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Green, Yellow, Red: How Personalized Nutrition Feedback Shifts Grocery Purchases

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Abstract

We studied whether personalized nutritional feedback on past grocery purchases shifts subsequent consumer choices. In September 2020, Finland's largest grocery retailer added a Nutrition Calculator to its digital purchase-history service. The calculator summarizes the nutritional profile of customers' purchases, evaluates it against national nutrition recommendations, and presents feedback using green, yellow, and red indicators. Using retailer transaction data, we estimate a difference-in-differences event study. Our primary specification compares 9,743 consumers who had used the service for at least six months before the launch of the calculator with a matched control group that had not activated the service.

The clearest effect is for sugar-intensive purchases, whose budget share falls by 0.25 percentage points on average and by up to 0.43 percentage points at the peak. The budget share of salt-intensive purchases also declines, although some of this movement predates the launch, making the evidence less conclusive. We found no systematic changes in the budget share of fat-intensive purchases. The effects are most pronounced among women and consumers under the age of 55.

Tiivistelmä

Vihreä, keltainen, punainen: Personoidun ravitsemuspalautteen vaikutus ruokaostoksiin

Tutkimme, vaikuttaako aiempiin päivittäistavaraostoihin perustuva ravitsemuspalaute kuluttajien myöhempiin ostopäätöksiin. Tutkimus hyödyntää syyskuussa 2020 S-ryhmän Omat ostot -palveluun lisättyä Ravintolaskuria, joka arvioi asiakkaan ostosten ravitsemuksellista profiilia suhteessa kansallisiin ravitsemussuosituksiin ja antaa palautetta vihreillä, keltaisilla ja punaisilla indikaattoreilla.

Analysoimme vähittäiskaupan ostotapahtuma-aineistoa erotukset-erotuksissa-tapahtumatutkimusasetelmalla. Pääanalyysi kattaa 9 743 kuluttajaa ja vertaa vähintään kuusi kuukautta ennen Ravintolaskurin käyttöönottoa Omat ostot -palvelua käyttäneitä kuluttajia kaltaistettuun verrokkiryhmään, joka ei ollut aktivoinut palvelua.

Selkein vaikutus havaitaan runsaasti sokeria sisältävien tuotteiden budjettiosuudessa, joka pienenee keskimäärin 0,25 prosenttiyksikköä ja enimmillään 0,43 prosenttiyksikköä. Myös runsaasti suolaa sisältävien tuotteiden budjettiosuus pienenee, mutta osa tästä kehityksestä alkaa jo ennen Ravintolaskurin käyttöönottoa, joten näyttö on tältä osin vähemmän yksiselitteistä. Runsaasti rasvaa sisältävissä ostoissa ei havaita systemaattista muutosta. Vaikutukset ovat selvimpiä naisilla ja alle 55-vuotiailla.

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Tämän työpaperin työstämisessä on hyödynnetty tekoälyä ihmistyön tukena Etlan eettisen ohjeiston mukaisesti (versio 14.1.2026, ks. https://www.etla.fi/ai-etiikka).

Keywords: Consumer choice, Food purchases, Behavioral economics, Bounded rationality, Salience, Digital feedback, Grocery shopping

Asiasanat: Kuluttajan valinta, Ruokaostokset, Käyttäytymistaloustiede, Rajoitettu rationaalisuus, Näkyvyys, Digitaalinen palaute, Päivittäistavaraostokset

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1. Introduction

Consumers frequently and habitually make grocery purchases. However, evaluating the nutritional profile of their accumulated choices is cognitively demanding. This difficulty is compounded by imperfect recall of what has actually been consumed. A systematic review comparing adults' short-term self-reports with observed or controlled intake documents errors at multiple stages of recall: consumed foods are omitted, uneaten foods are reported, food items are misclassified, and portion sizes are misestimated (Whitton et al., 2022). Although purchases and consumption are not equivalent, these limitations make it difficult for consumers to form an accurate picture of the nutritional implications of their past grocery choices. This is particularly true for dimensions such as salt, sugar, and fat, which must be aggregated across numerous products and shopping occasions rather than inferred from any single purchase.

Digital purchase-history services can reduce this informational burden by returning transaction-based records to consumers. This study examines the behavioral effects of introducing a nutrition-feedback feature within an already established digital grocery self-monitoring environment. Our analysis focuses on the Nutrition Calculator, launched in September 2020 within My Purchases ("Omat ostot"), a digital purchase-history service operated by S-Group, Finland's largest grocery retailer. The feature maps consumers' past grocery purchases into nutrient-based summaries and traffic-light-style indicators that evaluate nutritional composition relative to national recommendations. It differs from earlier forms of purchase feedback in an important respect: it reframes the consumer's purchase basket through a health-relevant mapping that highlights nutrient dimensions such as salt, sugar, and fat that are widely discussed in public health discourse but are cognitively costly for consumers to monitor in day-to-day shopping.

The literature demonstrates that personalized feedback, particularly on past environmental or energy-related behavior, can effectively influence consumer decisions (see, e.g., Allcott & Rogers, 2014; Delmas et al., 2013; Allcott & Kessler, 2019). In the context of grocery shopping, Koski et al. (2023) documented that access to purchase histories is associated with changes in the expenditure shares of different product categories, with the strongest and most immediate responses occurring in categories where feedback is most salient. These findings suggest that consumers respond to structured information about their own purchasing behavior; however, they also raise a further question. What happens when purchase history feedback moves beyond describing what was bought and instead frames the same purchases in terms of health-relevant nutritional dimensions?

We study these effects using monthly retailer transaction data and a difference-in-differences (DID) event-study design. Our primary analysis focuses on 9,743 consumers and compares changes in grocery purchases among consumers who had used the purchase-history service for at least six months before the Nutrition Calculator's launch with those of a matched control group of consumers who had not activated the service. This design allowed us to isolate the incremental effect of nutrition-specific feedback from the initial adoption of the underlying platform. We examine whether spending shifts away from product groups that are intensive in the three focal nutritional dimensions highlighted by the calculator: salt, sugar, and fat.

We find a clear decline in the share of total food and drink spending allocated to sugar-intensive products and suggestive evidence of a decline in the corresponding share for salt-intensive products following the launch of the Nutrition Calculator. The response is clearest for sugar-intensive products, whose budget share falls by 0.25 percentage points on average over the post-launch window and by up to approximately 0.43 percentage points in the strongest month. The budget share of salt-intensive products also declines by a comparable amount, although the evidence is less conclusive. For fat-intensive products, we find no statistically significant change in the budget share. The estimates for sugar and salt attenuate during the holiday season and re-emerge thereafter.

Subgroup analyses suggested variation in responses by gender and age. Among women, the budget shares of salt- and sugar-intensive products declined significantly. Consumers aged 35–54 years showed the broadest adjustment across nutrient categories, while those under 35 years reduced the budget shares of salt- and sugar-intensive products. We found no significant changes among consumers aged 55 and above.

Our study connects three streams of research that have often been examined separately: nutrition labeling, digital retail interfaces, and consumer self-monitoring. Nutrition-labeling research has largely examined evaluative information attached to individual products at the point of choice (Cornudet et al., 2025), while research on digital retail interfaces considers how technology shapes consumer behavior (Roggeveen & Sethuraman, 2020). A third stream examines how consumers use information about their own behavior to monitor and adjust subsequent choices (Jain et al., 2025). The Nutrition Calculator brings these elements together by transforming consumers' purchase histories into personalized, evaluative nutritional feedback.

More broadly, the results extend the literature on informational nudges (Thaler & Sunstein, 2008; Congiu & Moscati, 2022; DellaVigna & Linos, 2022) by showing that evaluative feedback based on consumers' own past behavior can affect repeated grocery choices. Evidence from field experiments suggests that grocery shopping provides a demanding setting for informational interventions; information-based nudges tend to be less effective in grocery stores than in restaurants and cafeterias (Cadario & Chandon, 2019). The Nutrition Calculator differs from many such interventions by combining interpretive, color-coded information with repeated and personalized feedback based on each consumer's own purchase history. In line with salience-based attention models (Bordalo et al., 2013; Chetty et al., 2009), the Nutrition Calculator reframes past purchases along nutritional dimensions that are relevant for health but otherwise less salient at the point of purchase.

Our findings also contribute to the research on heterogeneity in responses to information-based interventions (Taubinsky & Rees-Jones, 2018). Information-based interventions aimed at improving the nutritional quality of food purchases have often produced limited and heterogeneous effects (Downs et al., 2009; Hastings et al., 2021). Prior studies have also documented systematic differences in food preferences and the weight that consumers place on health-related attributes across demographic groups, with women generally valuing these attributes more highly than men (Wardle et al., 2004; Heiman & Lowengart, 2014; Konttinen et al., 2021). Despite these insights, prior evidence on how consumers respond to personalized and evaluative feedback based on their purchase histories remains limited.

The rest of the paper is organized as follows. Section 2 describes the institutional setting, including the My Purchases platform and Nutrition Calculator. Section 3 introduces the transaction data and outcome measures, and Section 4 presents the empirical strategy. Section 5 presents the results, beginning with the dynamic event-study estimates and then turning to heterogeneity by gender and age. Section 6 discusses the mechanisms and implications of the study. Finally, Section 7 concludes the paper.

2. Institutional Background

2.1 The My Purchases Platform

The empirical setting builds on S-Group's My Purchases ("Omat ostot") service, a digital purchase-history platform available to members of Finland's largest grocery retailer's loyalty program. Launched nationally in 2018, this service provides users with structured summaries of their past grocery purchases based on detailed point-of-sale transaction data. Purchase information becomes available shortly after the transactions and can be accessed through a mobile application or web interface.

The platform reached a substantial scale within a few years of its launch. In May 2021, S-Group reported that more than half a million Finns had used My Purchases. S-Group accounts for close to half of the Finnish grocery market, and its loyalty program covers roughly 2.3 million members in a country of 5.5 million.

Users can view historical purchases at different levels of aggregation, including total spending and category-level summaries, over monthly and yearly periods. Importantly for our analysis, users of the My Purchases service had access to detailed purchase histories well before the introduction of nutrition-related feedback. The subsequent launch of the Nutrition Calculator provides a setting in which to study the incremental effect of adding evaluative nutritional feedback to an already established purchase-history service.

2.2 The Nutrition Calculator

In September 2020, S-Group introduced the Nutrition Calculator as a new feature within the My Purchases service. The Nutrition Calculator translates consumers' grocery purchases into nutrient-based summaries by combining detailed transaction data with product-level nutritional information. Nutritional values for packaged products were obtained from mandatory food label disclosures, whereas values for unpackaged items, such as fresh fruits and vegetables, were sourced from the Finnish National Food Composition Database (Fineli), maintained by the Finnish Institute for Health and Welfare. The resulting information is aggregated at the consumer's shopping basket level.

This feature provides users with feedback on the nutritional composition of their purchases along several dimensions, including salt, sugar, fat, saturated fat, carbohydrates, fibers, and proteins. For each nutrient, the nutritional profile of the consumer's purchases over the selected period was evaluated relative to official Finnish nutrition recommendations, allowing users to assess whether the composition of their purchases aligned with the recommended intake ranges. The information can be viewed over different time horizons, including monthly summaries and twelve-month aggregates, and can be disaggregated to the product level to identify the main sources contributing to each nutrient.

To facilitate interpretation, the Nutrition Calculator complements numerical nutrient information with a traffic-light-style, color-coded indicator system. The aggregate nutrient shares were classified into three categories relative to the recommendations: green indicates that the share falls within the recommended range, yellow denotes moderate deviations, and red indicates larger departures. This visual coding summarizes complex nutritional information into coarse signals that allow users to assess the overall health profile of their purchase baskets.

By aggregating information across past purchases, the Nutrition Calculator may help consumers recall and assess the nutritional profile of their purchasing behavior. Without such aggregation, consumers would need to track multiple nutrient dimensions across many products and shopping occasions. This challenge is consistent with models of behavioral inattention, in which individuals allocate limited attention to only a subset of relevant attributes in complex decision-making environments (Gabaix, 2019). By making these nutritional dimensions salient, the calculator may reduce the cognitive effort involved in evaluating previous choices.

Importantly for identification, the Nutrition Calculator does not provide individualized recommendations, prescriptive advice, or financial incentives, nor does it alter prices, promotions, or product assortments. Instead, it reframes existing purchase histories from a health perspective using only historical transaction data. Therefore, its introduction constituted a discrete, platform-wide change in the informational environment faced by users. In the terminology of the labeling literature, the feedback is interpretive but non-directive: it evaluates the basket against a standard without telling consumers what to buy, a distinction that affects how consumers understand and trust the nutritional information (Mazzù et al., 2023).

3. Data

3.1 Data and sample construction

The analysis uses detailed point-of-sale transaction records from S-Group, Finland's largest grocery retailer, linked to information on consumers' use of the My Purchases digital platform. Transaction data record grocery purchases at the product level and are collected at the time of purchase. These records were merged with platform usage information indicating whether and when a consumer enrolled in the My Purchases service and thus had access to purchase history feedback and, after September 2020, to the Nutrition Calculator.

The monthly panel used for the estimation runs from August 2018 to February 2021. Event-time coefficients are reported for the 12 months from March 2020 to February 2021, spanning the six months prior to the introduction of the Nutrition Calculator, the launch month, and the five months that followed. The underlying transactions are recorded at the individual product level; for the analysis, we aggregate them to the consumer–month level, organizing purchases into the salt-, sugar-, and fat-intensive categories used by the My Purchases service, so that each observation summarizes a consumer's grocery purchases in a given calendar month. The length of the post-intervention window was determined by the data availability at the time of extraction.

To ensure that monthly expenditure shares reflect regular purchasing behavior, the main analysis was restricted to customers with at least €500 in annual grocery purchases recorded in the retailer's data. Customers below the €500 threshold made grocery purchases during only about two-thirds of the months in the 12-month pre-treatment period, compared with approximately 98% of the months among customers purchasing at least €500 annually. Consequently, they exhibited a substantially higher proportion of zero-purchase months, making monthly expenditure shares less reliable as indicators of purchasing behavior among infrequent shoppers.

The empirical sample consisted of consumers who either adopted the My Purchases service during the observation window or did not use the service at any point during the data coverage period. Because enrollment is voluntary, we used a matched control group of non-users; the matching procedure is discussed in Section 4 and Appendix A.

Our preferred specification focuses on a sample of early adopters who had used the My Purchases platform for at least six months before the Nutrition Calculator was introduced in September 2020. In this specification, treated consumers are experienced users, while the control group consists of matched non-users. Restricting the sample to experienced users minimized the potential confounding effect of initial platform adoption, allowing us to identify the incremental effect of nutrition-specific feedback beyond the behavioral changes associated with adopting the My Purchases service itself.

As a complementary analysis, we consider the full sample of adopters who enrolled in the My Purchases service between May 2019 and December 2020. In this broader sample, treatment was again defined relative to exposure to the Nutrition Calculator.

3.2 Outcome measures and descriptive statistics

Our primary outcomes capture the composition of food purchases using category-level budget shares. For each consumer and month, we calculated the share of total food and beverage expenditure allocated to each focal product group, allowing us to measure changes in purchase composition independently of changes in total spending.

To align the outcome measures with the information architecture of the Nutrition Calculator, we aggregated product-level purchases into three nutritionally motivated food baskets corresponding to three focal nutrient dimensions highlighted by the calculator: (i) salt-intensive foods (ready meals, bread, and cheese), (ii) sugar-intensive foods (candy, cookies and snacks, pastries and baked goods, and ice cream), and (iii) fat-intensive foods (cheese, cookies and snacks, pastries and baked goods, ice cream, and red meat). These food groups broadly correspond to important dietary sources of salt, sugar, and saturated fat identified in the Finnish FinDiet 2017 Survey (Valsta et al., 2018, Appendix Tables 1a–b, 2a–b, and 6a–b).[1]

The baskets are not mutually exclusive, as some food groups contribute to more than one nutrient dimension (e.g., cheese contributes to both salt and fat baskets). Product classification follows S-Group's internal food categories, which correspond to those presented to users in the My Purchases interface. Product-level nutrient quantities were not available in the research data, so these baskets proxy exposure to the focal nutrient dimensions rather than directly measuring nutrient intake. Therefore, the estimates should be interpreted as changes in the budget shares of nutrient-intensive food groups, not as changes in nutrient consumption itself.

Table 1 reports the descriptive statistics for the analysis sample over the six-month baseline period, including demographic composition, household S-Group spending share, and baseline shares of salt-, sugar-, and fat-intensive purchases. Because all outcomes were based on the same underlying analysis sample, descriptive statistics were reported at the sample level rather than separately for each outcome. The two groups are well balanced on the observed background characteristics (Appendix Table A1), and the identifying assumptions are set out in Section 4.

[1] Population-level dietary evidence further underscores the relevance of these nutritional dimensions. In particular, salt intake exceeds recommended levels for the vast majority of Finnish adults (Valsta et al., 2018).

Table 1. Descriptive statistics for the baseline period

Variable	N	Mean	SD	Minimum	Maximum
Female	9,730	0.634	0.482	0.000	1.000
Age: under 35	9,730	0.214	0.410	0.000	1.000
Age: 35–54	9,730	0.436	0.496	0.000	1.000
Age: 55 or older	9,730	0.350	0.477	0.000	1.000
S Group spending share (%)	9,730	93.914	4.881	90.000	100.000
Salt-related purchases (% of food expenditure)	9,727	6.824	2.311	0.000	30.174
Sugar-related purchases (% of food expenditure)	9,726	2.540	1.699	0.000	59.565
Fat-related purchases (% of food expenditure)	9,728	4.216	1.345	0.000	42.875

Notes: Purchase shares (% of total monthly food expenditure) were calculated as consumer-level monthly averages over the six-month baseline period preceding the Nutrition Calculator launch in September 2020.

Prior research using the same S-Group transaction data has assessed its representativeness. Koski et al. (2023) compared expenditure shares across major food categories with national food consumption statistics and found broadly similar patterns. Independent validation evidence from Finnish loyalty-card data likewise suggests that food purchases provide a moderately valid indicator of food consumption at the population level (Vepsäläinen et al., 2022). Because the data record actual purchases, they also avoid recall errors inherent in self-reported purchase histories.

4. Empirical strategy

The introduction of the Nutrition Calculator constituted a discrete change in the informational environment faced by users of the My Purchases service. Although adoption of the underlying service occurred at different points in time, our primary analysis focuses on consumers who had used My Purchases for at least six months before the calculator's launch. This allows us to isolate the effects of nutrition-specific feedback from those of initial platform adoption.

We estimate the dynamic effects using a difference-in-differences event study. In the preferred specification, event time is defined relative to the September 2020 launch of the Nutrition Calculator, as all treated consumers were already using the My Purchases service at that time. In the full sample, event time is defined relative to the first month in which a consumer had access to the Nutrition Calculator. For consumers who adopted My Purchases before September 2020, this is the calculator's launch month; for those who adopted My Purchases after the launch, the month of service adoption is event month 0. We use the interaction-weighted estimator of Sun and Abraham (2021), which accommodates heterogeneity in treatment effects across adoption cohorts and event time.

We estimate coefficients for the six months preceding treatment and for event month 0 and the five subsequent months, with the month immediately preceding treatment (M−1) serving as an omitted reference period. All specifications include consumer and calendar-month fixed effects, and the standard errors are clustered at the consumer level. The identifying assumption is that, in the absence of access to the Nutrition Calculator, treated consumers and their matched controls would have followed parallel outcome trends. We assess the plausibility of this assumption by examining the pre-treatment event-time coefficients and testing whether they are jointly equal to zero.

In the preferred specification, the treated group consists of established My Purchases users who were exposed to the Nutrition Calculator at launch, while the control group consists of matched non-users who were not exposed to either the platform or the Nutrition Calculator during the observation window. This design allows us to focus on the incremental effect of adding nutrition-specific feedback to an already established self-monitoring system. The treated sample consisted of consumers with recorded service use rather than registration alone: the least intensive treated user had accumulated 121 minutes of recorded use before the launch. This reduces concerns that the estimates were driven by consumers who enrolled without meaningfully engaging with their purchase histories.

As a complementary analysis, we use the full sample of consumers who adopted the My Purchases service between May 2019 and December 2020, allowing adoption to occur both before and after the Nutrition Calculator's introduction. Because this sample includes consumers who first gained access to the platform and the Nutrition Calculator simultaneously, the estimates may combine platform-adoption and nutrition-feedback effects.

Because the adoption of the *My Purchases* service is voluntary, users and non-users may differ systematically along both observable and unobservable dimensions. We therefore constructed a matched control group of non-users using pre-treatment demographic characteristics and municipality-level indicators. Matching details are reported in Appendix A.

Matching cannot eliminate selection on unobservables: consumers who choose to use the platform may differ from non-users in health preferences or other traits that are not observed in the data. However, the individual fixed effects absorb any time-invariant unobserved differences between treated and control consumers. The main remaining concern is differential changes in unobserved factors around the introduction of the Nutrition Calculator. Under the parallel-trends assumption and in the absence of such differential changes, we interpret the estimated post-launch deviations as the causal effects of the Nutrition Calculator.

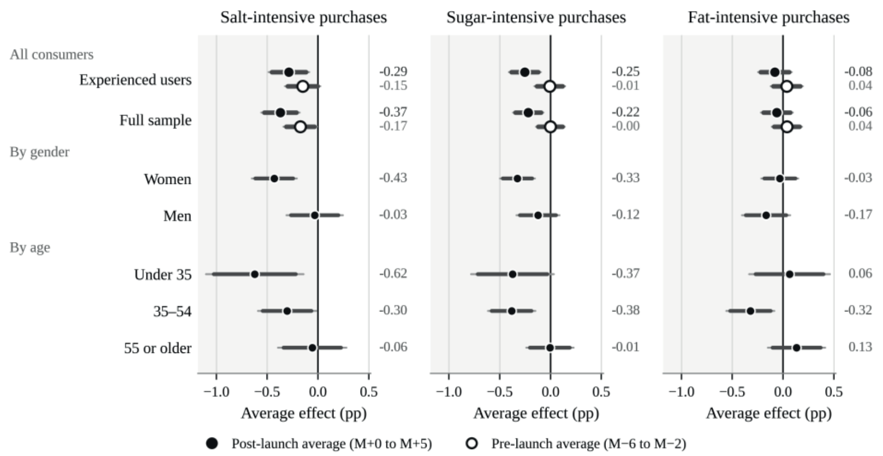
5. Results

5.1 Dynamic effects

We first examine the dynamic effects of the Nutrition Calculator on salt-, sugar-, and fat-intensive purchases. Figure 1 presents the average pre- and post-launch estimates from the preferred specification, while Table 2 reports the underlying month-by-month event-study coefficients for the preferred specification (Panel A) and the full sample (Panel B).

Figure 1 averages the event-study coefficients over the six post-launch months and the five pre-launch months. The average post-launch estimates were −0.29 percentage points for salt-intensive purchases (p = 0.005) and −0.25 percentage points for sugar-intensive purchases (p = 0.002). The corresponding estimate for fat-intensive purchases is smaller and not statistically significant. The full-sample estimates show a similar pattern.

Figure 1. Average event-study estimates for salt-, sugar-, and fat-intensive purchases



Averages of the interaction-weighted event-study coefficients. Thick bars: 90% confidence intervals; thin bars: 95%. Subgroup rows are post-launch averages for the experienced-user sample. Shading marks reductions.

Attributing these declines to the Nutrition Calculator requires that purchases in the two groups evolved similarly before its launch. The pre-launch averages in Figure 1 assess this by summarizing the treated–comparison gap relative to the month before launch. For sugar-intensive purchases, the pre-launch average is essentially zero (−0.01 percentage points, p = 0.92), and adjusting the post-launch estimate for this movement leaves the decline virtually unchanged at −0.25 (p = 0.004). For salt-intensive purchases, the pre-launch estimates suggest some downward movement in the treated group relative to the comparison group (−0.15, p = 0.09). Adjusting for this pre-launch movement reduces the estimate to −0.14 (p = 0.17), making the evidence less conclusive. Fat-intensive purchases show neither meaningful pre-launch movement (+0.04, p = 0.66) nor a post-launch decline.

The monthly estimates show the clearest and most consistent effects for sugar-intensive products. In the preferred specification (Table 2, Panel A), the share of sugar-intensive purchases declined following the Nutrition Calculator's introduction. The effect is statistically significant in every post-launch month except the holiday month M+3 (discussed below) and is largest toward the end of the window, reaching about 0.43 percentage points at M+4 and 0.37 at M+5, roughly 15–17 percent of the average sugar budget share.

Turning to the other nutrient categories, the evidence is weaker. Salt-intensive purchases also declined after the launch, but this pattern is harder to attribute to the Nutrition Calculator because treated consumers had already reduced salt-intensive purchases relative to the comparison group before the launch. In the preferred specification, the post-launch estimates are negative in every month, statistically significant at launch and M+2, and marginally significant at M+4 and M+5. Their magnitude is economically meaningful, but the pre-launch movement and month-to-month variation warrant interpreting the salt estimates as suggestive rather than conclusive findings.

The evidence for fat-intensive purchases is even weaker. The post-launch coefficients are generally negative but small, and only the M+4 estimate reaches statistical significance in the preferred specification. Therefore, the results provide little evidence that the Nutrition Calculator generated a systematic adjustment in fat-intensive purchases.

Table 2. Dynamic effects of the Nutrition Calculator on nutrient-intensive purchases

Panel A. Experienced users (≥ 6 months prior use)

Event time	**Salt**	**Sugar**	**Fat**
M-6	-0.219* (0.130)	-0.101 (0.110)	-0.163 (0.120)
M-5	-0.122 (0.138)	-0.076 (0.137)	0.127 (0.132)
M-4	-0.178 (0.134)	-0.087 (0.142)	0.091 (0.138)
M-3	-0.247* (0.136)	0.185 (0.122)	0.132 (0.139)
M-2	0.014 (0.137)	0.040 (0.121)	-0.007 (0.133)
M+0 (launch)	-0.378*** (0.146)	-0.210* (0.127)	-0.153 (0.126)
M+1	-0.165 (0.140)	-0.213* (0.125)	-0.034 (0.131)
M+2	-0.463*** (0.151)	-0.250* (0.133)	-0.075 (0.137)
M+3	-0.107 (0.149)	-0.048 (0.117)	0.019 (0.155)
M+4	-0.284* (0.153)	-0.429*** (0.128)	-0.233* (0.137)
M+5	-0.322* (0.189)	-0.368** (0.174)	-0.007 (0.174)
Observations	298,076	296,479	297,818
Customers	9,743	9,743	9,744
R^2	0.535	0.435	0.456
Pre-treatment joint test: $\chi^2(5)$	6.29	4.81	4.78
Pre-treatment joint test: p-value	0.279	0.440	0.443
Customer fixed effects	Yes	Yes	Yes
Calendar-month fixed effects	Yes	Yes	Yes

Panel B. Full sample

Event time	Salt	Sugar	Fat
M-6	-0.211* (0.121)	-0.021 (0.106)	-0.075 (0.114)
M-5	-0.182 (0.130)	-0.047 (0.125)	0.104 (0.123)
M-4	-0.148 (0.126)	-0.172 (0.133)	0.041 (0.129)
M-3	-0.234* (0.129)	0.170 (0.113)	0.134 (0.129)
M-2	-0.046 (0.129)	0.065 (0.113)	0.012 (0.124)
M+0 (launch)	-0.448*** (0.134)	-0.194 (0.121)	-0.117 (0.118)
M+1	-0.321** (0.130)	-0.231* (0.119)	-0.044 (0.121)
M+2	-0.508*** (0.141)	-0.210* (0.123)	-0.083 (0.128)
M+3	-0.178 (0.138)	-0.060 (0.111)	0.018 (0.144)
M+4	-0.336** (0.143)	-0.355*** (0.122)	-0.156 (0.129)
M+5	-0.454** (0.178)	-0.259 (0.163)	-0.010 (0.163)
Model statistics			
Observations	338,561	336,748	338,267
Customers	11,087	11,087	11,089
R^2	0.532	0.435	0.458
Pre-treatment joint test (χ^2, df = 5)	5.77	5.76	2.44
Pre-treatment joint test: p-value	0.330	0.330	0.785
Customer fixed effects	Yes	Yes	Yes
Calendar-month fixed effects	Yes	Yes	Yes

Notes: Coefficients are relative to M−1, the omitted reference period. In Panel A, M+0 denotes the September 2020 launch of the Nutrition Calculator. In Panel B, M+0 denotes the first month in which the consumer had access to the Nutrition Calculator: September 2020 for consumers who had already adopted My Purchases and the month of My Purchases adoption for consumers who adopted the service after the Calculator's launch. Clustered standard errors at the customer level are in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Notably, the treatment effects are not statistically significant in the third post-launch month (M+3), which coincides with the peak holiday season. This temporary attenuation is consistent with strong seasonal consumption patterns that may reduce the responsiveness to informational interventions. Prior evidence documents pronounced within-year variation in diet quality, with improvements in January, followed by a steady deterioration over the remainder of the year (Cherchye et al., 2020). Importantly, treatment effects re-emerged in subsequent months, particularly for sugar-intensive products.

The effects were broadly similar across the two samples (Table 2, Panels A and B), with sugar responses somewhat stronger among experienced users and salt responses somewhat stronger in the full sample. These average effects may nonetheless mask systematic variations across consumers, which we examine next along two dimensions: gender and age.

5.2 Heterogeneity by gender and age

We summarize each subgroup's response as an average post-treatment effect over the post-launch window (M+0 to M+5). Gender effects arise from the interaction of treatment with sex within the event study model.

Gender

Gender differences were concentrated in salt- and sugar-intensive products. For women, the average post-treatment effects are negative and statistically significant for both salt and sugar, whereas the corresponding estimates for men are smaller and not statistically significant. The female–male differences are statistically significant at the 1% level for salt and at the 10% level for sugar. For fat-intensive purchases, there is no evidence of a stronger response among women.

Table 3. Gender differences in average post-treatment effects

	Salt	**Sugar**	**Fat**
Female	-0.430*** (0.113)	-0.326*** (0.088)	-0.032 (0.093)
Male	-0.032 (0.142)	-0.123 (0.108)	-0.167 (0.121)
Difference (F-M)	-0.398*** (0.147)	-0.203* (0.109)	0.135 (0.126)
Observations	298,076	296,479	297,818
Customers	9,743	9,743	9,744
R^2	0.535	0.435	0.456
Pre-treatment joint test (χ^2, df = 5)	8.18	2.78	2.64
Pre-treatment joint test: p-value	0.147	0.734	0.755
Customer fixed effects	Yes	Yes	Yes
Calendar-month fixed effects	Yes	Yes	Yes

Notes: Female and male estimates are the arithmetic averages of the interaction-weighted event-study coefficients for M+0 through M+5. The difference (female − male) is the difference between these averages. Clustered standard errors (customer level) are reported in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.*

Importantly, we find no evidence of differential pre-trends between female and male consumers prior to the Nutrition Calculator's introduction. The stronger responses among women are consistent with documented gender differences in the importance placed on health-related food attributes (Wardle et al., 2004; Konttinen et al., 2021) and with evidence that women respond more strongly to front-of-package nutrition labels (Ikonen et al., 2020).

Age

Next, we examine heterogeneity by age by estimating the baseline event-study specification separately for three age groups: under 35, 35–54, and 55 and above. The pre-treatment coefficients are noisier in these subgroup analyses. Joint pre-trend tests are insignificant in most cases, with one exception: salt for the 35–54 group (p = 0.002).

Among consumers under 35, we find statistically significant reductions in salt- and sugar-intensive purchases, while the effect on fat-intensive purchases is not distinguishable from zero. Consumers aged 35–54 show reductions across all three nutrient categories, although the salt estimate warrants caution because of the significant pre-trend. Among consumers aged 55 and above, we find no statistically significant changes in any of the three categories.

Table 4. Average post-treatment effects by age group

	Salt	**Sugar**	**Fat**
Panel 1. Under 35			
Average post-treatment effect	-0.622** (0.245)	-0.374* (0.208)	0.064 (0.203)
Observations	62,950	62,596	62,858
Customers	2,082	2,081	2,082
R^2	0.473	0.410	0.424
Pre-treatment joint test (χ^2, df = 5)	1.36	10.72	5.04
Pre-treatment joint test: p-value	0.929	0.057	0.411
Customer fixed effects	Yes	Yes	Yes
Calendar-month fixed effects	Yes	Yes	Yes
Panel 2. 35-54			
Average post-treatment effect	-0.304** (0.146)	-0.383*** (0.119)	-0.322*** (0.121)
Observations	130,433	129,995	130,357
Customers	4,244	4,244	4,244
R^2	0.520	0.428	0.453
Pre-treatment joint test (χ^2, df = 5)	19.06	4.22	6.61
Pre-treatment joint test: p-value	0.002	0.518	0.252
Customer fixed effects	Yes	Yes	Yes
Calendar-month fixed effects	Yes	Yes	Yes
Panel 3. Over 54			
Average post-treatment effect	-0.056 (0.172)	-0.006 (0.119)	0.133 (0.144)
Observations	104,693	103,888	104,603
Customers	3,417	3,418	3,418
R^2	0.579	0.441	0.478
Pre-treatment joint test (χ^2, df = 5)	1.33	7.88	5.99
Pre-treatment joint test: p-value	0.932	0.163	0.308
Customer fixed effects	Yes	Yes	Yes
Calendar-month fixed effects	Yes	Yes	Yes

Notes: Average post-treatment effects are the arithmetic averages of the interaction-weighted event-study coefficients for M+0 through M+5. Clustered standard errors (customer level) are reported in parentheses. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

6. Discussion

This study examines whether reframing consumers' own grocery purchase histories along nutrient-specific dimensions changes subsequent purchasing behavior. The clearest result was the reduction in sugar-intensive purchases. The effect appears immediately after access to the Nutrition Calculator, remains negative throughout the observed post-treatment period, and is also present in a broader sample of adopters. Salt-intensive purchases also declined, although some downward movement is already visible before treatment, making the evidence less conclusive. We find little evidence of a systematic response to fat-intensive purchases.

The findings extend research on informational nudges and digital consumer interfaces by showing that feedback based on consumers' own accumulated purchase histories can influence subsequent choices, rather than only information attached to individual products at the point of purchase. Most nutrition labels provide information about individual products at the point of choice, whereas the Nutrition Calculator evaluates consumers' accumulated purchase history. The results are consistent with salience-based accounts in which making a previously underweighted attribute more prominent affects choice (Bordalo et al., 2013; Gabaix, 2019).

Two mechanisms are particularly plausible in this regard. The first is *learning*. Consumers may have limited or inaccurate knowledge of the nutritional composition of their accumulated purchases because reconstructing patterns across frequent shopping occasions from memory is difficult. Related evidence from dietary recall shows substantial omissions and measurement errors, with particularly weak correspondence between self-reported and measured sodium intake (Whitton et al., 2022; Freedman et al., 2015). By replacing recall with a transaction-based record, the Nutrition Calculator can reveal patterns that consumers may not otherwise recognize or remember. This differs from interventions that rely on consumers to recall prior consumption (Oh et al., 2023) and complements evidence that nutritional information can affect subsequent choices differently when paired with a reference point (Oh et al., 2021).

The second mechanism is *salience*. Nutritional information may affect choices by directing greater attention to health attributes (Bollinger et al., 2011). The Nutrition Calculator reinforces this channel by evaluating purchases against official recommendations, making discrepancies from a salient standard visible (Carver & Scheier, 1982; Kluger & DeNisi, 1996). This may help explain the responses observed for salt and sugar: Finnish dietary evidence indicates substantial scope for deviation from recommendations, particularly for salt (Valsta et al., 2018), whereas sugar-specific labeling has been shown to shift consumers toward lower-sugar products (Mauri et al., 2021).

The Nutrition Calculator combines numerical information with a simple traffic-light evaluation, which may make complex nutritional information easier to interpret and act upon. Prior research shows that both information format and visual presentation shape consumer responses (Guha et al., 2018; Romero et al., 2025), while interpretive nutrition labels can facilitate healthier choices by reducing the effort required to evaluate nutritional quality (Cecchini & Warin, 2015; Ikonen et al., 2020). However, greater prominence is not always more effective, suggesting that feedback must attract attention without becoming distracting or overly demanding (Schweiger et al., 2023). Color-coded information may influence purchases through both reduced quantities and switching to healthier alternatives (Oh, van der Lans, & Mukhopadhyay, 2022). Our expenditure-share outcomes cannot distinguish between these channels, but the results are consistent with the idea that simple evaluative feedback can help consumers translate personalized nutritional information into changes in purchasing.

The subgroup results indicated larger salt and sugar responses among women. This pattern is consistent with evidence that women place greater weight on health-related food attributes (Wardle et al., 2004; Konttinen et al., 2021), although responses to actual purchases need not mirror reactions to color cues in single-product judgments (Meng & Chan, 2022). Age-specific estimates suggest broader adjustment among consumers below the age of 55 and little detectable response among those aged 55 and above. This pattern is consistent with Koski et al. (2023), who document larger behavioral adjustments among younger users following service adoption, and with age-related differences in attention and behavioral stability (Taubinsky & Rees-Jones, 2018; Steenkamp & Maydeu-Olivares, 2015). More broadly, these patterns suggest that responses to nutritional information may vary across demographic groups and contexts. The observed heterogeneity contrasts with Cawley et al. (2020), who find little systematic demographic variation in responses to restaurant calorie labeling after accounting for multiple comparisons.

The magnitude of the observed effects is consistent with prior evidence that nutritional and health information can produce modest but meaningful changes in food choice. Restaurant calorie labels affect food choices and calories ordered (Cawley et al., 2020; Ellison et al., 2014), while health information can reduce purchases of unhealthy foods (Oster, 2018). At the market level, warning labels have shifted purchases away from labeled products, and point-of-sale information can help align grocery purchases with stated intentions (Barahona et al., 2023; Frank & Brock, 2018). Our findings extend this literature by showing that personalized, evaluative nutritional feedback based on accumulated purchase histories can alter the composition of subsequent grocery purchases.

The temporal pattern also cautions against the assumption that informational effects are stable over time. The response weakens during the December holiday period and then re-emerges, consistent with the evidence of seasonal variation in diet quality (Cherchye et al., 2020). More generally, the effectiveness of self-monitoring and feedback may decline as novelty and attention fade (Etkin, 2016; Polman & Maglio, 2024), while incentive-based improvements in healthier purchasing may not persist once an intervention ends (Hinnosaar, 2022). Our six-month observation window could not determine whether the effects persisted, strengthened with repeated use, or decayed over time.

These findings have implications for both retailers and public health actors. Digital loyalty and purchase history platforms can provide consumers with feedback based on their realized behavior rather than generic product information, making personally relevant patterns easier to recognize and evaluate. Simultaneously, the heterogeneity and nutrient specificity of the effects caution against assuming that more information benefits all consumers equally. Therefore, effective design may depend on making feedback interpretable, personally relevant, and easy to use in subsequent purchase decisions (Guthrie et al., 2015).

7. Conclusion

This study provides large-scale field evidence that personalized nutritional feedback based on consumers' own grocery purchase histories can alter subsequent purchasing behavior. The strongest and most robust response was a reduction in sugar-intensive purchases. Salt-intensive purchases also declined, although the pre-treatment movement in this outcome warrants a more cautious interpretation, while fat-intensive purchases showed no systematic change. Subgroup estimates further suggest stronger responses among women and consumers below the age of 55.

This study has some important limitations. Although the analysis sample was randomly drawn from the user population, access to the Nutrition Calculator was not randomly assigned. Therefore, the causal interpretation relies on the matched difference-in-differences design and the parallel-trends assumption. The outcomes measure expenditure shares in nutrient-intensive product categories rather than nutrient intake itself, and the six-month post-treatment window does not establish long-run persistence. Future research should examine the durability of personalized feedback and study how different forms of evaluative feedback affect repeated consumer decisions.

Despite these limitations, the findings highlight a broader role for digital retail platforms in shaping consumer attention and self-monitoring. Personalized feedback can convert transaction records that would otherwise remain passive data into evaluative information about consumers' past choices. In this sense, digital retail platforms can function not only as marketplaces but also as feedback environments in which past behavior becomes an input into future decision making, potentially supporting more informed choices.

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Appendix A. Matching and covariate balance

The comparison group is constructed using one-to-one nearest-neighbor matching of non-users to treated consumers based on pre-treatment characteristics plausibly related to service adoption and grocery purchasing. These include sex, given documented gender differences in engagement with food- and health-related information (Ek, 2015); age and household type, which are associated with food expenditure (Salo et al., 2021); municipality of residence, reflecting spatial variation in technology adoption (Hägerstrand, 1967; Lengyel et al., 2020); and the household's share of grocery spending at S-Group, which captures the extent to which the household concentrates its grocery spending at the retailer. Pre-treatment S-mobile use is further included in the matching as a proxy for digital engagement.

The matching procedure uses the full set of pre-treatment covariates, including indicators for 283 municipalities. Appendix Table A1 reports covariate balance in the resulting analytical sample. All standardized mean differences are below 0.025, indicating close balance on the observed matching covariates. Municipality indicators are omitted from the table for brevity. S-mobile use is also omitted because it was used in constructing the match but was not retained in the final analytical dataset.

Appendix Table A1. Covariate balance in the analytical sample

Variable	Treated	Control	Difference	SMD	p-value
Female	0.636	0.632	0.004	0.008	0.694
Age: under 35	0.216	0.212	0.004	0.009	0.640
Age: 35–54	0.434	0.438	-0.004	-0.008	0.704
Age: 55 or older	0.350	0.350	-0.000	-0.000	0.995
Single-adult household	0.191	0.195	-0.003	-0.009	0.672
Two-adult household	0.454	0.450	0.004	0.007	0.716
Household with children	0.355	0.355	-0.000	-0.001	0.977
S-Group spending share (%)	93.970	93.853	0.117	0.024	0.238

Notes: Difference = treated mean − control mean. SMD denotes the standardized mean difference, calculated as the difference in group means divided by the pooled standard deviation. The unit of observation is the consumer.

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