Predicting restaurant menu choices

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Preface

Here, I present you my work in the context of my dissertation project for my Master's degree in Data Science: Business & Governance. In this thesis, the results of an analysis of previously collected eye movements during restaurant menu choice are presented. I want to thank Dr. Frouke Hermens and Dr. Andrew Hendrickson for being my supervisor. I want to thank Dr. Grzegorz Chrupala for being my second reader. I also want to thank Stefanie van Schaik, Emma Janssen, Thomas Sips and Aaron Wijnker for their support and feedback.

Abstract

The deterioration of peoples' health due to the consumption of unhealthy foods has major consequences for society. Therefore, it is useful to research how people can be driven to eat healthier. This can be done by analysing peoples behaviour while they make a food choice from a restaurant menu. In this study, twenty-five people have each looked at thirty menus. They filled in a questionnaire to collect personal data and their eye movements were tracked while they looked at the menus. Analyses have been performed to find out which aspects play a role in making a food choice. Classification with the random forest algorithm has been used to make predictions. This study shows that people probably need more education about calorie content in foods. Furthermore, it might be advisable to design uncluttered menu cards with a clear distinction between menu items with high and low calories, to make it easier for people to choose something healthy.

Introduction

Problem statement

Health is strongly influenced by nutrition. Unhealthy diets can cause diseases such as type two diabetes, coronary heart disease and cancer (Tilman & Clark, 2014). Therefore, unhealthy diets can lead to increased health care costs and additional costs due to missed working days and reduced outputs of workers (Asay, Roy, Lang, Payne, & Howard, 2016; S.-H. Kim, Tanner, Foster, & Kim, 2015). One way in which people could be made aware of unhealthy foods is the use of food labels. While supermarkets use food labelling to indicate the nutritional contents of foods (Grunert, Wills, & Fernández-Celemín, 2010), such labelling is not commonly used in restaurants.

People increasingly eat out, where meals tend to be bigger and of less nutritional value than those consumed at home (Young & Nestle, 2002). To be able to steer people towards healthier food choices, it is important to understand how people choose what they eat. In furtherance of understanding how people make choices from a restaurant menu, one could systematically vary how the options are presented and ask people to repeatedly make choices as has been done in previous studies (Roseman, Mathe-Soulek, & Higgins, 2013). This approach, however, has the disadvantage that only the final choice is known, while there is little to say about the thinking steps that precede it. Studies which aimed to analyze thinking steps, by tracking the eye movements, did not make use of actual restaurant menus (E. Kim, Tang, Meusel, & Gupta, 2018; Yang, 2012). An alternative approach is introduced here, namely by making use of data about eye movements on real world menus that will give a much more detailed account of the process leading to a food choice from a real world restaurant menu. Therefore, this study will give new insight in this field.

In the present study, pre-existing data is used to examine how people select from actual restaurant menus by (1) measuring their eye movements, (2) recording their choices, (3) coding menu items, and (4) recording demographic information that may relate to choices from restaurant menus. With these data, some of the following aspects will be investigated: (1) where the foods are positioned on the menu, (2) the prices of items, (3) the presence of images of the foods on the menus, (4) whether participants are on a diet (5) and the presence of food labels (6) (calories, fat, and salt) on the menu.

The available data included choices, demographic information and eye movements of twenty-five participants for thirty actual restaurant menus. Classification is used to examine how well peoples' choices can be predicted from the information available. A good classification performance indicates that the features used are important for how people choose from menus. Understanding the drivers behind people's choices could be helpful to instruct restaurant owners to design menus that steer people to more healthy choices or even to adjust legislation for menu cards designs.

Context

This is not the first study looking into food choices in restaurants (E. Kim et al., 2018; Roseman et al., 2013; Yang, 2012). Roseman et al. (2013) found that knowledge of consumers about nutrition labels in supermarkets and their wish of getting nutritional information in restaurants lead to more healthy food choices in restaurants. The biggest part of these consumers are probably woman, as women tend to care about nutritional information more than men (Din, Zahari, & Shariff, 2012). Not all studies have found that nutritional information leads to healthier food choices. Burton, Howlett, and Tangari (2009) explained that the link between real nutritional values and the expected nutritional values influences food choices the most.

Relevance

Food related illnesses, such as obesity, are a major problem for society. Not only because of peoples' health in itself but also because of the costs it entails. Health care costs for obese people are, on average, thirty-seven percent higher than those of people with a healthy weight (Thorpe, Florence, Howard, & Joski, 2004). Furthermore, people who are not able to work and the increased number of sick days because of health related issues also lead to high costs. In the United States, these costs amount to 11.2 billion dollars per year (Asay et al., 2016). Studies have suggested that increased eating out may play an important role in this obesity epidemic (Kant & Graubard, 2004).

From a theoretical point of view, this study provides a better understanding of how people make decisions in more naturalistic, complex environments. Practically, the results provide guidelines on how to steer peoples' menu choices towards more healthy options.

Research question

The main research question is whether restaurant menu choices can be predicted from information about the participants and/or attention to regions of restaurant menus, measured by fixation times, while choosing a menu item. To address this question, several sub-questions will be addressed. These include:

- What aspects of a menu predict choice best? E.g. Price? Location on the menu?
- What aspects of the participants predict choice best? E.g. Diet or whether a participant is hungry or not?
- What is the relation between fixations and personal aspects among different menus?

Related Work

Problem definition

An increasing number of people have unhealthy eating habits (Baillie, 2008). Studies have suggested that food has a major impact on peoples' physical and mental health (Bellisle, 2004; Tilman & Clark, 2014). Unhealthy diets can contain more than recommended levels of saturated fat, sugar and salt (Tilman & Clark, 2014). Eating unhealthy food can cause health problems such as type two diabetes, heart disease and cancer, often in association with increased BMI or obesity (Tilman & Clark, 2014).

An important reason why a poor diet can lead to poor health is that poor diets are more likely to lead to high BMI levels and obesity. Today, 2.1 billion people worldwide have excessive body weight (Tilman & Clark, 2014). Obesity is a major risk factor for other diseases, such as diabetes (Thorpe et al., 2004). Other issues, such as low back pain, are also associated with obesity (Zhang et al., 2018). Health care costs for obese people are higher than those for people with a healthy weight (Schmier, Jones, & Halpern, 2006; Thorpe et al., 2004). There has been a twenty-nine percent increase in expenditures for obese people between 2001 and 2015 in the United States (Biener, Cawley, & Meyerhoefer, 2018). Higher health care costs due to high BMI levels or obesity are also a problem in the United Kingdom, where approximately 91.6 billion pounds go to bariatric surgeries per year (Gulliford et al., 2017). Furthermore, obese people have significantly higher expenditures on mental health issues like depression (Rudisill, Charlton, Booth, & Gulliford, 2016).

These higher costs have been suggested to be an important reason for the increase in health insurance costs (S.-H. Kim et al., 2015). This can lead to people having problems paying their health insurance. In 65.1% of the cases in which people are unable to attain health care in America, the high costs or lack of insurance are given as the reason (Himmelstein & Woolhandler, 1995).

Not only health insurance costs are affected by poor diets, employers also suffer from poor diets of their employees. There is a clear link between poor diets and absence from work of employees (Asay et al., 2016; Tucker & Friedman, 1998). The estimated costs of absent employees due to obesity are around 11.2 billion dollars per year in the United States (Asay et al., 2016). Studies also show that obesity-like BMI scores are associated with higher disability use and workplace injuries (Schmier et al., 2006). Fitzgerald, Kirby, Murphy, and Geaney (2016) not only found the relation between absence and obesity, but also found that healthy diets led to less absence from work.

Even without obesity, poor diets can lead to poor health. Gastric cancer, for example, is often caused by unhealthy dietary habits such as high salt intake (D'Elia, Galletti, & Strazzullo, 2014; Ferlay et al., 2010). High salt intake is also associated with hypertension, stroke and cardiovascular disease (Ha, 2014). The costs of illnesses related to poor diet, are predicted to cost over thirty trillion American dollars in the coming twenty years (Jacka, Sacks, Berk, & Allender, 2014). A better understanding of what people drives to their food choices in restaurants and being able to steer the choices in the future may have a significant pay off.

Menu design

Extensive research has led to several guidelines on how to design restaurant menus. Such guidelines aim to steer restaurant guests towards certain menu options (Feldman, Su, Mahadevan, Brusca, & Hartwell, 2014; Kozup, Creyer, & Burton, 2003). Applying such guidelines may therefore help steering people towards more healthy food options. For example, it has been suggested that placing boxes or using highlighting increases the chance of customers selecting that particular food item (Yang, 2012) (see Table 1). Feldman et al. (2014) have found that consumers could be driven towards healthier food choices by placing a box around healthier options. Nutritional labels did not have this effect in their study although Kozup et al. (2003) did find a connection between nutritional information and healthier food choices.

Others have indicated that placing items at the top or bottom of a menu increase the likelihood of a customer selecting that item (Yang, 2012). Such guidelines are often supported by more general psychological theories and mechanisms. For example, placement at the top or bottom agrees with the serial position effect (Yang, 2012), whereby people are more likely to remember items that appeared early or late in a list of items to remember.

More general recommendations include avoiding long food descriptions, using boldface font to highlight the item name, using a font size that can be read in low-lighting conditions, keeping the size of the menu in proportion to the size of the table, not overcomplicating (make sure the menu can be changed easily), making menus soil and water resistant, using colours that agree with the interior, having a style that suggests the style of the restaurant and using sufficient white space (Antun & Gustafson, 2005). Not all of these recommendations were upheld in studies. For example, Wansink, Painter, and Ittersum (2001) found that longer descriptions led to increased demand for that food item.

Ozdemir and Caliskan (2014) found that design choices involve four main dimensions: the position of menu items, the description of menu items, the labels of menu items and menu card characteristics. Such menu choices were found to influence consumers' perception of the value, quality and taste of the foods, as well as how healthy the food was perceived to be. In an experimental study at a large Mid-Atlantic University, Magnini and Kim (2016) found that italic fonts led participants to consider the restaurant to be upscale and have better service. Similar effects were found for heavier menus, while no effect of a gold (versus a white) background colour was found.

Pricing of menu items is another area that has been extensively investigated. People tend to choose cheaper foods (Horgen & Brownell, 2002; Steenhuis, Waterlander, & De Mul, 2011). Consumers are more likely to accept higher prices for menu items with detailed descriptions (Shoemaker, Dawson, & Johnson, 2005). The willingness to pay for food items could also be influenced by placing decoy items on the menu that no one is likely to choose (Shomaker, 1993). Naipaul and Parsa (2001) suggested that prices ending in 0 indicated quality, whereas prices ending in 9 indicated value.

Characteristics of the restaurant visitor

Aspects of the restaurant visitor also need to be taken into account. People who have less money are more likely to buy unhealthy food, because of the fact that unhealthy food is cheaper (Drewnowski, 2009). Likewise, personality aspects, such as high openness to

Table 1
Overview of recommendations from the literature on how to design a menu

Subject	Recommendation	Reference
Position	Place items at the bottom or top	(Yang, 2012)
Position	Place items in boxes	(Yang, 2012)
Position	Place items in boxes for healthier choices	(Feldman et al., 2014)
Price	Cheaper items are more often selected	(Horgen & Brownell, 2002)
Price	Prices ending in 0 indicate quality	(Naipaul & Parsa, 2001)
Price	Prices ending in 9 indicate value	(Naipaul & Parsa, 2001)
Lay out	Highlighted items are chosen more often	(Yang, 2012)
Lay out	Use boldface font to highlight the item name	(Antun & Gustafson, 2005)
Lay out	Italic font increases perception of good service	(Magnini & Kim, 2016)
Lay out	Italic font increases perception of being upscale	(Magnini & Kim, 2016)
Lay out	Use decoy items	(Shomaker, 1993)
Usability	Use font size suitable for low-lighting conditions	(Antun & Gustafson, 2005)
Usability	Size of menu in proportion to size of the table	(Antun & Gustafson, 2005)
Usability	Do not over-complicate	(Antun & Gustafson, 2005)
Usability	Make menus soil and water resistant	(Antun & Gustafson, 2005)
Usability	Use sufficient white space	(Antun & Gustafson, 2005)
Style	Use colours that agree with the interior	(Antun & Gustafson, 2005)
Style	Use style that suggests the style of the restaurant	(Antun & Gustafson, 2005)
Information	Avoid long food descriptions	(Antun & Gustafson, 2005)
Information	Longer description increases demand for item	(Wansink et al., 2001)
Information	Nutritional labels do not lead to healthier choices	(Feldman et al., 2014)
Information	Nutritional information leads to healthier choices	(Kozup et al., 2003)
Information	Detailed descriptions increase willingness to pay	(Shoemaker et al., 2005)

experience, were found to be linked to higher vegetable and fruit and lower soft drink and meat consumption, whereas neurotic people are more likely to consume savoury and sweet foods (Keller & Siegrist, 2015). Many children are informed by their parents about the diets they have to follow in order to pursue an ideal image of the body (Lowes & Tiggemann, 2003). This is likely to influence the food choice of these children and as an adult in the future. Whether people care about their health is also likely to play a role. For example, Visschers, Hess, and Siegrist (2010) found that consumers with a health focus spent more time looking at nutritional labels than consumers with a taste focus.

Food labelling in supermarkets

Food labelling is a method aimed to influence food choices. The effectiveness of food labels has mostly been studied in supermarkets (Cowburn & Stockley, 2005). Most studies have relied on consumers self-reports, but a recent trend towards the use of eye tracking in studies can be seen (Graham, Orquin, & Visschers, 2012). The results of these studies suggest that people tend to over-report their use of food labels. This does not mean that food labels are not effective. People with the intention to buy products with a health label genuinely buy more products with a health label than people without this intention (Vyth et al., 2010). This suggests that health labels can really make a difference, as people are searching for products with the label. Interestingly, both people with a high and a low education level are guided less by health labels than people with a medium education level (Vyth et al., 2010). One way to increase attention to food labels, paradoxically, is to make them less clear. Food labels that are unclear about whether the item is healthy are looked at more often than food labels that are clear (Graham & Jeffery, 2012).

Food labelling in restaurants

Despite the fact that food labelling is more common in supermarkets, the effects of food labelling has also been tested in restaurants. Those studies have mainly focused on calorie labels. The results are ambiguous. Dumanovsky et al. (2011) found that calorie information in fast food restaurants results in a lower calorie intake. In contrast, Finkelstein, Strombotne, Chan, and Krieger (2011) found that the number of transactions and the amount of calories per transaction did not change as a result of calorie information in fast food restaurants. The solution might not be calorie information in itself, but education about calories, as another study indicated that people tend not to know what the recommended daily calorie intake for an adult is (Krukowski, Harvey-Berino, Kolodinsky, Narsana, & DeSisto, 2006).

Eye movements and attention

Previous research has found that eye movements and attention are related to the eating behaviour of people. Velazquez and Pasch (2014) have found that the dwell time and the frequency of looking at unhealthy food are related to consumption of the unhealthy foods. People who struggle with obesity tend to be more drawn to high fat food, but they spend less time looking at it than normal weight people do, possibly because they try to avoid the trigger (Werthmann et al., 2011).

Eye movements in supermarket food choices. The majority of the research on eye movements while people choose foods is from food choices in supermarkets, mostly in the context of marketing research. Peoples' attention can be measured directly by tracking the eye movements they make. Therefore, it is interesting to look at the eye movements of people in supermarkets. People tend to choose products that are in front of their field of view (Seva, Go, Garcia, & Grindulo, 2011). Products with unusual images attract attention, but the place on the shelves has a greater influence on the food choice than the pictures have (Seva et al., 2011). Children tend to pay more attention to healthy food with a media character on the package (Ogle, Graham, Lucas-Thompson, & Roberto, 2017). However, putting a media character on the package does not always make the children choose the product (Ogle et al., 2017).

Eye movements in restaurant food choices. The eye movements of people viewing a restaurant menu could reveal information about the attention of people while choosing an item. Yang (2012) found that people initially look at a restaurant menu in the same way as they do to a book: from left to right and from the top down. Another eye tracking study showed that customers' attention was drawn towards healthier items, and led to more frequent selections of these items, when labelling was used that indicated the amount of physical activity needed to burn off the calories of the food item (E. Kim et al., 2018). Consumers also preferred these formats over numeric or colour-coded labelling (E. Kim et al., 2018).

Predicting food choices

Relevance. The studies so far have examined what aspects of restaurant menus affect food choices, and whether food labelling can influence these choices (Antun & Gustafson, 2005; Dumanovsky et al., 2011; Yang, 2012). In order to examine to what extent these factors contribute to food choices overall, this study investigates whether it is possible to predict what kind of item will be selected from a menu, using fixation times on the menu (attention), and features of the restaurant visitor. The relative importance and the overall prediction performance will be evaluated.

Studies have suggested that people increasingly eat out, and in particular, the percentage of people eating large numbers of meals away from home has increased. This has led to increased obesity in this group of people (Kant & Graubard, 2004). More than twenty-five percent of people who are eighteen or older eat outside their homes once a week (Adams et al., 2015). For this reason, there is quite a bit to be gained from steering people towards more healthy food choices in food outlets. To be able to steer peoples' choices, it is important to know how people make their menu choices.

Features: menu features. To try to make people aware of what they eat, supermarkets make use of health labels (Grunert et al., 2010). The effect of labelling foods with nutrition information in supermarkets is that people buy less unhealthy products and more healthy products (Cawley et al., 2015). Simple traffic light symbols are more effective than information about the content of the food (Roberto et al., 2012). It is less common for restaurants to use food labelling, possibly out of a fear to effects on profits (Almanza, Nelson, & Chai, 1997). Legislation may therefore be important to ensure restaurants use food labels. Before introducing such measures, it is important to establish that they could be effective in restaurants, as people may go to such places with a different mind-set than to supermarkets (going out for food, they may be less concerned about eating healthily).

Along with food labels being a possible relevant predictor, images of foods on a menu might also be a relevant predictor. Hollands and Marteau (2016) found that placing images showing the negative effects of unhealthy foods leads to people choosing the healthier options. The influence of images is expected to depend on the restaurant visitor. Hungry people are more likely to draw their attention to food images than people who are not hungry. But this effect differs from person to person (Piech, Pastorino, & Zald, 2010).

The location of a menu item on the menu could also be taken into account. Dayan and Bar-Hillel (2011) found that food items are chosen more often when they are placed at the top or at the bottom of a list of items than items in the middle of a list. This implies that the healthy food items should be placed at the top or bottom and the items which are less healthy should be placed in the middle of a list. Furthermore, people are more likely to choose a healthy food item when it is placed on the left side of a restaurant menu, instead of the right side (Romero & Biswas, 2016).

Visual attention. The data set used for the study includes information about where people look when they are deciding what to choose from a restaurant menu. Eye movements are tracked and examined to determine their influence on menu choices (e.g,. the order in which a person views the menu and how long the person looks at each item). Eye movements are a way to measure what people pay attention to, as only information that is visually inspected can be processed (Rayner, 1998). In the context of binary food choices, for example, the analysis of eye movements has shown that there is a relation between fixation patterns and choices (Krajbich, Armel, & Rangel, 2010). Therefore, fixation data seems to be suitable to measure the importance of aspects on the menu to the participants.

Features: personal Aspects. Not only aspects of the menu will be important in predicting a restaurant menu choice. Personal aspects, such as dietary requirements and eating out habits, are also interesting to take into account. People who care about how healthy the foods are that they eat, go to fast food restaurants less often than people who do not care as much (French, Story, Neumark-Sztainer, Fulkerson, & Hannan, 2001). However, it has not been established whether the choices of people with dietary requirements differ from people who do not have dietary requirements. While age and gender would be interesting features, the data used for this study does not allow for the investigation of these features, as the age and gender of the participants are too homogeneous.

Methods

To extract possibly relevant features from the eye movement data, such as dwell times on various regions in the menu, or the last region fixated, R's *dplyr* and R-base are used. Data visualisation is performed using *ggplot* and *ggpubr*. To predict participants' food choices, classification is used. Random forest, implemented in R's *caret* package, was used to make the predictions. The performance of the classifier is examined using accuracy. The data used for this study are gathered at the university of Lincoln. This section will explain how the study was conducted.

Experimental setup

Participants. A total of twenty-five participants took part in the study, all in return for course credit. Participants were students in psychology at the University of Lincoln (UK). They all provided informed consent for the study that was approved by the local ethics committee.

Stimuli. Thirty menus were downloaded from various restaurant websites, including high-end restaurants, bistros, pubs, and fast-food outlets. Some of the menus showed images of the foods, but most only included descriptions. Most menus indicated the prices of the different food items, but some did not include prices. Figure 1 shows an example of one of the menus used in the study.

Figure 1. Example of one of the menus shown during the study.

The original menus were modified into an alternative version using the Gimp software to include information about fat contents, salt contents or calories. One third of menus were modified to include calorie symbols (doughnut shapes), one third to include fat symbols (circles, see Figure 1), and one third to include salt symbols (salt shakers). Half of these shapes indicated low values (green symbols, as in Figure 1) and half of these high values (red symbols). For each menu, half of the participants were presented the original version of the menu, and half of the participants the modified version.

Apparatus. Stimuli were presented on a flat screen, connected to a Windows PC using the Experiment Builder software (SR Research) to present the menus. Eye movements were collected with the Eyelink 1000 system (SR Research), which consists of a small camera, positioned below the screen, and a IR unit, producing the corneal reflection to monitor eye movements. Responses were collected with a standard keyboard (participants indicating that they had reached a decision), and a standard optical mouse (clicking on the menu item they selected).

Design. Participants each viewed all thirty menus, of which half contained a food contents symbol, with half of these food symbols indicating a low value and half a high value. Of these food symbols, equal numbers of calorie, fat, and salt information were shown. The order of the menus was randomly chosen for each participant. No practice trials were used.

Procedure. After participants entered the lab, they received verbal and written instruction about the background of the study and their task (see Figure 2). They were explained that they would see thirty menus in sequence on a computer screen, and their task would be to decide which item they would like from that menu, by using the computer mouse to click on the preferred item. They were also asked to imagine having to pay for the item that they chose. If there was nothing on the menu that appealed to them, they were asked to indicate that they did not want to choose by clicking outside the menu. In order to separate eye movements during the actual decision process and during the selection with the mouse, participants were asked to press the space-bar of the computer keyboard to indicate they had reached a decision, after which the mouse cursor appeared and they could click on their preferred food. During this task the eye movements of the participants were tracked, for which participants were asked to place their head on a head-and-chin rest to reduce the influence of head movements on the eye movement recordings.

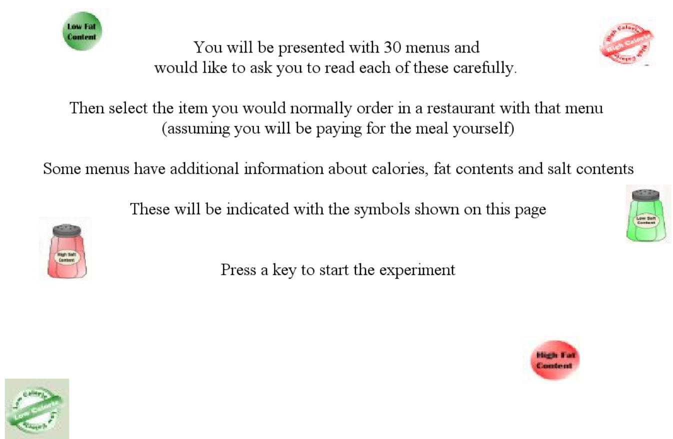


Figure 2. Example of the instructions shown to the participants.

After going through all thirty menus, eye tracking was stopped and participants were asked to complete a short pen-and-paper questionnaire probing demographic information and restaurant behaviour (questions shown in Table 2).

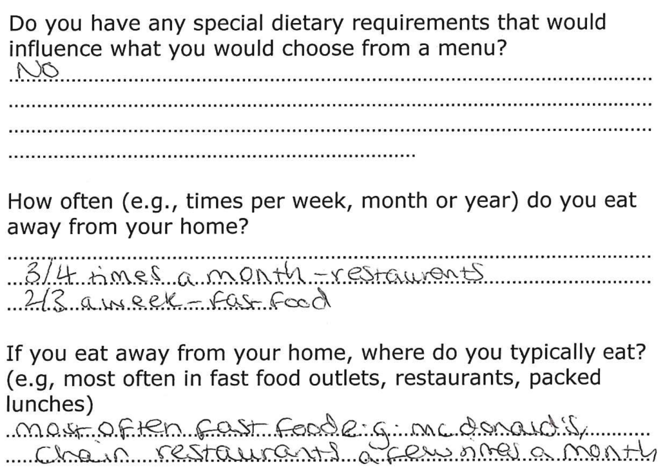
Table 2
Questions in the questionnaire

Question	Type of question
Age	open
Gender	open
Dietary requirements	open
Frequency of eating out	open
Type of food eating away from home (e.g., restaurant, fast food, packed lunch)	open
Importance of salt, calories, sat. fat, price, taste, quantity	rank order
Food-label check in supermarkets	open
Currently hungry?	open
Currently trying to lose weight?	open

Data set description

Three types of data files were obtained. The first data set contained scans of peoples' answers to the pen-and-paper questionnaire. The second data file contained peoples' mouse clicks on the menus. The third data file contained the eye movement data of the participants. All were converted to data frames that can be loaded into the *R* software package used for analysis. Data were downloaded from the website Open Science Framework, using a direct link provided by the initial thesis supervisor (Dr Hermens).

Figure 3 provides an example of a section of the scanned pen-and-paper questionnaire. The questions asked are listed in Table 2. As can be seen in the example scan, participants wrote free text to several of the questions. In order to be able to process this information in an automatic way, the information was converted to categories and entered into an Excel table. For example, for the participant in Figure 3, the answer to the question about eating away from home, 'fast food' and 'restaurant' were entered into the table using different columns to separate these pieces of information. For the question in which participants were asked to rank the importance of items from one to six, all of the items were spread over six columns representing the importance from one to six. This made it possible to make it a binary data-frame.

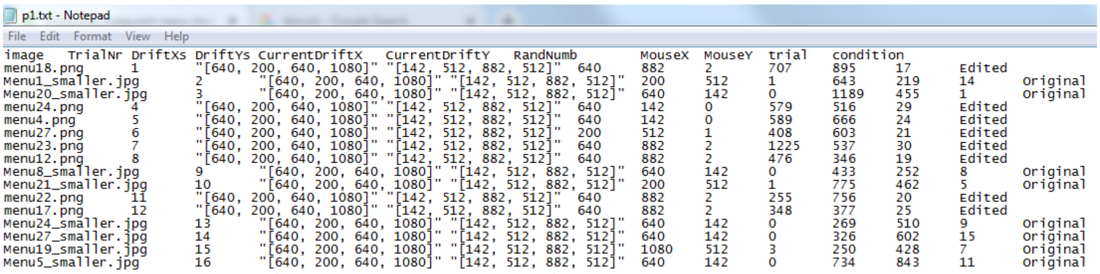

Do you have any special dietary requirements that would influence what you would choose from a menu?
NO

How often (e.g., times per week, month or year) do you eat away from your home?
3/4 times a month - restaurents
2/3 a week - fast food

If you eat away from your home, where do you typically eat? (e.g, most often in fast food outlets, restaurants, packed lunches)
most often fast food e.g. mc donald's
chain restaurants a few times a month

Figure 3. Screen-shot of a section of a pen-and-paper questionnaire.

Figure 4 provides an example of a section of the mouse click data. The image column indicates the menu seen on that trial by the participant. Menu names with _smaller indicate original versions of the menu, and those without this information in the name the modified versions. The trial number indicates the order in which the participant saw the menus. DriftX, driftY, and currentdriftX and currentdriftY and RandNumb columns indicate where the fixation point was presented before the menu was shown (randomly chosen to be left, right, above or below the menu). MouseX and MouseY indicate where on the screen the participant clicked. Trial indicates the original trial number before randomisation. The condition column indicates whether the menu was original or modified. In order to determine which food item was selected, the MouseX and MouseY coordinates were combined with the regions of interest versions made from the menus (to be explained later).



```
p1.txt - Notepad
File  Edit  Format  View  Help
image    TrialNr DriftXs DriftYs CurrentDriftX   CurrentDriftY   RandNumb       MouseX  MouseY  trial   condition
menu18.png      1       "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     882     2       707     895     17      Edited
Menu1_smaller.jpg       2       "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  200     512     1       643     219     14      Original
Menu20_smaller.jpg      3       "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     142     0       1189    455     1       Original
menu24.png      4       "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     142     0       579     516     29      Edited
menu4.png       5       "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     142     0       589     666     24      Edited
menu27.png      6       "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  200     512     1       408     603     21      Edited
menu23.png      7       "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     882     2       1225    537     30      Edited
menu12.png      8       "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     882     2       476     346     19      Edited
Menu8_smaller.jpg       9       "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     142     0       433     252     8       Original
Menu21_smaller.jpg      10      "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  200     512     1       775     462     5       Original
menu22.png      11      "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     882     2       255     756     20      Edited
menu17.png      12      "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     882     2       348     377     25      Edited
Menu24_smaller.jpg      13      "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     142     0       269     510     9       Original
Menu27_smaller.jpg      14      "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     142     0       326     602     15      Original
Menu19_smaller.jpg      15      "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  1080    512     3       250     428     7       Original
Menu5_smaller.jpg       16      "[640, 200, 640, 1080]" "[142, 512, 882, 512]"  640     142     0       734     843     11      Original
```

Figure 4. Example of a mouse clicks data file.

Figure 5 shows a section of a raw eye movement data file. This file has four columns: the time-stamp, the horizontal location, the vertical location and the pupil diameter. Additionally, lines indicate the start of the image on the screen (in this example: MSG Image). The file also contained information about the start and end of fixations, periods during which the eye remains still, and saccades (rapid eye movements to the next fixation position). This information was automatically extracted by the Eyelink system using an algorithm looking for fast movements of the eye (based on velocity and acceleration). The fixations are the most interesting for this study, these were automatically extracted from the raw eye movement data files using a Python script.

ROI coding. In order to automatically code the selections of the participants and the regions on the menu fixated, ROI (regions of interest) images were created for each menu using the Gimp software. An example is shown in Figure 6 which is the codified version of Figure 7. In a first step, as many different regions were defined as possible (e.g., title of item one on the menu, price of item one on the menu). Fixations and mouse clicks were automatically classified by projecting the positions onto the menus (taking into account the position and size of the menu on the screen) and looking up the colour code (RGB values) in a custom-built table specifying which RGB combination for which menu was associated with what region on the menu.

Classifiers

The aim of classification is to predict a categorical variable on the basis of (often multiple) categorical and/or continuous variables. For example, in the present context, the aim of classification is to predict the food choice on the basis of variables such as dwell time

```
146680  631.1   878.5   775.0   ...
146681  629.7   878.2   780.0   ...
146682  629.0   878.6   784.0   ...
146683  629.0   879.0   782.0   ...
146684  629.2   879.3   780.0   ...
146685  629.4   879.4   778.0   ...
146686  629.8   878.7   775.0   ...
146687  630.1   878.0   773.0   ...
146688  630.4   877.5   776.0   ...
146689  630.3   878.1   781.0   ...
146690  630.6   878.6   785.0   ...
146691  630.8   878.8   784.0   ...
146692  631.0   878.9   783.0   ...
MSG     146693 -11 Image
MSG     146693 -10 !V DRAW_LIST ../../runtime/dataviewer/p1/graphics/VC_1.vcl
146693  630.9   879.3   783.0   ...
146694  631.0   879.7   786.0   ...
146695  631.0   879.8   790.0   ...
146696  631.8   878.9   788.0   ...
146697  632.8   878.1   782.0   ...
146698  633.7   877.5   778.0   ...
146699  633.4   877.5   780.0   ...
146700  632.8   877.6   783.0   ...
146701  632.2   878.1   785.0   ...
146702  631.9   878.6   786.0   ...
146703  632.0   879.1   787.0   ...
146704  632.9   878.5   787.0   ...
146705  633.7   878.0   787.0   ...
146706  634.2   877.8   786.0   ...
```

Figure 5. A section of the raw eye movement data file.

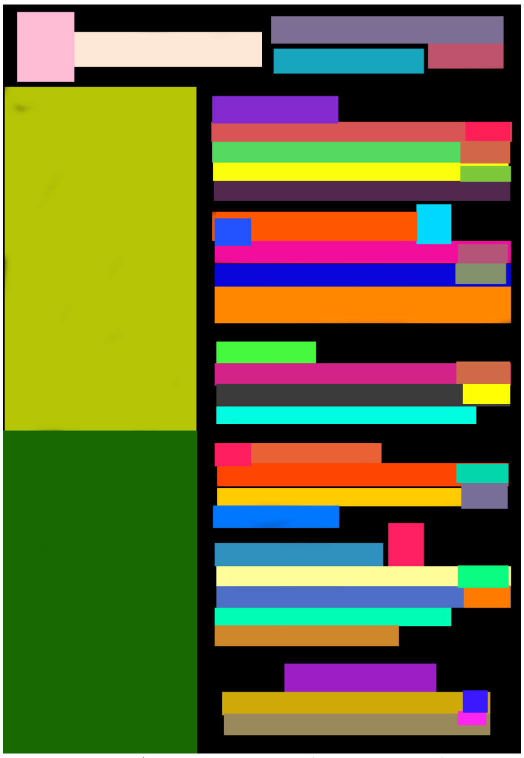


Figure 6. An example of regions of interest on a menu.

Figure 7. An example of a shown menu during the experiment.

on the item (continuous variable) or diet of the participant (categorical variable). Several algorithms can be used for classification. One of the possible algorithms is random forest.

Random forest. Random forest makes use of decision trees and at each split, the algorithm takes a random combination of features. This causes the random forest algorithm to be suitable for data sets with correlating features (James, Witten, Hastie, & Tibshirani, 2013). The number of random features picked during each random sample is expressed by 'mtry'. The ability of this algorithm to work with correlated features makes it an interesting algorithm for this study because of the fact that the data has many features compared to the observations for which the reason will be further explained in the section about predicted categories.

Predicted categories

Being able to predict the exact item that people choose would greatly contribute. But most menus contain many items and the number of choices available in the data set is limited (there are twenty five participants). Therefore, this study will aim to predict broader categories of selection, namely whether participants chose an option with a high calorie level or a low calorie level and whether participants chose an option which was more expensive or less expensive. The division of the classes is subjective which could make it harder to predict.

When only taking the personal aspects into account as features in the prediction of high or low calorie choices and high or low price choices, it was possible to analyse the data all together. Ideally, the data sets would consist of 750 observations each as we have thirty menus and twenty-five participants. However not all menus were dividable into high or low calories and prices, not all people chose a menu item every time and in some cases it was not clear what item people chose. Especially in cases where a menu item was available in different portions. This resulted in a data set with 277 observations for predicting high or low calorie choice and 223 observations for predicting high or low price choice.

When taking the fixation times on regions of the menu into account as being a feature and when comparing the performance of fixation data and personal information per menu, the menus for which it was possible to divide them into the categories were analysed separately. This resulted in very few observations. In order to prevent the amount of observations to decrease further, the information about whether the menu was provided with labels about fat content, salt content and calorie level was added as a binary feature to the fixation data.

Feature selection

All information from the questionnaire was converted into binary features which can be found in Appendix B. To select relevant features for the prediction *varImp()* function was used for the data containing personal aspects. When only taking the personal aspects into account, models only containing the five most important features were generated. Irrelevant features were eliminated based on the difference in accuracy after leaving out features. The order in which features were left out was based on the results generated by the *varImp()* function.

The feature selection of the fixation data has been done by calculating the variance of each feature (i.e. fixation times on regions of the menu) in the menu. Only the five features with the highest variance were implemented in the models. When comparing the performance of the models with fixation features and the personal information features, the personal information features were again sorted with the *varImp()* function, but this time it was done for each menu separately. Only the five most important personal information features were included in the models.

Training and test set

Commonly in machine learning, a single split of the data in a training and test set (sometimes with an additional validation set) is made. However, this strategy is less suitable for the present context, because of the relatively small number of observations (in our case: participants). The approach taken here is therefore to use leave one out cross validation. This method is useful when working with small data sets as it is trained as much times as there are observations and then takes the average score.

Measures of performance

To examine the performance of the classifiers, accuracy scores are used. Accuracy reflects the number of correct predictions out of the total number of predictions (Ishibuchi & Nojima, 2007). Accuracy is a good performance measure since in predicting high or low calorie choice and high or low priced food item choice, both classes carry meaning with the same importance. The accuracy outcomes of the models was compared to the baselines. Baselines were the proportion of observations of the majority class out of the total observations.

Exploratory Data Analysis

Exploratory data analysis has been done to facilitate the interpretation of further results. In these analyses the questionnaire has been looked into as well as the coherence between fixation times and food choice. Furthermore, the attention to food labels has been analysed.

Questionnaire

Visual descriptions of the outcomes of the data in the pen-and-paper questionnaire can be found in the Appendix A. The majority of the participants were nineteen or twenty years old, with a few twenty one or older (for these participants the exact age was not recorded). Participants were also mostly female, which can possibly be explained from the fact that participants were drawn from a sample of psychology students.

Most participants indicated not to have dietary requirements, but quite a number (N = 9) indicated to be on some sort of diet. When asked what kind of diet, there were similar numbers of healthy, less meat, no fish and vegetarian responses.

Participants ate out quite regularly, with most eating out one or more times per week. When eating out, most went to a restaurant, with fast food chains and cheap restaurants visited less often. Packed lunches were not very popular.

When choosing food items, taste was most important, followed by price and quantity, with health related aspects, such as calories, fat, and salt contents, less important. This is in line with the assumption that when people are going out for food, they mey aim to enjoy the food more than care about whether it is healthy or not.

In supermarkets, about half of the participants check food labels with calories and fat checked more often than other aspects. This means that we may expect the calorie and fat labels in restaurants to be checked more frequently than the salt labels.

About half of the participants indicated to be hungry at the time of the experiment. It may therefore be interesting to examine whether these participants choose other items than those not hungry.

Finally, around one third of participants indicated that they were trying to lose weight. Those on a diet may be expected to check food labels for calories more often than those not on a diet.

Coherence between fixation times and food choice

Figure 9 shows the dwell times on the different regions of the first menu, showing the most fixated regions for people who chose the 6_pieces_bargain_bucket (in blue) against those who picked something else (in red). An image of the menu is shown in Figure 8. This menu was suitable to plot because almost half of the participants chose the 6_pieces_bargain_bucket for this menu and so it was easy to make two classes and look at the differences in attention.

The dwell times suggest that people who chose a particular item (in this case the 6_pieces_bargain_bucket) looked at the title of this item for longer than those not choosing the item (both the title of the section, and the title of the menu item itself). Moreover, people who chose the 6_pieces_bargain_bucket looked at a region which includes 'bargain bucket' longer than people who did not choose this menu item five out of seven times.

Figure 8. Menu 1 as shown to the participants.

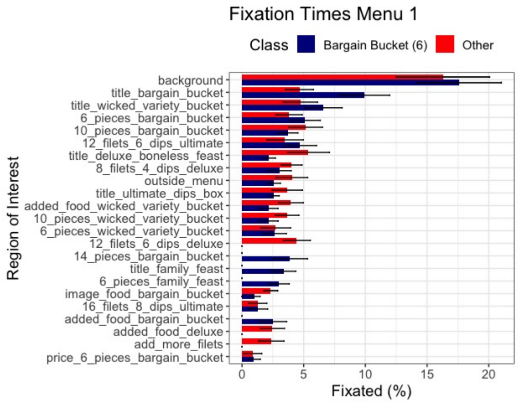


Figure 9. Dwell times on the most often fixated regions of menu one. When a bar is absent, this means that the average dwell time was zero. Error bars show the standard error of the mean.

Across groups, the dwell times for this first menu suggest that people mostly looked at the titles of the food items. Moreover, people do not seem to look at price much (these ROIs did not often make it to the top fixated items), suggesting it may be quantity rather than price that drives people towards the 6_pieces_bargain_bucket. Interestingly, the images of the foods were not fixated very often, so participants seem to choose on the basis of the description more than on the basis of what the food looks like (although one may argue that because the restaurant is well known, people may already know what the food looks like).

Figure 11 compares the dwell times on the most fixated ROIs of people who chose the Brooklyn Spaghetti (in blue) and those who chose something else (red) for menu ten, Figure 10. Almost half of the participants chose the Brooklyn Spaghetti. Interestingly, for this menu, participants did look at the images, which may be because it was a less familiar restaurant than for the first menu, but the size of the images relative to the text may also play a role. People who chose the Brooklyn Spaghetti looked for longer at the image of this food item. In contrast to the first menu, no such longer dwell times were found for the title. Instead, people who chose the Brooklyn Spaghetti looked longer at the dish description. All together dwell times seem to represent peoples' interest in menu items as people who chose the Brooklyn spaghetti looked much longer at the image and description of this food item.

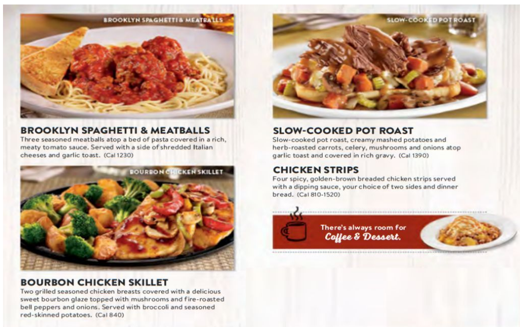


Figure 10. The image shown to participants for menu ten.

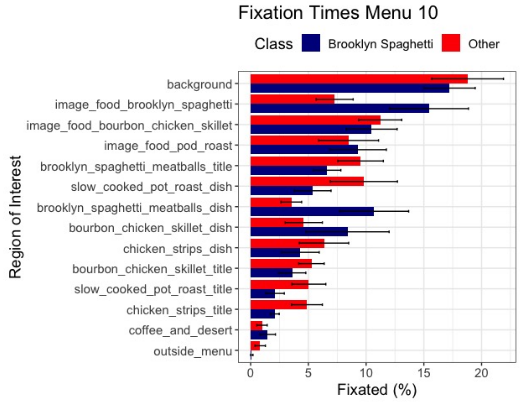


Figure 11. Dwell times on the most often fixated regions of menu ten. When a bar is absent, this means that the average dwell time was zero. Error bars show the standard error of the mean.

Attention to food labels

To see whether people who say they check calories in supermarkets look at calorie labels more on restaurant menus, two plots are made with information about people checking high and low calorie information on the menus. Figure 12 shows the fixation times on low calorie labels. A total of fifteen participants did look at the low calorie labels on the menus, the other ten participants did not look at the low calorie labels at all. Of the participants who did look at the label, there is not a clear indication that people who check calorie labels in supermarkets also check the low calorie label on a restaurant menu. Except for the person who looked at the low calorie label on the menu for the longest time, this participant indicates that he or she checks calories in supermarkets.

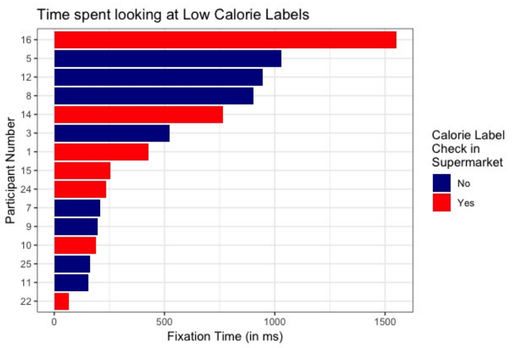


Figure 12. Fixation time on low calorie labels. A distinction is made between people who indicated checking calorie labels in supermarkets and people who indicated not to check calorie labels in supermarkets.

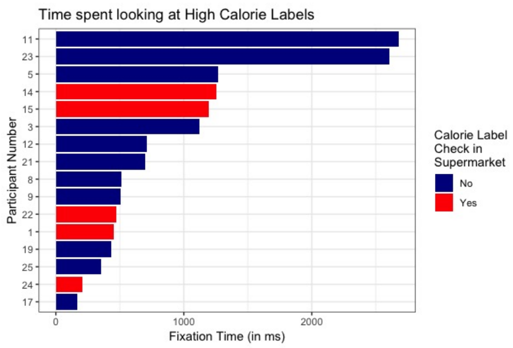


Figure 13. Fixation time on high calorie labels. A distinction is made between people who indicated checking calorie labels in supermarkets and people who indicated not to check calorie labels in supermarkets.

Figure 13 shows the fixation times on high calorie labels on the restaurant menus. A total of sixteen out of the twenty five participants looked at the high calorie labels. There is also not a clear indication that people who check calories in supermarkets do check high calorie labels on restaurant menus more. In fact, those who looked at the high calorie labels the most indicated they do not check calorie labels in supermarkets. The people who looked at the low and high calorie labels were not necessarily the same people. This could mean that they looked at the labels by accident.

People seem to look longer at the high calorie labels than the low calorie labels. The question is whether this is worth mentioning, as it is measured in milliseconds and so both of the labels seem not to be interesting to the participants. Figure 14 shows the total time spent looking at calorie labels compared to the total time that the menu was looked at. The relative time spent looking at the calorie labels is almost negligible.

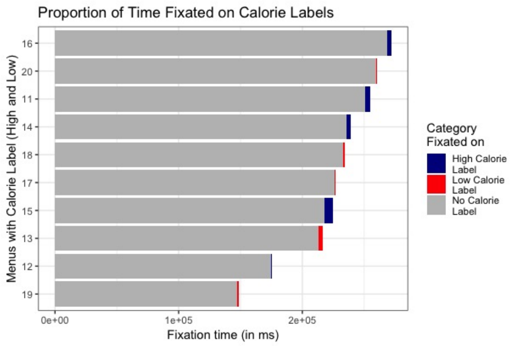


Figure 14. Fixation time on calorie labels as a proportion of total fixation time on menus with those labels.

Figure 15 and Figure 16 show the fixation times on high and low salt labels. It does not seem the case that people who find salt content important to take into account in their food choice (blue) fixate at the salt shakers more than people who do not (red). It is questionable whether people consciously looked at the salt labels since the people who looked at the salt shakers the longest, indicated not to care about salt intake that much. Overall, participants do not seem to be very interested in food labels on restaurant menus.

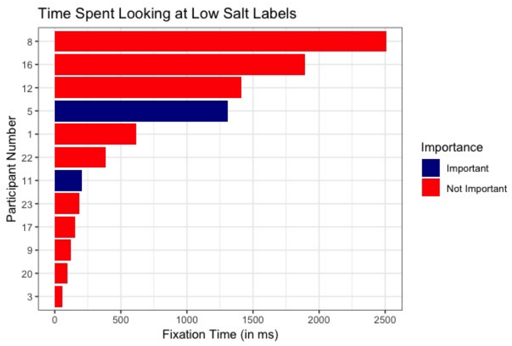


Figure 15. Fixation time on low salt labels. Participants who are not included, did not look at the labels at all.

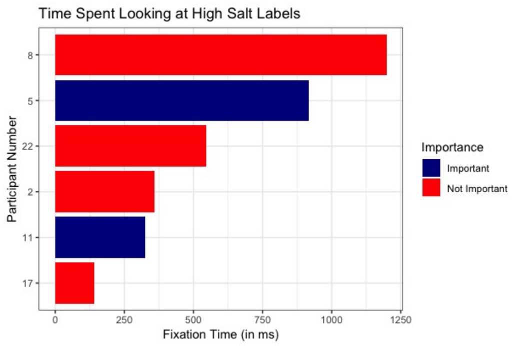


Figure 16. Fixation times on high salt labels. Participants who are not included, did not look at the labels at all.

Results

In this section, the results of the study will be discussed. First, models to predict high or low calorie choice and high or low price choice with only personal aspects as features will be discussed. Second, menus for which it was possible to divide them into high and low calorie choices and high and low priced food items will be discussed individually in terms of predictability of the choices by fixation times on regions of the menu. Third, these menus will be discussed individually in terms of predictability by fixation times on regions of the menu versus predictability by personal aspects.

Personal aspects

Calories. Figure 17 shows the models for predicting a high or low calorie food choice by personal aspects. Model two with mtry two and the features calories4, cafe, calorie_check and sugar, model three with mtry two or three and the features calories4, cafe and calorie_check and model four with mtry two and the features calories4 and cafe all have an accuracy of 0.581. Model one additionally includes salt. Some features are probably mutually correlating since the accuracy does not change when adding calorie_check and sugar as a feature. It is also possible that some features do not say anything. The baseline is 0.534, this means that the model is not performing much better than the baseline. Therefore, this model is not suitable for predicting high or low calorie choice.

Price. Figure 18 shows the models for predicting a high or low priced food choice by personal aspects. Model two with mtry two, three or four and the features cafe, calories4, salt and saturated_fat2, and model three with mtry two and features cafe, calories4 and salt, have the highest accuracy of 0.619. Model one additionally includes losing_weight as a feature. The baseline is 0.596 and so this model does not perform well enough to be able to predict whether people will choose a high or low priced menu item. Since model two and three have the same accuracy, again, it is likely that some features are mutually correlating or do not say anything.

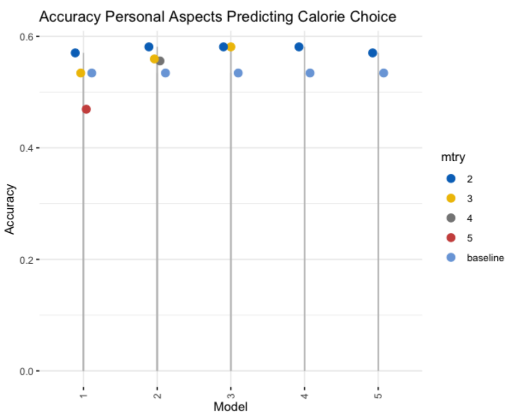


Figure 17. Different models predicting high or low calorie choice by personal aspects. The baseline is 0.534.

Figure 18. Different models predicting high or low price choice by personal aspects. The baseline is 0.596.

Fixations on the menu

Calories. Figure 19 shows the accuracy outcomes of predictions of high or low calorie food choice by fixation times on certain regions of the menu compared to the baselines of these menus. For the menus three, six, ten, twenty three, twenty eight and twenty nine, the accuracy outcomes did not reach above the baseline for the menu, which means that the fixation times on certain locations on the menus did not help us predicting whether people chose a high or a low calorie item for these menus. Table 3 shows the accuracy outcomes compared to the baselines of menus for which the accuracy outcomes reached above the baseline. Only the mtry of the highest accuracy outcome is reported in the table and when more than one mtry levels have the same (highest) accuracy outcome all those levels are reported. The accuracy outcomes of models for menu two, seventeen twenty-four and twenty-six are twenty-five percent or more above the baseline. Accuracy outcomes for menu nineteen, twenty-one and thirty are very low.

Table 3
Accuracy outcomes predicting calorie choice by fixation times on regions of the menu for menus with an accuracy above the baseline from low to high scores

Menu	Baseline	Accuracy outcome	Mtry
21	0.762	0.81	2, 3, or 5
30	0.538	0.615	2 or 5
19	0.708	0.792	2, 3, or 5
17	0.625	0.875	2, 3 or 5
26	0.565	0.826	2
2	0.56	0.84	2
24	0.5	0.833	2 or 5

Figure 20 shows the accuracy outcomes of predictions using fixation times on certain regions of the menu plus a feature containing the information about whether the menu contained information about salt content, fat content and calories compared to the baselines of the menus. Adding this feature in none of the cases pulls a low accuracy outcome above the baseline.

Price. Figure 21 shows the accuracy outcomes of fixation times on certain regions of the menu compared to the baselines of the menus. For the menus four, six, twenty eight and twenty nine the accuracy outcomes did not reach above the baseline for the menu, which means that the fixation times on certain regions of these menus did not help in the prediction about whether people chose a high or a low priced item. Table 4 shows the accuracy outcomes compared to the baselines of menus for which the accuracy outcomes reached above the baseline. Only the mtry of the highest accuracy outcome is reported in the table and when more than one mtry levels have the same (highest) accuracy outcome all those levels are reported. The accuracy outcomes of the models for menu two and three are more than ten percent above the baseline and the accuracy outcome of model twenty-four is more than twenty-five percent above the baseline. Accuracy outcomes for menu five, twenty-one, twenty-six and twenty-seven are very low.

Figure 22 shows the accuracy outcomes of predictions using fixation times on certain regions of the menu and a feature containing information about whether the menu contained information about salt content, fat content and calories compared to the baselines for the

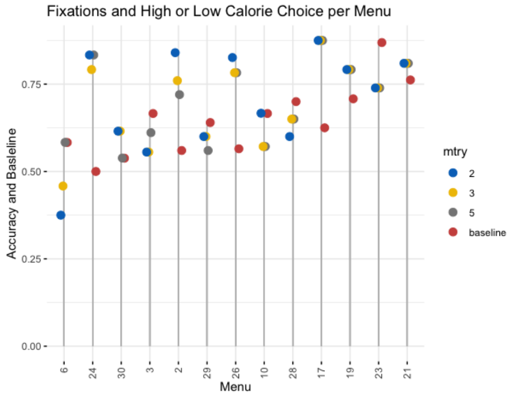


Figure 19. Fixation times on certain regions of the menu and high or low calorie food choice, with the five regions with the highest variance included as features.

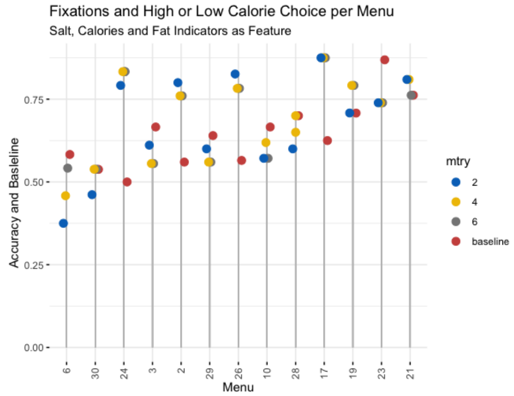


Figure 20. Fixation times on certain regions of the menu and high or low calorie food choice, with the five regions with the highest variance and the feature about the food labels.

Table 4
Accuracy outcomes predicting price choice by fixation times on regions of the menu for menus with an accuracy above the baseline from low to high scores

Menu	Baseline	Accuracy outcome	Mtry
26	0.565	0.609	5
27	0.824	0.882	2 or 3
5	0.846	0.923	2, 3 or 5
21	0.524	0.619	5
2	0.56	0.68	2
3	0.56	0.722	2
24	0.583	0.875	2

menus. Again, adding this feature in none of the cases pulls a low accuracy outcome above the baseline.

Fixations versus personal aspects

Calories. Figure 23 shows the accuracy outcomes of models containing personal aspects as features and the fixation times on different regions on the menu as features versus the baseline per menu. Only the highest accuracy score was plotted, lower accuracy scores of models with another mtry were left out. For menu twenty three, both models did not score above the baseline. Table 5 shows the accuracy outcomes of models containing fixation times versus models containing personal aspects as features, of models for which the accuracy reach above the baseline of the menu.

Menus three, six, ten, twenty-eight and twenty-nine did not have accuracy scores above the baseline using fixation times as features. The accuracy of the model for menu three using personal aspects is very low. Menus six, ten, twenty-eight and twenty-nine have an accuracy score of ten percent or more above the baseline for the menu using personal aspects as features. The accuracy of the model using fixation times as features and the model using personal aspects as features for menu twenty-one are both very low. Menu

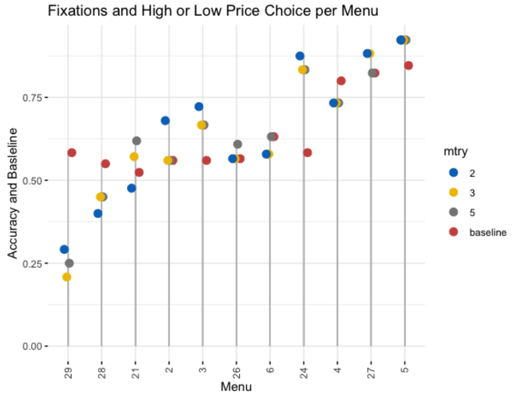


Figure 21. Fixation times on certain regions of the menu and high or low priced food choice, with the five regions with the highest variance included as features.

Figure 22. Fixation times on certain regions of the menu and high or low priced food choice, with the five regions with the highest variance and the feature about the food labels.

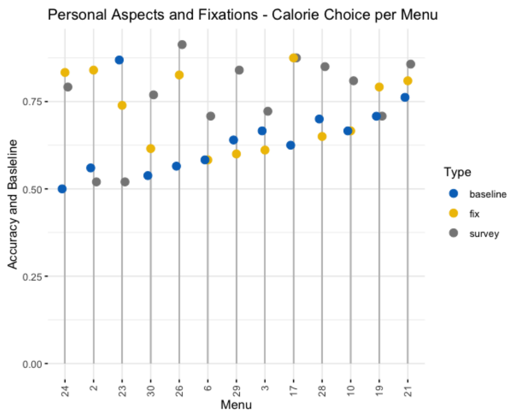


Figure 23. Predicting calorie choice per menu: models containing personal aspects as features (survey) versus models containing fixation times as features (fix).

Table 5

Accuracy outcomes predicting calorie choice by fixation times on regions of the menu versus personal aspects for menus with an accuracy above the baseline

Menu	Baseline	Fixation Times Accuracy	Mtry Fixation Times	Personal Aspects Accuracy	Mtry Personal Aspects
19	0.708	0.791	2, 3 or 5	-	-
2	0.56	0.84	2	-	-
6	0.583	-	-	0.708	2, 3 or 5
28	0.7	-	-	0.85	2, 3 or 5
3	0.666	-	-	0.722	2
10	0.666	-	-	0.809	2 or 3
29	0.64	-	-	0.84	5
21	0.762	0.809	2, 3 or 5	0.857	5
30	0.538	0.615	2 or 3	0.769	2, 3 or 5
17	0.625	0.875	2, 3 or 5	0.875	2
26	0.565	0.826	2	0.913	2 or 3
24	0.5	0.833	2	0.792	2

thirty has a mentionable accuracy score when using personal aspects as features, but the accuracy using fixation times is very low. Models predicting high or low calorie choices for menus seventeen, twenty-four and twenty-six perform well, having an accuracy score of twenty-five percent or more above the baseline for models with fixation times and models with personal aspects. Menus twenty-four and twenty-six even score more than twenty-five percent above the baseline. Figure 24 shows an image of menu twenty-four and Figure 25 shows an image of menu twenty-six.

Figure 24. The image shown to participants for menu twenty-four.

Figure 25. The image shown to participants for menu twenty-six.

Overall, accuracy scores for models that aim to predict a high or low calorie choice are higher for models using personal aspects rather than fixation times as features. The features used for the individual menus are shown in Table 6. The features calories2, salt and calorie_check are present three times in the feature composition for menus with an accuracy outreaching the baseline and therefore seem to be the most important ones. Features which are present two times are calories4, calories3, calories1, saturated_fat2, saturated_fat1, taste4, price5, quantity4, currently_hungry and cafe. The rest of the features only occurs once. The important features predicting high or low calorie choice seem to be logical, however, the feature sets for predicting high or low calorie choice is quite variable for every menu. This could imply that the features are mutually correlating.

Price. Figure 26 shows the accuracy outcomes of models containing personal aspects as features and models containing fixation times on different regions of the menu as features versus the baseline per menu. Only the highest accuracy score was plotted, lower accuracy scores of models with another mtry were left out. For menu twenty nine it was not possible to predict a low or high price choice with fixation times or personal aspects at all. Table 7 shows the accuracy outcomes of models containing fixation times versus models containing personal aspects as features, of models which reach above the baseline.

The accuracy outcomes for menu two and five did not reach above the baseline for models with personal aspects as features. Menu six and twenty-seven had a low accuracy

Table 6

Features used in models to predict calorie choice for individual menus with an accuracy outcome above the baseline

Menu	Features
6	calories2, taste4, month, cheap_restaurant, price5
28	no_fish, saturated_fat6, calories2, quantity4, currently_hungry
3	calories4, salt_content2, sat_fat2, calorie_check, taste6
10	sugar, dietary_requirements, salt_content3, saturated_fat2, taste4
29	fast_food, calories2, price6, saturated_fat3, calorie_check
21	calories3, salt, price_check, saturated_fat1, losing_weight
30	quantity6, week, saturated_fat1, calories4, calories1
17	calories3, calories1, quantity4, taste5, calorie_check
26	salt, salt_content1, protein, cafe, price4
24	cafe, salt, price5, calories6, currently_hungry

outcome for models with personal aspects as features. For menu four, twenty-six and twenty-eight the accuracy outcome of models with personal aspects was more than ten percent above the baseline. For menu four, six and twenty-eight the accuracy outcomes of models containing fixation times as features did not reach above the baseline. Accuracy scores of models with fixation times as features for menu two, five twenty-six and twenty-seven were low. The accuracy scores for the models with fixation times as features and personal aspects as features both reached more than fifteen percent above the baseline for model three and more than twenty percent for menu twenty-four.

Figure 26. predicting price choice per menu: models containing personal aspects as features (survey) versus models containing fixation times as features (fix).

In predicting price, again, personal aspects seem to be better to use for prediction. However, the results are less accurate than the results of the calorie prediction. The features used for the individual menus are shown in Table 8. Features which seem to be important are taste4 and salt_content1 as they are present three times in the feature composition for menus with an accuracy outreaching the baseline. Features which are present two times are calories2, calories4, quantity1, calorie_check, losing_weight, taste6 and currently_hungry. The rest of the features only occurs once. Again, the features change quite much for every menu which may be because of the correlation between features.

Table 7
Accuracy outcomes predicting price choice by fixation times on regions of the menu versus personal aspects for menus with an accuracy above the baseline

Menu	Baseline	Fixation Times Accuracy	Mtry Fixation Times	Personal Aspects Accuracy	Mtry Personal Aspects
5	0.524	0.619	2, 3 or 5	-	-
2	0.56	0.68	2	-	-
6	0.632	-	-	0.684	2
4	0.8	-	-	0.933	2, 3 or 5
28	0.55	-	-	0.7	2, 3 or 5
27	0.824	0.882	2 or 3	0.882	2 or 3
26	0.565	0.609	5	0.739	2, 3 or 5
3	0.56	0.722	2	0.722	2, 3 or 5
24	0.583	0.875	2	0.792	2

Table 8
Features used in models to predict price choice for individual menus with an accuracy outcome above the baseline

Menu	Features
6	price6, taste5, calories4, calorie_check, taste4
4	saturated_fat3, calories2, saturated_fat5, quantity1, salt_content1
28	losing_weight, no_fish, taste4, taste6, calories2
27	calorie_check, calories6, taste4, cafe, quantity2
26	price6, fat, salt_content1, week, quantity1
3	calories4, currently_hungry, losing_weight, salt_content1, taste6
24	cafe, salt, price1, dietary_requirements, currently_hungry

Discussion

In this section, the outcomes of the current study will be discussed. An interpretation of the results will be linked to the theoretical background. Furthermore, a short paragraph will look into recommendations for future research.

The prediction model with personal aspects included as features had a low accuracy score for the data in which outcomes for all suitable menus were put together. The fact that it was hard to make a prediction about the high or low calorie choice using the personal aspects could mean that people (1) are not aware of the calorie level in the menu items for a number of menus, (2) are led by aspects of the menu rather than personal beliefs for certain menus or (3) do not care as much about the calorie levels in foods when eating out.

For the models with fixation times as features, menus for which it was hard to divide items into high and low calorie items, overall, had lower accuracy scores than menus with a clear distinction between high and low calorie food. The subjectivity in classifying the menu items into low and high calorie items and the high baselines for certain menus may have played a role, but it could also be that participants were not aware of the calorie level in the foods. This would mean that educating people about the calorie level in foods, rather than simply placing nutritional labels labels, could help them make a healthier food choice. Because people are not only not aware of their recommended daily calorie intake (Krukowski et al., 2006), but they might also do not know how to match that advised daily calorie intake.

Another explanation for the difference in accuracy outcomes might be that for most of the menus for which the model performed good, the high calorie items were placed together on the menu and low calorie items were placed together on the menu. It could be that people who chose a low calorie item, looked at low calorie items more and people who chose a high calorie item looked at high calorie items more. Which could mean that people were consciously searching for a low or a high calorie item on the menu. It could also simply mean that people looked at the item they chose significantly longer than at other items.

The feature with information about whether the menu contained a high or low calorie label, a high or low salt label or a high or low fat label did not pull a low accuracy score above the baseline in any case. This means that for the menus containing the food labels, the participants were not necessarily making a more targeted food choice than for the menus which did not contain a label, even though the participants were almost all women and we expected them to care about the food labels more than men. These findings contrast with the findings of (Dumanovsky et al., 2011), who found that calorie information can lead to healthier food choices. However, the findings are in line with the findings of (Feldman et al., 2014) who also found that nutritional food labels do not encourage people to make healthier food choices.

When analysing the menus one by one with personal aspects and fixation times separately, two menus were more predictable using fixation times rather than personal aspects. This could imply that people forget about their personal beliefs when viewing these menus and let themselves steer by aspects of the menu. The menus for which this was the case are designed in a crowded and cluttered way compared to the other menus. It could be that people are distracted and therefore act more impulsive to these menus. Also, these menus do not have a very clear distinction between low and high calories so it might be that people do not know which option is the healthiest and therefore let themselves guide by impulses more easily. It could also mean that people had a similar way of dealing with impulses from these menus, but that the classification task was harder because of the bigger number of regions of interest.

However, outcomes of models with personal aspects for the individual menus might support the option of people making a well-considered choice when it comes to high or low calories from menus with a clear distinction between high and low calorie items. Two menus for which the the model performed good using fixation times as features also have high accuracy rates for models with personal aspects as features. This may imply that the actual interest of people (fixations and food choices) might be in line with their personal beliefs for these menus.

The high accuracy scores for the models for menus which are accurate using both fixation and personal data might be the result of the clear difference in high and low calorie items. In menu twenty six (Figure 25) the distinction is made by the titles 'Light Bites' versus 'Something for the Game - all Served with French Fries' and in menu twenty four (Figure 24) the distinction is made by the titles 'Small Plates' versus 'Large Plates'. This could encourage people to stick to their personal beliefs. They immediately choose for a high or low calorie item before they are distracted by all the individual options. In other words, they have been given the opportunity to focus on a certain type of item without being distracted, which might have helped people to choose something healthy. This might be comparable to the findings of Feldman et al. (2014) who state that people are more likely to choose healthier foods when the foods are placed in boxes. Furthermore, both menus are well-organised and calmly arranged without images of foods, which may also lead to less distraction and a more well-considered food choice.

Overall, a high or low calorie choice is better predictable using personal aspects rather than fixation times as features. This might imply that people stay well with their personal beliefs when choosing from a restaurant menu. The features which seem the most important when looking at the individual menus are calories2, salt and calorie_check which all are present three times in the feature composition for menus with an accuracy outreaching the baseline. Features which are present two times are calories4, calories3, calories1, saturated_fat2, saturated_fat1, taste4, price5, quantity4, currently_hungry and cafe. Therefore, it seems that we might be able to make predictions about a high or low calorie items choice when we know something about how important people find calories, taste, price, quantity and saturated fat, whether they check salt content and calories in supermarkets, whether they are hungry or not and whether people go to a cafe when eating out.

Predicting the choice of a high priced or a low priced item is also easier for menus which have a big price difference. This possibly means that significant price difference can steer peoples choices. However, people might be less focused on prices of foods when they are eating out (Wakefield & Inman, 2003). This may be confirmed by the finding that in predicting price, it is harder to say whether personal aspects or fixation times are more valuable for price choice than for the calorie choice. This may indicate that people are less steadfast about the price they want to pay for a menu item than the calorie level they are willing to take.

The features which seem to be the most important, when looking at the individual menus, are taste4 and salt_content1. These features are present three times in the feature composition for menus with an accuracy outperforming the baseline. Features which are present two times are calories2, calories4, quantity1, calorie_check, losing_weight, taste6 and currently_hungry. However, some features such as salt_content1 are seem random when it comes to predicting price. Features such as taste, currently_hungry and quantity referring to the importance of taste and quantity and the information about whether someone is hungry or not may be interesting to further analyse to find out what makes people willing to pay more.

In future research it might be interesting to look at different educational levels. As people with different educational levels also respond differently on health labels (Vyth et al., 2010), there also might be a difference in predictability with fixation times and personal aspects or there might be a different response to different menu designs. Furthermore, it might be useful to instruct people to click on either one of the options for items for which it was possible to choose two volumes, so that less data has to be thrown away. Lastly, it would be interesting to further research the effect of separating high and low calorie items from each other on the menu and the effect of designing uncluttered menus.

Conclusion

The results of this study could be interesting in practice since this study worked with real world menus. First of all, in order to steer consumers towards healthier food choices, people probably need better education about the daily calorie intake they need and the calorie level that is in the foods they consume. Furthermore, it might be useful to focus on the design of restaurant menus instead of labelling menu items with nutritional labels. Design recommendations might include keeping the menus uncluttered and divide the menu into high calorie options and low calorie options. If further research also indicates these aspects to help people make healthier food choices or keep with their personal beliefs, a new legislation for restaurant holders might be an option.

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Appendices

Appendix A

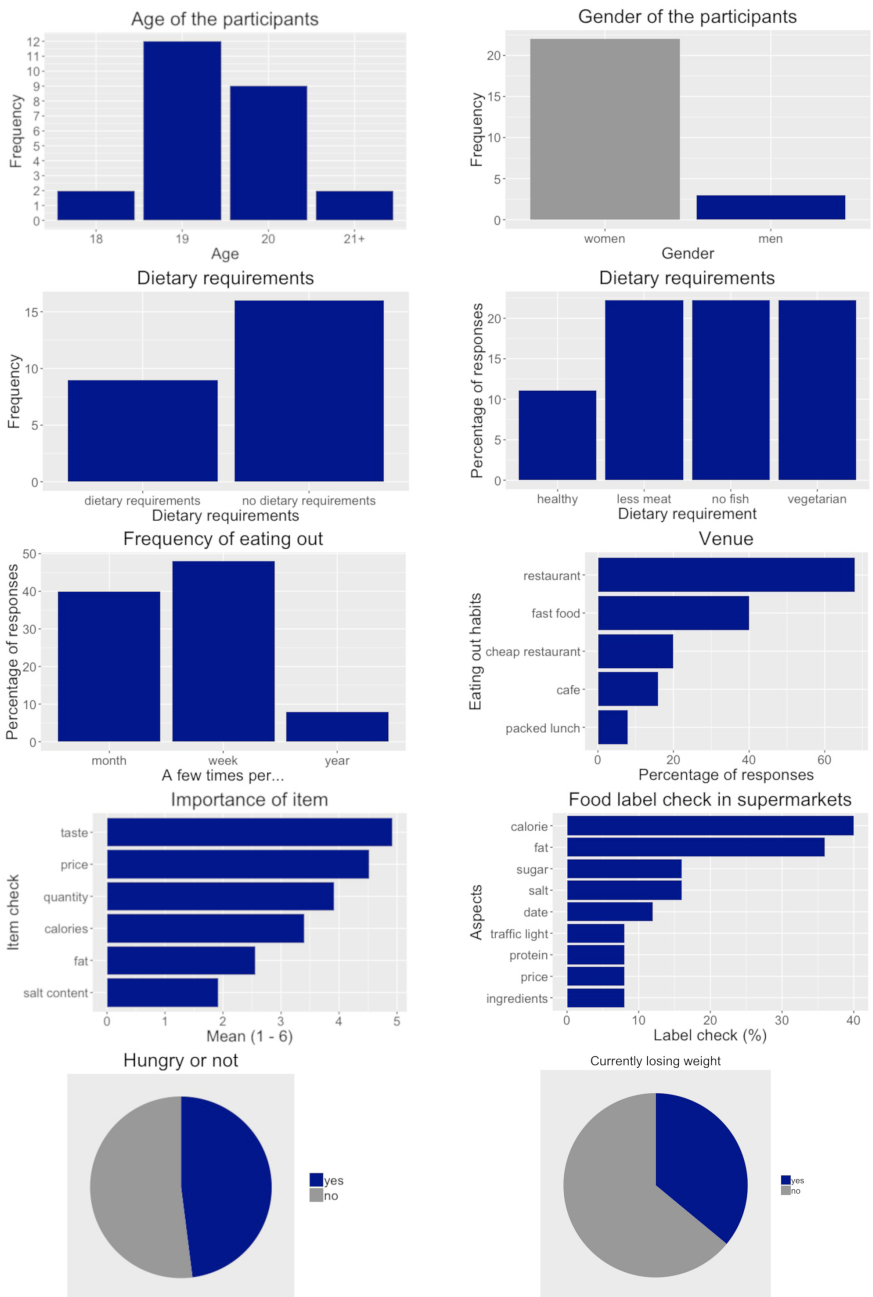

Figure A1. Distribution of responses in the pen-and-paper questionnaire given to participants at the end of the study.

Appendix B

Table B1
All features about personal aspects

Feature	Meaning
dietary_requirements	participant indicated to have dietary requirements or not
vegetarian	participant indicated to be vegetarian or not
healthy	participant explicitly stated healthiness of foods to be a important or not
less_meat	participant explicitly stated to eat less meat or not
no_fish	participant explicitly stated to eat no fish or not
week	eating out a once a week or more or not
month	eating out once a month or more or not (not more than once a week)
year	eating out once a year or more or not (not more than once a month)
fast_food	participant eats fast food when eating out or not
restaurant	participant goes to a restaurant when eating out or not
cheap_restaurant	participant goes to a cheap restaurant when eating out or not
packed_lunch	participant takes packet lunch when eating out or not
cafe	participant goes to a cafe when eating out or not
salt_content1	salt importance ranked at one or not
salt_content2	salt importance ranked at two or not
salt_content3	salt importance ranked at three or not
salt_content4	salt importance ranked at four or not
salt_content5	salt importance ranked at five or not
salt_content6	salt importance ranked at six or not
calories1	calorie importance ranked at one or not
calories2	calorie importance ranked at two or not
calories3	calorie importance ranked at three or not
calories4	calorie importance ranked at four or not
calories5	calorie importance ranked at five or not
calories6	calorie importance ranked at six or not
saturated_fat1	fat importance ranked at one or not
saturated_fat2	fat importance ranked at two or not
saturated_fat3	fat importance ranked at three or not
saturated_fat4	fat importance ranked at four or not
saturated_fat5	fat importance ranked at five or not
saturated_fat6	fat importance ranked at six or not
price1	price importance ranked at one or not
price2	price importance ranked at two or not
taste3	price importance ranked at three or not
taste4	price importance ranked at four or not
taste5	price importance ranked at five or not
taste6	price importance ranked at six or not
quantity1	quantity importance ranked at one or not
quantity2	quantity importance ranked at two or not
quantity3	quantity importance ranked at three or not
quantity4	quantity importance ranked at four or not
quantity5	quantity importance ranked at five or not
quantity6	quantity importance ranked at six or not
ingredients	participant checks ingredients in supermarket or not
calorie_check	participant checks calories in supermarket or not
fat	participant checks fat in supermarket or not
sugar	participant checks sugar in supermarket or not
price_check	participant checks price in supermarket or not
salt	participant checks salt in supermarket or not
date	participant checks the date in supermarket or not
colour_coordinate	participant checks colour coordinate in supermarket or not
protein	participant checks protein in supermarket or not
currently_hungry	participant is hungry at the time of the experiment or not
losing_weight	participant is trying to loose weight at the time of the experiment or not