Frontiers in Behavioral Economics

TYPE Original Research
PUBLISHED 20 November 2024
DOI 10.3389/frbhe.2024.1402624

OPEN ACCESS

EDITED BY
Ji Lu,
Dalhousie University, Canada

REVIEWED BY
Xiaoyu Guan,
Beijing Normal University, China
Weijie Wang,
University of Missouri, United States

*CORRESPONDENCE
Cameron McRae
cameron_mcrae@sfu.ca

RECEIVED 18 March 2024
ACCEPTED 16 October 2024
PUBLISHED 20 November 2024

CITATION
McRae C and Dubé L (2024) Availability bias and heterogeneity in saliency, recency, and frequency of promotions for plant-based foods: a naturalistic observation.
Front. Behav. Econ. 3:1402624.
doi: 10.3389/frbhe.2024.1402624

Availability bias and heterogeneity in saliency, recency, and frequency of promotions for plant-based foods: a naturalistic observation

Cameron McRae[1,2]* and Laurette Dubé[2,3]

[1]Centre for Infectious Disease Genomics and One Health (CIDGOH), Simon Fraser University, Burnaby, BC, Canada, [2]Department of Marketing, Desautels Faculty of Management, McGill University, Montreal, QC, Canada, [3]McGill Centre for the Convergence of Health and Economics (MCCHE), McGill University, Montreal, QC, Canada

Availability bias influences decisions by how readily certain events, objects, or people can be brought to mind. This "*out of sight, out of mind*" effect depends on whether these elements are present during decision-making. To promote sustainable food consumption, understanding this bias is crucial, as marketing promotions exhibit heterogeneity in terms of the salience, recency, and frequency with which they are administered. Our research examines the impact of different promotions that vary across these three dimensions on the demand for plant-based food products and their interaction with price sensitivity. We analyzed weekly purchases of 21 plant-based beverage brands across 242 stores in Quebec, Canada, from 2015 to 2016 using two-level mixed-effect regression models across four studies. Results from Study 1 indicate that flyer promotions that had high salience, recency, and frequency were most effective ($B = 0.417$, $p < 0.001$), compared to mobile promotions with low salience and variable recency and frequency ($B = 0.233$, $p < 0.001$) or in-store promotions of high salience but low recency and frequency ($B = 0.073$, $p < 0.001$). Of the mobile promotions evaluated in Study 2, advertisements promoting bonus loyalty points were the most effective in driving demand ($B = 0.776$, $p < 0.001$), followed by general advertisements ($B = 0.125$, $p < 0.001$). Demand was elastic across all models, and most promotions increased price sensitivities in Studies 3 and 4 regardless of their salience, recency, or frequency. The findings highlight the synergistic effect of promotional elements delivered both before and at the decision-making moment in overcoming availability bias to boost demand for sustainable products. However, frequent promotions may increase price sensitivities due to anchoring to promotional prices. This article has implications for theory and practice.

KEYWORDS

availability bias, heuristics, sustainability, loyalty programs, food marketing, mobile promotions, food prices, food systems

1 Introduction

Economic performance and growth have been the primary focus of businesses, disregarding their health, environmental, and social impacts, traditionally the responsibility of government and civil society. This focus, while generating wealth, has led to negative consequences (Dubé et al., 2014, 2012). There is an urgent need for businesses to prioritize health, environmental, and social outcomes alongside traditional business metrics in their core business strategies, as current Corporate Social Responsibility (CSR) efforts are insufficient (Dubé et al., 2014, 2022). The agri-food sector, a major emitter of greenhouse gases, illustrates this need, with calls to decrease meat consumption and shift to more sustainable food products (Clark et al., 2020; Poore and Nemecek, 2018; Willett et al., 2019). Food retailers are well-positioned to facilitate this sustainability transition as the interface between consumers and other actors from the agri-food system. However, plant-based food adoption lags, causing serious financial consequences for manufacturers and retailers. Recently in 2023, the revenue and volume of plant-based food products sold decreased respectively by 2% and 9% compared to the prior year (Pierce et al., 2024). This declining trend motivates the need for a better understanding of the drivers and barriers of plant-based product consumption and related business practices.

To address these barriers, understanding the intricacies of cognitive biases is paramount for designing effective marketing promotions that seek to boost demand for sustainable products. A cognitive bias is a systematic pattern of deviation from what would be the optimal choice, as determined by a utility function and full consideration of all aspects pertinent to the decision (Tversky and Kahneman, 1974). These biases often arise from the reliance on heuristics, also called "rules of thumb," that act as simplifying strategies for quick and efficient judgments (Gigerenzer and Gaissmaier, 2011; Tversky and Kahneman, 1974). Heuristics lead to systematic errors in decision-making, causing individuals to behave in ways that are suboptimal. The availability bias is a type of cognitive bias that affects an individual's ability to recall events, objects, or people at the time they are making a decision (Tversky and Kahneman, 1973). This "out of sight, out of mind" effect depends on whether such elements are present (physically, digitally, or mentally) at the decision-making moment. The availability bias can influence choices, as individuals tend to rely on easily accessible information. The context in which decisions are made further shape the availability of information, with factors such as situational cues affecting what is brought to mind.

Availability bias, also referred to as the availability heuristic, has been extensively studied in judgment and decision-making contexts (Dube-Rioux and Russo, 1988; Jacoby et al., 1989; Kahneman, 2011; Oppenheimer, 2004; Schwarz et al., 1991; Taylor and Thompson, 1982; Watkins and LeCompte, 1991), with a notable emphasis on risk in the financial context (Barber and Odean, 2008; Ganzach, 2000). Past work has shown that an individual's risk judgments are shaped by the availability of information like past personal experiences or media coverage (Lichtenstein et al., 1978), as well as information from their social networks (Hertwig et al., 2005). Factors like salience, recency, and frequency enhance information availability and retrieval from memory (Kahneman, 2011; Tversky and Kahneman, 1974). Salience refers to the prominence or vividness of information relative to its surroundings in a given context, drawing attention and making it more likely to be recalled and considered during decision-making (Bordalo et al., 2022). Recency, on the other hand, pertains to the timing of the information, with more recent information being more easily accessible from memory (see Baddeley and Hitch, 1993). Frequency of exposure is another key factor in shaping availability bias, as high frequency items are easier to store in long-term memory, associate with context, and access via working memory (Popov and Reder, 2020). As consumers are repeatedly exposed to the same promotional content, it becomes more accessible in their cognitive processes at decision-making moments. These three factors play crucial roles in shaping judgments and decisions, as they influence the ease with which information can be retrieved as inputs to the decision-making process. Thus, the salience, recency, and frequency of information is connected to availability bias because it suggests that individuals tend to give undue weight to information that is more readily available to them at the moment of decision-making (Dube-Rioux and Russo, 1988).

Availability bias is an important consideration for the design of marketing promotions. Based on the aforementioned research, we would expect that promotions that are more salient and more recent would have a greater effect on decisions than those that are less salient or more distant in time. Marketing promotions can range in salience and recency depending on when and where the promotion is placed. For example, an on-the-shelf promotion may be less salient but more recent, compared to a billboard promotion in a store parking lot, when choosing a product from the selection on a shelf. Understanding the optimal salience and timing of promotional strategies during the consumer journey is crucial for marketers aiming to influence sustainable consumption practices. In fact, most of the research on availability bias has been limited to financial decision-making, as previously mentioned, and yet been investigated within the context of food choices, particularly around sustainable food choices. In addition, price is another critical factor in consumer decisions, as it directly impacts perceived value and affordability (Tellis and Gaeth, 1990). Price is frequently mentioned as a barrier to sustainable consumption (ElHaffar et al., 2020; Fogelholm et al., 2024), which is partially driven by price premiums that are often placed on products with sustainability attributes (Li and Kallas, 2021). Investigating the interactions of price considerations with availability bias are essential; they have both been found to impact decision-making but have not been investigated at the same time. In this article, we aim to address these gaps while also addressing the critical societal issue of boosting demand for plant-based products. Considering both the theoretical and societal relevance, we proposed the following two research questions:

1. Do marketing promotions that are more salient, recent, and frequent have a greater influence on demand for plant-based products than those that are less salient, recent, or frequent?
2. How do marketing promotions of different saliency, recency, and frequency interact with price sensitivity to impact demand for plant-based products?

To answer the research questions, we obtained loyalty program data from a large grocery retailer in Quebec, Canada. The dataset contained sales transactions for all plant-based beverages purchased at one of their 242 stores and was linked to promotional data at the store level over nearly 2 years. Plant-based beverages are a good example of a sustainable product with a smaller environmental footprint than animal-based milks. Comparatively, plant-based products emit less carbon, require less land, cause less biodiversity loss, and reduce water pollution (Benton et al., 2021; Xu et al., 2021). A series of four studies were designed to answer the research questions using econometric methods applied to the panel dataset. We evaluated the impact of marketing promotions that varied in salience, recency, and frequency on demand for plant-based beverages. Our regression analyses focused on comparing the impact of the promotions and their interactions with price sensitivity while controlling for other variables known to affect demand.

This work makes several contributions. First, it provides empirical evidence on the impact of salience, recency, and frequency of promotions on consumer demand for sustainable products, specifically within the context of the agri-food sector. By examining different types of promotions (mobile, flyer, and in-store), this study offers insights into how marketers can effectively play off the availability bias by presenting promotions at the right time and place to ensure they are brought to mind closer to the moment of decision-making. Second, it explores the trade-offs between pricing and promotions, shedding light on the potential challenges of balancing profitability with the promotion of sustainable products. Third, we contribute to the information systems literature by investigating how a particular aspect of mobile loyalty program apps and mobile promotions can directly increase purchases of sustainable products in physical stores, highlighting the effectiveness of cross-channel communications from a digital channel to in-store shopping behaviors. Lastly, the findings of this study have practical implications for retailers and policymakers aiming to promote sustainable consumption practices, suggesting that a nuanced understanding of promotion timing and placement is crucial for strategies for effective behavior change.

2 Theoretical background

Drawing from literature in behavioral economics, several interventions to promote sustainable food choices have been studied (for a review, see Abrahamse, 2020). Many of the interventions focused general education that occurs outside the immediate decision-making environment, often assuming that increased knowledge will lead to behavior change (Ran et al., 2022). However, the effectiveness of general education is limited unless it is combined with other interventions that target specific barriers like high prices (Grilli and Curtis, 2021). Referencing bounded rationality, consumers may struggle to process and retain sustainability information when it is delivered outside the immediate decision context, as their cognitive limitations and limited attention make it difficult to prioritize and remember information that is not directly relevant to their immediate choices (Kahneman, 2011). Beyond general education, information can also be provided at targeted points in time and space that affect buying behavior closer to when and where a food choice is made. Based on work examining the availability bias (Kahneman, 2011; Tversky and Kahneman, 1974), information provided closer to the decision should be more impactful than general education provided before a consumer enters the food environment.

Along these lines, much of the work leveraging behavioral economics for sustainability has focused on how changes to choice architecture in the food environment, often referred to as nudging (Thaler and Sunstein, 2009), can guide consumers toward sustainable options without restricting their freedom of choice or the economic incentives involved. Broadly, nudges within the context of sustainable food consumption can be classified by three categories (i) cognitively oriented, (ii) affectively oriented, or (iii) behaviorally-oriented nudges (Vandenbroele et al., 2020). Nudges under the first category of cognitively oriented include descriptive sustainability labels (e.g., organic, fair trade) and evaluative labels (e.g., star ratings, traffic light warnings). Cognitively oriented nudges are designed to influence decision-making by targeting consumers' cognitive processes, such as knowledge, awareness, or understanding (Vandenbroele et al., 2020). Food labels provide information on a product's environmental footprint and are placed on the front-of-pack, similar to what has already been done for nutrition labels (Dubois et al., 2021). Although these front-of-pack labels can boost sales of sustainable products (Elofsson et al., 2016; Vanclay et al., 2011), their overall effect is generally limited and insufficient to reduce purchases of animal-based products (Brunner et al., 2018; Vlaeminck et al., 2014). Visibility enhancements also act as a cognitively oriented nudge where short messages or cues, such as a sign or shelf sticker, draws attention toward a sustainable product in store, or when the placement of the product is changed so that is more salient to the consumer (Vandenbroele et al., 2020). For example, placing a healthy product at eye-level in store boosted its purchases in past research (Foster et al., 2014). Also in regard to placement of items of restaurant menus, changing the position of sustainable options to be more salient has been effective in the past (Kurz, 2018), as well as improving the general availability of options (Garnett et al., 2019).

Affectively oriented nudges are strategies designed to influence consumer behavior by appealing to their emotions and senses rather than relying on cognitive reasoning (Vandenbroele et al., 2020). These interventions use sensory cues—such as visual, auditory, taste, smell, and touch stimuli—or emotional triggers, like social influence, to create a positive affective response toward a sustainable product. Enhancements to visual packaging and displays, taste, auditory and sound, or touch and tactile sensations, or smell can all affect consumer buying behavior (see Vandenbroele et al., 2020 for a review). As well, social norms can act as an affectively oriented nudge by playing off consumer's desire for social desirability (Cadario and Chandon, 2020). Interventions using descriptive norms (e.g., highlighting common behaviors) and injunctive norms (e.g., showing approval or disapproval with symbols like smileys) can influence sustainable consumer choices, but their effectiveness is mixed and depends on context (Elgaaied-Gambier et al., 2018; Schultz et al., 2007).

Behaviorally oriented nudges are interventions designed to influence consumer behavior by making certain choices easier, more convenient, or more appealing through changes in the food environment (Cadario and Chandon, 2020). Much of the research in this area has focused on healthy vs. unhealthy product choices, but can be extended theoretically to the context of sustainability. Convenience-based strategies, like placing healthier options at the beginning of a buffet or positioning them closer to consumers, have shown mixed effectiveness, depending on the product type (Broers et al., 2019; Kongsbak et al., 2016). Changing default options (e.g., automatically offering healthy side dishes) have been more consistently successful in encouraging healthier choices (Loeb et al., 2017; van Kleef et al., 2018), while size-based interventions, such as offering smaller portions, can reduce consumption but may also have unintended effects, such as increasing overall intake when multiple small portions are offered (Zlatevska et al., 2014).

Economic incentives are an additional influence on sustainable purchasing behavior in addition to general education and nudges. Price has been frequently mentioned as a barrier for the purchasing of sustainable products (ElHaffar et al., 2020). Although a barrier, pricing can also be used as a lever to influence demand through discounting products during short periods of time—also referred to as a price promotion (Kuntner and Teichert, 2016). Price promotions can be administered via several channels ranging from an in-store promotion, coupon, cashback, or loyalty points that are redeemable on a future purchase. Regardless of the channel, the study of changes in demand given a relative change in price is referred to as price sensitivity (Tellis, 1988). To strengthen the effectiveness of these economic incentives, reference prices play a crucial role by anchoring consumers' perceptions of what constitutes a "normal" or "fair" price, influencing their response to subsequent price promotions or discounts depending on the difference between the sale price and their reference price (Mazumdar et al., 2005). Little attention has been paid to compare how price sensitivity differs between plant-based products and their animal-based counterparts. Thus far, scholars have focused on comparing organic and non-organic foods, finding that consumers are more price sensitive to organic options (Aschemann-Witzel and Niebuhr Aagaard, 2014; Buder et al., 2014; Millock et al., 2004; Padel and Foster, 2005). The interaction of economic incentives and nudges, however, is not well understood. Some studies have found that combining pricing and nudging strategies is more effective at increasing food sales than using either alone (Gillebaart et al., 2023; Hoenink et al., 2020; Stuber et al., 2021). Preliminary findings indicate that a healthy eating nudge is equivalent to about a 10% price reduction (Cadario and Chandon, 2020); more work is needed to understand how prices and nudges interact and whether the results differ for products with sustainability claims vs. health claims investigated in prior work. Furthermore, how nudges compare to different types of economic incentives (e.g., coupons or loyalty points) remains to be investigated. Also, work is needed to understand how nudges and economic incentives delivered across different channels (e.g., in-store or mobile app) impact shopping behaviors. In sum, studying how nudges compare to different types of economic incentives across diverse channels is a theoretically and practically important topic to revisit.

Behavioral interventions, whether educational, nudges, or economic, may be deployed across different channels. These channels refer to the various mediums or platforms used to deliver these interventions to consumers, such as physical spaces (e.g., in-store displays) or digital platforms (e.g., mobile apps). Several studies have found that loyalty program app adoption can increase consumers' interest and purchase intentions (Bellman et al., 2011) and increase real-world purchases and point redemption (Kim et al., 2015; Son et al., 2020). However, the impact of mobile promotions delivered within such apps remains under-investigated. Studies evaluating the impact of mobile promotions have traditionally been contained within a specific channel (e.g., online shopping), neglecting how they can also impact consumer behaviors across other channels like in-store. Examples of mobile promotions include in-app advertisements, coupons, or bonus points for specific products. In one study of a mobile e-book platform, mobile promotions had heterogeneous effects depending on whether the promoted product was similar to something the consumer bought before or not (Fong et al., 2019). Mobile ads can be more effective in crowded areas (Andrews et al., 2016) or while consumers are on public transit (Ghose et al., 2019), but it depends on competitive dynamics at their location (Fong et al., 2015). Other related research has found that SMS messages can be effective (Luo et al., 2014), but it also depends on the time, location, and redemption timeline (Danaher et al., 2015). Notably, each of these prior studies evaluated mobile promotion effectiveness in isolation from other marketing activities. This body of research has also not yet delved systematically to disentangle the impact of mobile promotions relative to those that can be deployed in a physical retail channel like in-store promotions or weekly flyers.

Overall, this study leverages behavioral economics principles to examine how various marketing interventions—both economic (e.g., price discounts, loyalty points, and coupons) or nudge (e.g., mobile ads and Every Day Low Price (EDLP) advertisements)—can effectively promote sustainable consumption behaviors, with a particular focus on mobile promotions. These promotions differ in their salience, recency, and frequency; three factors that influence availability bias and how readily consumers recall information at the moment of decision-making (Tversky and Kahneman, 1973). Additionally, this research explores the relatively under-studied digital component of marketing promotions, particularly the use of mobile apps to deliver incentives and nudges. By investigating the interaction between different types of incentives and price sensitivity, this research addresses an important gap in understanding how economic and nudge incentives work together to shape demand for sustainable food products. This interplay is crucial for designing effective marketing strategies to encourage more sustainable choices, particularly given the challenges in boosting the consumption of sustainable products in markets today (Pierce et al., 2024).

3 Methods

3.1 Data collection

Data were obtained from a loyalty card program operated by a prominent grocery retailer in Quebec, Canada. The dataset contained transactions for food purchases made by loyalty card members between February 1, 2015, and December 31, 2016. All data about transactions involving plant-based beverages were extracted from the transactional dataset and linked to product and store data. It is important to note that all data were aggregated at the store level and by individual brand (vs. parent brand) for each store and week, as well as by the type of promotion used.

Neighborhood demographic data was obtained by linking to the 2016 Canadian census via store postal codes. This data included measures of population density (Ma et al., 2021), which is a measure of the population divided by the land size. We also leveraged a previous work that coded each store's postal code as low, middle, or high SES (McRae et al., 2022). The SES measure was calculated by clustering census data for the income, educational attainment, and employment of each postal code in the province of Quebec.

3.2 Data coding for promotional activities

The retailer used a variety of promotions for plant-based beverages during the study period. For each transaction in the dataset (i.e., each item scanned at checkout), details regarding whether the item was on promotion or not are recorded, including the type of promotion if one is running. Promotions were coded as being either a mobile promotion, flyer promotion, or in-store promotion. The retailer had reported that approximately 70% of cardholders had downloaded the mobile app where mobile promotions were administered, but specific usage details were not available and are a limitation of this study. The three categories of promotions (i.e., mobile, flyer, and in-store) promotions varied by their salience, recency, and frequency relative to the time and place where food choices were made in the grocery store.

Figure 1 presents a conceptual framework of the three types of promotions—mobile, flyer, and instore—focusing on their salience and recency in relation to the moment consumers decide to add an item to their shopping basket. Table 1 further elaborates on these promotions by comparing their recency, salience, and frequency. Mobile promotions exhibit variable recency, depending on when the consumer accesses the app, and have lower salience since they are not visible at the moment of decision in-store. Their frequency is also variable, contingent on how often consumers engage with the app. Flyer promotions, on the other hand, are highly frequent because they are visible in both the paper flyer at the store entrance and through shelf signage, which reinforces the promotion close to the moment of decision. These flyer promotions are highly salient at the decision point due to their clear presence on the shelf. In-store promotions have high recency, being displayed directly at the point of decision, but lower frequency since they are only visible when the consumer is physically near the product in the store. This distinction between recency (timing of exposure), salience (visibility at the moment of decision), and frequency (how often the promotion is encountered) is critical in understanding how different promotional types influence consumer behavior. More information regarding the three categories of promotions is detailed below.

First, **mobile promotions** were designed as components of the retailer's mobile app, which could be viewed by loyalty card members anytime they opened the app, whether before entering the store, while shopping, or when deciding about a product on the shelf (i.e., the moment of decision). The loyalty dataset allowed us to further decompose mobile promotions into four sub-types: (i) mobile product advertisement, (ii) mobile product advertisement with EDLP, (iii) mobile price discount coupon, and (iv) mobile bonus loyalty points. Because we did not have access to app usage data, we could not determine the recency of the promotion aside from its general placement on the app. However, mobile

TABLE 1 Recency, salience, and frequency of mobile, flyer, and in-store promotions.

Promotion type	Recency	Salience	Frequency
Mobile	Variable	Low	Variable
Flyer	High	High	High
In-store	High	High	Low

Mobile promotions vary in receny and frequency depending on mobile app usage.

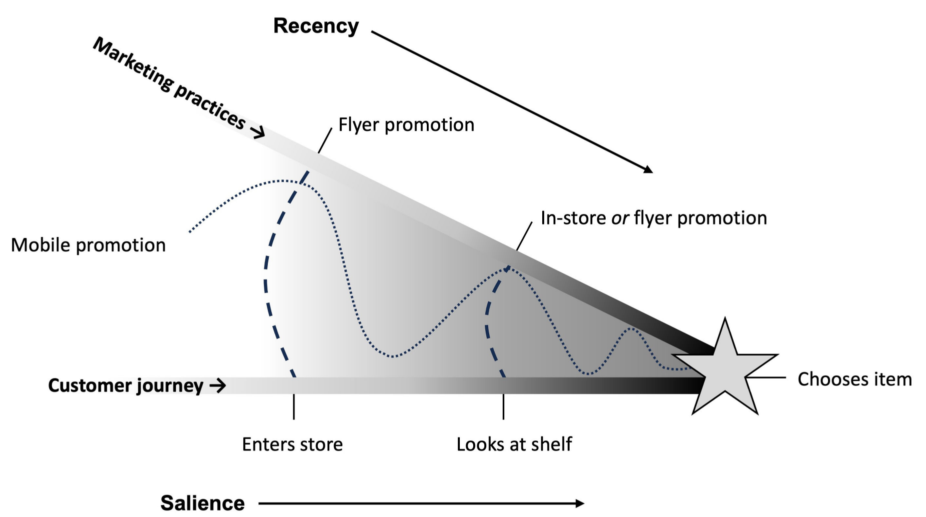

FIGURE 1
Conceptual overview.

promotions are less salient than other physical promotions in-store, as mobile promotions are visually hidden from the line of sight within a consumer's phone, which is often in their pocket or bag.

Second, **in-store promotions** were store-specific and were products that had displays or signs advertising EDLP for a given brand of plant-based beverage. Sometimes, in-store promotions were used to markdown inventory for clearance due to nearing expiry dates. In-store promotions were denoted by signs on the shelf or physical stickers on items and salient when a consumer was browsing the aisles. They are also a high recency promotion due to their presence when a consumer was making their choice among the selection of products on the shelf in a particular category.

Last, **flyer promotions** were included as part of the retailer's weekly sales strategy. Each week, a selection of products are placed on promotion during a cycle from Thursday to Wednesday, which is why the data were aggregated on a weekly timescale. These items are cross-promoted in stores with a paper flyer that is available when a consumer enters the store, signage on the shelf where the product is placed in-store, and posting of the virtual flyer on the retailer's website and within the mobile app. While being as salient as an in-store promotion while browsing aisles, the placement of the paper flyer at the beginning of the store and virtually online makes the promotion high frequency.

The conceptual frameworks for the four studies are depicted in Figure 2, reflecting our focus on how promotions impact consumer demand and interact with price. Study 1 examined the overall impact of mobile promotions on demand, comparing them with a flyer or in-store promotions. Study 2 delved into the effects of specific types of mobile promotions, including everyday low-price advertisements, regular advertisements, coupons, or loyalty points. In Study 3, we explored how different promotion types (mobile, flyer, and in-store) influenced price sensitivity. Finally, Study 4

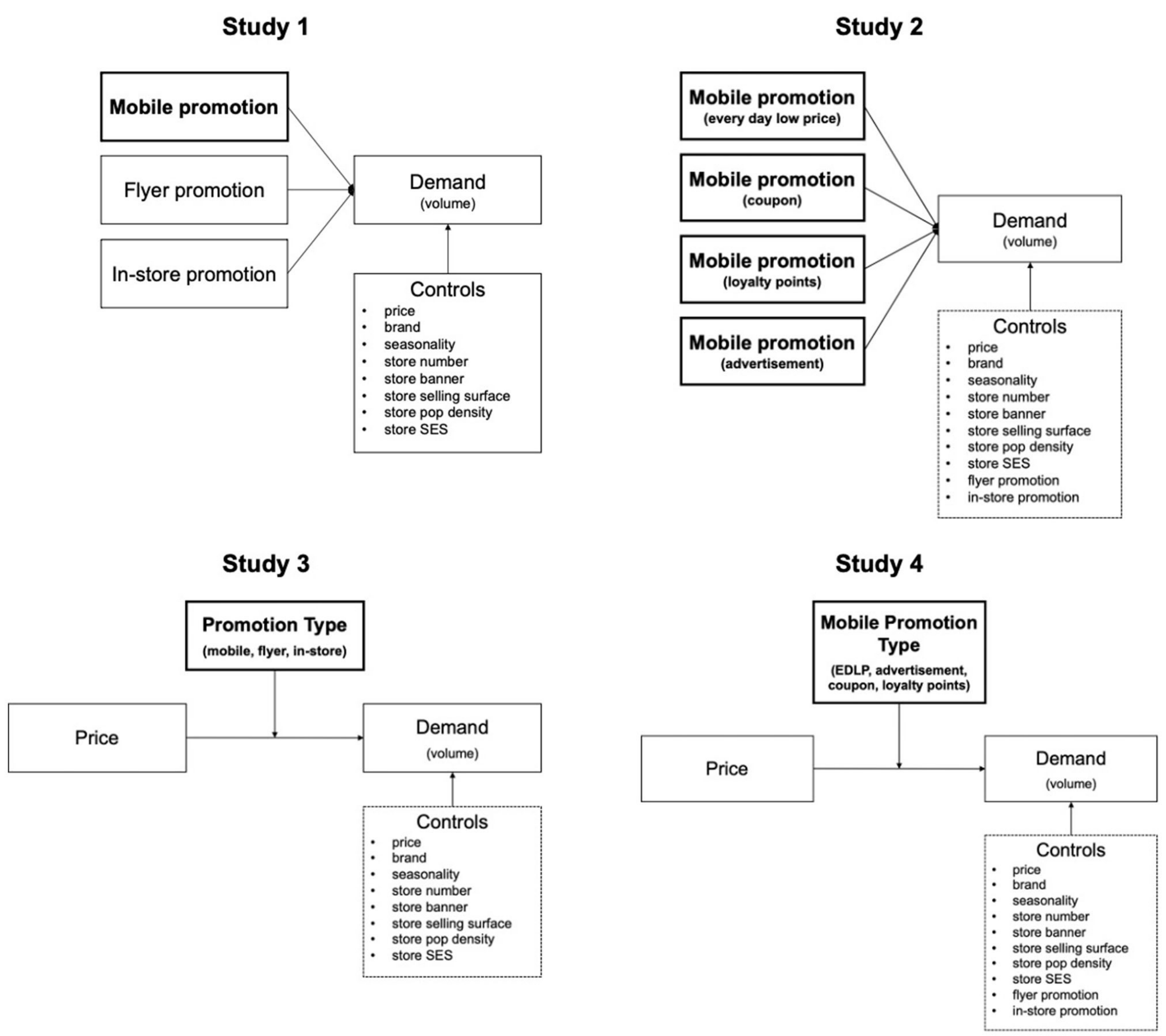

FIGURE 2
Conceptual models for the four studies.

TABLE 2 Overview of variables.

Variable	Definition	Type	Reference group	Model			
				1	2	3	4
Volume	Log of the volume of beverage purchased (milliliters), by store and brand	Continuous	n/a	X	X	X	X
Price	Log of the average final price paid (dollars per gram), by store and brand	Continuous	n/a	X	X	X	X
Promotion-Flyer	Indicator for presence of a flyer promotion	Binary	No flyer promotion	X	X	X	X
Promotion-Store	Indicator for presence of an instore promotion	Binary	No in-store promotion	X	X	X	X
Promotion-Mobile	Indicator for presence of a mobile promotion at store check-out	Binary	No mobile promotion	X		X	
Promotion-Mobile ad	Indicator for presence of a regular mobile advertisement prior to store check-out	Binary	No mobile advertisement promotion		X		X
Promotion- Mobile ad with EDLP	Indicator for presence of an EDLP advertisement prior to store check-out	Binary	No mobile EDLP promotion		X		X
Promotion- Mobile loyalty points	Indicator for accumulation of mobile loyalty points	Binary	No mobile loyalty points		X		X
Promotion- Mobile coupon	Indicator for redemption of a mobile coupon at store check-out	Binary	No mobile coupon promotion		X		X
Store neighborhood population density	Standardized store's neighborhood population density	Continuous	n/a	X	X	X	X
Store SES cluster	Measure of the store's neighborhood SES; 3 factors for low, middle, and high SES	Factor	High SES	X	X	X	X
Store selling surface	Standardized store selling surface (ft2)	Continuous	n/a	X	X	X	X
Store banner	Retail banner; 2 factors for each	Factor	Mid-tier retail banner	X	X	X	X
Year	Year of purchase; one factor for the second year of the dataset	Factor	Year 2015	X	X	X	X
Week	Week of purchase; 52 factors for each of the 53 weeks	Factor	Week 1	X	X	X	X
Brand	Brand of beverage; 20 factors for each of the 21 brands	Factor	Brand 1	X	X	X	X
Store ID	ID used to cluster observations by store number	Random effect, levels defined by ID	n/a	X	X	X	X

analyzed the interaction of the four subtypes of mobile promotions with price sensitivity.

3.3 Variable operationalization

Table 2 presents a summary of the variables utilized along with their definitions. The four studies incorporate a range of variables across four corresponding regression models to evaluate the impact of different marketing promotions and pricing on the demand for plant-based beverages. The dependent variable, **Volume**, represents the log of the volume of beverages purchased (in milliliters) by store and brand and is used as a continuous variable in all four models (Models 1, 2, 3, and 4). Similarly, **Price**, which denotes the log of the average final price paid (in dollars per gram) by store and brand, is a continuous variable included across all models to control for the influence of price on demand.

Several binary variables are used to measure the effects of different types of promotions. **PromotionFlyer** indicates the presence of a flyer promotion and is included in all four models, with "no flyer promotion" as the reference group. **Promotion-Store**, which captures whether an in-store promotion is present, is also included in all four models, using "no in-store promotion" as the reference group. The variable **Promotion-Mobile**, indicating a mobile promotion at store check-out, is included in Models 1 and 3 to assess its impact on demand compared to no mobile promotion.

Further, specific types of mobile promotions are evaluated. **Promotion-Mobile Ad** (a regular mobile advertisement before store check-out) is included in Models 2 and 4, while **Promotion-Mobile Ad with Every Day Low Price (EDLP)** (an advertisement with an EDLP message) is also included in Models 2 and 4. EDLP is a retail pricing strategy where products are consistently offered at low, stable prices without relying on promotions or temporary discounts, meaning it is advertised at the regular price with no other economic incentive (Lal and Rao, 1997). **Promotion-Mobile Loyalty Points**, representing the accumulation of mobile loyalty points, and **Promotion-Mobile Coupon**, indicating the redemption of a mobile coupon at store check-out, are both included in Models 2 and 4. Each of these variables uses “no promotion” of the corresponding type as the reference group.

Control variables were added for factors known to influence demand for food, including population density (Ma et al., 2021), neighborhood SES (Aggarwal and Drewnowski, 2019), the surface area of the selling surface in the store which is a proxy measure for variety (Sevilla et al., 2019), and retail banner (Jacob et al., 2022). **Store Neighborhood Population Density** (a continuous variable for the standardized population density of the store's neighborhood) is included in all four models. **Store SES Cluster** (a factor variable representing the socioeconomic status of the store's neighborhood, with categories for low, middle, and high SES) is also used in all models, with “high SES” as the reference group. **Store Selling Surface** (standardized store selling surface in square feet) is a continuous variable included across all models. **Store Banner** (a factor variable for the retail banner, categorized into two levels, with the mid-tier banner as the reference group) is also used in all four models.

We also controlled for seasonality (Ma et al., 2021) and the brand of food (Akbay and Jones, 2005). Time-related controls include **Year** (representing the year of purchase, with the 2nd year of the dataset as a factor) and **Week** (capturing the week of purchase, with factors for each of the 53 weeks), both of which are incorporated in all four models to account for temporal effects. **Brand** (a factor variable indicating the individual beverage brand, with 20 factors representing each of the 21 brands) is included in all models to control for brand-specific effects. Note that we measured by individual brand, which differs from a family or corporate brand in terms of a brand hierarchy. Additionally, **Store ID** is included in all models as a random effect to cluster observations by store number, accounting for within-store correlations over time.

3.4 Statistical modeling

All statistical analyses were conducted using Stata version 18.0. Two-level mixed-effects regression models were used in all four studies. The decision to use mixed-effects regression models was based on the hierarchical structure of the data, with observations nested within higher-level groupings such as products within stores or repeated measures of product purchases over time. Mixed-effects models are ideal for this type of data as they allow for both fixed effects (overall trends) and random effects (variations within groups like stores) (Borenstein et al., 2010), making them well-suited for modeling how marketing promotions influence consumer behavior across different geographical contexts. Additionally, the model addresses unobserved heterogeneity by capturing factors that vary across groups but are not directly measured (Borenstein et al., 2010). This is especially important given the known differences between urban and rural food consumption behaviors that may lead to consumption differences across stores in different regions (Lacko et al., 2020). While other econometric models, such as Tobit (Torres-Reyna, 2007), could be appropriate in contexts with frequent zero outcomes (particularly at the consumer level), this study's store-level aggregation minimizes the presence of zeroes, reducing the need for Tobit models, which handle censored data. Compared to other alternatives, such as fixed-effects models that would discard between-group variation, mixed-effects regression offers greater flexibility and precision by retaining group-level differences and ensuring that both within-group variations and broader trends are captured (Borenstein et al., 2010). The mixed-effects regression equations can be generally written for store $I = 1,\ldots,N$ that is observed at several periods $t = 1,\ldots, T$.

$$y^*_{it} = \alpha + x'_{it}\beta + Z_{it}'\gamma + C_i + \varepsilon_{it} \tag{1}$$

where y^*_{it} is the dependent variable, α is the intercept, x'_{it} is a K-dimensional row vector of explanatory continuous variables, β is a K-dimensional column vector of parameters, Z'_{it} is a M-dimensional row vector of explanatory factor variables, γ is an M-dimensional column vector of parameters, C_i is a store-specific random effect and ε_{it} is the error term. We included a random effect for each store to calculate standard errors for clustered data, as the responses from each store can be correlated over time (Torres-Reyna, 2007).

4 Results

Data were included for all sales transactions of 21 plant-based beverage brands across 242 stores in the province of Quebec across 2 years. The summary statistics are provided in Table 3. Notably, about 28% of purchases were made during an in-store promotion, whereas only about 3% were under a flyer promotion and 4% were under a mobile promotion. Upon further sub-analysis, 96% of the instore promotions were advertising EDLP. This in-store promotion practice was enacted across all stores throughout the 2 years of study. Of the types of mobile promotions offered, most were under the influence of a mobile advertisement (4%), while fewer were made under a mobile EDLP promotion (1%), mobile

TABLE 3 Descriptive statistics.

Variable	Mean	Standard deviation
Volume (log liters)	9.21	1.4
Price (log dollars)	−5.91	0.31
Promotion - binary	0.35	0.48
Promotion - flyer	0.03	0.17
Promotion - store	0.28	0.45
Promotion - mobile	0.04	0.2
Promotion - mobile ad	0.04	0.18
Promotion - mobile ad with EDLP	0.01	0.09
Promotion - mobile points	0.01	0.08
Promotion - mobile coupon	0.00	0.02
Store population density	2,100	3,059
Store SES cluster	2.04	0.73
Store selling surface	22,309	7,814
Store banner	0.63	0.48

loyalty points (1%), or mobile coupon (<1%). 25% of stores were in neighborhoods with high SES, 46% in those with middle SES, and 29% in those with low SES. The average population density of neighborhoods where stores were located was 2,099 people per square kilometer. 63% of the stores were operated under the premium retail banner and their average selling surface was 22,309 square feet.

4.1 Study 1 results

Study 1 aimed to assess the effectiveness of mobile promotions delivered through the retailer's mobile app compared to flyer and in-store promotions. All three types of promotions had a direct and significant impact on demand, as shown in Table 4. Flyers had the greatest influence (B = 0.417, $p < 0.001$), followed by mobile promotions (B = 0.233, $p < 0.001$), and in-store promotions (B = 0.073, $p < 0.001$). Control variables for week and brand were mostly significant, but their results are omitted here due to space limitations. Refer to the Supplementary Table 1 for the full regression results.

4.2 Study 2 results

The aim of Study 2 was to assess the direct effects of four subtypes of mobile promotions while including controls for flyer and in-store promotions. The results are presented in Table 4. Mobile promotions offering loyalty points had the most substantial impact on demand (B = 0.776, $p < 0.001$). Mobile advertisements also had a significant effect (B = 0.125, $p < 0.001$), but the coefficient's magnitude was considerably smaller than that of loyalty points. Mobile advertisements featuring EDLP messaging had a very slight, yet still significant, impact on demand (B = −0.063, $p = 0.028$). However, mobile coupons did not show a significant effect.

TABLE 4 Full regression model main results.

	Study 1			Study 2			Study 3			Study 4		
Variable	B	SE	P>|z|	B	SE	P>|z|	B	SE	P>|z|	B	SE	P>|z|
Promo-flyer	0.417	0.013	0.000	0.413	0.013	0.000	−9.122	0.333	0.000	0.420	0.013	0.000
Promo-store	0.073	0.005	0.000	0.076	0.005	0.000	−2.691	0.097	0.000	0.077	0.005	0.000
Promo-mobile	0.233	0.012	0.000				−5.152	0.219	0.000			
Promo-mobilead				0.125	0.014	0.000				−1.857	0.265	0.000
Promo-mobilepoints				0.776	0.029	0.000				−1.720	1.447	0.234
Promo-mobilecoupon				0.000	0.126	1.000				2.700	2.152	0.210
Promo-mobileEDLP				−0.063	0.029	0.028				−4.193	0.527	0.000
Price	−1.339	0.008	0.000	−1.336	0.008	0.000	−1.069	0.011	0.000	−1.315	0.009	0.000
Price*promo-flyer							−1.556	0.054	0.000			
Price*promo-store							−0.468	0.016	0.000			
Price*promo-mobile							−0.897	0.036	0.000			
Price*promo-mobilead										−0.329	0.044	0.000
Price*promo-mobilepoints										−0.395	0.230	0.086
Price*promomobilecoupon										0.450	0.359	0.210
Price*promo-mobileEDLP										−0.699	0.088	0.000
Store-sescluster2	−0.105	0.053	0.050	−0.105	0.054	0.051	−0.104	0.054	0.051	−0.104	0.054	0.052
Store-sescluster3	−0.166	0.061	0.006	−0.166	0.061	0.006	−0.166	0.061	0.007	−0.166	0.061	0.007
Store-sellsurface	0.157	0.031	0.000	0.158	0.031	0.000	0.158	0.031	0.000	0.158	0.031	0.000
Store-popdensity	0.326	0.024	0.000	0.327	0.024	0.000	0.327	0.024	0.000	0.327	0.024	0.000
Store-banner	0.016	0.063	0.801	0.016	0.063	0.801	0.017	0.063	0.791	0.016	0.063	0.802
Year	−0.219	0.005	0.000	−0.231	0.005	0.000	−0.226	0.005	0.000	−0.228	0.005	0.000
Week × 52	See Supplementary Table 1			See Supplementary Table 2			See Supplementary Table 3			See Supplementary Table 4		
Brand × 20	See Supplementary Table 1			See Supplementary Table 2			See Supplementary Table 3			See Supplementary Table 4		
Log likelihood	−346,850			−346,640			−345,945			−346,523		
n observations	237,971			237,971			237,971			237,971		
n clusters	242			242			242			242		

Once again, the full results for the control variables can be found in Supplementary Table 2.

4.3 Study 3 results

Following the observation of significant direct effects of mobile, flyer, and in-store promotions on demand, Study 3 was designed to investigate their interaction effects with price. The findings are detailed in Table 4. Overall, price had a negative, direct, and significant impact on demand (B = 1.069, $p < 0.001$). The interaction between price and the three types of promotions revealed that all three significantly heightened price sensitivity, as evidenced by their negative coefficients. Flyer promotions increased price sensitivity most (B = −1.556, $p < 0.001$). Mobile promotions (B = −0.897, $p < 0.001$) and in-store promotions (B = −0.468, $p < 0.001$) also increased price sensitivity, though to a lesser extent. The full regression results are reported in Supplementary Table 3.

4.4 Study 4 results

Study 4 aimed to assess whether and how different types of mobile promotions interacted with price to influence demand. The outcomes are detailed in Table 4. Once again, price exhibited a negative and significant effect on demand (B = −1.315, $p < 0.001$). Again, we noted negative coefficients for the interaction terms suggesting that the mobile promotions increased price sensitivity. However, only mobile advertisements featuring EDLP messaging (B = −0.699, $p < 0.001$) and general mobile advertisements (B = −0.329, $p < 0.001$) were significant. The interaction between mobile loyalty points and price was borderline significant (B = −0.395, $p = 0.086$). Mobile coupons did not show a significant interaction with price ($p = 0.210$). The full regression results are provided in Supplementary Table 4.

We conducted a sensitivity analysis to assess the robustness of the main results across different model specifications, focusing on variations in promotional effects and price. We compared base models (Table 5) with their corresponding full models (Table 4). In Base Model 1, promotional effects of flyers (B = 0.774, $p < 0.001$) and mobile (B = 0.159, $p < 0.001$) were positive, while instore promotions showed a slight negative effect (B = −0.049, $p < 0.001$); in Full Model 1, after controlling for store, brand, and time covariates, the in-store promotional effect became positive (B = 0.076, $p < 0.001$). Base Model 2 revealed positive effects for mobile ads (B = 0.379, $p < 0.001$) and mobile points (B = 0.771, $p < 0.001$), while mobile coupons (B = −0.051, $p < 0.001$) and mobile EDLP ads (B = −1.416, $p < 0.001$) were negative; in Full Model 2, mobile coupons lost significance ($p > 0.10$) and the coefficient for mobile EDLP ads approached zero (B = −0.063, $p = 0.028$).

Interaction terms in Base Model 3 showed that flyer promotions (B = −0.884, $p < 0.001$) amplified the negative effect of price, while in-store promotions (B = 0.481, $p < 0.001$) and mobile promotions (B = 0.175, $p < 0.001$) offset price increases. However, in full Model 3, all price interaction terms became negative, with flyers (B = −1.556, $p < 0.001$), in-store promotions (B = −0.468, $p < 0.001$), and digital ads (B = −0.897, $p < 0.001$) showing reduced effectiveness as prices rose. Base Model 4 further

TABLE 5 Base regression model main results.

	Study 1			Study 2			Study 3			Study 4		
Variable	B	SE	P>|z|	B	SE	P>|z|	B	SE	P>|z|	B	SE	P>|z|
Promo-flyer	0.774	0.016	0.000	0.204	0.016	0.000	−4.754	0.395	0.000	0.775	0.016	0.000
Promo-store	−0.049	0.006	0.000	−0.456	0.033	0.000	2.812	0.110	0.000	−0.050	0.006	0.000
Promo-mobile	0.159	0.013	0.000	−1.344	0.150	0.000	1.189	0.263	0.000			
Promo-mobilead				0.379	0.033	0.000				−0.584	0.318	0.066
Promo-mobilepoints				0.771	0.016	0.000				9.923	1.745	0.000
Promo-mobilecoupon				−0.051	0.006	0.000				1.695	2.630	0.519
Promo-mobileEDLP				−1.416	0.009	0.000				−5.081	0.625	0.000
Price	−1.405	0.009	0.000	0.204	0.016	0.000	−1.561	0.011	0.000	−1.406	0.009	0.000
Price*promo-flyer							−0.884	0.064	0.000			
Price*promo-store							0.481	0.018	0.000			
Price*promo-mobile							0.175	0.043	0.000			
Price*promo-mobilead										−0.131	0.053	0.013
Price*promo-mobilepoints										1.654	0.278	0.000
Price*promomobilecoupon										0.508	0.439	0.247
Price*promo-mobileEDLP										−0.911	0.104	0.000
Log likelihood	−394,659			−394,346			−394,180			−346,523		
n observations	237,971			237,971			237,971			237,971		
n clusters	242			242			242			242		

highlighted that mobile promotion interactions with price varied, with mobile ads (B $= -0.131$, $p = 0.013$) and display ads (B $= -0.911$, $p < 0.001$) showing significant negative interactions while mobile points was positive (B $= 1.654$, $p < 0.001$). In Full Model 4, the interaction between price and mobile points flipped direction (B $= -0.395$, $p = 0.086$). Overall, these results suggest that promotional effectiveness, particularly in mitigating the impact of price increases, diminishes when store, brand, and temporal covariates were included, underscoring the importance of contextual factors in shaping promotional outcomes. This suggests that the promotional strategies that seemed to alleviate the impact of price in the base models are less robust when contextual factors like store characteristics, brand, and timing are accounted for. Essentially, the base models show an optimistic view of promotions' ability to counteract price increases, but the full models reveal that this impact diminishes in real-world conditions, highlighting the importance of considering broader market and contextual dynamics when evaluating promotional strategies.

5 Discussion

This study illustrates how behavioral economics principles can be leveraged to understand and promote sustainable food consumption, focusing on curtailing availability bias by accounting for the salience, recency, and frequency of promotions in relation to the purchase decision making point. Understanding these factors is crucial for designing effective interventions aimed at boosting plant-based food consumption, critically needed for both manufacturers in the sector and for the broader agri-food system to meet carbon reduction targets (Willett et al., 2019). By examining how marketing promotions, which differ in the salience, recency, and frequency, interact with product prices to impact on demand for plant-based food products, this research sheds light on how marketers can address cognitive biases through pricing and promotion strategies that direct consumer behavior toward a more sustainable direction.

The results indicate that promotions that are more recent, salient, and frequent were most effective at directly boosting demand for plant-based beverages. Flyers had the strongest influence, followed by mobile promotions, then in-store promotions; all were positive and significant factors that increased demand. Flyer promotions had high recency and salience at the decision point due to sale signs placed on the shelf, in addition to being high frequency due to the presence of flyers at the front of store, as well as some end-caps (i.e., the end-of-aisle displays) and the flyer's availability within the mobile app. These findings align with past work on availability bias, which suggests that information more readily available or salient at the decision-making moment tend to have a greater influence on choices (Schwarz et al., 1991; Tversky and Kahneman, 1973). The smaller influence of in-store promotions could be tied to the fact that the large majority of them were for Every Day Low Price (EDLP) advertising without any further economic incentive. A major challenge with EDLP advertising for plant-based beverages may be tied to the reluctance of consumers to pay a premium for them relative to animal-based substitutes like cow milk (Onwezen et al., 2021; Rombach et al., 2023). The EDLP messaging along with a relatively higher price for plant-based beverages may have posed a conflict for consumers and would be an interesting avenue for further research to dissect.

Mobile promotions, particularly those offering loyalty points, were effective in driving demand for plant-based beverages. Albeit having low salience and variable recency and frequency, the results highlight the potential of administering promotions via mobile apps as components of retail loyalty programs. Consumer adoption of loyalty program mobile apps is high in grocery retailing, with most consumers belonging to multiple, and often competing, loyalty programs (Stweart, 2021). The relatively strong influence of loyalty point promotions through the mobile app could be tied to the psychological appeal of accumulating points, which taps into consumers' desire for delayed, direct rewards of a higher value compared to immediate ones of lesser value (Keh and Lee, 2006). Loyalty programs may tap into affective salience as points-based promotions can foster a sense of exclusivity and progress, as consumers feel they are accessing special deals not available to non-members (Rosenbaum et al., 2005). The results from Study 2 also found that general mobile advertisements, without direct economic incentives, nudged consumers toward the purchasing of plant-based beverages, albeit to a lesser extent than economic promotions mobile loyalty points. Mobile advertisements may be considered a cognitively-oriented nudge (Vandenbroele et al., 2020), given that they are only providing information and are still rely on cognitive processes by the consumer to pay attention to, remember, and act on the information provided. Other affective or behavioral nudges may be more effective but were not within the scope of this article. Overall, the results of the four studies suggest that mobile promotions can be a useful tool in encouraging sustainable purchasing behaviors and that their implementation does not necessarily require financial incentives to have an impact.

The non-significant findings related to mobile coupons provide important insights into the varying effectiveness of mobile promotions. Unlike loyalty points or general mobile advertisements, mobile coupons did not significantly impact demand for plant-based beverages, which aligns with prior research indicating that mobile coupons often face barriers such as low consumer engagement, the need for active redemption, and friction associated with expiration dates or complex redemption conditions (Danaher et al., 2015). Additionally, mobile coupon redemption is influenced by factors like product type and shopping motivation, with utilitarian shoppers requiring greater personalization and location convenience to redeem offers compared to more hedonic shoppers (Khajehzadeh et al., 2015). The cognitive effort and perceived lack of control involved in redeeming mobile coupons can further deter consumers, especially when compared to more seamless promotional methods such as loyalty points (Dickinger and Kleijnen, 2008). Moreover, research suggests that mobile coupons are less effective when they do not align with the consumer's main shopping goals, particularly for shoppers focused on practical, essential purchases like groceries (Khajehzadeh et al., 2014). These findings suggest that while mobile coupons have potential, their design and delivery need to be optimized to reduce friction and increase salience, possibly through integration with other high salience promotions.

Price sensitivity is a significant factor influencing consumer behavior, particularly for sustainable products, which are often perceived as more expensive (ElHaffar et al., 2020). The study revealed that promotions, regardless of their salience, recency, or frequency, increased price sensitivity. This suggests that promotions can influence not only demand but also consumers' price perceptions. One possible behavior mechanism relates to reference prices and price anchoring (Mazumdar et al., 2005; Tversky and Kahneman, 1974). About 34% of the purchase transactions in the dataset were made when a promotion was present. The large proportion of sales with a promotion suggests that consumers could be using lower promotional prices as an anchor or reference price. Evidence for price anchoring could be tied to the high frequency of EDLP in-store promotions. When a promotion ends, consumers may be reluctant to pay the regular price and wait for the next promotion or purchase an alternative product. The over-reliance of consumers on promotions has been noted within the context of mobile apps for loyalty programs in prior research (Son et al., 2020). Marketers should be cautious in their promotion strategies, as frequent promotions may lead to consumers anchoring their reference prices to promotional prices over time.

This study makes several notable contributions to the fields of behavioral economics, marketing, and information systems, particularly within the scope of promoting sustainable household decisions. First, it enriches the literature on availability bias by demonstrating how promotional strategies with varying salience, recency, and frequency can influence sustainable consumption behaviors. Specifically, our findings align with the availability bias framework (Tversky and Kahneman, 1973), confirming that promotions placed closer to the decision point had a more pronounced effect, particularly flyer promotions visible at both the store entrance and the shelf. This reinforces prior research on the salience of promotional cues at critical decision-making moments (Schwarz et al., 1991). Second, this study adds to the body of work on marketing and sustainability by illustrating how different types of promotions—flyer, in-store, and mobile—heightened price sensitivity for sustainable plant-based food products, which is already a major barrier to the adoption of sustainable products (ElHaffar et al., 2020). Frequent promotions may anchor consumer reference prices, potentially increasing reliance on discounts to stimulate demand (Mazumdar et al., 2005). Third, this study extends the literature on information systems by exploring how mobile loyalty program applications can directly increase purchases of sustainable products when shopping in physical stores (Kim et al., 2015; Son et al., 2020). The efficacy of mobile promotions, particularly those offering loyalty points, underscores how digital innovations can support sustainable household decision making by encouraging the adoption of plant-based beverages. Overall, these findings align with the focus of the Research Topic for this journal, which is focused the role of innovations, technologies, and behavioral strategies in transforming household lifestyles toward more environmentally friendly and socially responsible practices.

5.1 Practical and policy implications

Loyalty programs can serve as an entry point for sustainable transformation due to their large-scale adoption, with approximately 72% of the Canadian adult population using one or more loyalty programs in 2021 (Stweart, 2021). In designing these programs, the findings suggest that marketers should focus on enhancing the salience, recency, and frequency of individual promotional efforts to influence consumer decision-making regarding sustainable plant-based foods. Strategically positioning promotional materials, such as flyers at store entrances and shelf signage at the point of purchase, can address availability bias, increasing the likelihood that these products are recalled during critical decision moments. Mobile promotions, though less salient at the point of purchase, may be effective when paired with incentives like loyalty points, which can increase consumer engagement. However, the observed increase in price sensitivity due to frequent promotions suggests that marketers should avoid over-promoting sustainable products. Instead, lowering baseline prices over time could offer a more sustainable approach to maintaining demand, without the need for constant discounting.

From a policy perspective, the findings highlight the need for interventions that address the underlying pricing structures of sustainable plant-based foods. To reduce baseline prices over time and decrease reliance on frequent promotions, policymakers could consider implementing subsidies for sustainable food producers, which could allow manufacturers and retailers to offer these products at lower prices without compromising profitability (Yu et al., 2018). Tax incentives for retailers who prioritize the stocking and promotion of plant-based products could also encourage price reductions like what has been done for green energy (Cansino et al., 2010). Additionally, policies that support supply chain efficiencies, such as grants or funding for sustainable agriculture and food processing technologies, could help lower the production costs of plant-based foods, making it easier to reduce baseline prices. For example, the Government of Canada has invested over 300 million dollars in Protein Industries Canada, an innovation cluster designed to spur plant-based product innovation and improve supply chain efficiencies (Protein Industries Canada, 2022). These policy levers, when aligned with behavioral insights, could help ensure that sustainable foods are both accessible and affordable to consumers, promoting long-term shifts in consumption patterns without over-reliance on temporary discounts.

5.2 Limitations

Some limitations merit discussion. First, there is a risk of selection bias due to the reliance on loyalty program data from a single grocery retailer in Quebec, Canada. This dataset may not fully represent the broader consumer population, as it only includes individuals who are members of the retailer's loyalty program and actively engage with it. However, it is important to note that the retailer operated 242 stores across Quebec and had over 1 million active members in the loyalty program. Considering the population of Quebec was just over 8 million including children, and the average household size was 2.29 (Statistics Canada, 2015), the retailers dataset covers a sizeable amount of the population.

The representativeness of the data sample also poses implications for the study's external validity. The data reflects purchasing behavior from a specific region (Quebec) and period

(2015–2016), which may not be reflective of broader geographic or temporal contexts. Consequently, the findings may not fully extrapolate to other regions, countries, or timeframes where consumer behavior, market conditions, and promotional strategies might differ. To enhance the study's external validity, future research could incorporate data from multiple retailers and regions, include a broader demographic sample, or employ methods to adjust for potential selection and measurement biases. Second, measurement bias might arise from the way promotional exposure and consumer responses are recorded. For example, the exact timing and frequency of mobile promotions seen by consumers cannot be precisely determined due to the lack of detailed app usage data, which could affect the accuracy of the measured impact of these promotions on demand. Furthermore, while the study controls for various store and neighborhood characteristics, it is important to note that these measures are aggregated at the store level, which may not capture individual-level heterogeneity in responses to promotions. Third, we only studied one product category here which limits generalizability. Future work may explore other sustainable product categories. Also, we only study plant-based food products and not in comparison to their status-quo equivalents. While such comparison could be helpful for comparing status-quo vs. sustainable impact, we believe that a direct focus on how to promote sustainable products may be more useful for actual transition at scale in business practices. Last, the nature of our study being cross-sectional limits our capacity to establish causality. Although a longitudinal approach allows for evaluating changes within individuals over time, establishing causation remains challenging and should be the subject of future research studies in this area. Controlled experiments in the lab or in the field would be useful to disentangle causal effects in future research.

6 Conclusion

This study highlights the importance of salience, recency, and frequency in the effectiveness of marketing promotions for sustainable plant-based foods. Together, these three dimensions work together to address availability bias through information provision at the right time and place. Flyer promotions, with their high salience and frequency at key decision points, had the greatest impact on demand, followed by mobile and in-store promotions. However, the increased price sensitivity associated with these promotions underscores the need for strategic balance in their use. These findings provide critical insights for academic theory and marketers aiming to influence consumer behavior through the optimal timing and placement of promotional efforts, addressing cognitive biases to drive sustainable consumption.

Data availability statement

The data analyzed in this study is subject to the following licenses/restrictions: the dataset used in our study is subject to several restrictions due to a Non-Disclosure Agreement (NDA) with the grocery retailer. As a result, we are limited in the level of detail we can share about the data. These restrictions ensure that we respect the confidentiality of the retailer's business operations and the privacy of the consumers who are part of the loyalty card program. Requests to access these datasets should be directed to cameron_mcrae@sfu.ca.

Ethics statement

Ethical approval was not required for the study involving humans in accordance with the local legislation and institutional requirements. Written informed consent to participate in this study was not required from the participants or the participants' legal guardians/next of kin in accordance with the national legislation and the institutional requirements.

Author contributions

CM: Conceptualization, Formal analysis, Methodology, Writing – original draft, Writing – review & editing. LD: Conceptualization, Resources, Supervision, Writing – review & editing.

Funding

The author(s) declare financial support was received for the research, authorship, and/or publication of this article. The authors acknowledge support from the Canadian Institutes of Health Research (CIHR) [Grant No. 02083-000, 2021-2027] and the Public Health Agency of Canada (PHAC) [Grant No. 1516-HQ- 000069, 2016-2019]. CM also thanks the Center de développement de la formation et de la maind'œuvre Huron-Wendat (CDFM) and Social Sciences and Humanities Research Council (SSHRC) [Grant No. 767-2021-2688, 2021-2024]. The authors would like to thank Simon Fraser University's Central Open Access Fund for covering the open-access fees for this publication.

Acknowledgments

The authors thank the grocery retailer who provided access to the dataset. The authors also thank Claire Burgoyne who volunteered at the McGill Center for the Convergence of Health and Economics (MCCHE) and contributed to data preparation and early work that inspired this article.

Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/frbhe.2024.1402624/full#supplementary-material

References

Abrahamse, W. (2020). How to effectively encourage sustainable food choices: a mini-review of available evidence. *Front. Psychol.* 11:589674. doi: 10.3389/fpsyg.2020.589674

Aggarwal, A., and Drewnowski, A. (2019). Plant-and animal-protein diets in relation to sociodemographic drivers, quality, and cost: findings from the Seattle obesity study. *Am. J. Clin. Nutr.* 110, 451–460. doi: 10.1093/ajcn/nqz064

Akbay, C., and Jones, E. (2005). Food consumption behavior of socioeconomic groups for private labels and national brands. *Food Qual. Prefer.* 16, 621–631. doi: 10.1016/j.foodqual.2005.01.005

Andrews, M., Luo, X., Fang, Z., and Ghose, A. (2016). Mobile ad effectiveness: hyper-contextual targeting with crowdedness. *Market. Sci.* 35, 218–233. doi: 10.1287/mksc.2015.0905

Aschemann-Witzel, J., and Niebuhr Aagaard, E. M. (2014). Elaborating on the attitude–behaviour gap regarding organic products: young Danish consumers and in-store food choice. *Int. J. Consum. Stud.* 38, 550–558. doi: 10.1111/ijcs.12115

Baddeley, A. D., and Hitch, G. (1993). The recency effect: implicit learning with explicit retrieval? *Memory Cogn.* 21, 146–155. doi: 10.3758/BF03202726

Barber, B. M., and Odean, T. (2008). All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. *Rev. Financ. Stud.* 21:785818. doi: 10.1093/rfs/hhm079

Bellman, S., Potter, R. F., Treleaven-Hassard, S., Robinson, J. A., and Varan, D. (2011). The effectiveness of branded mobile phone apps. *J. Interact. Market.* 25, 191–200. doi: 10.1016/j.intmar.2011.06.001

Benton, T. G., Bieg, C., Harwatt, H., Pudasaini, R., and Wellesley, L. (2021). *Food System Impacts on Biodiversity Loss. Three Levers for Food System Transformation in Support of Nature.* London: Chatham House.

Bordalo, P., Gennaioli, N., and Shleifer, A. (2022). Salience. *Annu. Rev. Econom.* 14:521544. doi: 10.1146/annurev-economics-051520-011616

Borenstein, M., Hedges, L. V., Higgins, J. P., and Rothstein, H. R. (2010). A basic introduction to fixed-effect and random-effects models for meta-analysis. *Res. Synth. Methods* 1, 97–111. doi: 10.1002/jrsm.12

Broers, V., Van den Broucke, S., Taverne, C., and Luminet, O. (2019). Investigating the conditions for the effectiveness of nudging: Cue-to-action nudging increases familiar vegetable choice. *Food Qual. Prefer.* 71, 366–374. doi: 10.1016/j.foodqual.2018.08.010

Brunner, F., Kurz, V., Bryngelsson, D., and Hedenus, F. (2018). Carbon label at a university restaurant–label implementation and evaluation. *Ecol. Econ.* 146, 658–667. doi: 10.1016/j.ecolecon.2017.12.012

Buder, F., Feldmann, C., and Hamm, U. (2014). Why regular buyers of organic food still buy many conventional products: product-specific purchase barriers for organic food consumers. *Br. Food J.* 116, 390–404. doi: 10.1108/BFJ-04-2012-0087

Cadario, R., and Chandon, P. (2020). Which healthy eating nudges work best? A meta-analysis of field experiments. *Market. Sci.* 39, 465–486. doi: 10.1287/mksc.2018.1128

Cansino, J. M., Pablo-Romero, M. d. P., Román, R., and Yñiguez, R. (2010). Tax incentives to promote green electricity: an overview of EU-27 countries. *Energy Policy* 38:60006008. doi: 10.1016/j.enpol.2010.05.055

Clark, M. A., Domingo, N. G., Colgan, K., Thakrar, S. K., Tilman, D., Lynch, J., et al. (2020). Global food system emissions could preclude achieving the 1.5 and 2 C climate change targets. *Science* 370, 705–708. doi: 10.1126/science.aba7357

Danaher, P. J., Smith, M. S., Ranasinghe, K., and Danaher, T. S. (2015). Where, when, and how long: factors that influence the redemption of mobile phone coupons. *J. Market. Res.* 52, 710–725. doi: 10.1509/jmr.13.0341

Dickinger, A., and Kleijnen, M. (2008). Coupons going wireless: Determinants of consumer intentions to redeem mobile coupons. *J. Inter. Market.* 22, 23–39. doi: 10.1002/dir.20115

Dubé, L., Jha, S., Faber, A., Struben, J., London, T., Mohapatra, A., et al. (2014). Convergent innovation for sustainable economic growth and affordable universal health care: innovating the way we innovate. *NYAS* 1331:119. doi: 10.1111/nyas.12548

Dubé, L., Pingali, P., and Webb, P. (2012). Paths of convergence for agriculture, health, and wealth. *Proc. Nat. Acad. Sci.* 109, 12294–12301. doi: 10.1073/pnas.0912951109

Dubé, L., Silveira, P. P., Nielsen, D. E., Moore, S., Paquet, C., Cisneros-Franco, J. M., et al. (2022). From precision medicine to precision convergence for multilevel resilience—the aging brain and its social isolation. *Front. Public Health* 10:720117. doi: 10.3389/fpubh.2022.720117

Dube-Rioux, L., and Russo, J. E. (1988). An availability bias in professional judgment. *J. Behav. Decis. Mak.* 1, 223–237. doi: 10.1002/bdm.3960010403

Dubois, P., Albuquerque, P., Allais, O., Bonnet, C., Bertail, P., Combris, P., et al. (2021). Effects of front-of-pack labels on the nutritional quality of supermarket food purchases: evidence from a large-scale randomized controlled trial. *J. Acad. Market. Sci.* 49, 119–138. doi: 10.1007/s11747-020-00723-5

Elgaaied-Gambier, L., Monnot, E., and Reniou, F. (2018). Using descriptive norm appeals effectively to promote green behavior. *J. Bus. Res.* 82, 179–191. doi: 10.1016/j.jbusres.2017.09.032

ElHaffar, G., Durif, F., and Dubé, L. (2020). Towards closing the attitude-intention-behavior gap in green consumption: a narrative review of the literature and an overview of future research directions. *J. Clean. Prod.* 275:122556. doi: 10.1016/j.jclepro.2020.122556

Elofsson, K., Bengtsson, N., Matsdotter, E., and Arntyr, J. (2016). The impact of climate information on milk demand: evidence from a field experiment. *Food Policy* 58, 14–23. doi: 10.1016/j.foodpol.2015.11.002

Fogelholm, M., Vepsäläinen, H., Meinilä, J., McRae, C., Saarijärvi, H., Erkkola, M., et al. (2024). The dynamics in food selection stemming from price awareness and perceived income adequacy: a cross-sectional study using 1-year loyalty-card data. *Am. J. Clin. Nutr.* 119, 1346–1353. doi: 10.1016/j.ajcnut.2024.03.003

Fong, N., Zhang, Y., Luo, X., and Wang, X. (2019). Targeted promotions on an e-book platform: crowding out, heterogeneity, and opportunity costs. *J. Market. Res.* 56, 310–323. doi: 10.1177/0022243718817513

Fong, N. M., Fang, Z., and Luo, X. (2015). Geo-conquesting: competitive locational targeting of mobile promotions. *J. Market. Res.* 52, 726–735. doi: 10.1509/jmr.14.0229

Foster, G. D., Karpyn, A., Wojtanowski, A. C., Davis, E., Weiss, S., Brensinger, C., et al. (2014). Placement and promotion strategies to increase sales of healthier products in supermarkets in low-income, ethnically diverse neighborhoods: a randomized controlled trial. *Am. J. Clin. Nutr.* 99, 1359–1368. doi: 10.3945/ajcn.113.075572

Ganzach, Y. (2000). Judging risk and return of financial assets. *Organ. Behav. Hum. Decis. Process.* 83, 353–370. doi: 10.1006/obhd.2000.2914

Garnett, E. E., Balmford, A., Sandbrook, C., Pilling, M. A., and Marteau, T. M. (2019). Impact of increasing vegetarian availability on meal selection and sales in cafeterias. *Proc. Nat. Acad. Sci.* 116, 20923–20929. doi: 10.1073/pnas.1907207116

Ghose, A., Kwon, H. E., Lee, D., and Oh, W. (2019). Seizing the commuting moment: contextual targeting based on mobile transportation apps. *Inform. Syst. Res.* 30, 154–174. doi: 10.1287/isre.2018.0792

Gigerenzer, G., and Gaissmaier, W. (2011). Heuristic decision making. *Annu. Rev. Psychol.* 62, 451–482. doi: 10.1146/annurev-psych-120709-145346

Gillebaart, M., Blom, S., De Boer, F., and De Ridder, D. (2023). Prompting vegetable purchases in the supermarket by an affordance nudge: examining effectiveness and appreciation in a set of field experiments. *Appetite* 184:106526. doi: 10.1016/j.appet.2023.106526

Grilli, G., and Curtis, J. (2021). Encouraging pro-environmental behaviours: A review of methods and approaches. *Renew. Sustain. Energy Rev.* 135:110039. doi: 10.1016/j.rser.2020.110039

Hertwig, R., Pachur, T., and Kurzenhäuser, S. (2005). Judgments of risk frequencies: tests of possible cognitive mechanisms. *J. Exper. Psychol.* 31:621. doi: 10.1037/0278-7393.31.4.621

Hoenink, J. C., Mackenbach, J. D., Waterlander, W., Lakerveld, J., Van Der Laan, N., and Beulens, J. W. (2020). The effects of nudging and pricing on healthy food purchasing behavior in a virtual supermarket setting: a randomized experiment. *Int. J. Behav. Nutr. Phys. Activ.* 17, 1–12. doi: 10.1186/s12966-020-01005-7

Jacob, J., Vieites, Y., Goldszmidt, R., and Andrade, E. B. (2022). Expected SES-based discrimination reduces price sensitivity among the poor. *J. Market. Res.* 59, 1083–1100. doi: 10.1177/00222437221097100

Jacoby, L. L., Kelley, C., Brown, J., and Jasechko, J. (1989). Becoming famous overnight: limits on the ability to avoid unconscious influences of the past. *J. Pers. Soc. Psychol.* 56:326. doi: 10.1037//0022-3514.56.3.326

Kahneman, D. (2011). "Thinking, fast and slow," in *Farrar, Straus and Giroux.*

Keh, H. T., and Lee, Y. H. (2006). Do reward programs build loyalty for services? The moderating effect of satisfaction on type and timing of rewards. *J. Retail.* 82, 127–136. doi: 10.1016/j.jretai.2006.02.004

Khajehzadeh, S., Oppewal, H., and Tojib, D. (2014). Consumer responses to mobile coupons: the roles of shopping motivation and regulatory fit. *J. Bus. Res.* 67:24472455. doi: 10.1016/j.jbusres.2014.02.012

Khajehzadeh, S., Oppewal, H., and Tojib, D. (2015). Mobile coupons: what to offer, to whom, and where? *Eur. J. Market.* 49, 851–873. doi: 10.1108/EJM-04-2014-0252

Kim, S. J., Wang, R. J.-H., and Malthouse, E. C. (2015). The effects of adopting and using a brand's mobile application on customers' subsequent purchase behavior. *J. Inter. Market.* 31, 28–41. doi: 10.1016/j.intmar.2015.05.004

Kongsbak, I., Skov, L. R., Nielsen, B. K., Ahlmann, F. K., Schaldemose, H., Atkinson, L., et al. (2016). Increasing fruit and vegetable intake among male university students in an ad libitum buffet setting: a choice architectural nudge intervention. *Food Qual. Prefer.* 49, 183–188. doi: 10.1016/j.foodqual.2015.12.006

Kuntner, T., and Teichert, T. (2016). The scope of price promotion research: an informetric study. *J. Bus. Res.* 69, 2687–2696. doi: 10.1016/j.jbusres.2015.11.004

Kurz, V. (2018). Nudging to reduce meat consumption: Immediate and persistent effects of an intervention at a university restaurant. *J. Environ. Econ. Manage.* 90, 317–341. doi: 10.1016/j.jeem.2018.06.005

Lacko, A., Ng, S. W., and Popkin, B. (2020). Urban vs. rural socioeconomic differences in the nutritional quality of household packaged food purchases by store type. *Int. J. Environ. Res. Public Health* 17:7637. doi: 10.3390/ijerph17207637

Lal, R., and Rao, R. (1997). Supermarket competition: the case of every day low pricing. *Market. Sci.* 16, 60–80. doi: 10.1287/mksc.16.1.60

Li, S., and Kallas, Z. (2021). Meta-analysis of consumers' willingness to pay for sustainable food products. *Appetite* 163:105239. doi: 10.1016/j.appet.2021.105239

Lichtenstein, S., Slovic, P., Fischhoff, B., Layman, M., and Combs, B. (1978). Judged frequency of lethal events. *J. Exper. Psychol.* 4:551. doi: 10.1037/0278-7393.4.6.551

Loeb, K. L., Radnitz, C., Keller, K., Schwartz, M. B., Marcus, S., Pierson, R. N., et al. (2017). The application of defaults to optimize parents' health-based choices for children. *Appetite* 113, 368–375. doi: 10.1016/j.appet.2017.02.039

Luo, X., Andrews, M., Fang, Z., and Phang, C. W. (2014). Mobile targeting. *Manage. Sci.* 60, 1738–1756. doi: 10.1287/mnsc.2013.1836

Ma, Y., McRae, C., Wu, Y.-H., and Dubé, L. (2021). Exploring pathways of socioeconomic inequity in vegetable expenditure among consumers participating in a grocery loyalty program in Quebec, Canada, 2015–2017. *Front. Public Health* 9:634372. doi: 10.3389/fpubh.2021.634372

Mazumdar, T., Raj, S. P., and Sinha, I. (2005). Reference price research: review and propositions. *J. Mark.* 69, 84–102. doi: 10.1509/jmkg.2005.69.4.84

McRae, C., Nie, J. Y., and Dubé, L. (2022). "Heterogeneity in feature importance and prediction performance for sales at the market and store levels: the case of branded yogurt products in Quebec," in *2022 IEEE International Conference on Big Data (Big Data)* (IEEE), 4088–4096. doi: 10.1109/BigData55660.2022.10020567

Millock, K., Wier, M., and Andersen, L. M. (2004). "Consumer demand for organic foods–attitudes, values and purchasing behavior," in *13th annual EAERE Conference* (Budapest).

Onwezen, M. C., Bouwman, E. P., Reinders, M. J., and Dagevos, H. (2021). A systematic review on consumer acceptance of alternative proteins: pulses, algae, insects, plant-based meat alternatives, and cultured meat. *Appetite* 159:105058. doi: 10.1016/j.appet.2020.105058

Oppenheimer, D. M. (2004). Spontaneous discounting of availability in frequency judgment tasks. *Psychol. Sci.* 15, 100–105. doi: 10.1111/j.0963-7214.2004.01502005.x

Padel, S., and Foster, C. (2005). Exploring the gap between attitudes and behaviour: understanding why consumers buy or do not buy organic food. *Br. Food J.* 107, 606–625. doi: 10.1108/00070700510611002

Pierce, B., Ignaszewski, E., Gertner, D., and Leet-Otley, T. (2024). *U.S. retail market insights for the plant-based industry*. Available at: https://gfi.org/marketresearch/ (accessed September 4, 2024).

Poore, J., and Nemecek, T. (2018). Reducing food's environmental impacts through producers and consumers. *Science* 360, 987–992. doi: 10.1126/science.aaq0216

Popov, V., and Reder, L. M. (2020). Frequency effects on memory: a resource-limited theory. *Psychol. Rev.* 127:161. doi: 10.1037/rev0000161

Protein Industries Canada (2022). *Protein Industries Canada receives federal funding for another five years.* Available at: https://www.proteinindustriescanada.ca/news/protein-industries-canada-receivesfederal-funding-for-another-five-years (accessed September 4, 2024).

Ran, Y., Lewis, A. N., Dawkins, E., Grah, R., Vanhuyse, F., Engström, E., et al. (2022). Information as an enabler of sustainable food choices: a behavioural approach to understanding consumer decision-making. *Sustain. Prod. Consumpt.* 31, 642–656. doi: 10.1016/j.spc.2022.03.026

Rombach, M., Dean, D. L., and Bitsch, V. (2023). "Got milk alternatives?" Understanding key factors determining US consumers' willingness to pay for plant-based milk alternatives. *Foods* 12:1277. doi: 10.3390/foods12061277

Rosenbaum, M. S., Ostrom, A. L., and Kuntze, R. (2005). Loyalty programs and a sense of community. *J. Serv. Market.* 19, 222–233. doi: 10.1108/08876040510605253

Schultz, P. W., Nolan, J. M., Cialdini, R. B., Goldstein, N. J., and Griskevicius, V. (2007). The constructive, destructive, and reconstructive power of social norms. *Psychol. Sci.* 18, 429–434. doi: 10.1111/j.1467-9280.2007.01917.x

Schwarz, N., Bless, H., Strack, F., Klumpp, G., Rittenauer-Schatka, H., and Simons, A. (1991). Ease of retrieval as information: another look at the availability heuristic. *J. Pers. Soc. Psychol.* 61:195. doi: 10.1037/0022-3514.61.2.195

Sevilla, J., Lu, J., and Kahn, B. E. (2019). Variety seeking, satiation, and maximizing enjoyment over time. *J. Consumer Psychol.* 29, 89–103. doi: 10.1002/jcpy.1068

Son, Y., Oh, W., Han, S. P., and Park, S. (2020). When loyalty goes mobile: effects of mobile loyalty apps on purchase, redemption, and competition. *Inf. Syst. Res.* 31:835847. doi: 10.1287/isre.2019.0918

Statistics Canada (2015). *Estimated number of households and average household size by domain, Canada*. Ottawa. Available at: https://www150.statcan.gc.ca/n1/pub/62f0026m/2017001/app-ann-g-eng.htm (accessed September 4, 2024).

Stuber, J. M., Hoenink, J. C., Beulens, J. W., Mackenbach, J. D., and Lakerveld, J. (2021). Shifting toward a healthier dietary pattern through nudging and pricing strategies: a secondary analysis of a randomized virtual supermarket experiment. *Am. J. Clin. Nutr.* 114, 628–637. doi: 10.1093/ajcn/nqab057

Stweart, S. (2021). *Loyalty Programs – Canada – 2021. [Market Report]*. Mintel Group. Available at: https://store.mintel.com/us/report/loyalty-programs-canada-2021/

Taylor, S. E., and Thompson, S. C. (1982). Stalking the elusive "vividness" effect. *Psychol. Rev.* 89:155. doi: 10.1037//0033-295X.89.2.155

Tellis, G. J. (1988). The price elasticity of selective demand: a meta-analysis of econometric models of sales. *J. Market. Res.* 25, 331–341. doi: 10.1177/002224378802500401

Tellis, G. J., and Gaeth, G. J. (1990). Best value, price-seeking, and price aversion: the impact of information and learning on consumer choices. *J. Mark.* 54, 34–45. doi: 10.1177/002224299005400203

Thaler, R. H., and Sunstein, C. R. (2009). "Nudge: improving decisions about health, wealth, and happiness," in *Amsterdam Law Forum; HeinOnline: Online* (Penguin).

Torres-Reyna, O. (2007). *Panel data analysis fixed and random effects using Stata (v. 4.2).* Data and Statistical Services, Princeton University, 1–40.

Tversky, A., and Kahneman, D. (1973). Availability: a heuristic for judging frequency and probability. *Cogn. Psychol.* 5, 207–232. doi: 10.1016/0010-0285(73)90033-9

Tversky, A., and Kahneman, D. (1974). Judgment under uncertainty: heuristics and biases. *Science* 185, 1124–1131. doi: 10.1126/science.185.4157.1124

van Kleef, E., Seijdell, K., Vingerhoeds, M. H., de Wijk, R. A., and van Trijp, H. C. (2018). The effect of a default-based nudge on the choice of whole wheat bread. *Appetite* 121, 179–185. doi: 10.1016/j.appet.2017.11.091

Vanclay, J. K., Shortiss, J., Aulsebrook, S., Gillespie, A. M., Howell, B. C., Johanni, R., et al. (2011). Customer response to carbon labelling of groceries. *J. Consumer Policy* 34, 153–160. doi: 10.1007/s10603-010-9140-7

Vandenbroele, J., Vermeir, I., Geuens, M., Slabbinck, H., and Van Kerckhove, A. (2020). Nudging to get our food choices on a sustainable track. *Proc. Nutr. Soc.* 79:133146. doi: 10.1017/S0029665119000971

Vlaeminck, P., Jiang, T., and Vranken, L. (2014). Food labeling and eco-friendly consumption: experimental evidence from a Belgian supermarket. *Ecol. Econ.* 108, 180–190. doi: 10.1016/j.ecolecon.2014.10.019

Watkins, M. J., and LeCompte, D. C. (1991). Inadequacy of recall as a basis for frequency knowledge. *J. Exper. Psychol.* 17:1161. doi: 10.1037//0278-7393.17.6.1161

Willett, W., Rockström, J., Loken, B., Springmann, M., Lang, T., Vermeulen, S., et al. (2019). Food in the Anthropocene: the EAT–Lancet Commission on healthy diets from sustainable food systems. *Lancet* 393:447492. doi: 10.1016/S0140-6736(18)31788-4

Xu, X., Sharma, P., Shu, S., Lin, T.-S., Ciais, P., Tubiello, F. N., et al. (2021). Global greenhouse gas emissions from animal-based foods are twice those of plant-based foods. *Nat. Food* 2, 724–732. doi: 10.1038/s43016-021-00358-x

Yu, J. J., Tang, C. S., and Shen, Z.-J. M. (2018). Improving consumer welfare and manufacturer profit via government subsidy programs: subsidizing consumers or manufacturers? *Manuf. Serv. Oper. Manag.* 20, 752–766. doi: 10.1287/msom.2017.0684

Zlatevska, N., Dubelaar, C., and Holden, S. S. (2014). Sizing up the effect of portion size on consumption: a meta-analytic review. *J. Mark.* 78, 140–154. doi: 10.1509/jm.12.0303