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Do Grocery Feedback Systems Enabling Access to Past Consumption Impact Individual Food Purchase Behavior?

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Abstract

This article empirically explores whether and how providing consumers with detailed access to their past food purchase data at different levels of aggregation affects their subsequent food purchase behavior. We employ unique data covering more than 84,000 quarterly observations on Finnish consumers' purchases of various food items from August 2018 to January 2021, as well as their usage of a digital application that provides past purchase data. The data indicate that a digital feedback application that provides consumers with detailed visual and numerical information about their past food item purchases, including both monetary and health-related measures, can impact their future purchase patterns. We find apparent food item-specific and sex-, age- and household-type-specific differences in the ways that the usage of digital feedback applications affects consumers' food purchase patterns. We find that the feedback system's usage had the most noticeable and comprehensive impact on the purchase of fruit and vegetables, which was its most promoted and salient feature and provided more detailed purchase information than that for any other food category since the launch of the feedback system. Our empirical findings thus indicate that information salience does matter.

Tiivistelmä

Vaikuttavatko kuluttajan ruokaostohistoriasta kertovat palautejärjestelmät ostokäyttäytymiseen?

Tutkimuksemme tarkastelee ainutlaatuisen aineiston valossa sitä, miten kuluttajien ostokäyttäytyminen muuttuu heidän tarkasteltuaan aiempaa ostohistoriaansa digitaalisen palvelusovelluksen kautta. Aineisto kattaa yli 84,000 neljännesvuositason havaintoa suomalaisten kuluttajien elintarvikeostoista elokuusta 2018 tammikuuhun 2021 sekä kuluttajien Omat ostot -palvelusovelluksen käyttömääriä koskevia tietoja. Omat ostot -palvelu antaa kuluttajille yksityiskohtaista visuaalista ja euromääräistä tietoa heidän aiempien ruokaostostensa määrästä tuotekategorioittain. Löydämme palvelun käytön vaikutuksissa kuluttajien ostokäyttäytymiseen sekä tuotekategoriakohtaisia että kuluttajien sukupuoleen, ikään ja kotitaloustyyppiin liittyviä eroja. Omat ostot -palvelun käyttö lisäsi eniten, pienemmillä viiveellä palvelun käyttöönoton jälkeen ja eri käyttäjäryhmien osalta laajimmin kuluttajien hedelmä- ja vihannesostosten määrää. Hedelmät ja vihannekset on ollut Omat Ostot -palvelun käyttöönotosta alkaen mainostettu, näkyvin ja tarkinta ostohistoriatietoa sisältävä tuotekategoria. Aineistoanalyysiin perustuvat löydöksemme viittaavat vahvasti siihen, että tuoteryhmäkohtaisella näkyvyydellä (salience) kuluttajan ostohistoriaa koskien on vaikutusta tulevaan ostokäyttäytymiseen.

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Keywords: Behavioral economics, consumer choice, bounded rationality, salience, food purchases, digital feedback applications, nudging

Asiasanat: Käyttäytymistaloustiede, kuluttajakäyttäytyminen, rajoitettu rationaalisuus, näkyvyys (salience), ruokaostot, digitaaliset palautejärjestelmät, tuuppaus

JEL: D12, D83, D9, O33

Yhteenveto

Markkinoilla on tarjolla kasvava määrä sovelluksia, jotka antavat kuluttajalle mahdollisuuden tarkastella henkilökohtaista käyttäytymishistoriaansa esimerkiksi aktiivisuuden tai treenauksen (esim. Apple Smartin Workout App), liikkumisen (esim. Google maps) tai energiankulutuksen osalta (esim. Smappee älysähkömittari). Oman datan käytön vaikutuksista kuluttajien käyttäytymiseen tiedetään kuitenkin varsin vähän. Tutkimuksemme tarkastelee ainutlaatuisen aineiston valossa sitä, miten kuluttajien ostokäyttäytyminen muuttuu heidän tarkasteltuaan aiempaa ostohistoriaansa digitaalisen palvelusovelluksen kautta. Aineisto kattaa yli 84,000 neljännesvuositason havaintoa suomalaisten kuluttajien elintarvikeostoista elokuusta 2018 tammikuuhun 2021 sekä kuluttajien Omat ostot -palvelusovelluksen käyttömääriä koskevia tietoja. Omat ostot -palvelu antaa kuluttajille yksityiskohtaista visuaalista ja euromääräistä tietoa heidän aiempien ruokaostostensa määrästä tuotekategorioittain.

Hedelmät ja vihannekset on ollut Omat Ostot -palvelun käyttöönotosta alkaen mainostettu, näkyvin ja tarkinta ostohistoriatietoa sisältävä tuotekategoria. Euromäärien lisäksi hedelmien ja vihannesten osalta kuluttaja näkee ostoshistoriansa keskimäärin grammoina per päivä ja kilogrammoina kuukausitasolla 12 edeltävän kuukauden ajalta. Muista tuotekategorioista ei ole ollut saatavilla ostoshistoriatietoja vastaavalla tarkkuudella. Aineistoanalyysimme osoittaa, että Omat ostot -palvelun käyttö lisäsi eniten, pienemmillä viiveellä palvelun käyttöönoton jälkeen ja eri käyttäjäryhmien osalta laajimmin kuluttajien hedelmä- ja vihannesostosten määrää. Hedelmien ja vihannesten osuus kuluttajan ruokaostoskorissa kasvoi palvelun käyttöönoton jälkeen keskimäärin 0,31 prosenttiyksikköä. Tilastollisesti merkitsevä muutos oli havaittavissa jo kolme kuukautta palvelun käyttöönoton jälkeen, toisin kuin missään muussa tuotekategoriassa. Aineistoanalyysiin perustuvat löydöksemme viittaavat vahvasti siihen, että tuoteryhmäkohtaisella näkyvyydellä (salience) kuluttajan ostohistoriaa koskien on vaikutusta tulevaan ostokäyttäytymiseen.

Palvelun käytön vaikutuksissa kuluttajien ostokäyttäytymiseen on sekä tuotekategoriakohtaisia että kuluttajien sukupuoleen, ikään ja kotitaloustyyppiin liittyviä eroja. Alle 35-vuotiaat kuluttajat ja yhden hengen taloudessa asuvat henkilöt lisäsivät hedelmien ja vihannesten osuutta ostoistaan muita käyttäjäryhmiä enemmän. Omat ostokset -palvelun käyttö lisäsi hedelmien ja vihannesten osuutta ostoskorissa ensimmäisen viidentoista kuukauden aikana keskimäärin 0,71 prosenttiyksikköä yhden hengen talouksissa ja 0,65 prosenttiyksikköä alle 35-vuotiaiden ryhmässä, ts. vaikutus oli yli kaksinkertainen kuin koko otoksessa. Alle 35-vuotiaat ja naispuoliset kuluttajat muuttivat ostokäyttäytymistään eniten palvelun käytön aloittamisen jälkeen vähentäen erityisesti terveydelle haitallisina pidettyjen elintarvikkeiden kuten keksien ja välipalojen ja jäätelön osuutta kokonaisostoksistaan. Nämä löydökset viittaavat siihen, että naiset eivät pelkästään, kuten aiemmat tutkimukset toteavat, etsi ja käytä terveyteen liittyvää tietoa miehiä enemmän, vaan tiedolla on myös vaikutusta ostokäyttäytymiseen. Vanhemmat, yli 54-vuotiaat Omat ostot -palvelua käyttävät kuluttajat eivät juurikaan ole muuttaneet ostokäyttäytymistään palvelun käytön seurauksena.

Empiirinen analyysimme tarkasteli Omat ostot -palvelun käytön vaikutuksia kuluttajien ostokäyttäytymiseen neljännesvuositasolla viisitoista kuukautta palvelun käytön aloituksesta. Tuotekategorioissa, joita koskien havaitsimme tilastollisesti merkitsevän muutoksen kuluttajien ostokäyttäytymisessä, vaikutus ei tyypillisesti heikentynyt aineiston kattamien neljännesvuosien aikana. Yli vuoden palvelun käyttöönoton jälkeen havaitut tilastollisesti merkittävät käyttäytymismuutokset

saattavat heijastella sitä, että Omat ostot -palvelun käytöllä on pidemmän aikavälin muutoksia palvelun käyttäjien ostokäyttäytymiseen. Käyttäytymismuutosten pysyvyys on kuitenkin empiirinen kysymys, johon tuleva tutkimus toivottavasti antaa vastauksen.

1. Introduction

Advances in digitalization have enabled retailers to collect detailed, high-frequency point-of-sales data on customers' transactions and to apply it to, for instance, sales forecasting, inventory management, and marketing. Empirical research exploring consumer purchase data has further shed light on the price effects, motivation and other attributes of retail purchases (see, e.g., Dubois et al., 2014). During the last few decades, with the advent of behavioral economics, it has become increasingly apparent that there are serious limits to consumers' information-based decision-making. For example, consumers' ability to process information becomes bounded when the information on healthy nutrition, for example, is too complicated (Downs et al., 2009). This article empirically explores whether and how giving consumers access to their past food purchase data at different levels of aggregation affects their subsequent food purchase behavior. This intriguing question has not, to the best of our knowledge, been previously empirically analyzed with the use of such extensive data.

Our analysis focuses on the effects of digital applications that provide users with information about their previous food purchases. We employ unique data covering more than 84,000 quarterly observations of Finnish consumers' purchases of different food items from August 2018 to January 2021 as well as their usage of a digital application that provides past purchase data. We find convincing empirical evidence that this type of digital feedback application, which gives consumers detailed visual and numerical information about their past food item purchases, including monetary and health-related measures, can impact their future purchase patterns. The purchase feedback system that summarizes and visualizes consumers' former purchase choices is, in a way, expanding consumers' cognitive capacity by providing a structured and easy-to-understand picture of consumers' past purchase behavior.

The economic literature has also considered to salience detection as a critical attentional mechanism enabling humans to focus their limited cognitive resources on a relevant subset of the available data. This view, taken by psychologists, has been applied to theories of choice under risk (Bordalo et al., 2012) and consumer choice (Bordalo et al., 2013). The most promoted and salient feature since the launch of the feedback system whose impacts are investigated here is one that provides information on the user's fresh produce purchases using data on the weight and cost of past purchases aggregated daily, weekly, monthly, or annually. This level of information was not provided for other food categories. the greater detail of the information on fresh produce purchases made these food items more salient[1] or more likely to stand out and draw consumers' attention. This allows us to test the prediction of the literature that salient attributes are overweighted in individual decision making. Our empirical findings indicate that information salience does matter. We found that fruit and vegetables was the food category for which the feedback system's usage had the most noticeable and comprehensive impact on purchase behavior among different user groups (i.e., sex, age, household type).

Quite generally, food attitudes and choices are deeply rooted in underlying values and cognitive structures, and policy interventions, for instance, those aimed at improving the nutritional quality of food of purchased by low-income households, have a limited impact on individual food choices (see, e.g.,

[1] The salient attributes of a good make it stand out or are unusual in the sense of being furthest from those of the "reference good" (Bordalo et al., 2013).

Hastings et al., 2021).[2] Studies conducted in different countries have shown apparent sex-specific differences in individual food preferences. While making food choices, women tend to respond more favorably to nutritional information and value different aspects, such as health and physical appearance, than men (Heiman & Lowengart, 2014; Wardle et al., 2004). A Finnish study using survey data assessing food motives suggests that women are more interested in health and ethical issues. In contrast, men rate the relative importance of price value higher than women do (Konttinen et al., 2021). The same study suggests that older and more educated customers are more health conscious. Less is known about how food information relates to actual consumption behavior (e.g., Heiman&Lowengart 2014).[3] Our empirical findings measuring consumers' actual choices via food purchases suggest that the effects of the feedback system that provides information on users' past purchases are gender specific. The feedback system exerts a more substantial impact on the purchases of women and under 35 years old consumers, notably increasing their relative consumption of healthy food items such as fruits and vegetables and reducing the consumption of food with negative health associations, such as cookies, snacks, and ice cream. Instead, the usage of the feedback system does not, for most food item categories, affect the purchase behavior of consumers who are older than 54 years.

Our study contributes to the vast literature on the impacts of information and attitudes on individual choices. The first studies in the systematic cognitive limits of choice behavior, which is known today as behavioral economics, originated as early as the 1970s (Simon, 1972; Tversky & Kahneman, 1974). However, only Richard Thaler's and Cass Sunstein's (2008) classic book *Nudge: Improving decisions about health, wealth, and happiness* launched a broader international debate on how to subtly guide citizens by manipulating their choice architecture, or the environment in which they make decisions (in the spirit of soft libertarian paternalism). Thaler and Sunstein (2008) defined a 'nudge' as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives". Nudging techniques differ. Behavior can be affected by the design of the operating environment by changing the default values, such as when retirement savings are automatically withheld from pay, which favors ease of donation (to charity for example, in the context of fundraising) by simplifying complex information, such as nutrition, through warnings and the reporting of errors (see Baldwin, 2014). In recent years, different versions of nudging have highlighted, among other things, the benefits of digital tools ('digital nudging', which focuses on user interface design) (Weinmann et al., 2016), self-management techniques ('self-nudging') (Reijula, Hertwig 2020) and a new type of market manipulation ('hyper nudging') (Ball, Webster, 2020; Darmody, Zwick 2020; Yeung, 2017).

A quantitative review of Hummel and Maeche (2019) on nudging that uses 100 publications indicates that studies on nudging are most often conducted in the health[4] or environmental context and in a conventional environment rather than the digital environment. They conclude that nudges seem to affect

[2] Relatedly, the medical research concerning smoking, alcohol, diet, and physical activity indicates that nudging works for the educated and the wealthy, whose life management is already in good shape (e.g., Hollands et al., 2013). In contrast, nudging often does not produce results for less skilled people with fewer financial resources.

[3] Various studies explore, for instance, how brands and trademarks affect consumer choices (see, e.g., Bronnenberg et al., 2012; Thogersen and Nielsen, 2016).

[4] See Ledderer et al. (2020) for a review of empirical research on public health interventions, primarily aiming at influencing diet or nutrition.

behavior, but the application context and the nudge category or type modifies the size of the effect. In environmental economics research, the effect of past consumption on current consumption has been extensively studied (see, e.g., Alcott, 2015; Alcott&Kessler, 2019). The literature generally supports the short-term effects of nudging, for instance by indicating that experiments based on environmental information result in notable reductions in individual electricity consumption (see, e.g., Delmas, 2013; DellaVigna & Linos, 2022). Studies on energy-related nudgings, such as the Home Energy Report (HER), which provide information on U.S. households' energy consumption as compared to that of their neighbors, have also reported persistent energy reduction effects. Alcott and Roberts (2014) find that the short-term effects persisted, for the most part, for two years after the discontinuation of the HER intervention. The empirical study of Brandon et al. (2017) further indicates that technology adoption may substantially impact the persistence of nudging effects.

The rest of the paper is organized as follows. Section 2 introduces the consumption feedback application, and Section 3 presents the data used in the empirical analysis. Section 4 describes our empirical strategy, and Section 5 presents the results of the empirical estimations. Section 6 concludes.

2. My Purchases feedback application

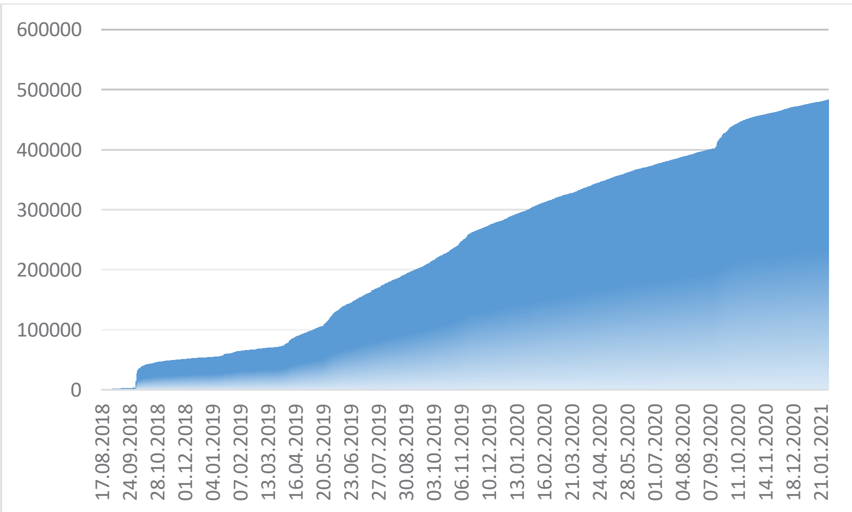
The My Purchases (in Finnish: Omat ostot) service is a consumption feedback system targeted at S-group, one of the largest Finnish grocery chain loyalty customers. The service is free, but it is exclusive to members. Currently, the S-group has 2.3 million loyalty members and 3.9 million individuals overall who belong to the loyalty program either directly or through household invitation. This is a significant figure, especially considering that Finland has 5.5 million residents and S-group loyalty members are mostly from Finland. Hence, the loyalty program represents the Finnish population relatively well, but there is significant variation in levels of member activity. The My Purchases feedback application has five significant design characteristics: (1) it provides feedback based on historical purchase data, (2) it provides multiple means of enriching purchases with product data, (3) the application is embedded in the loyalty app, (4) it supports household-level purchase aggregation and (5) it uses a modular design that supports the development of new feedback perspectives (widgets). We elaborate in more detail on these design principles below.

S-group collects purchase data for cash-back calculation and analytics. Data are processed based on legitimate interest; therefore, customers also have the right to deny processing. The feedback application uses already collected data while continuously collecting further purchase data. The service is provided based on a loyalty value-added service contract, which customers explicitly activate. New purchases appear in the service within minutes. Hence, the service provides the capability to browse the impact of one's purchases immediately after shopping. The S-group loyalty program includes multiple businesses, and grocery is the core business line in Finland with over 40% of the market share. In addition, the S-group loyalty program includes department stores, service stations, hotels, restaurants, and various partner services such as teleoperators and insurance providers.

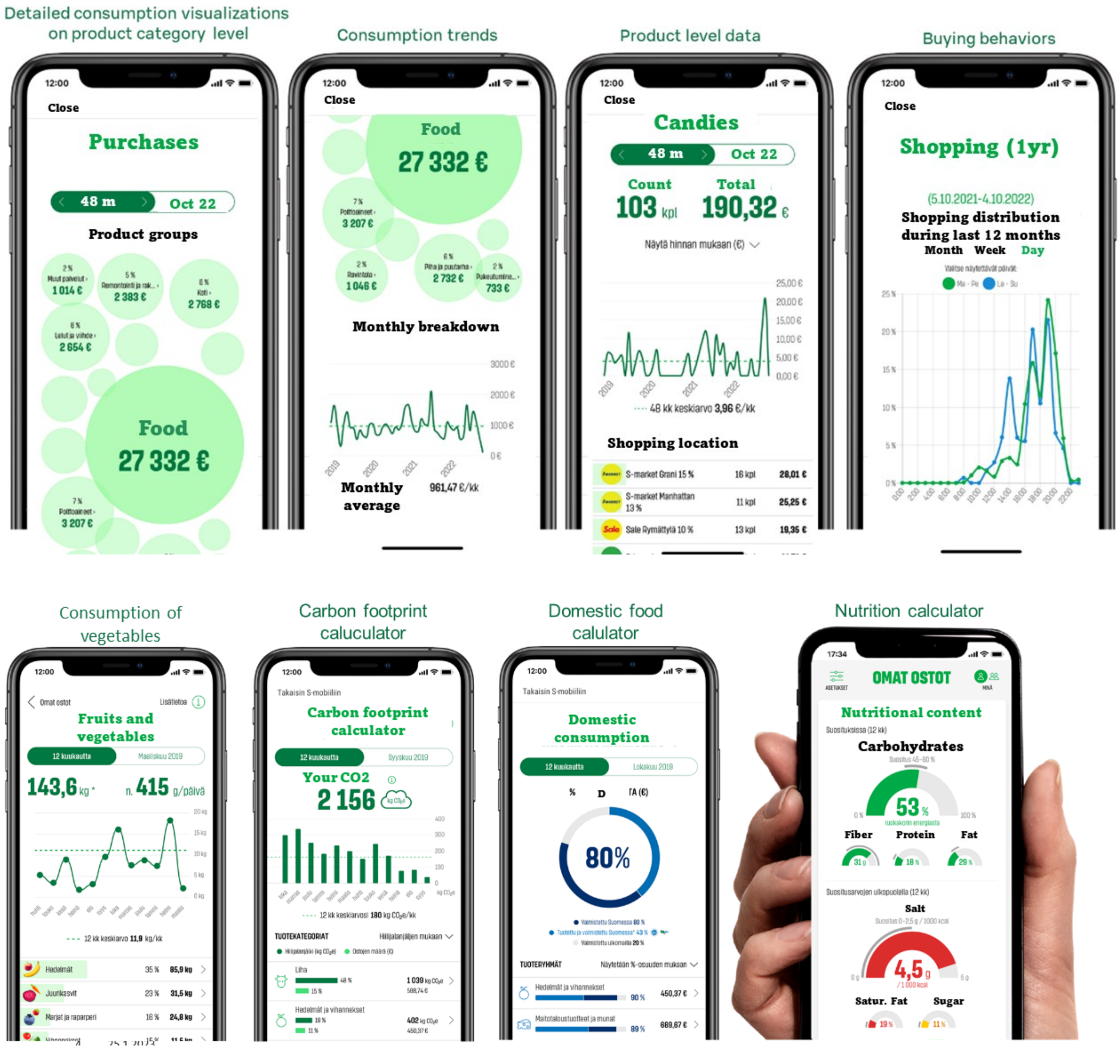
The purchase data provided by the service include the GS1 GTIN codes of each product. With this product code, it is possible to combine the purchase with multiple product data enrichments, such as product category, product origin information, nutrition content, and weight. S-group has developed different views of purchase history based on these product enrichments. Each of these views is developed independently and introduced step-by-step. In addition, the S-group contracts a research agency to provide reference metrics for carbon footprints based on product categories.

Initially, the service was developed as a component of the S-group loyalty web portal. The first version was released in the autumn 2018. In the beginning, there was a limited amount of different product enrichments, which limited the visualization possibilities. By April 2019, the component was embedded into the mobile application, significantly expanding the service use due to increased usability. The number of service adopters grew relatively fast, reaching 54 000 consumers by the end of 2018 and over 480 000 consumers by January 2021 (Figure 1). Currently, over 95% of service use happens through a mobile application. However, it is notable that some customers still prefer the web interface for accessibility reasons or to enable a better view of the dashboard using a monitor. The loyalty app has almost 2 million active users, of which, on average, 100 000 users (ranging from 60 000 to 120 000) visit the monthly My Purchases service. The service is the most popular among 25- to 34- and 35- to 44-year-old loyalty members.

Figure 1. The cumulative number of users of the My Purchases service: 08/2018-01/2021



Groceries are usually purchased for the entire household. For this reason, it is crucial that grocery shopping is aggregated across all members of the household. The My Purchases service has a specific feature that allows users to consent to the aggregation of their purchases. Then, the user can select whether the visualizations reference the individual or household level. For user simplicity and development modularity, each view has a specific perspective. Each view has a timeline, and it is possible to choose whether the visualization is based on a monthly or a yearly aggregate. The core functionalities of the feedback system are described in more detail in the following pictures.



The service's most popular and original visualization dashboard focuses on shopping basket calculations at the product category and individual product levels. The view allows customers to browse their shopping expenses over annual or monthly timeframes and include trends. It is possible to navigate the product hierarchy through three levels and end up at the product level. The feedback application also enables shopping behavior analysis. Since the service's launch, the feedback system has provided a view combining the data of fruit and vegetable purchases with the weight information of the purchased produce to visualize the kilogram purchase total for fruits and vegetables and compare these items. This characteristic of the feedback system was promoted in the launch of the service and addressed in various newspaper articles about the feedback system that were published in Finland.

In addition, the feedback system provides feedback on the carbon footprint generated in a high-level product category. Another view shows the distribution of an item's original and production country and whether the production is domestic. This view also allows product category navigation and visualizes the origin of individual products. Finally, there is a view that combines each product's nutritional information and calculates the relative energy content of each core nutritional group (carbohydrates, fat, and protein, and in addition salt, unsaturated fat, sugar, and fiber) with respect to the shopping basket's total energy.

3. Data

Data used in the empirical exploration were extracted from S-group's extensive and detailed level point of sale retail purchase data and the My Purchases service. The consumption data were collected from two types of consumers: i) persons who had adopted the My Purchases service between May 2019 and December 2020 and ii) the control group of persons who had never used the My Purchases service previously. We used the matching approach (see Section 4 for a detailed description) to form a control group of similar background characteristics to those of the selected individuals in the My Purchases service user group. Consumption data were extracted from periods both before and after a person began using the My Purchases service. The extracted data cover individual-quarter purchasing observations at a 5-digit level through January 2021. We used My Purchases service classifications, as past food purchases are visualized for the users, as a basis to form more aggregate food categories from the S-Group's 5-digit level food purchase data for the estimations. The sample food categories comprise the following: 1) fruit and vegetables, 2) meat, 3) dairy products and eggs, 4) cheese, 5) bread, 6) nonalcoholic beverages, 7) alcoholic beverages, 8) yogurt, curd, and pudding, 9) candy, 10) fish, 11) cookies and snacks, and 12) ice cream, and 13) cereal products.

Table 1. The mean share of purchases of the sample consumers compared to the national account consumption shares in 2019

Food category	**Sample data** **Mean share of purchases (%) in 2019**	**National accounts** **Share of purchases (%) in 2019**
Meat	15,3	14,1
Fruit&vegetables	14,8	13,3
Dairy products&eggs	11,2	8,9*
Cheese	7,1	5,6
Bread	6,8	6,2
Non-alcoholic beverages	6,4	6,6
Alcoholic beverages	6,4	n.a.
Yogurt, curd & pudding	4,5	n.a.
Candy	4,1	4,7
Fish	3,9	3,5
Cookies and snacks	2,3	n.a.
Ice cream	1,9	1,3
Cereal products	1,8	1,8

** Not exactly comparable as national accounts data includes part of the sample dairy products for miscellaneous food products*

We assessed the representativeness of the food purchase patterns of the sample consumers by comparing the mean share of the purchases in different food categories to the overall food consumption in Finland in 2019, according to the national accounts of Statistics Finland. Table 1, which ranks the food categories from the largest to the smallest by their share of total consumption, shows that the food consumption patterns of the sample consumers reflect, by and large, the overall food consumption in Finland. For instance, the average quarterly share of food purchases made by the sample consumers was 15,3 percent for meat and 14,8 percent for fruit and vegetables, while the corresponding national accounts' food purchase shares were 14,1 and 13,3 percent, respectively. Given that the sample mean purchases are counted as the average share of purchases when a consumer has purchased from the given food category during at least during one of the sample months, slight differences are expected.

4. Empirical strategy

We used the difference-in-difference strategy to explore the impact of a change in consumers' information use regarding their past food purchases on their (future) food purchase patterns. The fundamental identifying assumption underlying this estimation strategy is that in the absence of My Purchases service use, the difference-in-difference estimator would result in a value of 0. In other words, the service users (i.e., the treatment group) and nonusers (i.e., the control group) should show parallel trends over time in their food purchases. This means that the dependent variables of our estimations (i.e., the quarterly shares of purchases in the food and drink item categories to the total purchases of food and beverages) should have similar trends – but not necessarily levels, as the differences in levels during the service preadoption quarters for the treatment and control groups are differenced out in the estimations. Thus, to identify the causal impact of My Purchases service usage, we first need to establish a control group in which food purchase patterns developed in a parallel manner to that of the treatment group prior to the service adoption.

A further problem with identifying the causal impact of one's past purchase data use arises as a result of consumers deciding whether to adopt the My Purchases service and to what extent to use it. Consequently, the error terms may violate the assumption of being uncorrelated with the treatment variables. The endogenous selection problem can be solved, or at least substantially alleviated, if we can measure a sufficient set of the factors that influence My Purchases service adoption and then use them as background characteristics in the matching analysis. Furthermore, we need to find a set of variables that explain the differences in the individual's food purchasing patterns. In selecting such variables, we rely here on the prior literature.

We include sex in the variables used in the matching, as empirical research suggests that women are more willing and motivated to seek and engage with food- and health-related information than men are. For instance, Ek (2015) reports using cross-sectional survey data from Finland showing that women are more interested in how the products they buy affect their health and seek more active health information than men in all age groups. Sex is thus likely to play a critical role in consumers' decision to adopt the My Purchases service, which, particularly in its early stages, was promoted as a tool for measuring a person's consumption, e.g., that of fruit and vegetables.

Since the 1960s, the literature on innovation diffusion has acknowledged the importance of the spatial dimension in the adoption of new technologies. The empirical literature has observed that innovation adoption rates tend to rise quickly in large cities and in proximity to the initial locations of technology adoption (Hägerstrand, 1967). The social contagion phenomenon explains the importance of large towns; people's decisions to adopt new technologies are affected by their social networks (of technology adopters) and the media. In the context of digital service use, Lengyel et al. (2020) analyzed the adoption of a popular social media platform in Hungary (during its lifecycle) from 2002 to 2012. They found that the early adoption of the social media platform was concentrated in large cities and scaled quickly with the size of the population. The prior literature suggests that early adoption rates are particularly affected by spatial factors, and it is, indeed, the sample of the early adopter population that is captured by our data. We therefore control the municipality-specific idiosyncrasies by the set of municipality-level dummy variables.

We further use the variables capturing a consumer's age, household type, and (a proxy for) income as the empirical exploration of Salo et al. (2021) finds, in line with other previous studies, that the individual-specific variation in these factors determines the level of consumer spending on food.

The data for the empirical analysis were formed as follows. The idea was to obtain a sample of active users of the My Purchases service, excluding the service adopters with exceptionally heavy or negligible usage. The one percent of most active users and those with a service usage history showing less than 120 minutes of total service platform use were removed from the data. The extracted data comprised 13,000 My Purchases service adopters throughout the country with a minimum of 120 minutes of service usage history, which began using the service between May 2019 and December 2020 (i.e., the adoption times are staggered). We chose this specific time frame for service adopters, as it represented the time when service was already well-developed and available via the mobile application with vastly improved usability. December 2020 was the last data point of adopters available during data extraction.

The base of the control group was first picked from the S-group co-op and consumer registry using one-to-one matching and assigning each treated unit a control unit with similar background characteristics. The background characteristics used in the matching were the municipality (i.e., 310 municipalities in Finland), gender, age group (i.e., under 25 years old, 25-34, 35-44, 45-54, 55-64 and over 64 years old), household type (i.e., young adults, adults, seniors divided into singles and couples; families with kids in the age groups 0-6, 7-12 and over 13 years old), and the household's annual purchases in S-Group. In the second stage, the final control group was formed by selecting consumers with the closest Euclidian distance to those of My Purchases services users regarding their registered loyalty purchases one, three, and 12 months before the treated person began using the service.

The data, however, comprised consumers with a varying degree of centralization of their grocery shopping to S-Group retail stores. As the data covering consumers with a relatively small share of their grocery purchases made among the S-group stores would not reliably enable us to estimate changes in the consumers' purchases, we kept in the sample used for the estimations only those consumers that purchased at least 80 percent of their food from the S-group stores. The final sample comprises over 11,000 consumers but varies across food categories because some consumers do not have any purchases in some food item categories (e.g., vegans may not buy meat or dairy products).

Table 2 shows the descriptive statistics of sample background characteristics for the treatment and control group. The t-test indicates no statistically significant differences between the two groups concerning any variables.

Table 2. Descriptive statistics

Variable	Treated: mean	Control: mean	dif	St Err	t value	p-value
Male	0.358	.362	-.004	.009	-.4	.69
Female	0.635	.638	-.003	.009	-.3	.764
Age: under 35	0.216	.220	-.004	.008	-.5	.602
Age: 35-54	0.430	.426	.004	.009	.4	.671
Age: over 55	0.354	.353	0	.009	0	.991
One person household	0.198	.191	.007	.007	.95	.348
Couple without children	0.450	.455	-.005	.009	-.5	.614
Household with children	0.352	.353	-.002	.009	-.2	.829
Estimated share of purchases concentrated to S-Group	93.730	93.858	-.129	.093	-1.4	.168

In the next stage of the analysis, we estimated the difference-in-difference model to assess the changes in the food purchasing behavior of both My Purchases service users and the control group. The individuals who adopted the My Purchases service were coded as "treated" since the individual had begun to use the service. The treated individuals were not compared to individuals who obtained "treatment" in the past. The sampled service adopters continued using the service until the end of the sample time.

The difference-in-differences approach eliminates bias that might arise from nontime-varying differences between individuals irrespective of their My Purchases service use. These include time-invariant aggregate factors such as food price level changes and unobserved individual-specific factors such as the level of interest in healthy eating or in controlling expenditures, given that these do not substantially change over time. An emerging and rapidly increasing stream of studies, however, suggests that staggered estimations with different treatment times may not produce valid causal effect estimates but rather lead to severely biased estimates (see, e.g., Baker et al., 2022; Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021). We might alleviate this problem as we use effective comparison units, i.e., consumers that adopted My Purchases service were compared to consumers that never used the service. However, we cannot neglect the possibility of bias in our estimates in light of the recent literature.

To correct potential bias arising from the staggered adoption design, we employ a three-stage estimation procedure proposed by Sun and Abraham (2021) to estimate the cohort average treatment effects on the treated My Purchase service adopters (i.e, the cohort-specific average difference in food purchases relative to never used the My Purchases service). In the first stage, the treatment dummy is interacted with a cohort indicator for My Purchases service adoption, that is, in the case of the control group, the counterfactual adoption time. We estimate the cohort average treatment effects using the following linear two-way fixed effects regression model with interactions terms to capture the impact of My Purchases service use in the three quarters before and five quarters after its adoption, following the standard practice and setting the preceding period before treatment as the reference period (Baker et al., 2021):

$$Y_{ijt} = \alpha_i + \gamma_t + \sum_{l\#-1} \delta_{\mathrm{ql}} \mathbf{1}\{Q_i = q\} D_{it}{}^{l} + \varepsilon_{it} \tag{1}$$

where Y_{ijt} denotes a consumer i's purchases in food product category j at quarter t in relation to his or her total food and beverage purchases. Q_i is the quarter when the consumer first time adopted the My Purchases service, $l = t - Q_i$ (i.e., the relative quarterly times to the adoption of service, or the three quarters before and five quarters after an individual adopted My Purchases service), and α_i and γ_t are the unit and time fixed effects. We categorize consumers into different cohorts based on their first treatment or the My Purchases service adoption timing. The variable $D_{it}{}^{l}$ is a dummy variable that gets a value of 1 for treated individuals in the relative times, l, and 0 if an individual had never used the My Purchases service previously.

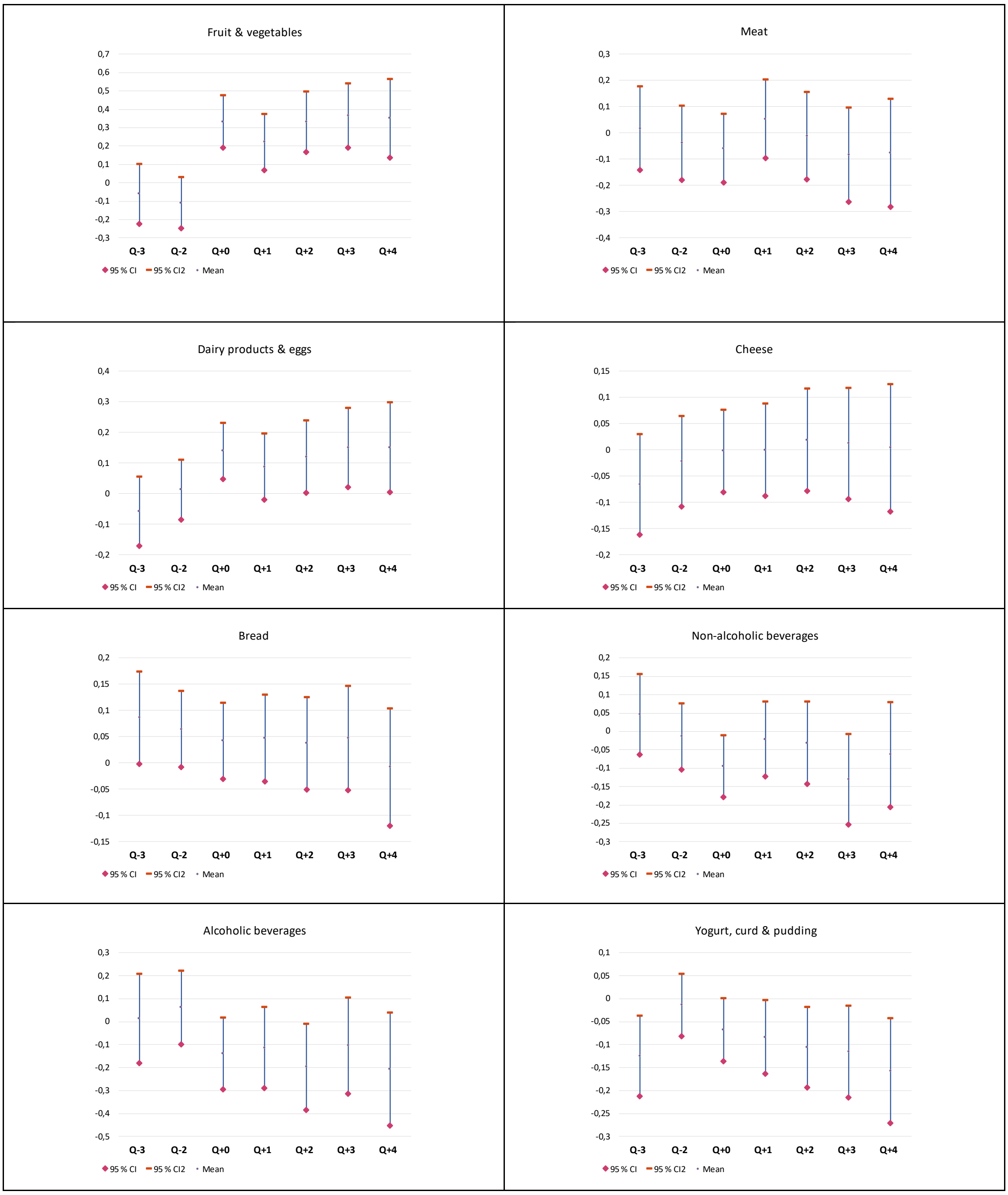
In the second stage, following Sun and Abraham (2021), the weights are estimated based on the sample shares of each cohort in each service adoption quarter. In the third stage, the interaction weighted (IW) estimator is formed by taking a weighted average of estimates for CATT, which we obtain from equation (1) estimations, using the weights from the second stage.

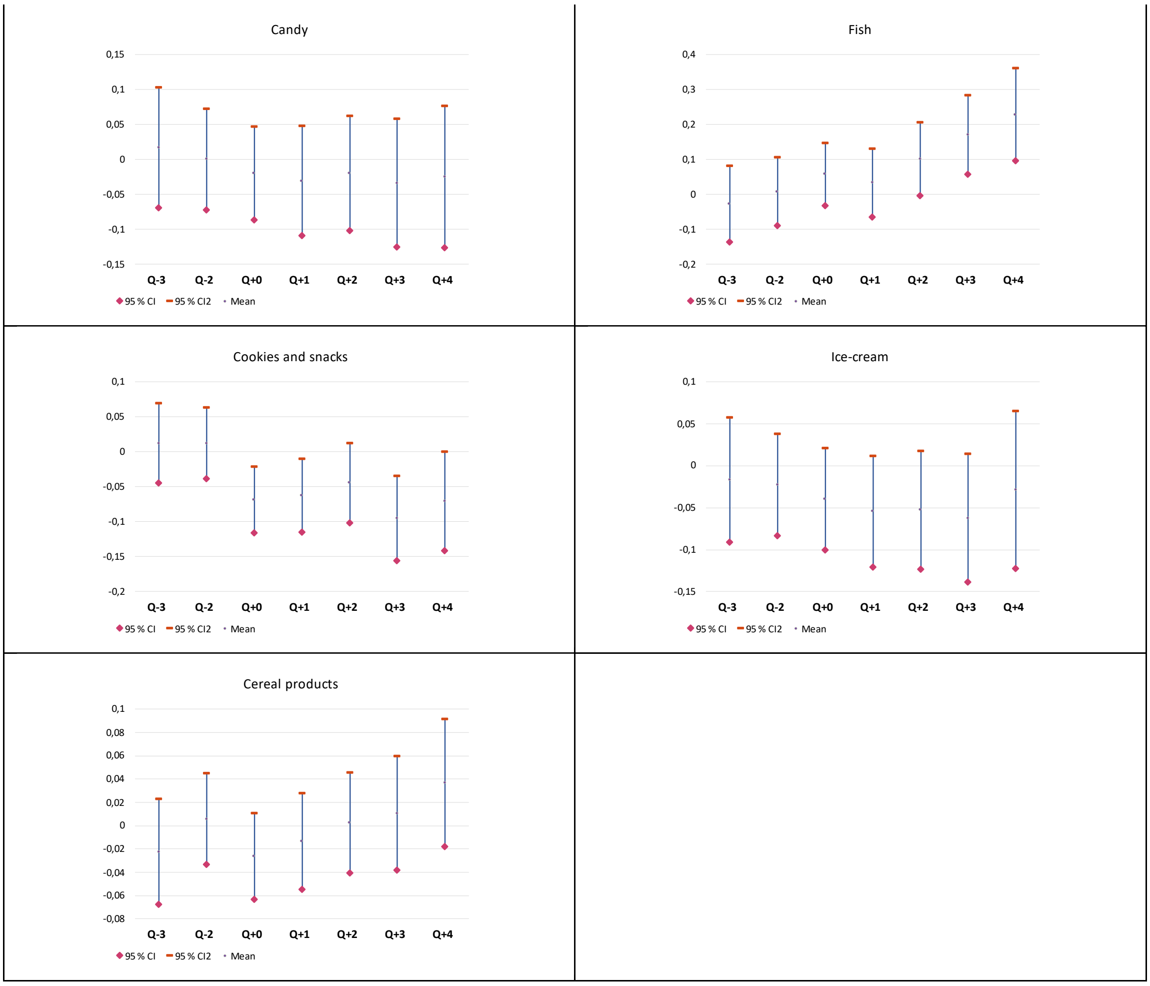
To explore, whether there are sex-, household-type- and age-specific differences in the ways that the usage of digital feedback applications affects consumers' food purchase patterns we further estimated the models in which there were separate coefficients for the treatment variable for i) sex (female vs. male consumers) ii) different household types and iii) different age groups.

5. Estimation results

Table 3 presents the estimated impacts of My Purchases service use on quarterly purchases in the sample 13 food categories. Figure 2 shows the 95 % confidence intervals for the estimated coefficients of two (Q-2) and three (Q-3) quarters prior to and five quarters following (Q-0,…,Q-5) the consumer's adoption of the My Purchases service. The coefficients associated with quarters Q-3 and Q-2 are, by and large, not statistically significant, indicating that the parallel trend assumption is likely not violated. Only for "yogurt, curd & pudding" the estimated coefficient for the quarter Q-3 gets a negative and statistically significant coefficient suggesting that there is a pre-trend difference between the treatment and control group and that we need to be cautious in the assessment of the causal impacts of My Purchases service use with this food group. Table 4 further shows the estimated average quarterly impacts over the first 15 months of usage.

Figure 2. Dynamic treatment effects of My Purchases service adoption on the quarterly food purchases (%-units)





Note: *X-axis shows the time (quarter) to the My Purchases service adoption.*

The estimation results reflect interesting differences between the purchase patterns of My Purchases service users and those of nonusers within 15 months after service adoption. The estimation results indicate that both the female and male users of service increased their share of fruit and vegetables in their total purchases during all quarters within 15 months of beginning to use the service over that of nonusers. We observe a statistically significant (i.e., p-value < 0.05) increase in fruit and vegetable purchases already during the first three months after service adoption compared to those of nonusers. My purchase users' average change in fish purchases was positive and statistically significant after the first six postadoption months. We further find intriguing gender-specific effects that are generated by access to one's historical shopping data: the adoption of My Purchases service decreases the relative share of cookies and snacks and ice cream and increases the share of dairy products & eggs in the total purchases of female service users but not for male users.

Table 3. The estimated quarterly impacts of My Purchases service use on the quarterly food purchases

Food category		Q-3	Q-2	Q+0	Q+1	Q+2	Q+3	Q+4	Nobs	R-squared
Fruit & vegetables	Coeff.	-.059	-.107	0.335	.224	.335	.368	.353	83,316	0.76
	Std.Error	.083	.071	0.073	.078	.084	.09	.11		
Meat	Coeff.	.018	-.038	-0.058	.054	-.011	-.083	-.075	83,312	0.75
	Std.Error	.081	.072	0.067	.076	.085	.092	.105		
Dairy products & eggs	Coeff.	-.057	.014	0.141	.089	.122	.152	.152	83,769	0.79
	Std.Error	.058	.05	0.047	.055	.06	.066	.075		
Cheese	Coeff.	-.065	-.021	-0.001	.001	.02	.013	.005	83,205	0.71
	Std.Error	.049	.044	0.040	.045	.05	.054	.062		
Bread	Coeff.	.087	.065	0.043	.048	.038	.048	-.007	83,591	0.69
	Std.Error	.045	.037	0.037	.042	.045	.051	.057		
Non-alcoholic beverages	Coeff.	.048	-.012	-0.093	-.02	-.03	-.129	-.062	83,401	0.78
	Std.Error	.056	.046	0.043	.052	.057	.063	.073		
Alcoholic beverages	Coeff.	.015	.063	-0.137	-.112	-.195	-.102	-.205	68,995	0.78
	Std.Error	.099	.082	0.080	.09	.096	.107	.126		
Yogurt, curd & pudding	Coeff.	-.124	-.013	-0.067	-.083	-.105	-.114	-.156	81,688	0.74
	Std.Error	.045	.035	0.035	.041	.045	.051	.058		
Candy	Coeff.	.018	.001	-0.019	-.03	-.019	-.033	-.024	82,365	0.70
	Std.Error	.044	.037	0.034	.04	.042	.047	.052		
Fish	Coeff.	-.026	.009	0.059	.035	.103	.172	.23	76,083	0.66
	Std.Error	.056	.05	0.046	.05	.054	.058	.068		
Cookies and snacks	Coeff.	.013	.013	-0.068	-.062	-.044	-.095	-.07	81,581	0.63
	Std.Error	.029	.026	0.024	.027	.029	.031	.036		
Ice cream	Coeff.	-.016	-.022	-0.039	-.054	-.052	-.062	-.028	75,705	0.61
	Std.Error	.038	.031	0.031	.034	.036	.039	.048		
Cereal products	Coeff.	-.022	.006	-0.026	-.013	.003	.011	.037	82,125	0.61
	Std.Error	.023	.02	0.019	.021	.022	.025	.028		

In food categories such as bread, meat, cheese, and cereal products, we observe no statistically significant differences in the consumption patterns before and that after the initiation of service use between users and nonusers.

Table 4. The estimated average impacts of My Purchases service use on the food purchases over the first 15 months

Food category		Coeff.	Std.Error	z	P>z	95% confidence interval	
Fruit & vegetables	All	0.315	0.066	4.800	0.000	.187	0.444
	Female	0.292	0.083	3.520	0.000	0.130	0.455
	Male	0.363	0.107	3.390	0.001	0.153	0.573
Meat	All	-0.025	0.065	-0.380	0.706	-0.153	0.103
	Female	-0.083	0.077	-1.070	0.283	-0.235	0.069
	Male	0.083	0.118	0.700	0.485	-0.149	0.314
Dairy products & eggs	All	0.126	0.047	2.660	0.008	0.033	0.219
	Female	0.118	0.058	2.030	0.042	0.004	0.232
	Male	0.145	0.082	1.770	0.076	-0.015	0.305
Cheese	All	0.008	0.039	0.210	0.833	-0.068	0.085
	Female	-0.007	0.047	-0.150	0.877	-0.100	0.085
	Male	0.035	0.068	0.520	0.606	-0.098	0.169
Bread	All	0.044	0.036	1.220	0.223	-0.027	0.115
	Female	0.076	0.043	1.750	0.079	-0.009	0.161
	Male	-0.003	0.064	-0.050	0.962	-0.129	0.123
Non-alcoholic beverages	All	-0.068	0.045	-1.530	0.127	-0.156	0.019
	Female	-0.038	0.051	-0.750	0.454	-0.138	0.062
	Male	-0.113	0.084	-1.340	0.179	-0.279	0.052
Alcoholic beverages	All	-0.136	0.077	-1.770	0.077	-0.288	0.015
	Female	-0.095	0.081	-1.180	0.240	-0.254	0.064
	Male	-0.213	0.156	-1.360	0.174	-0.519	0.094
Yogurt, curd & pudding	All	-0.092	0.036	-2.540	0.011	-0.163	-0.021
	Female	-0.112	0.045	-2.490	0.013	-0.201	-0.024
	Male	-0.058	0.061	-0.950	0.343	-0.178	0.062
Candy	All	-0.025	0.034	-0.750	0.451	-0.091	0.040
	Female	-0.038	0.041	-0.920	0.357	-0.118	0.043
	Male	0.003	0.059	0.050	0.960	-0.112	0.118
Fish	All	0.092	0.042	2.200	0.028	0.010	0.175
	Female	0.083	0.051	1.610	0.106	-0.018	0.183
	Male	0.106	0.073	1.440	0.150	-0.038	0.249
Cookies and snacks	All	-0.067	0.023	-2.950	0.003	-0.112	-0.023
	Female	-0.090	0.029	-3.150	0.002	-0.146	-0.034
	Male	-0.027	0.038	-0.720	0.472	-0.102	0.047
Ice cream	All	-0.052	0.029	-1.790	0.074	-0.109	0.005
	Female	-0.077	0.036	-2.130	0.034	-0.147	-0.006
	Male	-0.060	0.046	-1.320	0.188	-0.151	0.030

Cereal products	All	-0.006	0.018	-0.330	0.738	-0.041	0.029
	Female	0.013	0.022	0.570	0.571	-0.031	0.056
	Male	-0.036	0.031	-1.160	0.247	-0.096	0.025

Table 5 displays the estimation results of the model in which the average impact of the My Purchases service use is estimated separately for different household types. After adopting the My Purchases service, all household types increased the relative share of their fruit and vegetable purchases. One-person households increased the share of their fruit and vegetable purchases to their entire food and beverage purchases by approximately 0,7 percentage unit as opposed to the 0,3-percentage unit increase that occurred among the total sample (Table 5). While the coefficient is statistically significant among all household types, its magnitude is only approximately one-fourth for couples without children and 37 percent for households with children. The estimation results further indicate prominent differences in how consumers change their purchase patterns after adopting in the ways that consumers change their purchase patterns after adopting My Purchases service across different household types. One-person households decreased the relative share of purchases of alcoholic beverages and couples without children cut the purchases of cookies and snacks after accessing their historical shopping information. Households with children have responded to the usage of My Purchases service by increasing their purchases of dairy products & eggs and fish and decreasing their purchases of ice cream.

Table 5. The estimated average impacts of My Purchases service use on the food purchases over the first 15 months by household type

Food category		One person household	Couple without children	Household with child(ren)	Nobs	R-squared
Fruit & vegetables	Coeff.	0.713	0.188	0.265	84398	0.76
	Std.Error	0.145	0.091	0.090		
Meat	Coeff.	0.218	-0.088	-0.063	84,365	0.75
	Std.Error	0.130	0.091	0.091		
Dairy products & eggs	Coeff.	0.140	0.092	0.169	84,847	0.79
	Std.Error	0.088	0.064	0.070		
Cheese	Coeff.	-0.079	0.035	0.029	84,250	0.71
	Std.Error	0.082	0.054	0.053		
Bread	Coeff.	-0.049	0.095	0.014	84,657	0.73
	Std.Error	0.070	0.052	0.048		
Non-alcoholic beverages	Coeff.	-0.048	-0.074	-0.065	84,421	0.77
	Std.Error	0.093	0.061	0.063		
Alcoholic beverages	Coeff.	-0.515	-0.057	-0.052	69,532	0.78
	Std.Error	0.161	0.109	0.101		
Yogurt, curd	Coeff.	-0.207	-0.049	-0.094	82,665	0.74

& pudding						
	Std.Error	0.081	0.048	0.053		
Candy	Coeff.	0.023	-0.029	-0.048	83,316	0.70
	Std.Error	0.062	0.044	0.053		
Fish	Coeff.	0.131	0.071	0.102	76,840	0.66
	Std.Error	0.087	0.062	0.053		
Cookies and snacks	Coeff.	-0.080	-0.077	-0.047	82,425	0.63
	Std.Error	0.047	0.031	0.033		
Ice-cream	Coeff.	-0.052	-0.004	-0.128	76,189	0.61
	Std.Error	0.064	0.039	0.041		
Cereal products	Coeff.	-0.057	0.003	0.012	83,095	0.61
	Std.Error	0.038	0.024	0.027		

Table 6 shows the estimated impact of My Purchases service use among different age groups (i.e., under 35 years old, 35-54, and over 54 years old). The shopping basket of the youngest groups, comprising those under 35 years old, has undergone the most notable change as a result of obtaining access to their historical shopping data. This consumer group reduced the share of cookies and snacks and ice cream and increased the share of vegetables and fruit, fish, and dairy products in their total food purchases. Consumers aged 35-54 years old bought relatively more fruit and vegetables and less ice-cream after adopting the My Purchases service. However, the increase in the consumption of fruit and vegetables was substantially higher among the youngest age group. The group of under 35 years old service users increased the share of fruit and vegetable purchases in their total food and beverage purchases by approximately 0,7 percentage units. In comparison, the respective increase in the purchases of service users aged 35-54 was less than 0,4 percentage units. Among the over 54 years old service users, the estimated average impact of My Purchases service use on fruit and vegetable users was zero. This oldest age group's shopping behavior was overall unaffected by their access to past shopping data.

Table 6. The estimated average impacts of My Purchases service use on the food purchases over the first 15 months by age group

Food category		Age: Under 35	Age: 35-54	Age: over 54	Nobs	R-squared
Fruit & vegetables	Coeff.	0.654	0.377	0.036	84,398	0.76
	Std.Error	0.140	0.085	0.098		
Meat	Coeff.	-0.071	-0.109	0.117	84,365	0.75
	Std.Error	0.129	0.087	0.097		
Dairy products & eggs	Coeff.	0.226	0.116	0.076	84,847	0.79
	Std.Error	0.097	0.063	0.068		
Cheese	Coeff.	0.064	-0.004	0.001	84,250	0.71
	Std.Error	0.077	0.050	0.061		
Bread	Coeff.	-0.000	0.018	0.091	84,657	0.73

	Std.Error	0.061	0.046	0.060		
Non-alcoholic beverages	Coeff.	-0.148	-0.033	-0.055	84,421	0.77
	Std.Error	0.103	0.058	0.058		
Alcoholic beverages	Coeff.	-0.258	-0.094	-0.126	69,532	0.78
	Std.Error	0.160	0.100	0.114		
Yogurt, curd & pudding	Coeff.	-0.103	-0.152	-0.022	82,665	0.74
	Std.Error	0.081	0.049	0.049		
Candy	Coeff.	-0.042	-0.045	0.009	83,316	0.70
	Std.Error	0.071	0.046	0.046		
Fish	Coeff.	0.309	0.095	-0.036	76,840	0.66
	Std.Error	0.073	0.054	0.069		
Cookies and snacks	Coeff.	-0.176	-0.052	-0.015	82,425	0.63
	Std.Error	0.053	0.030	0.030		
Ice-cream	Coeff.	-0.131	-0.090	0.027	76,189	0.61
	Std.Error	0.062	0.037	0.043		
Cereal products	Coeff.	0.013	-0.019	-0.000	83,095	0.61
	Std.Error	0.043	0.023	0.026		

6. Conclusions

An increasing number of applications provide consumers with access to their past behavioral data, such as their activity or workout history (e.g., Workout App of Apple Smart), movement history (e.g., Google maps), or energy consumption (e.g., Smappee). Little is known about how they impact user behavior, however. In this study, we address the question of whether and how consumers' purchasing patterns change as a result of access to well-structured, detailed and easy-to-understand information on their past purchase behavior. We use unique data containing more than 280,000 food category-specific observations on Finnish consumers' purchases and their usage of the feedback application to capture information on their past shopping behaviors from August 2018 to January 2021. We are unaware of prior studies that would have used such large-scale data to conduct an empirical investigation of the topic.

Our empirical study suggests that digital feedback systems giving consumers detailed visual and numerical information on their past food item purchase patterns impact their future purchase patterns. Our estimation results show substantial food item-specific differences in how the usage of the My Purchases service affects consumers' food purchase patterns, however. Exploring one's past shopping data changed the purchases of fruit and vegetables most noticeably and comprehensively among different user groups. The average increase in the share of fruit and vegetables of total food and beverage consumption over the first fifteen months of usage was approximately 0,32 percentage units. The changes in the purchase patterns of fruit and vegetables were statistically significant first quarter after the consumer began using the service, unlike in any other sample food item category. By and large, the changes in purchase behavior in other food item categories took place more than six months after the persons' initial use of the digital feedback platform.

The strong empirical evidence our data provide on how a person's access and use of past historical purchase data increases that person's fruit and vegetable purchases seem sensible in light of the salience theory, which suggests that consumers overweight salient attributes in their decision-making. In developing the My Purchases service, particular attention was given to visualizing the information on one's past purchases in this food category. Since the service's launch, users have seen not only an increase in the amount of money spent on fruits and vegetables but also the total weight purchased over the past 12 months, monthly, and separately as their average fruit and vegetable purchases in grams per day. This information being provided by the online platform enables consumers to assess not only their total money spent on fruit and vegetables but also how closely they meet the Finnish food authority's recommendation to consume a minimum of 500 grams of fruits and vegetables every day. Such detailed purchase information was not provided in any other food categories.

We further found apparent sex-, age- and household type-specific differences in the effects of My Purchases service use. In particular, younger consumers in the under-35 age group and members of one-person households increased their purchases of fruit and vegetables more than other user groups. The average impact of My Purchases service usage on the share of fruit and vegetables in one's shopping basket over the first fifteen months was 0.71 percentage units for one person household and 0.65 percentage units for the under 35 years old group (i.e., more than twice of the estimated average impact among total sample). Under 35 years old and female consumers generally reacted the strongest to the information on their past grocery shopping. They specifically reduced their purchases of food and beverage item categories that are considered harmful, such as cookies and snacks and ice cream. These findings are consistent with the previous literature suggesting that female consumers seek out and use health-related information more actively than their male counterparts. Interestingly, the older age groups, i.e., those over 54 years old, do not generally shift their food purchasing patterns as a response to obtaining access to data on their prior purchase patterns.

We exploited quarterly food purchase data to measure the impact of digital feedback application use for up to 15 months after a person initiated the service. In those food item categories where we observed a statistically significant change in purchase behavior over the sample quarters, the impact did not generally subside during the sample time. For some food categories, like fish, the behavioral changes occurred with the quarters lag after the adoption of the service, possibly reflecting the learning effects related to the use of the online service. The notable behavioral changes observed over a year after service adoption potentially reflect longer-term changes in service users' purchasing patterns. The level of permanence of these behavioral changes is an empirical question that, hopefully, future research can answer through the use of more extended post-service adoption data.

References

Alcott, H. (2015). Site Selection Bias in Program Evaluation. *Quarterly Journal of Economics 130* (3), 1117–1165.

Alcott, H. & Kessler, J.B. (2019). The Welfare Effects of Nudges: A Case Study of Energy Use Social Comparisons. *American Economic Journal: Applied Economics 11* (1), 236–276.

Alcott, H. & Rogers, T. (2014). The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation. *American Economic Review 104* (10), 3003–3037.

Andreyeva, T., Long, M. W., & Brownell, K. D. (2010). The impact of food prices on consumption: a systematic review of research on the price elasticity of demand for food. *American journal of public health*, *100*(2), 216-222.

Baker, A.C., Larcker, D.F & Wang, C.C.Y. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics* 144, 370-395.

Baldwin, R. (2014). From Regulation to Behaviour Change: Giving Nudge the Third Degree. *Modern Law Regulation*, 77(6), 831-857, DOI:10.1111/1468-2230.12094

Ball, K., & Webster, W. (2020). Big Data and surveillance: Hype, commercial logics and new intimate spheres. *Big Data & Society*, 7(1), 2053951720925853

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). Salience theory of choice under risk. *The Quarterly journal of economics*, *127*(3), 1243-1285.

Bordalo, P., Gennaioli, N., & Shleifer, A. (2013). Salience and consumer choice. *Journal of Political Economy*, *121*(5), 803-843.

Brandon, A., Ferraro, P.J, List, J.A., Metcalfe, R.D., Price, M.K. & Rundhammer, F. (2017). Do The Effects of Nudges Persist? Theory and Evidence from 38 Natural Field Experiments. NBER Working Paper No. 23277

Bronnenberg, B.J., Dubé, J-P.H., & Gentzkow, M. (2012). The Evolution of Brand Preferences: Evidence from Consumer Migration. *American Economic Review*, 102 (6): 2472-2508.

Callaway, B. & Sant’Anna, P.H.C. (2021). Difference-in-differences with multiple time periods. *Journal of Eonometrics* 225, 200-230.

Darmody, A., & Zwick, D. (2020). Manipulate to empower: Hyper-relevance and the contradictions of marketing in the age of surveillance capitalism. *Big Data & Society*, *7*(1), 1-12.

DellaVigna, S. & Linos, E. (2022). RCTs to Scale: Comprehensive Evidence from Two Nudge Units. Econometrica, 2022, *90* (1), 81–116.

Delmas, M. A., Fischlein, M., & Asensio, O. I. (2013). Information strategies and energy conservation behavior: A meta-analysis of experimental studies from 1975 to 2012. *Energy Policy*, *61*, 729-739.

Downs, J. S., Loewenstein, G., & Wisdom, J. (2009). Strategies for promoting healthier food choices. *American Economic Review*, *99*(2), 159-64.

Dubois, P., Griffith, R. & Nevo, A. (2014). Do Prices and Attributes Explain International Differences in Food Purchases? *American Economic Review*, 104 (3): 832-67.

Ek, S. (2015). Gender differences in health information behaviour: a Finnish population-based survey. *Health Promotion International* 30, 736–745, https://doi.org/10.1093/heapro/dat063

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Eonometrics* 225, 254-277.

Hastings, J., Kessler, R. & Shapiro, J.M. (2021). The Effect of SNAP on the Composition of Purchased Foods: Evidence and Implications." *American Economic Journal: Economic Policy*, 13 (3): 277-315.

Heiman, A., & Lowengart, O. (2014). Calorie information effects on consumers' food choices: Sources of observed gender heterogeneity. *Journal of Business Research*, *67*(5), 964-973

Hollands, G. & Shemilt, I., Marteau, T., Jebb, S., Kelly, M., Nakamura, R. & Ogilvie, D. (2013) Altering micro-environments to change population health behaviour: towards an evidence base for choice architecture interventions. *BMC public health* 13 (1), 1-6.

Hummel, D. & Maedche, A. (2019). How effective is nudging? A quantitative review on the effect sizes and limits of empirical nudging studies. *Journal of Behavioral and Experimental Economics* 80, 47-58.

Hägerstrand, T. (1967). *Innovation diffusion as a spatial process*. University of Chicago Press.

Jones, R. & Pykett, J. & Whitehead, M. (2010). Big society's little nudges: The changing politics of health care in an age of austerity. *Political Insight* 1 (3), 85-87.

Konttinen, H., Halmesvaara, O., Fogelholm, M., Saarijärvi, H., Nevalainen, J., & Erkkola, M. (2021). Sociodemographic differences in motives for food selection: results from the LoCard cross-sectional survey. *International Journal of Behavioral Nutrition and Physical Activity*, *18*(1), 1-15.

Ledderer, L., Kjaer, M., Madsen, E., Busch, J. & Fage-Butler, A. (2020) Nudging in Public Health Lifestyle Interventions: A Systematic Literature Review and Metasynthesis. *Health Education & Behavior* 47 (5). DOI:10.1177/1090198120931788

Lengyel, B., Bokányi, E., Di Clemente, R., Kertész, J. & González, M.C. (2020). The role of geography in the complex diffusion of innovations. *Nature Scientific Reports*, 10: 15065.

Reijula, S., & Hertwig, R. (2022). Self-nudging and the citizen choice architect. *Behavioural Public Policy, 6*(1), 119-149. doi:10.1017/bpp.2020.5

Salo, M, Savolainen, H., Karhinen, S. & Nissinen, A. (2021). Drivers of household consumption expenditure and carbon footprints in Finland. *Journal of Cleaner Production* 289.

Simon, H.A. (1972) Theories of bounded rationality. *Decision and organization* 1(1), 161-176.

Simon, H.A. (1979) Rational decision making in business organisations. *The American Economic Review* 69 (4), 493-513.

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