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Cognitive aids and food choice: Real-time calorie counters reduce calories ordered and correct biases in calorie estimates

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A R T I C L E I N F O

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A B S T R A C T

Studies of the effect of calorie information on food choices in food-away-from-home settings have identified minor to insignificant changes in calories ordered. An element of the choice process that may play an important role in influencing the total caloric content of a meal has received little attention: how individuals track the total number of calories selected when choosing multiple items. We study the effects of automating this potentially costly cognitive process using technology. We compare the number of calories ordered in a sequential food choice task in two conditions: one in which participants have access to calorie information for all options available and a second in which they are also exposed to automatically updating information about the number of calories they have ordered. Participants with access to calorie summation ordered significantly fewer calories than those without access to calorie summation. Participants without access to calorie summation significantly underestimated the number of calories they had ordered, while those in the calorie summation condition did not. The calorie summation seems to work in part through adjustment of sequential choices: calories ordered in the first choice category were very similar in the two conditions but diverged increasingly in later categories. Technologies that help individuals keep track of the nutritional consequences of cumulative choices may help promote healthier diets.

1. Introduction

Obesity rates have steadily risen in the US population in recent decades (Hales, Fryar, Carroll, Freedman, & Ogden, 2018). Obesity has been tied to a host of negative outcomes, including poorer health; higher risks of non-communicable diseases, such as type-2 diabetes, various cancers, and heart disease; lower wages (Cawley, 2004); and a decreased life expectancy (Preston, Vierboom, & Stokes, 2018). Obesity is also costly. There are direct costs borne by the individual, such as higher healthcare expenses, and indirect economic costs, such as higher rates of absenteeism (Cawley, 2015). Obesity has additionally been found to diminish individuals' quality of life through various pathways, including experiences of social stigma, lower self-esteem, depression, and decreased physical function, though this varies by gender, ethnicity, and other individual characteristics (Wee, Davis, Chiodi, Huskey, & Hamel, 2015).

Overconsumption of highly processed, energy-dense foods has been identified as a significant behavioral contributor to obesity (along with insufficient physical activity). High consumption of these processed, energy-dense foods also tends to crowd out foods with important nutrients, which contributes to a positive association between micronutrient deficiencies and obesity (García, Long, & Rosado, 2009).

To combat the obesity epidemic and dietary risk factors, a common policy response in the US has been to increase the amount of nutrition information that consumers have access to. With access to information about the nutritional attributes of foods, consumers can identify which foods are healthy, helping them improve the quality of their diet. In the early 1990s, the Nutrition Labeling and Education Act (NLEA) required nutrition facts panels to be provided on most packaged food products (1990, 21 U.S.C. 301). Recently, requirements for the provision of nutrition information has been extended to food-away-from-home (FAFH) settings. Introduced as part of the Affordable Care Act (ACA) (Section 4205 [March 2010]), these new requirements affect restaurants and other retail outlets selling prepared foods that have 20 or more locations (Center for Science in the Public Interest, 2014). After repeated delays, the rule, which requires that food retailers post calorie amounts and provide information about other nutrients upon request, was implemented on May 7, 2018.

While the ACA restaurant nutrition labeling rule has only recently been implemented, a number of local governments in places across the

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US, including New York City and Kings County, Washington, adopted similar labeling rules years earlier. Data from early adopters let researchers study the effectiveness of calorie labeling in FAFH settings. While some studies find small, significant reductions in calories ordered (Bassett et al., 2008; Bollinger, Leslie, & Sorensen, 2011; Ellison, Lusk, & Davis, 2013; Wisdom, Downs, & Loewenstein, 2010), others find no change (Cantor, Torres, Abrams, & Elbel, 2015; Elbel, Kersh, Brescoll, & Dixon, 2009; Finkelstein, Strombotne, Chan, & Krieger, 2011; Tandon et al., 2011). Meta-analyses of calorie labeling in FAFH settings do not provide clear, consistent evidence that calorie labeling affects diners' food choices (Bleich et al., 2017; Cantu-Jungles, McCormack, Slaven, Slebodnik, & Eicher-Miller, 2017; Kiszko, Martinez, Abrams, & Elbel, 2014; Littlewood, Lourenço, Iversen, & Hansen, 2016; Long, Tobias, Cradock, Batchelder, & Gortmaker, 2015; Sinclair, Cooper, & Mansfield, 2014; VanEpps, Roberto, Park, Economos, & Bleich, 2016).

Recent studies on food choice suggest that information about health can be effective in changing behavior if the information is delivered in a way that makes the health trade-off more salient—by framing information to draw attention to trade-offs (Downs, Wisdom, & Loewenstein, 2015), prompting people to explicitly consider their health (Hare, Malmaud, & Rangel, 2011), or through the use of behavioral economic nudges (Wisdom et al., 2010). Studies examining these factors find larger effects on individuals' choice of food items. Highlighting key nutrients or providing a ranked nutritional score has been found to promote healthier choices (Cawley et al., 2015; Fernandes et al., 2016; Kiesel & Villas-Boas, 2013; Zhu, Lopez, & Liu, 2016) particularly if the decision-maker faces time or attentional constraints while making their food choices (Crosetto, Muller, & Ruffieux, 2016). Data from a recent natural experiment comparing per-ingredient and per-item calorie labeling show that providing per-ingredient calorie information, which highlights trade-offs at a more fine-grained level than traditional per-item calorie labeling, results in significant decreases in calories ordered, while per-item calorie labeling does not (Gustafson & Zeballos, 2018).

Interventions that make the choice of healthier items easier have also been promising. Making the healthier option slightly more convenient reduces the number of calories ordered (Cantor et al., 2015). Inviting customers in a fast-food restaurant to reduce their portion size in order to decrease the number of calories they consume leads to a significant drop in the number of calories ordered among customers who accept the offer, though at most one-third of customers who were approached as part of the study agreed to downsize their portion size (Schwartz, Riis, Elbel, & Ariely, 2012). Similar to the ingredient-specific calorie information (Gustafson & Zeballos, 2018), using heuristic-based labels, such as traffic lights or letter grades, and purposefully organizing calorie information to facilitate easy comparison among food items (Downs et al., 2015) also reduces the total number of calories ordered. These findings—that making it easier for consumers to identify trade-offs in calories leads to reductions in calories ordered—are particularly important for policies attempting to use information to promote lower-calorie choices given cognitive capacity limitations that may constrain the processing of complex information (Marois & Ivanoff, 2005).

In many FAFH settings, individuals order multiple food and beverage items, each of which contributes to the overall calorie content of the meal. This includes restaurants in which individuals order a main item, a side, a drink, and possibly a dessert. Perhaps even more explicitly this applies to settings in which individuals choose the ingredients of their main food item (in addition to sides, drink, and dessert). Examples of foods that are sold at restaurants in this manner include sandwiches, burritos, rice bowls, and pizzas. In both cases, calorie information at the per-item (or per-ingredient) level will jointly play a role in influencing choices.

Because these decisions jointly determine the total caloric content of the meal, understanding how consumers make choices in a multi-choice environment is important. A key difference in this environment is that consumers must keep track of the total calories ordered if they are to account for the caloric content of the entire meal, which is a more complex task than responding to a single piece of information—that is, the number of calories that one food item contains. Even when per-item calorie information is available, customers must correctly add up the number of calories contributed from each item while making subsequent selections if they are to accurately account for their caloric intake, which may increase the likelihood that individuals' use of calorie information in the decision-making process will be affected by heuristics, biases, or simple mathematical errors. Recent research has documented a tendency to underestimate consumption of nutritional attributes like calories (Block et al., 2013) and sodium (Moran, Ramirez, & Block, 2017) in meals purchased in restaurants. Other studies have found that other factors—like eating in unconventional or irregular circumstances, such as on an airplane—can lead individuals to ignore or discount the effect of calories consumed (O'Brien, Kahn, Zenko, Fernandez, & Ariely, 2018; Sussman, Alter, & Paley, 2016).

The rise in online and app-based ordering presents new opportunities to potentially influence the total number of calories that an individual consumes through websites or apps that feature built-in calorie (or other nutrient) tracking and summation capabilities. Some restaurants, such as HuHot Mongolian Grill, have a built-in total calorie count that automatically updates as items are added to the order (www.huhot.com, accessed December 28, 2018). Other restaurants' websites—such as McDonalds—require that customers seek out nutritional information online, but do provide access to a feature that updates the total calories ordered as meal choices change (www.mcdonalds.com, accessed January 9, 2019). Some restaurants' websites provide only basic nutrition information per item, without providing an automatic way for users to view a running total of the number of calories they have ordered.

Real-time calorie summation has the potential to influence consumer food choices through two main pathways: 1) by reducing random errors or tendencies to use heuristics to keep track of calories ordered by decreasing cognitive costs of keeping track of calories, and 2) correcting for systematic under-counting of calories ordered, which could be rooted in biases or motivated reasoning. The distinction is important. If calorie estimation errors are truly random, calorie summation should merely tighten the distribution of calories ordered without necessarily decreasing the number of calories ordered. However, if individuals are systematically under-estimating the number of calories they have ordered, the presence of calorie summation could lead to a decrease in the total caloric content of the meal.

The first effect would result from a reduction in the cognitive costs of keeping track of calories ordered. Accurately recalling and tallying the total number of calories ordered while selecting additional items is a complex task, which may make the decision-maker prone to random errors or reliant upon simplifying heuristics (such as rounding) while attempting to keep track of the number of calories ordered. If calorie summation simply reduces these errors, the main effect of calorie summation would be to make customers' estimates of the number of calories they had ordered more precise. It could also reduce the range of calories ordered if people's estimates of the number of calories they have selected in earlier ingredient categories influence their choices in later categories. Here, an individual who underestimates the number of calories ordered in the first two ingredient categories in the absence of calorie summation might reduce the number of calories ordered in the third through fifth ingredient categories when exposed to calorie summation. However, this could also result in a boomerang effect for some individuals. An individual who overestimates the number of calories ordered in the early rounds might increase the number of calories ordered in later rounds when they have access to easy, accurate information about calories ordered, due to a licensing effect resulting from these individuals having made less caloric choices than they had initially estimated (Khan & Dhar, 2006).

The second effect that a calorie summation device could have is reducing the ability of motivated individuals to systematically under-account for calories that had already been added to the individual's food order. Motivated reasoning may lead individuals—consciously or subconsciously—to undercount the number of calories they have ordered to maintain a self-image, justify their choices, or support beliefs (Bénabou & Tirole, 2016). Calorie summation increases the salience of calorie information, making it harder to ignore, and keeps an accurate and updated account of the total number of calories ordered at every point in time during the ordering process.

In this article, we examine the effect of a calorie summation device on food ordering in the context of a sandwich-building choice task. We study hypothetical sandwich ingredient choices of residents of the United States. Participants were randomly assigned to one of two conditions. In the “calorie information” (CI) condition, participants received calorie information for each ingredient they could potentially select. In the “calorie summation” (CI Sum) condition, participants received per-ingredient calorie information but were also exposed to a running tally of the total number of calories they had selected.

We first examine differences in the total number of calories ordered in the two calorie information conditions, CI and CI Sum. We next compare the actual total number of calories ordered with each participant's estimated total number of calories ordered in each condition, which provides evidence about whether participants in the CI condition were making random errors in accounting for calories ordered or whether they were systematically undercounting calories ordered. Finally, we study the average calories ordered in each ingredient category in the sequential choice context, which provides some evidence on the nature of the effect of calorie summation.

2. Materials and methods

We study the effect of a simple calorie summation tool on the number of calories ordered in a multi-item hypothetical food choice task. This research was conducted online with participants recruited from Amazon's Mechanical Turk (mTurk) worker pool between April 24 and May 3, 2018. Participants completed an online nutrition labeling experiment involving a hypothetical sandwich choice, followed by a survey about demographics, health, and nutritional characteristics and behaviors. Respondents were required to be United States residents of at least 19 years of age and were only allowed to complete the survey once. Participants received $3.00 for completing the survey.

In the sandwich experiment, participants selected the ingredients for a sandwich, which they were instructed to imagine they were going to eat, from five categories: 1) meat/protein, 2) cheese, 3) spread/dressing, 4) bread, and 5) vegetable. Participants could select one item from each category, reflecting a common practice at build-your-own sandwich counters. In the experiment, participants were randomly assigned to a calorie information condition. In the first condition, *Calorie Info (CI)*, participants viewed the calories that each item would add to the sandwich. In the second condition, *Calorie Info Summation (CI Sum)*, participants again saw the calories that each item would add to the sandwich and, additionally, a calorie counter that was always visible to participants kept track of the total number of calories that the participant had ordered across ingredient categories. Table 1 displays the ingredients offered in each category, listed in alphabetical order, as well as the calories that each ingredient added. The ingredient categories were displayed in the same order for every participant, corresponding to the order of categories in Table 1. Ingredients within each category are presented in alphabetical order in Table 1. In the research, the presentation of ingredients within a category was randomized to avoid order effects. Participants could also select “I would not add any of these” if they did not want to add any of the options in a given category. Calorie information for each item was taken from the United States Department of Agriculture Food Composition Database (USDA, 2018) for the amount of each ingredient used in build-your-own sandwiches offered at the sandwich counter of a national chain of food retailers (Gustafson & Zeballos, 2018).

Table 1
Ingredients for sandwich choice experiment.

Ingredients	Number of Calories
Meat/protein	
Bacon	254
Ham	178
Prosciutto	140
Roast beef	207
Roast turkey	180
Salami	230
Tofu	90
Cheese	
American	104
Cheddar	115
Colby	112
Light American	36
Mozzarella	85
Provolone	98
Swiss	111
Spread/dressing	
Balsamic vinegar	14
Dijon mustard	10
Italian dressing	35
Light mayo.	71
Mayonnaise	188
Olive oil	119
Yellow mustard	6
Bread	
Bagel	250
Ciabatta	263
Croissant	406
Gluten-free	222
Marble Rye	233
Multigrain	265
Sourdough	319
Vegetables	
Avocado	47
Cucumber	3
Lettuce	4
Red onion	11
Red pepper	8
Spinach	7
Tomato	5

Source: Sandwich choice experiment.

The only difference in the choice setting between conditions *CI* and *CI Sum* was the presence of the calorie summation device. After completing their sandwich choice, participants were asked to estimate the total number of calories that their sandwich contained. Participants had not been alerted to the fact that they would be asked to estimate the number of calories they had ordered to avoid inducing them to pay more attention to calories than they would under natural conditions. Finally, participants completed a section of the survey containing demographic questions.

We analyze the data using summary statistics, t-tests, and regression analysis. Data analysis was conducted in R (R Core Team, 2018). We consider p-values < 0.05 to be statistically significant. The research was approved by the Institutional Review Board of the University of Nebraska-Lincoln (IRB protocol # 20171017580EX).

3. Results

Table 2 presents summary statistics on the participant sample. We received data on sandwich choices from 352 individuals. Eight of these respondents abandoned the survey before finishing it. In the analysis, we use the data from the 344 individuals who completed the survey: 174 in the CI Sum condition and 170 in the CI condition. Just over half of the participants were female (51 percent). The average age of participants was approximately 38 years old. Household pre-tax income (2017) was just under $50,000. Participants had completed an average of slightly less than 15 years of education, or roughly equivalent to the

Table 2
Summary statistics of participant characteristics in pooled, calorie information only (CI) and calorie information with updating calorie summation (CI Sum) conditions.

	Pooled	CI	CI Sum	P-value[a]
Female (1 = yes)	0.515	0.518	0.511	0.91
Age (yrs.)	37.96	38.15	37.77	0.76
Income ($1000s)	49.76	50.12	49.41	0.84
Education (yrs.)	14.66	14.71	14.62	0.64
Overweight/Obese (1 = yes)	0.587	0.592	0.581	0.85
Number of participants	344	170	174	

Source: Survey data.
[a] P-values represent the *t*-test of the difference in the value of variables in the CI and CI Sum conditions.

number of years required to obtain an associate's degree. Nearly 60 percent of participants' BMIs fell into the overweight or obese range, based on self-reported height and weight information. None of these variables were statistically different between the CI and CI Sum conditions (Table 2).

3.1. Calorie ordering

Participants in the *CI* condition ordered an average of 640.4 calories, while participants in the *CI Sum* condition ordered an average of 606.6 calories, a statistically significant difference of nearly 34 calories per order ($p < 0.02$). This difference between the CI and CI Sum conditions represents a decrease in total calories ordered of over 5 percent.

To control for individual characteristics that could influence the choice of calories, we examine calories ordered in a linear regression model, with condition (CI Sum; CI is omitted) as the variable of interest, and individual characteristics as control variables. Appendix Table 1 presents the results from four regressions, starting with (1) a dummy variable for CI Sum and then adding (2) a dummy variable for female participants, (3) continuous variables for age, income, and education; and (4) a dummy variable for overweight and obese individuals. Across all four regression models, the dummy variable for the condition CI Sum is estimated to result in a decrease of 32–34 calories ordered relative to the condition CI. The estimates are statistically significant (p-values ≤ 0.02 in all regressions). None of the other control variables is statistically significant.

3.2. Ordered versus estimated calories

We next examine the number of calories that participants ordered in the sandwich choice task compared to the number of calories that each participant estimated that they ordered. This is important because while estimated calories ordered likely drive subsequent choices, actual calories ordered and consumed will determine health outcomes. Comparing estimated and actual calories additionally provides evidence on how the presence of a calorie summation device influences decision-making. If individuals are simply more prone to make random calculation errors or rely on heuristics without the summation, we should not expect to find a significant difference in the mean number of estimated calories between conditions. However, we would expect to observe greater variance in estimate calories in the CI condition since participants in the CI Sum condition were presented with the total number of calories while selecting the ingredients in their sandwich. On the other hand, if individuals systematically under-count the number of calories they have ordered in the absence of a calorie summation device, we should observe a larger difference between estimated and ordered calories in the CI condition than the CI Sum condition.

Fig. 1 presents the mean ordered and estimated calories ordered by condition with error bars representing 95 percent confidence intervals.

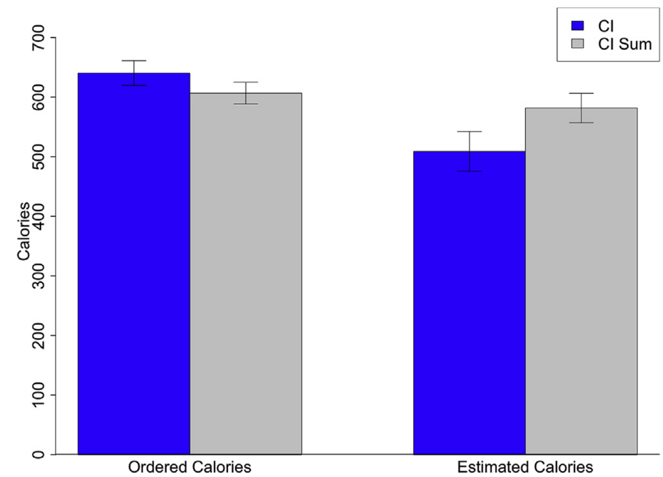

Fig. 1. Ordered calories and estimated calories in the calorie information only (CI) condition and calorie information with updating calorie summation (CI Sum) condition, with 95% confidence intervals.

The actual number of calories ordered in the CI condition, 640.4, is significantly higher than in the CI Sum condition, 606.6 ($p < 0.02$). However, when estimating the number of calories ordered, the relationship flips. Participants in the CI condition estimate that they order only 508.9 calories, which is significantly less than participants in the CI Sum condition estimate, 581.7 ($p < 0.001$).

To further examine this question, we created a new variable, CalEstError, that represents the error in estimated calories. CalEstError is calculated as the number of calories that each participant estimated they ordered, which was completed immediately after they finished the ordering task, minus the actual number of calories that the participant ordered. A *t*-test was used to test for differences in CalEstError between the CI and CI Sum conditions. Fig. 2 presents the distribution of the variable CalEstError by condition.

Over 70 percent of participants in the CI condition underestimated the number of calories they ordered, while 27 percent of participants overestimated the number of calories ordered. Less than two percent (three participants) correctly estimated the number of calories ordered. The mean value of CalEstError for participants in the CI condition was −130.7, meaning that participants estimated they had ordered approximately 130 fewer calories than they actually had ($p < 0.001$). There was also an imbalance in the size of the estimation error by those participants who underestimated the number of calories ordered versus those who overestimated the number of calories in their sandwich. Participants who underestimated the number of calories they had ordered thought they had ordered 235.4 fewer calories than they actually had on average, while participants who overestimated the number of

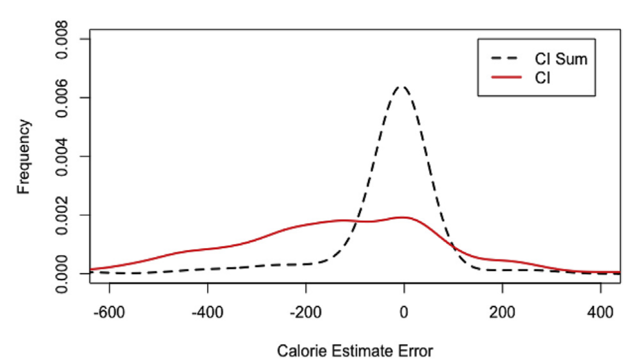

Fig. 2. Distribution of the error in estimated calories (estimated calories minus actual calories) in the calorie information only (CI) condition and the calorie information with updating calorie summation (CI Sum) condition.

calories ordered misjudged by a much smaller number. These participants only overestimated the number of calories ordered by 133.4.

In the CI Sum condition, participants were more evenly split between those who overestimated (or accurately estimated) the number of calories ordered and those who underestimated the calories in their sandwich. Fifty-four percent of participants in the CI Sum condition underestimated the number of calories ordered, while 26 percent accurately estimated the calories ordered and 20 percent overestimated the number of calories. The mean value of CalEstError in the CI Sum condition is −25.5, which is not significantly different from zero. In CI Sum, the estimation error among those who overestimated (62.1 calories) and those who underestimated (68.7 calories) the number of calories is much more evenly balanced. The difference between the mean value of CalEstError in the CI and the CI Sum conditions is statistically significant ($p < 0.001$).

We also find evidence that the relationship between estimated and actual calories ordered is correlated with the actual number of calories ordered, which suggests that individuals' estimates of the calories they order are in fact related to their actual choices. In both CI and CI Sum, there is a systematic relationship between the number of calories that participants estimate that they order and the actual number of calories ordered. Estimated and actual calories ordered for participants who overestimated, accurately estimated, and underestimated the number of calories ordered are presented for each condition in Fig. 3. Participants in both conditions who overestimate the number of calories they have ordered believe they have ordered more caloric sandwiches than those who underestimate the number of calories believe they have ordered, even though they actually ordered fewer calories.

The difference is more pronounced in the CI condition. Participants who overestimate the number of calories they have ordered believe they ordered sandwiches containing 716 calories, even though their actual orders only contained around 580 calories. Participants who underestimated calories believed they ordered 433 calories, whereas their orders actually contained nearly 670 calories on average. Only three participants correctly provided the number of calories actually ordered when asked to estimate how caloric their sandwich was, and the mean number of calories ordered for these three individuals was markedly lower than the average number of calories ordered, suggesting that these three participants may have been highly conscious of their caloric intake.

In the CI Sum condition, the difference in actual calories ordered between those who overestimated and underestimated is only 40 calories, compared to nearly 90 in the CI condition. Importantly, both those who overestimated and underestimated the number of calories actually ordered fewer calories in the CI Sum condition, which does not provide evidence of a boomerang effect among those who overestimate the number of calories they ordered when the calorie summation device is available. However, since the research design is between subjects, we cannot know for certain that participants who overestimate the number of calories ordered in CI Sum would have overestimated calories in condition CI.

3.3. Effect of condition on sequential ordering of calories

An important effect of having an accurate count of calories ordered in a sequential choice setting may be to lead the individual to choose less caloric options in the latter stages of choice. We examine this effect by looking at summary statistics for the total number of calories

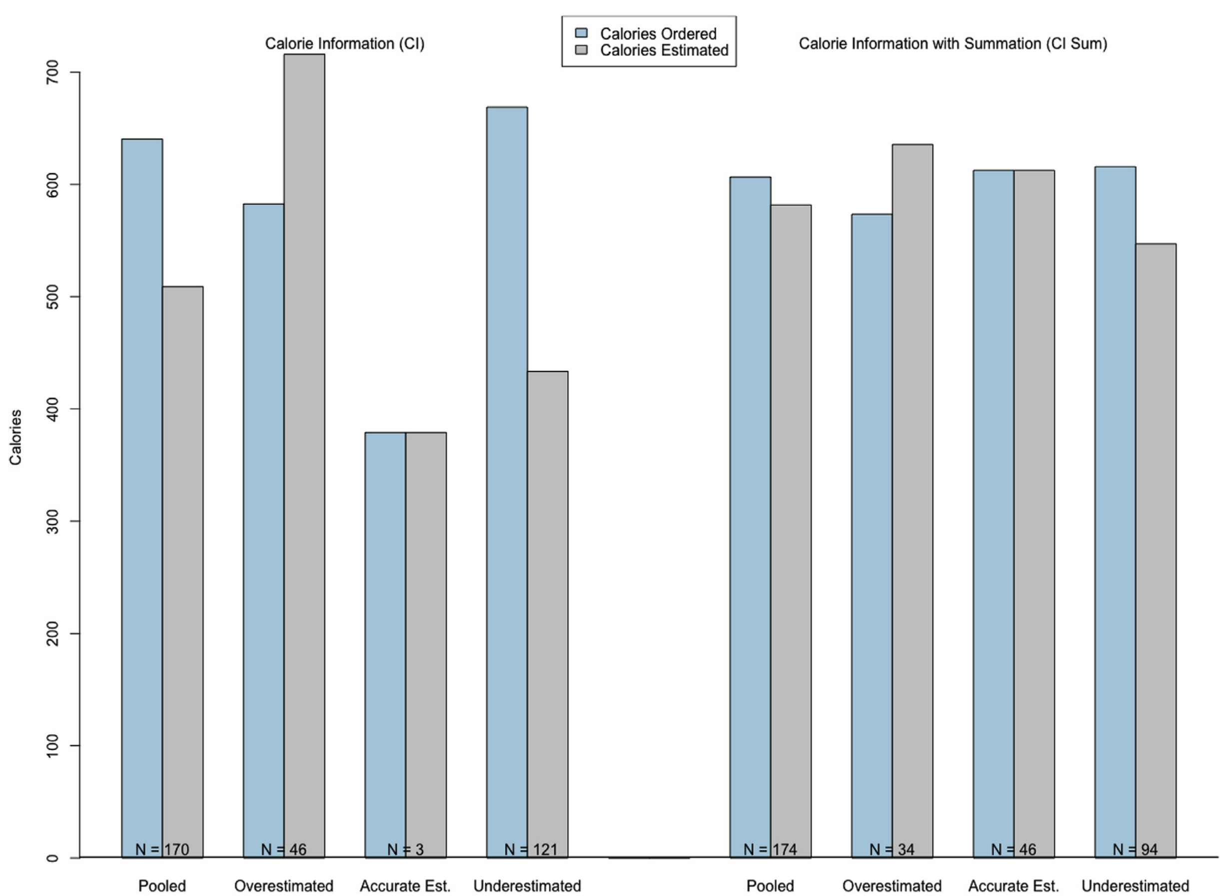

Fig. 3. The number of calories ordered and estimated by all participants (pooled) and participants who overestimated, accurately estimated, and underestimated the number of calories ordered in the calorie information (CI) condition and the calorie information with updating calorie summation (CI Sum) condition. The number of participants in each category is listed at the base of the bar.

Table 3
Differences in calories ordered per ingredient category for calorie information only (CI) and calorie information with updating calorie summation (CI Sum) conditions.

	CI (Calories)	CI Sum (Calories)	Difference (CI–CI Sum)	Calorie Range[a]
1. Meat/Protein	182.1	179.4	2.7	164
2. Cheese	95.4	89.1	6.3	79
3. Spread/ Dressing	76.0	69.0	7.0	182
4. Bread	274.6	257.4	17.2*	184
5. Vegetable	12.3	8.4	3.9*	44

*P-value < 0.05.
[a] Calorie Range is calculated as the highest calorie item in the ingredient category minus the lowest calorie item in the same ingredient category.

ordered per ingredient category for the CI and CI Sum conditions. Evidence that supports this effect would show that participants in both conditions ordered an equivalent number of calories for the earliest ingredient categories, with an increasing gap between CI Sum and CI—and fewer calories ordered in CI Sum—for later ingredient categories.

Every participant viewed sandwich ingredients in the following order: 1. meats/protein, 2. cheese, 3. spread/dressing, 4. bread, and 5. vegetables. However, participants were able to view all categories by scrolling down the page so were not forced to choose in this order. While this design choice reflects reality—customers are able to view all options available to them when ordering food—it likely also makes this a conservative estimate of an ordering effect because some participants may have started with a different ingredient category.

Table 3 displays the mean calories ordered per ingredient category and condition. Mean calories ordered in the meat/protein category are nearly identical between the CI (182.1 calories) and CI Sum (179.4 calories) conditions. In the cheese category, participants in the CI Sum condition selected cheeses that were over six calories lower than those chosen by participants in the CI category (89.1 calories versus 95.4 calories). Items in the spread/dressing category contributed seven fewer calories to sandwiches in the CI Sum category (69.0 calories) than the CI category (76.0 calories). For breads, participants in the CI Sum category ordered over 17 fewer calories per sandwich than those in the CI category (257.4 versus 274.6). Finally, in the vegetable category, the CI Sum category resulted in nearly four fewer calories ordered than in the CI category (8.4 versus 12.3). The differences in calories ordered in the final two ingredient categories are statistically significant using a *t*-test ($p < 0.02$). While smaller than previous categories, the minor difference in calories ordered from vegetables is likely due to the fact that all but one option added 11 or fewer calories per sandwich. If we focus only on categories that had similar ranges between the highest and lowest calorie items—1. meat/protein, 3. spread/dressing, and 4. bread—the pattern is particularly noticeable, going from a 2.7 calorie difference, to a 7.0 calorie difference, and then to a 17.2 calorie difference.

4. Discussion

In this article, we examine the effect on total calories chosen of displaying an updated count of calories ordered in a sequential sandwich-building experiment, relative to a condition in which participants receive calorie information about each ingredient but would have to keep track of the total number ordered themselves.

The total number of calories ordered decreased significantly when participants had access to an updating calorie counting tool. Participants in the calorie information and summation condition, CI Sum, ordered approximately 34 fewer calories than participants in the condition in which they were simply provided information about calories, CI. The incorporation of evidence on participants' estimates of the number of calories they ordered and differences in calories ordered sequentially between conditions shed light on how exposure to calorie summation information influences individuals' choices.

Pairing data on actual calories selected versus estimated calories ordered suggests that the calorie summation device corrects a tendency by individuals to underestimate the number of calories ordered. If the calorie summation simply alleviated the cognitive cost of adding up calories contributed by ingredients across categories—reducing mathematical errors or the use of unbiased heuristics—the effect should simply be to generate a more precise estimate of the number of calories ordered. To the extent that individuals' estimates of calories ordered affect subsequent choices, this could help those who have drastically underestimated the number of calories they have already ordered avoid unintentionally adding overly caloric items. However, the pattern of results suggests, rather, that individuals systematically underestimate the number of calories ordered—by more than 130 calories per sandwich—in the condition without calorie summation. Even many participants in the CI Sum condition did not accurately recall the number of calories ordered—only around 25 percent of participants correctly estimated the number of calories in their sandwich—which suggests that attention and memory may play important roles in response to nutrition information. Evidence from previous studies documents differences in attention to or outright avoidance of nutritional information. Previous studies have found that individuals fail to notice or recall publicly posted calorie information (Elbel et al., 2009; Block et al., 2013; Breck, Cantor, Martinez, & Elbel, 2014; Cantor et al., 2015). In eye-tracking studies, participants in a health-goal condition fixated longer on health information than participants in a taste-goal condition (Bialkova et al., 2014), which may influence information recall. Researchers have found differential attention to food cues among normal and overweight/obese individuals (see, e.g., Nijs, Muris, Euser, and Franken (2010)) and individuals may—consciously or not—avoid nutrition information that would suggest that they should not choose a preferred item (Thunström, Nordström, Shogren, Ehmke, & Veld, 2016). In this study, participants were encouraged to choose as if they would then eat the sandwich, which likely resulted in a mix of personal objectives that included both taste and health aims and may explain why many individuals who had been provided with an updating count of the total calories ordered did not correctly estimate that total.

However, despite the fact that estimation errors do still occur, we find that providing calorie summation significantly decreases the average calorie estimation error. Estimates of participants in CI Sum were distributed closely around the true number of calories ordered, and the estimate of the number of calories ordered did not differ significantly from the actual number of calories ordered.

An examination of category-by-category selections in the food choice task provides evidence that participants respond to information about the number of calories ordered by changing subsequent choices. Participants in the CI Sum condition order increasingly fewer calories relative to participants not exposed to calorie summation in later rounds. In fact, the differences in calories ordered between CI and CI Sum are statistically significant in the final two categories. This pattern, an increasing divergence in the number of calories ordered in later rounds by participants in the two conditions, suggests that individuals' estimates of calories ordered do influence subsequent choices. Providing summary nutritional information may also influence people's choices in later meals, which could result in even more marked reductions in total calories consumed. Future research can investigate whether calorie summation extends across meals.

Our findings also relate to work on motivated beliefs. A significant amount of evidence on motivated beliefs has accumulated in recent years (see Bénabou & Tirole, 2016). This research finds that individuals seek out, incorporate, and evaluate information differently depending on whether the information is beneficial or harmful to their desires or self-concept. For instance, Thunström et al. (2016) show that diners avoid calorie information to facilitate making a more indulgent food choice. In other situations, people update their beliefs differently depending on whether the signal they receive is positive or negative, placing more weight on positive than on negative signals (Eil & Rao, 2011). A unique contribution of our study is that all participants had full access to all calorie information. Even with full access to calorie information, participants who were not provided with an updating total of the number of calories for the items they selected significantly underestimated the number of calories they had ordered. This finding suggests that people were not (solely) subject to random addition errors. Instead, it appears that some form of motivated information editing occurred.

Our work is limited by the fact that the choices made in the experiment were hypothetical. Hypothetical food choices have been used in previous research on consumer choice in the context of food labeling (Crosetto et al., 2016), but hypothetical choices may be less influenced by cravings, feelings of hunger, or other important considerations than a real choice would be. However, it is not clear how the decision-making process would differ based on whether the choice task was hypothetical or binding. Food choices are highly habitual (Rangel, 2013). Individuals respond to taste more quickly (Sullivan, Hutcherson, Harris, & Rangel, 2015) and naturally (Hare et al., 2011) than to health attributes. Based on these findings, participants might be less likely to attend to health information in this context, particularly since the hypothetical nature of the choice task means that participants do not ingest the calories they order.

On the other hand, a desire to appear—or think of oneself as being—responsible may influence individuals to be more health-conscientious than they would be in a non-hypothetical environment (Hebert, Clemow, Pbert, Ockene, & Ockene, 1995). Any social desirability effect may have been attenuated by the fact that researchers had no interaction with participants and received no personally identifiable from the survey. Hypothetical bias related to a desire to think of oneself as responsible is a potential shortcoming of our study. However, a recent paper by Thunström (2019) shows that calorie labeling evokes an emotional response among participants even in a hypothetical choice setting. If biases related to self-image maintenance overrode people's fundamental preferences, information in a hypothetical choice setting should not elicit an emotional response. Thunström's (2019) findings suggest that the habitual nature of food preferences and choice (Rangel, 2013) remains—at least to an extent—even in hypothetical settings.

Since participant characteristics were well-balanced across conditions (Table 2), it is unlikely that our results were influenced by a failure to successfully randomize participants into the conditions. Future research should replicate this experiment design with real choices, ideally in a setting in which social desirability bias (Adams et al., 2005; Hebert et al., 1995) or experimenter demand effects (Nichols & Maner, 2008) could be minimized or eliminated.

While it is possible that hypothetical biases influenced our data, evidence from Block et al. (2013) provides some indication that our data do not differ significantly from data generated in the field. Block et al. (2013) conducted a cross-sectional survey of fast-food diners' calorie estimates of the meals they had selected (in restaurants in which calorie information was available), corresponding to the task that participants in the CI condition completed. In their study, at least 67 percent of respondents in each of three samples under-estimated the number of calories ordered, while in our study, around 70 percent of participants in the CI condition under-estimated the calories ordered. If we compare the estimation error in calories between adult participants in Block et al. (2013) and our results, we also find similarities. Participants in our study underestimated the number of calories ordered by 132, while adult respondents in Block et al. (2013) underestimated calories ordered by 175. While the actual number of calories ordered differed between the two studies, on a percentage basis, the estimation error is nearly identical. Participants in our studied underestimated the number of calories ordered by 20.6 percent and participants in Block et al. (2013) underestimated the number by 20.9 percent.

A second limitation, which is inherent in hypothetical food studies, but also present in many non-hypothetical studies, is that we are unable to examine food consumption. While the number of calories ordered determines calorie availability for a meal, it is ultimately consumption that influences energy balance and related health outcomes. In studies that examine both food choice and consumption, these two variables are typically correlated: when more calories are ordered, more calories tend to be consumed (see, for instance, Schwartz et al. (2012), Hammond, Goodman, Hanning, and Daniel (2013), or Platkin et al. (2014) for evidence on choice and consumption).

Despite limitations to the data resulting from the hypothetical nature of the task, this research provides initial evidence of the potential effectiveness of calorie summation tools enabled by current technologies. The results suggest that providing individuals with automatically updating information about the number of calories—or other nutritional attributes—contained in foods they have ordered prevents them from under-counting the cumulative contribution of each item, and influences subsequent choices to be less caloric. Although further research needs to be conducted to establish whether these results would hold in a non-hypothetical choice setting, these results show promise as a way to address overconsumption of calories.

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Appendix. Table 1: Linear regression of total calories ordered on condition and demographic variables.

Dependent variable: Calories Ordered	(1)	(2)	(3)	(4)
Intercept	640.36*** (9.99)	648.14*** (12.36)	503.91*** (116.06)	514.42*** (116.36)
CI Sum	−33.71* (14.06)	−33.80* (14.05)	−33.22* (14.05)	−31.91* (14.09)
Female		−15.04 (14.06)	−13.81 (14.48)	−14.86 (14.55)
Age			−0.32 (0.61)	−0.37 (0.62)
Natural Log of Income			12.82 (10.12)	12.56 (10.11)
Education			1.44 (4.29)	1.56 (4.30)
Overweight/Obese				−12.24 (14.32)
Adj. R2	0.014	0.014	0.011	0.010

Source: Data from the experiment.

Notes: *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$. Number of observations = 344.

References

Adams, S. A., Matthews, C. E., Ebbeling, C. B., Moore, C. G., Cunningham, J. E., Fulton, J., et al. (2005). The effect of social desirability and social approval on self-reports of physical activity. *American Journal of Epidemiology, 161*(4), 389–398.

Bassett, M. T., Dumanovsky, T., Huang, C., Silver, L. D., Young, C., Nonas, C., et al. (2008). Purchasing behavior and calorie information at fast-food chains in New York City, 2007. *American Journal of Public Health, 98*(8), 1457–1459.

Bénabou, R., & Tirole, J. (2016). Mindful economics: The production, consumption, and value of beliefs. *The Journal of Economic Perspectives, 30*(3), 141–164.

Bialkova, S., Grunert, K. G., Juhl, H. J., Wasowicz-Kirylo, G., Stysko-Kunkowska, M., & van Trijp, H. C. M. (2014). Attention mediates the effect of nutrition label information on consumers' choice. Evidence from a choice experiment involving eye-tracking. *Appetite, 76*, 66–75.

Bleich, S. N., Economos, C. D., Spiker, M. L., Vercammen, K. A., VanEpps, E. M., Block, J. P., et al. (2017). A systematic review of calorie labeling and modified calorie labeling interventions: Impact on consumer and restaurant behavior. *Obesity, 25*(12), 2018–2044.

Block, J. P., Condon, S. K., Kleinman, K., Mullen, J., Linakis, S., Rifas-Shiman, S., et al. (2013). Consumers' estimation of calorie content at fast food restaurants: Cross sectional observational study. *BMJ, 346*, f2907.

Bollinger, B., Leslie, P., & Sorensen, A. (2011). Calorie posting in chain restaurants. *American Economic Journal: Economic Policy, 3*(1), 91–128.

Breck, A., Cantor, J., Martinez, O., & Elbel, B. (2014). Who reports noticing and using calorie information posted on fast food restaurant menus? *Appetite, 81*, 30–36.

Cantor, J., Torres, A., Abrams, C., & Elbel, B. (2015). Five years later: Awareness of New York city's calorie labels declined, with No changes in calories purchased. *Health Affairs, 34*(11), 1893–1900.

Cantu-Jungles, T. M., McCormack, L. A., Slaven, J. E., Slebodnik, M., & Eicher-Miller, H. A. (2017). A meta-analysis to determine the impact of restaurant menu labeling on calories and nutrients (ordered or consumed) in U.S. Adults. *Nutrients, 9*(10), https://doi.org/10.3390/nu9101088.

Cawley, J. (2004). The impact of obesity on wages. *Journal of Human Resources, 39*(2), 451–474.

Cawley, J. (2015). An economy of scales: A selective review of obesity's economic causes, consequences, and solutions. *Journal of Health Economics, 43*, 244–268.

Cawley, J., Sweeney, M. J., Sobal, J., Just, D. R., Kaiser, H. M., Schulze, W. D., et al. (2015). The impact of a supermarket nutrition rating system on purchases of nutritious and less nutritious foods. *Public Health Nutrition, 18*(1), 8–14.

Center for science in the public interest (April 1, 2014). *State and menu labeling.* https://cspinet.org/resource/state-and-menu-labeling-policies, Accessed date: 1 February 2019.

Crosetto, P., Muller, L., & Ruffieux, B. (2016). Helping consumers with a front-of-pack label: Numbers or colors? *Journal of Economic Psychology, 55*(C), 30–50.

Downs, J. S., Wisdom, J., & Loewenstein, G. (2015). Helping consumers use nutrition information: Effects of format and presentation. *Am J Health Econ, 1*(3), 326–344.

Eil, D., & Rao, J. M. (2011). The good news-bad news effect: Asymmetric processing of objective information about yourself. *American Economic Journal: Microeconomics, 3*(2), 114–138.

Elbel, B., Kersh, R., Brescoll, V. L., & Dixon, L. B. (2009). Calorie labeling and food choices: A first look at the effects on low-income people in New York city. *Health Affairs, 28*(6), w1110–w1121.

Ellison, B., Lusk, J. L., & Davis, D. (2013). Looking at the label and beyond: The effects of calorie labels, health consciousness, and demographics on caloric intake in restaurants. *International Journal of Behavioral Nutrition and Physical Activity, 10*, 21.

Fernandes, A. C., Oliveira, R. C., Proença, R. P., Curioni, C. C., Rodrigues, V. M., & Fiates, G. M. (2016). Influence of menu labeling on food choices in real-life settings: A systematic review. *Nutrition Reviews, 74*(8), 534–548.

Finkelstein, E. A., Strombotne, K. L., Chan, N. L., & Krieger, J. (2011). Mandatory menu labeling in one fast-food chain in King County, Washington. *American Journal of Preventive Medicine, 40*(2), 122–127.

García, O. P., Long, K. Z., & Rosado, J. L. (2009). Impact of micronutrient deficiencies on obesity. *Nutrition Reviews, 67*(10), 559–572.

Gustafson, CR, Zeballos, E. The effect of ingredient-specific calorie information on calories ordered. Preventive Medicine Reports, 12, 186-190.

Hales, C. M., Fryar, C. D., Carroll, M. D., Freedman, D. S., & Ogden, C. L. (2018). Trends in obesity and severe obesity prevalence in US youth and adults by sex and age, 2007-2008 to 2015-2016. *JAMA*. https://doi.org/10.1001/jama.2018.3060 March.

Hammond, D., Goodman, S., Hanning, R., & Daniel, S. (2013). A randomized trial of calorie labeling on menus. *Preventive Medicine, 57*(6), 860–866.

Hare, T. A., Malmaud, J., & Rangel, A. (2011). Focusing attention on the health aspects of foods changes value signals in vmPFC and improves dietary choice. *Journal of Neuroscience, 31*(30), 11077–11087.

Hebert, J. R., Clemow, L., Pbert, L., Ockene, I. S., & Ockene, J. K. (1995). Social desirability bias in dietary self-report may compromise the validity of dietary intake measures. *International Journal of Epidemiology, 24*(2), 389–398.

Khan, U., & Dhar, R. (2006). Licensing effect in consumer choice. *Journal of Marketing Research, 43*(2), 259–266.

Kiesel, K., & Villas-Boas, S. B. (2013). Can information costs affect consumer choice? Nutritional labels in a supermarket experiment. *International Journal of Industrial Organization, 31*(2), 153–163.

Kiszko, K. M., Martinez, O. D., Abrams, C., & Elbel, B. (2014). The influence of calorie labeling on food orders and consumption: A review of the literature. *Journal of Community Health, 39*(6), 1248–1269.

Littlewood, J. A., Lourenço, S., Iversen, C. L., & Hansen, G. L. (2016). Menu labelling is effective in reducing energy ordered and consumed: A systematic review and meta-analysis of recent studies. *Public Health Nutrition, 19*(12), 2106–2121.

Long, M. W., Tobias, D. K., Cradock, A. L., Batchelder, H., & Gortmaker, S. L. (2015). Systematic review and meta-analysis of the impact of restaurant menu calorie labeling. *American Journal of Public Health, 105*(5), e11–e24.

Marois, R., & Ivanoff, J. (2005). Capacity limits of information processing in the brain. *Trends in Cognitive Sciences, 9*(6), 296–305.

Moran, A. J., Ramirez, M., & Block, J. P. (2017). Consumer underestimation of sodium in fast food restaurant meals: Results from a cross-sectional observational study. *Appetite, 113*, 155–161.

Nichols, A. L., & Maner, J. K. (2008). The good-subject effect: Investigating participant demand characteristics. *The Journal of General Psychology, 135*(2), 151–165.

Nijs, I. M. T., Muris, P., Euser, A. S., & Franken, I. H. A. (2010). Differences in attention to food and food intake between overweight/obese and normal-weight females under conditions of hunger and satiety. *Appetite, 54*(2), 243–254.

O'Brien, J. D., Kahn, R. M., Zenko, Z., Fernandez, J. R., & Ariely, D. (2018). Naïve models of dietary splurges: Beliefs about caloric compensation and weight change following non-habitual overconsumption. *Appetite, 128*, 321–332.

Platkin, C., Yeh, M.-C., Hirsch, K., Wiewel, E. W., Lin, C. Y., Tung, H. J., et al. (2014). The effect of menu labeling with calories and exercise equivalents on food selection and consumption. *BMC Obes, 1*, 21.

Preston, S. H., Vierboom, Y. C., & Stokes, A. (2018). The role of obesity in exceptionally slow US mortality improvement. *Proceedings of the National Academy of Sciences of the U S A, 115*(5), 957–961.

R Core Team (2018). *R: A language and environment for statistical computing.* Vienna, Austria: R Foundation for Statistical Computing. URL https://www.R-project.org/, Accessed date: 1 February 2019 Accessed .

Rangel, A. (2013). Regulation of dietary choice by the decision-making circuitry. *Nature Neuroscience, 16*(12), 1717–1724.

Schwartz, J., Riis, J., Elbel, B., & Ariely, D. (2012). Inviting consumers to downsize fast-food portions significantly reduces calorie consumption. *Health Affairs, 31*(2), 399–407.

Sinclair, S. E., Cooper, M., & Mansfield, E. D. (2014). The influence of menu labeling on calories selected or consumed: A systematic review and meta-analysis. *Journal of the Academy of Nutrition and Dietetics, 114*(9), 1375–1388.

Sullivan, N., Hutcherson, C., Harris, A., & Rangel, A. (2015). Dietary self-control is related to the speed with which attributes of healthfulness and tastiness are processed. *Psychological Science, 26*(2), 122–134.

Sussman, A. B., Alter, A. L., & Paley, A. (2016). Mental accounting for food in exceptional contexts. *ACR North American Advances, 44*, 174–178.

Tandon, P. S., Zhou, C., Chan, N. L., Lozano, P., Couch, S. C., Glanz, K., et al. (2011). The impact of menu labeling on fast-food purchases for children and parents. *American Journal of Preventive Medicine, 41*(4), 434–438.

Thunström, L. (2019). Welfare effects of nudges: The emotional tax of calorie menu labeling. *Judgm Decis Mak, 14*(1), 11–25.

Thunström, L., Nordström, J., Shogren, J. F., Ehmke, M., & Veld, K. V. (2016). Strategic self-ignorance. *Journal of Risk and Uncertainty, 52*(2), 117–136.

United States Department of Agriculture Agricultural Research Service. USDA food composition Database 2018. (2016). Available online: https://ndb.nal.usda.gov/ndb/, Accessed date: 19 March 2018 Accessed .

VanEpps, E. M., Roberto, C. A., Park, S., Economos, C. D., & Bleich, S. N. (2016). Restaurant menu labeling policy: Review of evidence and controversies. *Curr Obes Rep, 5*(1), 72–80.

Wee, C. C., Davis, R. B., Chiodi, S., Huskey, K. W., & Hamel, M. B. (2015). Sex, race, and the adverse effects of social stigma vs. other quality of life factors among primary care patients with moderate to severe obesity. *Journal of General Internal Medicine, 30*(2), 229–235.

Wisdom, J., Downs, J. S., & Loewenstein, G. (04/2010). Promoting healthy choices: Information versus convenience. *American Economic Journal: Applied Economics, 2*(2), 164–178.

Zhu, C., Lopez, R. A., & Liu, X. (2016). Information cost and consumer choices of healthy foods. *American Journal of Agricultural Economics, 98*(1), 41–53.