When do digital calorie counters aid consumers' food choices? Evidence from an online experiment

Diogo Souza-Monteiro
School of Natural and Environmental Sciences
Newcastle University
Newcastle, United Kingdom
email: diogo.souza-monteiro@ncl.ac.uk

Ben Lowe[1]
Kent Business School
University of Kent,
Canterbury, United Kingdom
email: b.lowe@kent.ac.uk

Iain Fraser
School of Economics
University of Kent,
Canterbury, United Kingdom
email: i.m.fraser@kent.ac.uk

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Diogo de Souza Monteiro is a Senior Lecturer in Agribusiness in the School of Natural and Environmental Sciences at Newcastle University, United Kingdom. His work has been published in journals such as the American Journal of Agricultural Economics, Agribusiness an International Journal, European Review of Agricultural Economics and Food Policy. He is Managing Editor of the International Food and Agribusiness Management Review. Email: diogo.souza-monteiro@newcastle.ac.uk.

Ben Lowe is Professor of Marketing at Kent Business School, University of Kent, United Kingdom. His work has been published in journals such as the European Journal of Marketing, Journal of Business Research, Technovation, Journal of Interactive Marketing, Journal of Public Policy and Marketing, Psychology & Marketing, International Marketing Review, the Journal of Marketing Management and many others. He is currently Associate editor at the European Journal of Marketing and is on the editorial review board of several other journals. Email: b.lowe@kent.ac.uk.

Iain Fraser is Professor of Agri-environmental Economics in the School of Economics at the University of Kent, United Kingdom. His work has been published in journals such as Environmental and Resource Economics, American Journal of Agricultural Economics, Ecology and Society, Global Business and Economics Review, Journal of Economic Behavior and Organization and many others. He was previously Editor of the European Review of Agricultural Economics. Email: i.m.fraser@kent.ac.uk

When do digital calorie counters reduce numeracy bias in grocery shopping? Evidence from an online experiment

Structured Abstract

Purpose
Numeracy skills hinder a consumer's ability to meet nutrition and calorie consumption guidelines. This study extends the literature on nutritional labelling by investigating how a calorie counter, which displays the total amount of calories consumers add to a shopping basket, aids them in making food choices. It aims to ascertain whether the calorie counter affects food choices and also how individual and situational factors moderate this effect.

Design/methodology/approach
To test the developed hypotheses, we designed an online shopping experiment and administered it to a national panel of British consumers. This included a sub-sample from the general population who did not report any food related health conditions (n=480) and a separate sub-sample from the same population who had reported a food related health condition, or lived with someone who had one (n=250).

Findings

The results show that the calorie counter leads to a large and statistically significant reduction in calories purchased when compared to the no nutritional information condition, and a small (but statistically insignificant) reduction in the number of calories chosen by consumers when compared to the nutritional information only condition. The main effect is moderated by individual factors such as whether or not the person has a health condition, and shopping situations which involve time pressure.

Research implications
Although the main effect of the calorie counter was not statistically significant when compared to the nutrition information only condition, the effect was in the correct direction and was statistically significant for consumers who had a food related health condition. Our conceptualization and findings are largely consistent with Moorman's (1990) nutrition information utilization process, but also suggest that situational factors should be considered when understanding nutrition information processing.

Practical Implications
The findings from this study provide the first evidence to suggest that aggregating calorie information through a calorie counter can be a useful way to overcome consumer numeracy biases, particularly for those with existing health conditions and who are most motivated to use nutritional information. Based on the descriptive statistics the main effect was comparable to the UK's sugar tax in its impact and we estimate this would lead to a reduction in calories consumed of about 5000 per year, even for consumers who did not report a health condition. Further testing is required with different formats but these results are encouraging and are worthy of further research.

Originality/value
This is the first study to investigate how consumers react to aggregated nutritional information for a basket of products, mimicking a real shopping situation. Such information has the potential to become more relevant and useful to consumers in the context of their overall diets. As technology advances rapidly there is a need to explore alternative ways of presenting nutritional information so it connects more easily with consumers. These results point very much to a more targeted and personally relevant approach to information provision, in contrast to existing mass communications approaches.

Keywords: Numeracy bias, calorie counter, grocery shopping, digital technologies, time pressure.

Introduction

There is broad consensus that a growing proportion of the population is consuming a significant amount of high-energy dense foods in their diets, often due to food choices based around convenience and speed. In the past decade British consumers, for example, have significantly increased their consumption of pre-prepared foods and 35% of the population eat ready meals at least twice a week (Mintel 2021). Consumption of such processed foods can lead to obesity (Machado et al 2020; Rauber et al 2020) and an increase in the incidence of diseases such as type II diabetes, cardiovascular disease, dental decay and some forms of cancer (NHS 2016; WHO 2016). To counter these trends governments have typically opted for information-based policies which involve the use of food labels to communicate clearer information about foods to consumers (e.g., calories and other nutrients). However, there is limited evidence that these information-based policies contribute to reducing levels of obesity in the population (Cowburn and Stockley 2005; Grunert and Wills 2007; Vecchio and Cavallo 2019). This could be due to a variety of personal, social and environmental factors (Block et al. 2011; Khan, Lee and Khan 2022; Lau et al. 2022; Mazzocchi, Traill and Shogren 2009), but an increasing body of evidence shows that consumers struggle to process the available information due to numeracy constraints and other cognitive limitations (Cowburn and Stockley 2005; Hagmann and Siegrist 2020; Just and Payne 2009; Vecchio and Cavallo 2019; Yan et al. 2016).

Providing consumers with better nutrition information should help to empower them to make healthier choices if they are motivated and have the ability to process such information (Moorman 1990). However, despite efforts to make nutrition information simpler and easier to understand (e.g., through the traffic light system and Recommended Daily Amounts - RDAs) consumers still find it difficult to relate the foods they consume to their overall diets (Bogomolova et al. 2021; Machin et al. 2010; Wijayaratne et al. 2018). Often consumers are faced with a choice context that is characterised by conflicting commercial marketing messages (Jo et al., 2016), time pressure and information that is too cognitively burdensome to process given that most shopping situations involve a "basket" of foods where information has to be processed, summated and then related to an overall RDA. For example, in order to purchase a "healthy" basket of foods when doing a weekly shop, a consumer would have to be able to process the nutrition information from the packages they put into their basket, aggregate this in some way and then make a judgment about how it relates to their dietary goals or guideline daily amount of calories and other nutrients (Just and Payne 2009; Liu et al. 2019). Thus, even highly motivated and able consumers are likely to find this a daunting task where they are unable to accurately process the nutritional information they are exposed to. This has led to calls by some researchers for new interventions and policies which take account of barriers to information processing, consumers' limited food literacy (Block et al. 2011; Wijayaratne et al. 2018) and the various numeracy impediments which exist (Hawkes et al. 2015; van Epps, Downs and Loewenstein 2016).

One approach to reduce numeracy biases in food consumption has been the use of technology to facilitate information processing. There is a large array of mobile apps designed to do this (e.g., Calorie Counter+, MyFitnessPal, MyNetDiary, MyPlate Calorie Tracker etc.). The use of such technologies is consistent with typical information processing models (e.g., Moorman 1990) as they can enhance a consumer's ability to process the complex array of nutritional information presented to them. Public health practitioners have started to assess the value of such technologies in helping us to make healthier food choices (Flaherty et al. 2017; Flaherty et al. 2021) and emerging literature in the marketing discipline outlines the benefits of using such technologies to create a more customisable food environment to enrich food consumption experiences (Batat and Addis, 2021). Some research has begun to assess how providing summated calorie information through a calorie counter, influences food choices. For example, when an individual, orders an individualised sandwich, research finds that consumers who are given summated calorie information end up building a sandwich with fewer calories (Gustafson and Zeballos 2019). Thus, technologies can help to reduce the numeracy burden that consumers face in food consumption situations and can help to promote healthier diets. However, research in this area is sparse and no research to date has assessed how providing consumers with sequentially updated calorie information, based on food choices, affects the healthiness of the foods they choose to put in their shopping baskets.

We address this challenge and add to the literature on food choice by proposing to aggregate nutrition information on a basket of meals through a calorie counter that updates sequentially when choices are made, and to determine to what extent it aids consumers in making healthier food choices for a basket of foods. Moorman's (1990) nutrition information utilization process is used as a guiding theoretical framework, by using stimulus characteristics and consumer characteristics as antecedents, and number of calories chosen in the basket as the dependent variable for food choice (an indicator of what Moorman terms "decision quality"). We first seek to determine whether exposure to a calorie counter (stimulus characteristics) reduces the total amount of calories chosen for a basket of products. We do this in the context of a typical but contrived shopping situation via an online experiment. Based upon literature in the area, we also assess how the effectiveness of the counter varies for consumers with an underlying food related health condition (consumer characteristics) as consumer motivation to process nutritional information is an important factor to consider (Block et al. 2011; Cowburn and Stocklye 2005; Grunert and Wills 2007; Moorman 1990). Based on the retailing and consumer behaviour literature (Nordfalt 2009; Young et al. 2012), we also enrich Moorman's (1990) nutrition information utilization process by taking account of a consumer's shopping situation, to assess how the effectiveness of the counter varies by shopping task and time pressure.

Our findings show that consumers choose a shopping basket comprised of fewer calories when they are exposed to a calorie counter. This is particularly evident when consumers have a food related health condition and when they are faced with time pressure. These results contribute to the literature on technology and healthy choices (Flaherty et al. 2017; Flaherty et al. 2021; Manika, Gregory-Smith and Antonetti 2017; Manika, Gregory-Smith and Papagiannidis 2017) and are in line with recent studies by Gustafson and Zeballos (2019) who also assess how a calorie counter can help consumers to make healthier food choices. However, our study diverges from their work as it tests the calorie counter in a more complex choice task where consumers make a much larger number of food choice decisions. This mimics a typical shopping situation that consumers are likely to find themselves in on a regular basis. Specifically, this research contributes by showing *when* a calorie counter, which provides aggregated nutritional information, can assist consumers in making healthier food choices in a typical food choice situation for a basket of products. This is the first research that we know of which tests how consumers respond to aggregated nutritional information for a basket of foods. The study also helps to refine existing nutrition information processing models (Moorman 1990) by highlighting the importance of situational factors such as time pressure. Our research has important implications for social marketers and public policy makers because it shows that such technologies can improve our food choices, particularly for those consumers who are most motivated to use it and in situations in which they can engage with it.

Information Technologies and Behaviour Change

There has been significant growth in the use of technology to track, manage and change food purchase patterns and consumption behaviour. There are a multitude of apps, for example, which exist to assist consumers in making better food choices. These tools help consumers track food purchase and consumption, exercise and even sleeping patterns (see for example Flaherty et al., 2017 or Flaherty et al., 2021). Such tools can enhance self-efficacy around health behaviours by enabling consumers to track what they purchase and consume more accurately and to reduce information processing impediments. There is some evidence that consumers attach a positive value to such technologies, although this varies by segment (Balcombe, et al. 2016; Lowe et al. 2013). The real promise of such technologies is that they can reduce the numeracy burden we face as consumers and help us to make better decisions. However, despite the rapid proliferation of such technologies, little is known about their impact on purchase and health behaviours especially with regard to healthy food choice. The effectiveness and usefulness of any digital technology to improve a consumer's ability to make healthier and more sustainable food choices hinges upon a number of factors, namely: a) the convenience of the tool; b) the relevance and accessibility of the information conveyed; and c) the ability to mitigate numeracy biases which prevent better choices (Lowe et al., 2015; Lowe et al., 2019). Here we focus on the latter two. We begin by reviewing the extant literature and generating our hypotheses.

Nutrition Information Processing, Numeracy Bias and Food Choices

Early work in the area of nutrition labelling takes an information processing perspective and assumes consumers can accurately process nutrition information on individual food items. For example, Moorman (1990) conceptualises the nutrition information utilisation process as having two key antecedents (stimulus characteristics and consumer characteristics), which influence motivation and ability to process nutrition information. Stimulus characteristics comprise consequence information and consequence and reference information. Consequence information relates to how a message presents the consequences of consuming a particular food type on one's health – i.e., that it is "bad" for you. Consequence and reference information relates nutrition information to established frames of reference used in a message so it is more understandable – i.e., relating it to a RDA. Consumer characteristics refer to individual characteristics such as familiarity with nutritional information, motivation to process nutrition information, education, age etc. Motivation and ability as the two key antecedents influence food consumption decision quality (e.g., choices of calories and other nutrients consistent with a healthy diet) and this causal process is mediated by information acquisition, information elaboration and information comprehension. Moorman's model is summarised in Figure 1. While intuitively appealing this type of information processing model assumes that consumers are able to accurately process nutrition information for the foods they purchase and relate this to their overall diets. It is also based upon processing nutritional information for *individual* products so may have more limited use when considering food purchasing decisions for a basket of products where the nutrition information can quickly become complicated, unless there is a mechanism that assists consumers to process this information quickly.

Numeracy is one element of comprehension and poor numeracy skills may derail the best intentioned and motivated consumer aiming to understand nutrition and diet information (Gardner et al 2011; Liu et al 2019). In one study on the impact of consumer numeracy in healthy food choices, Rothman et al. (2006) show that the numeracy of an individual is highly correlated to their understanding of nutrition labels. Miller and Cassady (2015) draw on insights from cognitive science and examine how nutrition knowledge determines food choice, through attention, comprehension and memory. Nutrition recommendations require mastering numeric skills at a basic level. For example, suggesting a maximum RDA level for a particular nutrient or energy (calories) implies the ability to add and relate the total sum to such a benchmark. In Moorman's (1990) model (Figure 1) this is accounted for by ensuring a message includes crucial reference information so consumers can relate it to an overall RDA. Even though individual products may include individual reference information such as an RDA, to simplify processing, making sense of all this information for a *basket* of products would quickly become overwhelming. Moorman's model can be used as a theoretical framework to guide the research here (for a basket of products) because we are primarily proposing that a calorie counter will do the information processing for consumers and make nutrition information more relevant to consumers by i) presenting it at an aggregate level, and ii) relating overall calories purchased to daily RDAs. So, in Moorman's terminology a calorie counter would be an example of a stimulus characteristic which makes the message more relevant to consumers.

In a recent paper Gustafson and Zeballos (2019) examine how a calorie counter changes the choices consumers make when they build their sandwich. Interestingly, although their study is implemented in a simpler context, they find support that the calorie counter helps people make healthier choices in terms of the fillings they choose and the calorie content of the sandwich they build. However, while congruent to what we are examining here, the context differs quite considerably to a shopping situation where multiple products are chosen. Therefore, we hypothesise that, on average, when consumers get aggregated information on the total amount of calories in a food basket this leads to a lower average daily amount of calories being chosen. Given our experimental design (see below), we formulate our first hypothesis in two parts:

> **H_{1a}:** Exposing consumers to calorie information leads to a reduction of the average daily amount of calories in a shopping basket.
>
> **H_{1b}**: Exposing consumers to calorie information and a calorie counter leads to a reduction of the average daily amount of calories in a shopping basket.

The impact of health status on food choices

In Moorman's (1990) framework consumer characteristics relate to individual characteristics that may affect how one processes information. This could include demographic characteristics such as age and education but also refers to one's overall ability or motivation to process nutrition information – for example, if a consumer had a food related health condition they would be more motivated to process nutrition information. The nutrition labelling literature is largely consistent and shows that an individual's personal health condition impacts the relevance they attribute to information that may improve or aggravate that condition. Naturally, if a person is diabetic they will be more concerned with the sugar content of food and will value more any information that may help them manage the condition (de Ridder at al. 2017). Mulders, Corneille, and Klein (2018) investigate how numeracy and involvement objectively affect nutrition label comprehension and find that involvement in nutrition information processing reduced the effect of numeracy on comprehension. This means that highly motivated consumers (for example, those with diet related health conditions) may perform better on a nutrition comprehension task despite their low numeracy skills. Hagmann and Siegriest (2020) note similar results when assessing alternative nutrition information formats in Switzerland. Likewise, Liu et al. (2019) show that those who use consumer labels more frequently may be more familiar with industry standards and their interpretation. Such consumers may therefore find the calorie counter more useful. Thus, consistent with the literature on nutrition label use, we posit that the impact of a calorie counter may be more relevant to those with individual or household diet related health conditions. This leads to our second hypothesis, which we state in two parts:

> **H_{2a}:** Consumers with a food related health condition exposed to calorie information will significantly reduce the average daily amount of calories in a shopping basket.
>
> **H_{2b}:** Consumers with a food related health condition exposed to calorie information and a calorie counter will significantly reduce the average daily amount of calories in a shopping basket.

The effect of type of shop and time pressure

Moorman's (1990) information processing model does not account for other situational influences that may affect consumer use of a calorie counter. Therefore, while we use Moorman's model as a theoretical framework we also augment it by referring to two key situation influences. We consider two factors: the type of shop and time pressure.

The literature on consumer behaviour in retail environments has documented the difference between planned and fill-in shops and how this relates to differences in consumer behaviour. Planned shopping involves greater use of cognitive resources as it involves more time and effort in most aspects of the shop from planning to execution. For example, it may include more careful consideration about what will be bought prior to the shopping trip (e.g., through writing shopping lists and a meal plan), consideration about what is spent, what products are chosen etc. This planning means that they tend to rehearse in advance what they will buy and activities such as generating a shopping list can be useful as a way to achieve this (Block and Morwitz 1999). Consumers who are motivated to purchase foods according to their dietary goals will therefore be more likely to consider in advance what they will be purchase and be less likely to choose based on other external cues. This is in contrast to fill-in shops which are shorter in duration and are undertaken to fulfil a specific need. As a consequence, they are usually more spontaneous and involve more impulse purchases without so much use of cognitive resources (Nordfalt 2009; Walters and Jamil 2003). In such situations, consumers prefer convenience which may be more likely to favour perceived taste as an attribute, in comparison to health related attributes (Hunneman, Verhoef and Sloot 2017). Some authors suggest that consumers even go so far as to change their mental purchase models when undertaking a planned shop (Nordfalt 2009), implying the use of different strategies based on the context.

When consumers are prompted to consider a planned shopping trip, we posit that they will be more likely to adopt a planned shopping behaviour and consider nutritional and health information in their choices. Consequently, when respondents are prompted to shop for a higher number of days they will be more likely to use the calorie counter and calorie information when making their choices. Thus, we posit:

> **H_3:** The effectiveness of the calorie counter and calorie information is moderated by type of shopping trip, such that consumers doing a planned shop are more likely to use the calorie counter and calorie information.

Time pressure is also likely to influence the use of nutrition information and the calorie counter (Stancu, Lahteenmaki and Grunert 2021). By time pressure we mean the speed at which decisions are made. In this context, when shoppers are under time pressure, they will tend to make quicker decisions that might rely on heuristics. Once shoppers start to rely on heuristics they tend to make more mistakes. Several studies confirm this assertion and have shown there is a trade-off between the accuracy and quality of decision making and time pressure (Young et al. 2012; Stancu, Lahteenmaki and Grunert 2021). van Herpen and van Trijp (2011) experimentally investigate the impact of "time pressure on attention for and use of" (p. 149) nutritional labels in healthy food choices. They find that in general time pressure can reduce the attention and use of nutrition labels, but the way the information is presented moderates the impact of time pressure. Similar research shows how time pressure leads to less accurate calorie estimates. For example, Panzone et al. (2020) examine the relative impact of traffic-light labels and time pressure on consumers' self-regulation by asking them to estimate the total amount of kilocalories and the carbon foot print for food products. They find that the traffic light label improves consumer knowledge of how healthy a product might be and the ability to rank the healthiness of products. However, time pressure reduces the positive impact of traffic light labelling on calorie and carbon footprint estimation.

So, if consumers are pushed to make quicker decisions it is less likely they use any type of nutrition or diet information in their choices. This is consistent with extant research in food decision making which highlights the role of time pressure in decisions about food through the habitual nature of consumers' daily routines (Dyen et al., 2018). Recent research also adds credence to this argument because consumers reading simplified nutrition information who were placed under time pressure tended to make less healthy food choices than those consumers not under time pressure. In contrast when consumers were exposed to more complex nutrition information time pressure did not seem to moderate the relationship (Blitstein, Guthrie and Rains 2020). Therefore, we posit that when consumers are under time pressure, they are less likely to use calorie information. Given our experimental design this leads to our fourth and final hypothesis:

H_{4a}: The effectiveness of calorie information is moderated by time pressure such that consumers under time pressure are less likely to use calorie information than consumers not under time pressure

H_{4b}: The effectiveness of calorie information and the calorie counter is moderated by time pressure such that consumers under time pressure are less likely to use calorie information and a calorie counter than consumers not under time pressure

In summary, we have developed four hypotheses that we examine experimentally, as described in the next section. These hypotheses are summarised in Figure 1, which couches them in Moorman's (1990) nutrition information utilisation model.

INSERT FIGURE 1 ABOUT HERE

Methods

Overview

To address the research questions and test the hypotheses, we designed and implemented an online experiment and administered it to a sample of British consumers in two waves, consistent with good practice from the literature (i.e., see Babin et al. 2020). The first wave was a national convenience sample of the UK population, and the second wave targeted the same population but screened for those who had a diet-related health condition, or who lived in a household with someone who had one. We targeted British consumers because increasing obesity and incidence of food related health conditions is a key issue in Britain (National Food Strategy 2021) and Britain has one of the highest rates of obesity among OECD countries (OECD 2017). Prior to launching the questionnaire, we ran a number of in-depth interviews and focus groups to enhance our understanding of the research issues (consumer shopping habits, food choices and use of nutrition information) and to assist in developing the treatments and stimuli. Finally, the instrument was piloted on a sample of university students and staff before being rolled out (in stages) to the full sample.

Experimental design, implementation and manipulations

In our online experiment, we asked respondents to assume they were involved in a grocery shopping task. They were asked to make choices that reflected their preferences. We chose this shopping context because it represents a common and familiar situation for respondents; what we put in our baskets is an important factor in determining our diets. This experimental setting enabled us to understand how consumers responded to calorie information for a basket of food compared to calorie information on individual products. Subjects were asked to make food choices as if they were shopping for meals for two adults. This was to provide a level of standardisation to the task. They were instructed to imagine they were selecting foods for themselves and their partner for two meals a day (lunch and dinner). For each meal, participants had to choose three components (i.e., a main dish, a drink and a side/dessert) and for each of these there were three choices, which varied by calorie content. The products were selected from the same food category and obtained from the product ranges available in a large UK online retailer at the time of the research (see Appendix A for the survey flow and an example of one of the food choices).

There were 12 treatments based around a 3x2x2 between subjects' experimental design. This included three information treatments: i) no calorie information; ii) product level calorie information but no calorie counter; and iii) product level calorie information and a calorie counter. These treatments explain the framing of the hypotheses introduced in the previous section. The calorie counter was only included in a treatment that always provided calorie information. We employed this experimental design feature in recognition of the fact that in any shopping context the calorie information will be available and that the calorie counter is an additional source of information. Our experimental design also included two shopping duration treatments (a three day shop and a five day shop); and a time pressure treatment (no time pressure and time pressure), simulated by a time counter which was salient to those respondents exposed to the time pressure treatment.

A between subjects' design was used as we were primarily interested in internal validity, and this allowed us to compare the number of calories that respondents put in their baskets depending on the condition they were exposed to. A within subjects' design would have introduced a threat to internal validity (as respondents would have seen multiple treatments) and would have made the questionnaire too lengthy.

When implementing the calorie counter treatments, the calorie counter mimicked the Traffic Light front of pack nutrition label used on food packaging in the UK to signal quantities of specific nutrients[2]. The graphical display presented the information on a meter measuring the total calories for the products chosen. It moved from green (if the choices were within the range of the daily recommendation) to amber (if the total calories chosen were up to 30% over the recommended guideline) to red (if the choices in the basket had a sum of calories above 30% of the recommended guideline). In addition, the calorie counter summed the calories of each product selected and then divided by a fraction of the RDA. An illustration of the counter is presented in Figure 2.

[2] For details see the FSA website: https://www.food.gov.uk/safety-hygiene/check-the-label

INSERT FIGURE 2 ABOUT HERE

As can be seen from Figure 2, participants exposed to the calorie counter treatment had explicit visual information on how many calories were in their “basket” and how the number of calories related to public health RDA guidelines. Importantly, the result of the calculations was displayed both in a numerical format (as a proportion of the amount of calories chosen for the daily allowance) and in a graphic visual at the top centre of the screen where participants made their choices, just like the Traffic Light labels seen in UK grocery stores. Participants could also experiment by changing their choices and assessing the impact on the numerical and graphical display of the information.

Another dimension of our experiment included factors that affected the use of information when making choices. In a planned shop, consumers may have more time and therefore might consider their choices more carefully. Then again, if shoppers are time pressed there may be little consideration for additional types of information.

The choice of calories as the main source of nutrition information was not taken lightly. We considered a number of ways to convey diet and nutrition information in an aggregate fashion. However, despite the limitations of using calories as a measure of food healthiness, we decided to use it as our aggregate level of nutrition information for several reasons. First, this is the common indicator of healthiness in similar consumer research studies (e.g., Panzone et al. 2020; Shimokawa 2016; van Epps, Downs and Loewenstein 2016). Second, calories are widely used by consumers, easily understood and actionable. Third, calorie information is easily accessed in retail environments and can be simply aggregated across products. We also believe that if some other numerical information was used as a dependent variable (e.g., fat content) the hypotheses would still apply as they primarily test how consumers process aggregated nutritional information (rather than a specific type of nutritional information), so the use of calories serves as a practical and widely understood vehicle to test the effects. Finally, in the UK, as in many other countries, public health authorities provide clear RDA guidelines for calorie consumption, that consumers are familiar with and could aim for.

Another key design decision of our experiment relates to the fact that nutrition is not the main criteria of food choice. Brands along with price information are among the main attributes consumers typically use for food choice and the inclusion of this type of information could well confound the results we present. This type of design choice is not unusual, as Hagmann and Siegriest (2020) observe, and is justified when the investigation is focusing on a novel aspect of choice. Consequently, to enhance internal validity of the design and to limit biases that may compromise the main goal of our analysis, we decided against using price and branding information for the products in our choice sets.

Finally, screening questions were used to ensure there were no vegetarians in the sample or people who do not eat certain meat products because this would also influence their decisions (given some of the choices contained meat). Moreover, we only used text descriptions of the products and no other nutrition information was provided by the product descriptions. A summary of our experimental design and the treatments is given in Table 1.

INSERT TABLE 1 ABOUT HERE

Measures

The variables we collected included the quantity of calories for the food selected and several latent variables capturing respondent characteristics plus observable socio-economic data. In terms of measuring the quantity of calories selected an important aspect of the survey is the within meal variation of the total calories on offer. This occurred because the combination of food items and associated minimum and maximum calories differed between the meals offered. Therefore, to take account of this variation in calories we re-calculated the difference in calorie consumption per day and by meal as a percentage, by normalising the data using the formula shown in equation (1):

$$AvNC = \frac{Actual\ Cal - Min\ Cal}{Max\ Cal - Min\ Cal} * 100 \quad (1)$$

where in equation (1)

- AvNC - is the average normalised calories;
- Max Cal - is the maximum calories that could be consumed from the given combination of products on offer for a given meal;
- Actual Cal - are the actual quantity of calories selected given the food option selected for a given meal; and
- Min Cal - are the minimum number of calories that could be selected given the food products offered for a given meal.

Using equation (1) generates values ranging from zero to 100, with zero indicating that the respondent selected a combination of food products that yielded the minimum number of calories possible for any specific meal. In contrast an estimate equal to 100 means then the respondent selected those food options that yielded the highest possible calorie combination.

By recasting the calorie data in this way, we can control for variation in actual calorie levels within any specific meal that can influence the simple calculation of calories consumed on a daily or total basis.

For the latent constructs we used and adapted existing measures of Nutritional Information Interest (NuInt) and Usage (NuUse), Health Orientation (HealthOr) and Technological Inertia (Inertia) to take account of individual differences in the processing of nutritional information with technology. The measures of NuInt (five items, α=0.95)[3] and NuUse (four items, α=0.83) were seven-point Likert scales adapted to the context here and were derived from Moorman (1998). A measure of HealthOr was adapted from the original fifteen-item scale used in Moorman and Matulich (1993) and described dietary behaviour and life balance behaviour. The original scale was too long and unwieldy for the questionnaire, so we reduced it to a more parsimonious scale based on typical scale purification procedures (α=0.72). Inertia represents a respondent's resistance towards the adoption of technology and was a three item (α=0.83) seven-point Likert scale taken from Meuter et al. (2005).

Sampling

The experiment was integrated into a questionnaire implemented in the Qualtrics online survey platform. The survey was administered to two samples of a British national panel of consumers (using a panel provider – Toluna) consistent with other recent research in the area (e.g., Hansen and Thomsen 2021; Khan et al. 2017; Thomas, Seenivasan and Wang 2021). The first sample of 486 respondents was collected from the general population and included respondents with no prior health condition, while the second included 256 subjects and was collected from a sub-population of people with self-declared food related health diseases. Both samples came from the same panel of respondents. We targeted these two sub-samples because i) this was a focus of hypothesis 2, and ii) the nutrition information literature consistently finds that subjects who are more highly motivated to process nutritional information use and process it in different ways (Cowburn and Stockley 2005; Grunert and Wills 2007; Grunert et al. 2010).

We administered 12 treatments to the sample of the general population, but for the sample of respondents with self-declared health issues we only used eight treatments. These eight treatments were the same as those of the main sample except we did not include the "no calorie information" treatment. This is because we assumed that those with diet related health

[3] The α reported is Cronbach's alpha a measure of internal consistency and reliability employed with multiple item constructs.

conditions would already have a basic knowledge of nutrition and consequently there might not be sufficient difference from the treatment with just calorie information on the products.

The criteria for selection of participants into the second sample was that they either had a food related health disease or had someone with those conditions in their household. Table 2 presents the key variables and data collected from the experiment.

INSERT TABLE 2 ABOUT HERE

Full details on sample composition by treatment including summary measures of socio-economic characteristics and the four latent constructs are provided in Table 1A Appendix B.

Results

Descriptive statistics

The survey generated a large amount of data and associated statistics. We summarise the results for differences in calories by key treatment effects as follows:

i) For participants in treatments with no calorie information the mean level of calories selected on average per day was 2767.3 with a standard deviation of 347.3;

ii) For participants in treatments where only calorie information per item was provided, the mean level of calories selected on average per day was 2528.6 with a standard deviation of 350.0; and

iii) For participants in treatments provided with calorie information and the calorie counter the mean level of calories selected on average per day was 2515.3 with a standard deviation of 340.5.

These results indicate a reduction in total calories across the treatments in the direction expected. The difference between no information and the calorie information with calorie counter is 252 calories per day, which corresponds to a 9% daily reduction.

Next, we break our results down for all 20 treatments. Table 3 presents some key descriptive statistics.

INSERT TABLE 3 ABOUT HERE

The results presented in Table 3 show the average number of calories per day by treatment. From the calorie data we can examine the variation by treatment if we consider the difference from the sample average mean for all treatments. These results illustrate that treatments, 5, 6, 11 and 12 have all yielded calorie levels significantly above the average. These treatments are the no information treatments (5 and 11) and time pressure only treatments (6 and 12). Furthermore, we conducted a *t*-test for all pairs of mean differences in calories, and we found that many of the differences between these four treatments, and all others, are statistically significant (taking account of the multiple comparisons issue by employing the required Bonferroni correction – see Table A2 for details). These initial results indicate the provision of calorie information and a calorie counter have had the effect identified in hypotheses H_{1a} and H_{1b}. Also, for treatments in which respondents who were provided with calorie information and the calorie counter, as opposed to just calorie information, they did have lower average daily calorie levels in three out of four cases, providing support for hypothesis H_{1b}.

Respondents identified as having a food related health issue (treatments 13-20) have on average selected lower calorie amounts than the general sample providing support for hypotheses H_{2a} and H_{2b}. Interestingly, there is no obvious difference between the planned and the fill-in shop and the use of the calorie counter which suggests no support for hypotheses H_{3a} and H_{3b}.

Finally, turning to the treatments that involved time pressure with and without the calorie counter we again see evidence in three out of four cases of reduced calories for when the calorie counter is employed.

Overall, what our results suggest is that the calorie information has generally yielded the anticipated result for almost all relevant treatments. The results for the calorie counter indicate that the desired impact on calories selected is as we anticipate in most cases although the statistical strength of this result is weak. Interestingly there does appear to be a moderating effect from the introduction of time pressure which is what we would expect.

Our final piece of descriptive analysis is an examination of calorie selection by gender. We can examine if in fact males selected meal combinations yielding more calories than females relative to their RDA. These results are presented in Table 4:

INSERT TABLE 4 ABOUT HERE

What we observe in Table 4 is that females on average selected 2,632 calories more than the 10,000 they should have over the week. For men average over consumption is 559. What this implies is that although males selected meal combinations with more calories they selected combinations of meal types that yielded a smaller overall increase in calorie consumption compared to male RDA.

Multivariate statistical analysis of calorie consumption by treatment

We began our multivariate statistical analysis by examining the relationship between the treatments employing a linear regression specification using AvNC as our dependent variable and a set of dummy variables for the set of experimental treatments as the explanatory variables. Given that treatments 5 and 11 can be viewed as our control treatments we have excluded them from the model specification although the impact of the treatments is captured via the model constant. The resulting estimates can be interpreted as changes from the constant and these are reported in Table 5:

INSERT TABLE 5 ABOUT HERE

The results in Table 5 show that there is a statistically significant reduction in calories for the majority of treatments. The only exceptions are T6 and T12 which are not statistically significant. However, these are both time pressure treatments and as such the positive estimates are as anticipated a priori (i.e., Hypothesis H_{4a}). What we also observe is that the use of information in the form of the calorie counter does seem to yield a change in behaviour, as expected (i.e., lower calories chosen), and this difference is statistically significant. This in part may reflect the fact that the calorie counter was only introduced in addition to the individual food calorie information. However, comparing the model estimates by treatment pairs (i.e., CI vs CC&CI) there is no obvious direction of change in the model estimates which might be expected if the calorie counter had a large impact on respondent choice. This finding indicates that support for hypothesis H_{1b} may not be as significant as initially considered.

Next, we examine differences by type of treatment using six linear regression models. These results are reported in Table 6.

INSERT TABLE 6 ABOUT HERE

The first model in Table 6 (i.e., Model 1) reports the results when we regress AvNC for all treatments against a dummy variable indicating the absence or presence of the calorie information (i.e., 0 – no information; 1 – provided information). We can see that the estimate for the calorie information is negative and statistically significant which supports hypothesis

H_{1a}. A similar result is reported for Model 2 except this time we consider the calorie counter. This model does suggest there is statistical evidence to support hypothesis H_{1b}, but we need to be careful given how the calorie counter information was introduced into the experiment. Indeed, we note the magnitude of the reduction in calories is less in Model 2 compared to Model 1.

To assess the relative contribution of the calorie information and calorie counter, we next estimated Model 3 that includes both measures. With Model 3 we find that including both calorie information and calorie counter results in the calorie counter variable no longer being statistically significant. This indicates that the reduction in calories associated with the calorie counter is actually being driven by the simultaneous provision of product level calorie information. Thus, exposure to a calorie counter has not generated a significant reduction in calories and as such we should reject hypothesis H_{1b}.

Model 4 now includes the time pressure variable and again we find no statistical evidence to indicate that time pressure gave rise to a reduction in calories. We do find that placing respondents under time pressure gives rise to a small increase in calories that is statistically significant which we can take as evidence supporting hypothesis H_{4a}.

Next, we significantly increased the number of explanatory variables first including a dummy for the health treatments and socio-economic data (Model 5) and then including interactions between the treatments and the health treatment dummy in Model 6. The results that we report remain consistent in that the calorie information has a statistically significant and negative impact on calories, the calorie counter has no statistically significant effect and importantly time pressure is also no longer statistically significant. In both Models 5 and 6, we find that the health dummy has a strong negative impact on calories consumed. In addition, we now see that there is a statistically significant positive relationship between calories and gender. This implies is that males are choosing on average relatively more than females and this is to be expected as we have noted (see Table 4). In addition, in Model 5, participants who have children appear to consume more calories but being older and having a higher level of income is associated with lower levels of consumption. These results conform to those we would expect for these specific socio-economic variables. Finally, for Model 6, the calorie information and health treatment interaction is positive indicating that for those with a health treatment the impact of the calorie information is less than those who are not affected by health concerns. In addition, we also see that the interaction between the calorie counter and the health dummy is not statistically significant and again reinforces the finding that the counter has not had a strong impact on behaviour during the experiment.

Our final set of results present linear regression results for four models that examine the relationship between our latent variables and our experimental treatments. The models estimated are reported in Table 7:

INSERT TABLE 7 ABOUT HERE

The first model in Table 7 is labelled as Inertia and it reveals that the interaction between the treatments and a measure of inertia (or resistance) in adopting new technology (Inertia). These results confirm our previous findings about calorie information. Also, we find a statistically significant positive effect for time pressure and a negative effect when time pressure is interacted with the inertia latent variable. Thus, respondents in our sample who consider themselves to be slow at adopting or using technology do appear to consume slightly higher levels of calories.

Turning to the second model, labelled NutUse, a latent variable which is a self-reported measure of nutritional use (NutUse). In this case, we see a statistically significant effect for the calorie counter as well as for calorie information, albeit quite weak and small. It is maybe not that surprising that individuals who are more likely to be users of nutritional information will make use, even marginally, of a tool such as a calorie counter. As a result, what this finding suggests is that the calorie counter reinforces a positive behaviour among people who are most likely to use or need it. Thus, we see some support for hypothesis H_{1b}, but this is found to be conditional on a type of individual latent characteristic.

Next for our model HealthOr we consider whether a respondent is health orientated (HealthOr). In this case, we find that the main explanatory power comes from the calorie information and health treatments with little or no obvious effect for any other channels. Finally, for the model NutInt which examines nutritional interest (NuInt), we find similar results to the HealthOr model. However, there is also an interaction effect between calorie information and nutritional interest that is to be expected.

Summary of Results

Overall, the results we have presented show that respondents have reacted positively to calorie information by reducing the quantity of calories purchased. We have also observed a similar effect for our group of respondents with a health-related issue or concern. We have only found minimal statistical evidence to support the impact of the calorie counter on reducing calorie intake although the direction of change is as we would expect. We have found stronger support for hypothesis H_{1b} in terms of the latent variable results, especially for respondents who we have described as using nutritional information.

We have evidence in support of hypothesis H_{2a} and our descriptive results indicate some support for H_{2b}. However, we have found no evidence in support of hypothesis H_{3a} or H_{3b}. For hypothesis H_{4a}, we find evidence of time pressure increasing calorie intake and there is again evidence in the data to indicate that the calorie counter has moderated this affect, but the result is statistically insignificant. Thus, our results demonstrate the impact of information on food choice as well as time pressure; albeit the effect of numerical calorie information is relatively weak and associated with a specific segment of the population.

Discussion

This research contributes to the emerging literature on the use of digital technologies to promote behaviour change in consumer choices by showing how aggregated nutritional information can change consumer choice. It enriches existing literature which has begun to examine the impact of technology on health-related behaviours (e.g., Flaherty et al. 2017; Flaherty et al. 2021; Manika, Gregory-Smith and Antonetti 2017; Manika, Gregory-Smith and Papagiannidis 2017), and also shows how information processing models (Moorman 1990) can be applied in new contexts and augmented based on changes to technology. Overall, our results are partly in line with recent studies examining the impact of digital technologies in reducing consumer numeracy biases (e.g., Gustafson and Zeballos 2019) and are strongly consistent with the literature on nutrition labelling more generally (Cowburn and Stockley 2005; Grunert and Wills 2007; Grunert et al. 2010; Moorman 1990) as we find evidence that such information should be more relevant to consumers and that our results are partly contingent upon motivation to process nutritional information. We also find that our results are contingent on time pressure, an important consumer behaviour variable that influences choices.

Effect of the calorie counter

Our results suggest that the calorie counter can help with reducing calories chosen on a daily basis. Therefore, our results suggest that calorie counters can be part of the solution to consumers' inability to correctly estimate the total amount of calories as reported by Panzone et al. (2020). However, it is important to be aware of the diminishing returns to the provision of information as this may explain the lower impact of the counter when consumers also have access to product level calorie information. So, while such a tool cannot completely solve the numeracy burden, as pointed out by Rothman et al. (2006), that hinders the effectiveness of nutrition labels, it does suggest such aggregated nutritional information has in principle the potential to improve choices. While other researchers have looked at calorie counters (e.g., Panzone et al. 2020) for individual products, our research is the first to examine this concept for a basket of goods and is thus a more realistic shopping context covering a greater array of choices.

Since consumers find it difficult to map their actual consumption accurately against RDAs and this is likely to lead to underestimation of calorie consumption (Forwood et al. 2013) our finding that the calorie counter treatment yielded reductions in calories selected (when various latent variables were controlled for) is very promising; especially because it may contribute to significant weight reduction over time. To illustrate, we put our findings in a policy context and compare them with the expected reduction in calories from the UK's sugar tax introduced in April 2018 (Cornelsen and Smith, 2018). Based on estimated changes in demand for fizzy drinks by Briggs et al. (2013) the daily reduction in calories is estimated to be 5 calories for a 20 percent tax whereas we observe a 9 calories reduction per day that we observe for our experiment (compared to the calorie only treatment). The caveat with this result depends on adoption and adherence of such technologies and on branding, price promotions and other factors in the marketing context. However, as an initial finding in a lab-based context these results are interesting.

Benefits to consumers with diet related health conditions

Our second hypothesis has support, as we found a statistically significant reduction of calories for our sub-sample of consumers with an identified health condition who used the calorie counter and calorie information. This result is largely consistent with findings in the literature as this group of respondents are more likely to take notice of diet related issues. However, some have found less support for this (Mulders, Corneille and Klein 2018) and it is the first time it has been tested in relation to a calorie counter and calorie information. Perhaps what is most interesting and promising from this finding is that such aggregation of nutritional information may be most helpful to those who need it most. So, interestingly, we find further support for the conjecture that nutrition information is most likely to be used by those with a strong motivation to process it (Cowburn and Stockley, 2005; Grunert and Wills, 2007; Grunert et al., 2010). Therefore, highly involved consumers may be more likely to use and benefit from such a counter as revealed by our analysis of latent factors.

Shopping trip and time pressure effects

We found little support for our third hypothesis which looked at the impact of shopping trip length on calories chosen in the basket. From the results presented here there was no difference in the amount of average normalised calories consumers put in the basket based on the length of their shopping trip (i.e., planned versus fill-in shop). While we may have expected this to be the case based on the theoretical justification it seems that there was no difference. This could be a function of the difficulty of estimating calories in a basket regardless of how many products are in there. For example, it seems likely that even for a small number of products in the basket, estimating the healthfulness of this combination of products may simply be too cognitively demanding for consumers. Therefore, according to our results it seems as if the calorie counter is useful regardless of the length of the shopping trip and we speculate that this may be because its utility begins with just a small number of products.

In contrast, we do find support for our fourth hypothesis about time pressure which illustrates that increased time pressure reduces the impact of the calorie counter and calorie information. This is clear in the results for treatments 6 and 12 where consumers under time pressure had higher total calories in their baskets. However, the effect of time pressure is somewhat reduced when we consider other latent variables and interactions (see tables 6 and 7). What our results seem to suggest is that while time pressure does lead to more intuitive choices where heuristics may be used, which (in our case) translate into higher amounts of calories being chosen, other factors may help moderate the effect of time pressure. Particularly both socio-demographic characteristics and, to a higher degree, latent variables such as nutritional orientation, use of labels and attitudes to nutrition and health reduce the effect of time pressure.

Theoretical Implications

While we did not explicitly test Moorman's (1990) information processing model, we used it as a theoretical framework to guide the development of our hypotheses. Moorman's model was developed before technology existed to aggregate nutritional information, so is based on the premise that individuals are able to pick up individual products and process the nutritional information on them and aggregate it accurately. There is much evidence to show that this is a cognitively burdensome and difficult task for most consumers so information processing models have been used less frequently in the literature. However, our results are consistent with an updated version of the model by showing that stimulus characteristics (i.e., calorie counters) and consumer characteristics (i.e., an existing food related health condition) affect decision quality in the form of number of calories chosen on a simulated shopping trip. By using it as a theoretical framework to guide the development of the hypotheses, we also show how technology can be used to provide more relevant information to consumers. We therefore enrich Moorman's initial model by showing that situational characteristics ought to be included in such information processing models (particularly time pressure) to add explanatory power.

Theoretically, our results are consistent with other work in marketing and suggest the need to integrate theory around information processing and consumer use of health technologies. For example, in a shopping context, van Ittersum et al. (2010) experimentally tested how well consumers can keep a tally of the total cost of a food shopping trip and relate it to a budget. They found that most participants could not give an accurate estimate of the total value of products in their baskets. If consumers find it challenging to add up prices of products to meet a given weekly or monthly shopping budget they should find it, at least as difficult to aggregate (sum) nutrition information, analogous to the findings here, because nutrition information has multiple dimensions and different daily recommended intake targets for different nutrients. This may explain why consumers revert to other simpler shopping cues – e.g., the health halo effect. When consumers lack numeracy skills and the ability to interpret numbers, they may resort to text cues to infer whether a given percentage of a nutrient is suitable. The health halo effect has been attributed to consumers' awareness and understanding of nutrition information as well as to their ability to use and act on that information (Visschers et al. 2013). In practice the health halo effect is associated with the ability to accurately learn and assess the true nutritional value of a food or set of foods. A device that can assist in providing aggregated information may be able to reduce the impact of such health halo effects by providing a more accurate estimation of the nutritional value of the food consumed. Likewise, the literature on nutrition labels finds consumers focus only on a subset of information on a label and overlook other types of information (Graham, Orquin and Visschers 2012; Pham, Morrin and Bublitz, 2019). This might be because most food choices are made using our reflexive, fast thinking processes (Kahneman, 2012; Vecchio and Cavallo 2019). For example, consumers may look at the sugar and fat content and dismiss the amount of salt in the food or meal they choose as these nutrients may signal better taste. This was found in a recent study that combined an analysis of preferences for alternative nutrition labels with a choice of products after a taste (Lima et al 2019). Therefore, there is a need to develop new theory which integrates existing nutrition information processing models (i.e., see Moorman 1990) with literature in the health technology area to provide consumers with a better opportunity to process the voluminous amount of information they are exposed to.

Public Policy and Managerial Implications

The results observed here suggest that aggregated nutritional information, provided through a digital calorie counter app as well as product level calorie information, can be an effective way to enable informed consumer choice, particularly for consumers who are more motivated to process nutritional information. Here we provide initial experimental evidence of the concept that aggregated calorie information can in principle allow consumers to make healthier choices in terms of the food items, and therefore calories they put in their baskets. However, such calorie counters need to be accessible and effective in most aspects of our lives (e.g., eating at home and eating out). This implies that such a calorie counter should be developed so it can be trialled in the field and its effectiveness assessed in normal day-to-day situations. However, the potential existence of different calorie counters by different retailers, for example, are unlikely to be effective as they may not unify the diverse food consumption situations that we find ourselves in. Indeed, food consumption is heterogenous and so pervasive to our daily lives. Therefore, it is unclear if significant public health benefits will emerge if the provision of this information is left to the private sector. A corollary of this is that the development of such a calorie counter should occur at a national level and as part of a government's national food and allied health strategy. A unified public policy approach seems needed. Such a calorie counter should have flexibility to provide nutritional information in different formats so it can be customised based on individual consumer needs (e.g., salt intake as opposed to calories, for example). While retailers may not be best placed to develop such an app they are an important part of the picture, as are restaurant chains, because information from their food products needs to be compatible with such an app. Involvement in such an initiative would be consistent with many retailers' CSR objectives as well as their ongoing efforts to meet the ever-growing demands of specific sub-sets of the population (i.e., glutton intolerance).

As illustrated by our results, providing aggregated information about individual food choice items can lead to healthier food choices in aggregate. Also, consistent with existing literature on nutritional labels this type of information is more likely to be meaningful for segments of the population with a pre-existing food health related condition. Therefore, efforts would need to be made to promote the app among segments of the population with a pre-existing reason to change their food consumption behaviours (e.g., people with existing health conditions). This is an actionable way to identify the people who would need and use the technology most.

Perhaps what is most striking about the results here is that they imply a more targeted approach to the provision of health-related information, enabled by technological advances and the pervasiveness of smart phones. This contrasts with existing food policy approaches, which seem to favour a mass communications approach to information provision where all consumers are largely exposed to some form of standardised information for individual products. Though this may be for historical reasons, the technology environment has now changed significantly, and technology can enable mass customisation of information to those who need it most (i.e., those with food related health conditions as in our sample). Andrews, Netemeyer and Burton (2009) argue that the key to successful nutrition information campaigns is segmentation based on the diverse needs and wants of consumers, which is largely in contrast to existing mass communication campaigns. Such information can be provided to consumers in customisable forms, enabled by technology, in a way that suits them most. For example, one consumer may be less concerned about calories consumed and more concerned about salt content. Another consumer may be more concerned about sugar or allergen information. Nonetheless, such information should ultimately be available in some kind of aggregated form, to enable better information processing consistent with our diets as a whole. In short, future food related health strategies should more closely take account of the role of technology in providing appropriate nutritional information about the foods we consume and offering it to consumers in more relevant formats (i.e., aggregated information around diets rather than individual products).

Limitations and Future Research

The experimental method offers a number of advantages over other research methods when assessing proof of concept; particularly when the focus is on internal validity as with this research. However, external validity is limited to the stimuli, conditions of the experiment and the sample used. As always, future research should examine the findings under different conditions and with different samples to enhance generalisability.

We acknowledge our results need to be tempered with the fact that we prompted the participants in our experiment to consider the British National Health Service daily calorie recommendations. Also, the fact that we tasked participants to buy for two adults rather than only themselves, which for some may not have been a natural situation. Likewise, the reliance on text descriptions of the products we proposed, and absence of both price and label information may also have impacted the results. Finally, the fact that we asked the participants to choose between a limited set of options and only across ready meals may have overly constrained their decisions and may not have represented a natural shopping context for them.

However, all these decisions were made to introduce consistency into the experimental task that respondents had to complete and try to minimise the possibility of extraneous influence from other factors such as personal situation, influence from marketing variables (in particular branding and price) and differences in product choice.

We also need to point out the possibility of a testing effect such that respondents knew this was an experiment and that it affected the answers they gave. For example, by seeing the calorie counter they may have guessed what the purpose of the experiment was and adjusted their choices accordingly. While this may have been an issue, we do not believe it was a serious one. First, all respondents read an introductory statement at the start of the questionnaire reassuring them that there were no right or wrong answers and that we were only interested in the choices they made and their opinions. Second, in one of the questionnaire's catch all questions at the end, we looked for evidence that respondents may have guessed the purpose of the experiment and gamed their choices accordingly and could not find any evidence in these qualitative comments. Third, if such an effect did exist, we had a big enough sample size for each experimental group (minimum 31) such that those effects would be randomised across treatments. Fourth, if such an effect did occur then it would mean that we are being conservative in interpreting the outcome and that in reality the effect could be bigger than what we observed here.

A key goal of future research would, therefore, be to assess how calorie counters work in more natural situations, through for example, a field experiment where individuals keep track of calorie information through a mobile app on a phone. As smart phones are pervasive then they would be an ideal environment in which to test such a calorie counter in more natural situations. Future research could investigate different ways to convey aggregate information in repeated meal choices and might provide more substantial evidence for the effectiveness of aggregated nutritional information in improving diets. It is now well established that the way information is framed has an impact on how a consumer responds. Therefore, we would conjecture that nutrition information does not need to be as detailed as required by a health professional but, at the same time, it does need to address the specific requirements of an individual. This is not necessarily being achieved by the current forms of public health nutrition information, which reflect a mass communications approach rather than one which is more targeted and relevant to individual consumers. This trade-off between too much and too little information may also help to ensure that the adoption of such an app is not simply a novelty effect that fades over time.

The type of digital technology suggested could not only track food purchased for home consumption but also food consumed away from the home. A recent example of the benefits of calories counters in food service contexts is the research by Gustafson and Zeballos (2019). But the counter has to have the ability to transcend various food consumption contexts in the home and outside of the home. Such digital technology could be adapted to help consumers make healthier food choices in food service venues that take account of the wider aspects of their diet. There is good reason to assume that efforts to address issues of healthy food choice and consumption need to be holistic and take account of all contexts throughout the day and the week.

Finally, calories as a form of nutritional information for healthy eating have been critiqued in the literature. However, they remain a widely understood and uniform way of providing nutritional information for consumers, and we use them here as the focal construct for this reason. We would expect the results here would apply to other forms of nutritional information (e.g., fats, sugars, salt) – contingent on those consumers exposed to this information having a basic understanding of it – as we are primarily testing how consumers process aggregated numerical information. Thus, while we use calories here as the nutrition information which consumers were exposed to, such an app could conceivably provide different forms of aggregated nutritional information targeted at consumers with a variety of healthy eating objectives. Nonetheless further research should confirm these findings using different types of nutritional information.

Conclusion

This research aimed to understand how aggregated nutritional information facilitates consumer shopping decisions through mitigating numeracy bias. Specifically, we aimed to find whether a calorie counter could mitigate numeracy issues in a nutrition information processing task. While our results suggest that a calorie counter can help consumers to reduce the calories they put in their basket, this main effect was strengthened by considering a number of other moderating conditions reflecting motivation, product specific calorie information, and time pressure, following and also building on Moorman's conceptualisation of nutrition information processing. Therefore, these findings provide some support for the proposition that providing consumers with aggregated nutritional information helps them to overcome numeracy biases and make better food choice decisions (comparable to other policy measures such as the UK's food tax). This is particularly the case when consumers are motivated to do so (i.e., when they or a family member have an underlying health condition). However, further testing of this proposition is needed under field conditions and with different technologies because there is good reason to believe that efforts to address issues of healthy food choice and consumption need to be holistic and take account of all contexts throughout the day and the week.

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Figure 1: Moorman's nutrition information utilization process

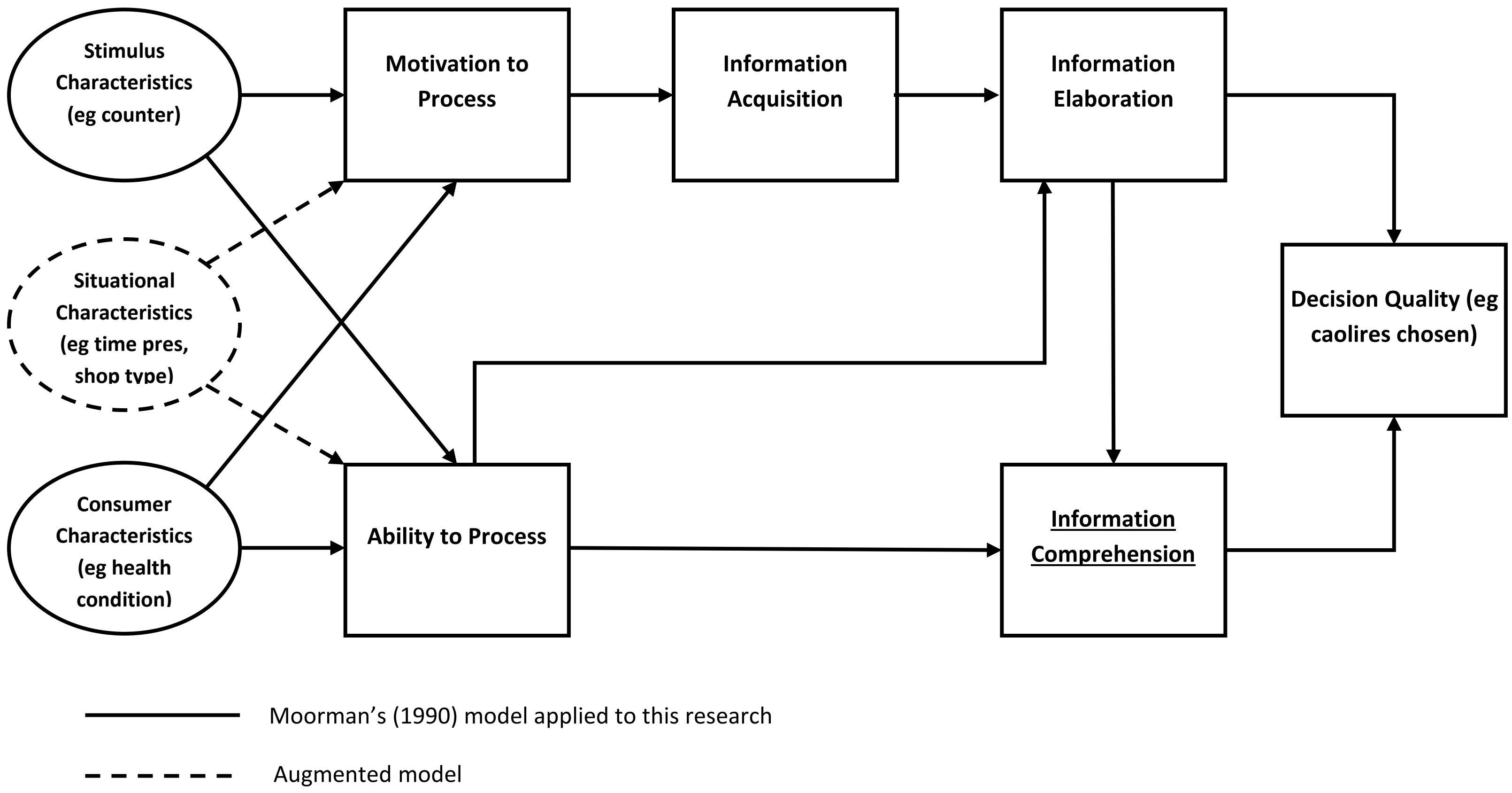

Figure 2: Illustration of the calorie counter used in the experiment

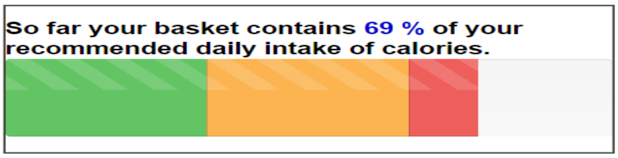

Table 1: Summary of Experimental Design and Treatments

Treatment (Label)	Calorie Counter (CC)	Time Pressure (TP)	Calorie Information (CI)	Days	Sample Type
1 (CC;CI)	Yes	No	Yes	5	General Population
2 (CI)	No	No	Yes	5	General Population
3 (CC;TP;CI)	Yes	Yes	Yes	5	General Population
4 (TP;CI)	No	Yes	Yes	5	General Population
5	No	No	No	5	General Population
6 (TP)	No	Yes	No	5	General Population
7 (CC;CI)	Yes	No	Yes	3	General Population
8 (CI)	No	No	Yes	3	General Population
9 (CC;TP;CI)	Yes	Yes	Yes	3	General Population
10 (TP;CI)	No	Yes	Yes	3	General Population
11	No	No	No	3	General Population
12 (TP)	No	Yes	No	3	General Population
13 (CC;CI)	Yes	No	Yes	5	Health Condition
14 (CI)	No	No	Yes	5	Health Condition
15 (CC;TP;CI)	Yes	Yes	Yes	5	Health Condition
16 (TP;CI)	No	Yes	Yes	5	Health Condition
17 (CC;CI)	Yes	No	Yes	3	Health Condition
18 (CI)	No	No	Yes	3	Health Condition
19 (CC;TP;CI)	Yes	Yes	Yes	3	Health Condition
20 (TP;CI)	No	Yes	Yes	3	Health Condition

Table 2: Key Variables and Definitions

Variable Name	Definition and Measurement
Treatment Variables	
Treat (Ti)	Treatment i=1,…,20
Counter	If counter available equal 1, zero otherwise
CalInfo	Calorie information given equal 1, zero otherwise
TimeP	Time pressure equal 1, zero otherwise
Health	Health equal 1 for treatments 13,…,20, zero otherwise
Outcome Variables	
Calories Per Day	Average total calories from selected meals per day
AvNC	Average Normalised Calories are the relative percentage of calories consumed per day given total calories available per day (0-100)
Perception and Latent Variables*	
Inertia	Technological Inertia
Nuint	Nutritional interest
NutUse	Nutritional usage
HealthOr	Health orientation
Socio-Economic Characteristics	
Gender	Female = 0; Male = 1
Age	18-25 =0; 26-35 =1; 36-45=2; 46-55=3; 56-65=4; 66-75=5; 76(over) =6
Education	Primary=0; Secondary =1; A-level=2; Under Grad=3; Post Gard =4
People	Number of people in household
Children	No children in house=0; Children in house=1
Job	No job=0; Job=1
Income	Monthly Income (£) before tax - Under 500=0; 501-1500=1; 1501-2500=2; 2501-3500=3; 3501-4500=4; over 4500=5

*Note: All perception questions employed a 7 point Likert scale Strongly Disagree (1); Disagree (2); Somewhat Disagree (3); Neither Agree nor Disagree (4); Somewhat Agree (5); Agree (6); and Strongly Agree (7)

Table 3: Key Descriptive Statistics by Treatment

Treatment	Sample Size	Calories Per Day	Mean Difference	AvNC
1 (CC;CI)	39	2596	56	36.1
2 (CI)	39	2502	-37	32.0
3 (CC;TP;CI)	40	2417	-122	28.6
4 (TP;CI)	40	2568	29	35.0
5	42	2801	261	45.8
6 (TP)	41	2782	243	45.1
7 (CC;CI)	41	2450	-90	30.2
8 (CI)	42	2489	-51	31.6
9 (CC;TP;CI)	37	2548	8	35.2
10 (TP;CI)	40	2559	19	36.7
11	44	2742	203	44.0
12 (TP)	41	2720	181	46.8
13 (CC;CI)	31	2435	-104	29.3
14 (CI)	32	2420	-120	28.9
15 (CC;TP;CI)	33	2492	-48	31.9
16 (TP;CI)	33	2534	-5	34.0
17 (CC;CI)	31	2368	-172	27.0
18 (CI)	32	2499	-40	32.6
19 (CC;TP;CI)	31	2355	-185	26.6
20 (TP;CI)	33	2515	-25	34.5
Av	37.05	2540	0	34.6
St Dev	4.50	131	131	6.3
Min	31	2355	-185	26.6
Max	44	2801	261	46.8

Notes: Mean Difference = Calories per Day (by Treatment) – Average;
CC – Calorie Counter; CI – Calorie Information;
TP – Time Pressure; AvNC – Average Normalised Calories (0-100).

Table 4: Average Daily Calorie Choice by Gender

	Day 1	Day 2	Day 3	Day 4	Day 5	Total
Female	2286.5	2505.5	2730.4	2661.7	2448.1	12632.2
Male	2378.1	2595.0	2888.0	2763.6	2434.3	13059.1
Amount Above RDA						
Female (RDA 2000)	286.5	505.5	730.4	661.7	448.1	2632.2
Male (RDA 2500)	-121.9	95.0	388.0	263.6	-65.7	559.1

Table 5: Regression of AvNC on Treatment Dummies

AvNC	Coefficient	SE	T Stat	P Value
Constant|	43.58***	1.50	28.97	0.00
T1	-5.22*	2.72	-1.92	0.06
T2	-11.59***	2.77	-4.19	0.00
T3	-14.93***	2.74	-5.44	0.00
T4	-8.59***	2.74	-3.13	0.00
T6	1.57	2.72	0.58	0.57
T7	-13.36***	2.72	-4.91	0.00
T8	-12.01***	2.68	-4.49	0.00
T9	-8.35***	2.82	-2.96	0.00
T10	-6.89**	2.74	-2.51	0.01
T12	3.19	2.72	1.17	0.24
T13	-14.27***	3.01	-4.74	0.00
T14	-14.65***	2.97	-4.92	0.00
T15	-11.66***	2.94	-3.96	0.00
T16	-9.62***	2.94	-3.27	0.00
T17	-16.62***	3.01	-5.52	0.00
T18	-11.02***	2.97	-3.70	0.00
T19	-16.98***	3.01	-5.64	0.00
T20	-5.63**	2.53	-2.22	0.03
R^2	0.15			
F Test	7.19***			0.00
n	742			

Note: *10%, **5%, ***1% Statistical Significance

Table 6: Regression Results for AvNC on Treatments and Socio-Economic Characteristics

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
AvNC	**Coeff**	**SE**	**Coeffs**	**SE**	**Coeffs**	**SE**	**Coeffs**	**SE**	**Coeffs**	**SE**	**Coeffs**	**SE**
Intercept	41.35***	0.98	36.97***	0.69	41.35***	0.98	40.09***	1.13	43.58***	1.78	46.5***	1.89
Counter			-5.66***	1.19	-1.73	1.35	-1.41	1.35	-1.61	1.32	-1.46	1.72
CalInfo	-9.15***	1.19			-8.30***	1.33	-8.14***	1.33	-7.68***	1.34	-11.89***	1.70
TimeP							2.54**	1.13	1.78	1.14	1.46	1.41
Health									-4.71***	1.13	-13.81***	2.34
Gender									2.99**	1.18	2.92**	1.17
Age									-0.09	0.33	0.04	0.33
Education									0.12	0.33	-0.02	0.33
People									-0.01	0.01	-0.003	0.01
Children									1.16**	0.55	1.14**	0.54
Job									-0.24	0.18	-0.26	0.17
Income									-0.93**	0.47	-0.88	0.47
CI*Health											11.21***	2.71
CC*Health											0.56	2.67
TP*Health											3.23	2.43
R^2	0.07		0.03		0.08		0.08		0.12		0.15	
F Test	59.45***		22.56***		30.61***		22.19***		9.05***		8.88***	
n	742		742		742		742		742		742	

Note: *10%, **5%, ***1% Statistical Significance

Table 7: Regression Results for AvNC Regressed Against Treatments and Latent Variables

	Model Inertia		**Model NutUse**		**Model HealthOr**		**Model NuInt**	
AvNC	**Coeff**	**SE**	**Coeff**	**SE**	**Coeff**	**SE**	**Coeff**	**SE**
Constant	45.00***	0.00	45.19***	0.00	45.25***	0.00	45.23***	0.00
Counter	2.16	0.46	-5.03*	0.08	-4.85	0.13	-4.26	0.16
CalInfo	-19.23***	0.00	-7.81**	0.01	-7.47**	0.03	-6.85**	0.03
TimeP	5.17**	0.03	0.83	0.72	0.22	0.93	-0.88	0.71
Health	-13.59***	0.00	-13.77***	0.00	-13.91***	0.00	-13.85***	0.00
CC*Inertia	-0.93	0.14						
CI*Inertia	1.85***	0.00						
TP*Inertia	-0.92*	0.06						
CC*NutUse			0.98	0.11				
CI*NutUse			-1.16*	0.8				
TP*NutUse			0.18	0.71				
CC*HealthOr					0.88	0.18		
CI*HealthOr					-1.17	0.10		
TP*HealthOr					0.29	0.58		
CC*NuInt							0.71	0.22
CI*NuInt							-1.29**	0.04
TP*NuInt							0.58	0.20
CI*Health	11.63***	0.00	11.41***	0.00	11.52***	0.00	11.77***	0.00
CC*Health	0.11	0.96	0.45	0.86	0.41	0.87	0.21	0.93
TP*Health	2.33	0.35	2.46	0.31	2.69	0.27	2.31	0.34
R^2	0.14		0.14		0.13		0.13	
F Test	12.02***		11.49***		11.42***		11.62***	

Note: *10%, **5%, ***1% Statistical Significance

Appendix A – Survey Flow and Procedure

1. Screening questions
2. Questionnaire introductory statement (i.e., welcome statement, task explanation, ethics statement and consent procedure)
3. Subjects exposed to scenario (i.e., explanation of the scenario, reminder about GDAs, and calorie counter – if relevant)
4. Sample task (i.e., subjects given a sample choice task and asked to make choices about meal combinations)
5. Subjects exposed to experimental treatments
6. Covariates and personal questions (e.g., demographics, psychological characteristics)

END

Sample choice task:

Before we start, here is an example of the task you will perform. You have three parts of a meal, please chose among these options for two adults.

Please select a product:
O Beef lasagne (1212 calories)
O Spaghetti Bolognese (1334 calories)
O Cheese and ham ravioli (1060 calories)

Please select a product:
O Spinach and rocket salad leaves (63 calories)
O Baby leaf and rocket salad (88 calories)
O Iceberg lettuce salad (33 calories)

Please select a product:
O Orange juice (210 calories)
O Pineapple juice (250 calories)
O Grape juice (315 calories)

Appendix B - Table 1A: Descriptive Statistics by Treatment

Treat	Gender	Age	Edu	People	Children	Income	Inertia	NuInt	NuUse	HealthOr
1	0.42	2.29	2.29	2.03	0.39	1.82	4.18	4.33	3.82	4.26
2	0.36	2.67	2.08	1.49	0.26	1.33	4.32	3.94	3.63	4.22
3	0.35	2.80	2.30	1.63	0.25	1.40	4.03	4.38	4.01	3.97
4	0.33	2.28	2.35	1.88	0.33	1.68	3.94	4.52	4.11	4.32
5	0.40	2.36	2.33	1.95	0.45	1.43	3.67	4.63	4.17	4.23
6	0.34	2.56	1.83	1.46	0.24	1.37	4.11	4.46	3.87	4.07
7	0.37	2.41	2.49	1.85	0.32	1.56	4.06	4.29	3.91	4.07
8	0.30	2.37	2.28	1.84	0.26	1.28	3.78	4.55	3.90	4.14
9	0.38	2.32	2.35	1.76	0.35	1.35	4.38	4.12	3.92	4.09
10	0.28	2.43	2.25	1.90	0.30	1.45	3.41	4.90	4.45	4.34
11	0.32	2.32	2.20	1.55	0.20	1.41	3.93	4.59	3.91	4.41
12	0.41	2.34	2.39	2.15	0.41	1.68	3.92	4.50	3.88	4.38
13	0.42	3.40	2.17	1.73	0.24	1.62	3.94	4.75	4.03	4.23
14	0.44	3.65	2.26	1.17	0.23	1.77	3.28	4.52	4.19	4.43
15	0.24	3.33	2.27	1.61	0.28	1.53	4.19	4.70	4.38	4.29
16	0.52	3.42	2.21	1.30	0.15	1.55	4.16	4.27	3.61	3.95
17	0.45	3.42	2.26	1.32	0.26	1.42	4.06	4.79	4.28	4.75
18	0.47	3.38	1.75	1.41	0.22	1.47	3.74	4.64	3.88	4.05
19	0.52	3.48	2.42	1.45	0.23	1.35	4.13	4.34	4.01	4.09
20	0.36	3.45	2.42	1.91	0.42	2.12	3.83	4.53	4.15	4.56
Av	0.38	2.83	2.25	1.67	0.29	1.53	3.95	4.49	4.01	4.24
StDv	0.07	0.53	0.18	0.27	0.08	0.21	0.28	0.23	0.22	0.20
Min	0.24	2.28	1.75	1.17	0.15	1.28	3.28	3.94	3.61	3.95
Max	0.52	3.65	2.49	2.15	0.45	2.12	4.38	4.90	4.45	4.75

Appendix C - Table 1B: Paired *t*-tests for all Treatments

Treatments	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	1.217	2.155	0.319	-3.124	-2.795	1.699	1.252	0.260	-0.153	-2.427	-3.523	1.921	2.018	1.100	0.569	2.847	1.015	2.563	0.446
2		1.019	-0.874	**-4.820**	**-4.377**	0.538	0.122	-0.985	-1.403	-3.964	**-5.306**	0.797	0.905	0.019	-0.538	-0.654	-0.170	1.524	-0.743
3			-1.812	**-5.827**	**-5.356**	-0.470	-0.826	-1.959	-2.353	**-4.943**	**-6.322**	-0.194	-0.081	-0.879	-1.428	0.549	0.498	0.570	-1.688
4				-3.472	-3.132	1.360	0.931	-0.070	-0.476	-2.764	-3.875	1.588	1.686	0.795	0.267	2.472	0.684	0.649	0.126
5					0.245	**5.280**	**4.516**	3.571	3.016	0.657	-0.411	**5.434**	**5.517**	**4.127**	3.525	**7.132**	**4.402**	**5.942**	**6.197**
6						**4.834**	**4.140**	3.203	2.683	0.393	-0.636	**5.000**	**5.084**	3.797	3.216	**6.509**	4.007	**5.525**	3.287
7							-0.379	-1.488	-1.889	**-4.428**	**-5.759**	0.265	0.375	-0.455	-1.003	1.057	-0.685	1.005	-1.234
8								-1.035	-1.424	-3.767	**-4.937**	0.624	0.727	-0.091	-0.616	1.403	-0.277	1.316	-0.810
9									-0.424	-2.815	-4.003	1.721	1.821	0.887	0.342	2.669	0.783	2.389	0.201
10										-2.307	-3.424	2.110	2.207	1.260	0.722	3.079	1.189	2.752	0.607
11											-1.056	**4.603**	**4.690**	3.450	2.873	**6.034**	3.617	**5.149**	2.915
12												**5.900**	**5.979**	**4.506**	3.892	**7.750**	**4.847**	**6.380**	4.044
13													0.109	-0.687	-1.226	0.743	-0.932	0.739	-1.465
14														-0.785	-1.320	0.617	-1.036	0.631	-1.564
15															-0.502	1.423	-0.169	1.347	-0.679
16																2.010	0.371	1.864	-0.149
17																	-1.780	0.107	-2.342
18																		1.631	-0.558
19																			-2.126

Notes: Using Bonferroni correction the associated critical value for 30 degrees of freedom is 4.11. All values in bold indicate statistically significant differences.