distance between the two items of a pair, the more likely the *revisited* item is likely to be chosen.

This result appears unsurprising when reflecting on the fundamental reason why *upgraded* items are created. Assuming that a large part of these food decisions is taken based on health benefits, the worth of an *upgrade* is literally the value of its nutritional distance to its *classic* counterpart.

Admittedly, even in the case of lower distance pairs, participants were still more likely to choose *revisited* items than *classic* ones, however, any institution which would wish to maximize the popularity of an *upgraded* item on the market would do well to ensure that it differs from its regular version by an unambiguous margin.

Still, that correlation tend to suggest the existence of a reluctance toward *upgraded* items among some participants that becomes balanced and overcome as the worth of the *upgrade* grows.

Conclusion

After several decades of creation of *upgraded* food items by the processed food industry, starting from the low-fat products of the ‘80s to the more recent gluten-free products, the trend does not seem likely to end soon. Understanding how decisions regarding this specific class of items are made therefore seems like a promising topic.

As previously studied by the existing literature (Schulte-Mecklenbeck, 2013; Gigerenzer, 2011), this study confirms the prevalence of decision strategies making use of limited searches and of unequally weighted attributes.

However, in the context of upgraded food items, more likely to be found and purchased in the aisles of grocery stores, the prevalence of limited searches and of between-option searches shows the inadequacy between the way nutritional labels are displayed and the way information regarding nutritional attributes is processed. While all nutritional information is available to consumers, the placement and numerical nature of nutritional labels make difficult the assessment of their preferred product by consumers, whatever the attributes they value the most.

While it appears unsurprising that an item being revisited with better values in its macronutrients and calories attributes is more likely to be selected along those criteria – particularly so in the case of fats – it is interesting to note that participants seem to prefer the ingredient composition of *classic* items (often including components such as sugar, butter or eggs) to that of *revisited* items (generally containing less components) illustrating the importance of non-nutritional aspects of a food item.

The result that the greater an *upgrade* is – quantitatively speaking – the more likely it is to be chosen, and the more rapidly it is to be, can also appear intuitive. Nevertheless, the apparent differences in

handling of food item pairs depending on their nutritional difference suggest the potential of future research in food item *upgrades* and in consumers' appreciation of the value of these *upgrades*.
The difference in weighting of the fat attribute compared to other macronutrients for example suggests that a nutritional distance weighting equally all attributes might not be the best metric to translate in a quantitative way the perception of the value brought to a consumer by an *upgrade*.

Finally, the qualitative aspects of an *upgrade* are probably equally worthy of interest. Given the suggestion that people perceive differently savory and sweet items or fat-rich and carbohydrate-rich items (Green, 1996), the threshold levels of values brought by an *upgrade* which necessary to appeal to a consumer are likely to depend on the type of items involved as well as the nutritional dimensions which are *upgraded*.

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Appendix

Appendix A: Food items attributes

	Chocolate mousse		Orange marmelade		Chips		Chocolate cake		Tzatziki		Strawberry sherbet	
	Revisited	Classic	Revisited	Classic	Revisited	Classic	Revisited	Classic	Revisited	Classic	Revisited	Classic
Ingredients	Chocolate, water	Milk, chocolate, egg, sugar	Oranges, pectins from orange skin	Oranges, sugar	Strawberries	Potatoes, oil, salt	Chocolate, water	Chocolate, sugar, egg, butter, milk	Cucumber, agar-agar	Cucumber, yogurt, olive oil, garlic, salt	Strawberries	Milk, sugar, strawberries
Calories	180	209	50	278	350	547	270	358	15	110	32	144
Carbohydrate	15	16	12	69	80	50	22	53	4	6	8	30
Fats	12	15	0	0	0	38	18	15	0	8	0	2
Proteins	2	4	1	0	0	7	3	5	0	3	1	1

Appendix B: One-sample t-test of basic metrics

One-Sample Test

	Test Value = 0					
	t	df	Sig. (2-tailed)	Mean Difference	95% Confidence Interval of the Difference	
					Lower	Upper
Completeness	23.053	719	.000	.425	.39	.46
SearchMetric	20.220	719	.000	.363	.33	.40
EqualWeight	33.321	719	.000	.607	.57	.64

Appendix C: Chi-square of basic metrics by choice

Crosstab

			Choice		Total
			Classic	Revisited	
EqualWeight	EqualWeight	Count	80	203	283
		Expected Count	95.9	187.1	283.0
	UnequalWeight	Count	164	273	437
		Expected Count	148.1	288.9	437.0
Total		Count	244	476	720
		Expected Count	244.0	476.0	720.0

Crosstab

			Choice		Total
			Classic	Revisited	
Completeness	Limited	Count	134	280	414
		Expected Count	140.3	273.7	414.0
	Complete	Count	110	196	306
		Expected Count	103.7	202.3	306.0
Total		Count	244	476	720
		Expected Count	244.0	476.0	720.0

Crosstab

			Choice		Total
			Classic	Revisited	
SearchMetric	Between	Count	160	299	459
		Expected Count	155.6	303.5	459.0
	Within	Count	84	177	261
		Expected Count	88.5	172.6	261.0
Total		Count	244	476	720
		Expected Count	244.0	476.0	720.0

Appendix D: Chi-square of favorite weighted attribute by choice

Crosstab

			Choice		Total
			Classic	Revisited	
IngDomin	IngredientNonDominant	Count	106	245	351
		Expected Count	119.0	232.1	351.0
	IngredientDominant	Count	138	231	369
		Expected Count	125.1	244.0	369.0
Total		Count	244	476	720
		Expected Count	244.0	476.0	720.0

Crosstab

			Choice		Total
			Classic	Revisited	
CalDomin	CaloriesNonDominant	Count	213	410	623
		Expected Count	211.1	411.9	623.0
	CaloriesDominant	Count	31	66	97
		Expected Count	32.9	64.1	97.0
Total		Count	244	476	720
		Expected Count	244.0	476.0	720.0

Crosstab

			Choice		Total
			Classic	Revisited	
CarbDomin	CarbsNonDominant	Count	203	389	592
		Expected Count	200.6	391.4	592.0
	CarbsDominant	Count	41	87	128
		Expected Count	43.4	84.6	128.0
Total		Count	244	476	720
		Expected Count	244.0	476.0	720.0

Crosstab

			Choice		Total
			Classic	Revisited	
ProtDomin	ProteinsNonDominant	Count	224	431	655
		Expected Count	222.0	433.0	655.0
	ProteinsDominant	Count	20	45	65
		Expected Count	22.0	43.0	65.0
Total		Count	244	476	720
		Expected Count	244.0	476.0	720.0

Crosstab

			Choice		Total
			Classic	Revisited	
FatDomin	FatNonDominant	Count	230	429	659
		Expected Count	223.3	435.7	659.0
	FatDominant	Count	14	47	61
		Expected Count	20.7	40.3	61.0
Total		Count	244	476	720
		Expected Count	244.0	476.0	720.0

Appendix E: ANOVA of decision time by nutritional distance group

Descriptives

TotalTime

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Low Distance	117	20914.75	10682.592	987.606	18958.67	22870.83	2793	74335
Medium Distance	362	11141.42	7196.354	378.232	10397.60	11885.23	535	44859
High Distance	241	13681.66	8536.417	549.879	12598.46	14764.87	557	70261
Total	720	13579.86	8971.557	334.350	12923.44	14236.28	535	74335

Appendix F: ANOVA of nutritional distance by choice

Descriptives

NutriDistance

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean		Minimum	Maximum
					Lower Bound	Upper Bound		
Classic	244	108.1038	61.56371	3.94121	100.3405	115.8671	29.24	235.02
Revisited	476	139.4914	71.33358	3.26957	133.0668	145.9160	29.24	235.02
Total	720	128.8545	69.73964	2.59904	123.7519	133.9571	29.24	235.02

Appendix G: Chi-square of nutritional distance group by choice

NutriGroup * Choice Crosstabulation

			Choice		Total
			Classic	Revisited	
NutriGroup	Low Distance	Count	53	64	117
		Expected Count	39.7	77.4	117.0
	Medium Distance	Count	131	231	362
		Expected Count	122.7	239.3	362.0
	High Distance	Count	60	181	241
		Expected Count	81.7	159.3	241.0
Total		Count	244	476	720
		Expected Count	244.0	476.0	720.0