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Impact of recent brand consumption on brand choice: The role of uncertainty

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ABSTRACT

Consumers often face uncertainty during grocery shopping. Theory suggests that consumers deal with this uncertainty by relying on internal information sources and hence focus on their memories about the product. Prior research mainly focuses on the role of purchase history during brand choices. However, recent brand consumption can also be an important internal source with potentially different types of information. Yet, the role of recent brand consumption during brand choice decisions is still unknown. In this paper, we use a unique dataset combining data from consumption diaries and purchase scanners for almost 4,000 households to study the impact of recent brand consumption on current brand choices and the moderating impact of variables that influence households' experienced uncertainty (i.e., brand price, the households' budget strictness, and brand experience). We find that recent brand consumption has an important impact on brand choice decisions above and beyond purchase history. Moreover, the role of recent brand consumption becomes stronger in more uncertain situations (i.e., when the brand price is higher, when the budget is more strict, and when the household has less experience with the brand). Overall, our findings contribute to extant choice literature by revealing the pivotal role of recent brand consumption during brand choices and explicating key contingency factors.

1. Introduction

Grocery shopping can be an unexpectedly complex process with many uncertainties (Aylott & Mitchell, 1998; Tsiros & Heilman, 2005; Van Ewijk et al., 2022), stemming typically from economic and behavioral factors. For instance, while many consumers indicate that getting the best value for their money is the top buying criterion (BCG European Consumer Sentiment Report, 2025),[1] uncertainty can arise because consumers have difficulties in estimating the quality of a product (van Ewijk, Gijsbrechts, & Steenkamp, 2022). Consequently, consumers are often uncertain whether purchased products will meet their expectations and satisfy their needs.

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[1] https://www.bcg.com/publications/2025/europeans-brace-for-more-uncertainty.

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Moreover, in times in which consumers feel less optimistic about their personal finances, due to, e.g., inflation and anticipated tax rises, uncertainty felt during grocery shopping magnifies. About half of all Americans indicate that the cost of groceries is a major source of stress in their daily life (The Associated Press-NORC Center for Public Affairs Research, 2025)[2] and more than half of the Europeans worry daily about personal finances (BCG European Consumer Sentiment Report, 2025). As prices increase, the level of stress that consumers experience increases, fortifying the uncertainty of grocery shopping as households face stricter budgets to work with (Pieters et al., 2023). To cope with uncertainty, research shows that consumers mainly rely on their direct personal experiences because these are considered reliable (Babutsidze, 2012; Hoch, 2002; Smith, R.E., & Swinyard, 1983). For instance, Gönül and Srinivasan (1996) show that consumers use their own previous purchases as an information source which helps them to reduce uncertainty during current purchase decisions.

While existing research provides valuable insights into how prior purchases affect brand choices during the grocery decision process (Ailawadi et al., 2007; Gönül & Srinivasan, 1996), the role of recent brand consumption has still to be examined. This is particularly important, as purchase and consumption cannot be considered the same. Sun and Morwitz (2010) conclude that goals activated during consumption can differ from the goals driving subsequent purchase behavior. To exemplify, food-related decisions involve a trade-off between short-term enjoyment and long-term health goals (Hoch & Loewenstein, 1991). The outcome of this goal-conflict can differ between prior consumption and subsequent purchase, given the time gap between the two behaviors (Simonson, 1999). Markman and Brendl (2000) conclude that goals determine how consumers process information. Specifically, consumers primarily focus on information important to the activated goal. As different goals may be activated during consumption and purchase, consumers process different types of information during both types of behavior. Information related to past purchases is often based on search attributes (Degeratu et al., 2000; Steenkamp, 1986) and mainly pertains to marketing actions, such as advertising and promotional activities (Narayanan & Manchanda, 2009). Past consumption-related information, in contrast, is mainly based on experiences and is collected using senses such as smell and taste (Chandon & Wansink, 2012; Higgs & Donohoe, 2011).

Because of different types of information processed during purchases and consumption, we argue that current brand choice models, which are typically based on prior purchase information, can be enhanced by adding information from recent brand consumption. This will help us better understand the consumers' brand choice decision process. Extant consumer behavior literature indicates that consumption can act as an important information source, because own consumption experiences are easy to retrieve (Higgs & Donohoe, 2011; Seguias & Tapper, 2018). Because consumers use senses during consumption, consumption memories tend to be very vivid which makes these memories more easily retrievable compared to less vivid memories such as purchases (Higgs & Donohoe, 2011; Nisbett & Ross, 1980; Roggeveen, Grewal, Townsend, & Krishnan, 2015).

While research suggests that prior consumption plays an important role in consumers' brand choice behavior, this is not yet established empirically. This is probably due to a lack of data, as datasets containing longitudinal consumption and purchase data are not readily available. We have access to a unique dataset, including both purchase data from household scanner data and consumption data from consumption diaries. This unique dataset, observing purchase and consumption behavior of a panel of 3770 households for several years, allows us to investigate the role of recent brand consumption in subsequent brand choice decisions in a grocery context, filling an important gap in the brand choice literature.

We seek to answer the following research question: "What is the impact of recent brand consumption on subsequent brand choice decisions beyond the impact of prior purchases?" Prior research has established that uncertainty plays a central role during grocery shopping (Tsiros & Heilman, 2005; Van Ewijk et al., 2022). However, the amount of uncertainty varies (Aylott & Mitchell, 1998), which implies that the role of recent brand consumption may also vary across shopping contexts. Therefore, we add the following research question: "Does the impact of recent brand consumption on subsequent brand choice decisions depend on moderators that influence the experienced uncertainty?"

By answering these research questions, this study reveals the impact of consumption as an uncertainty-reducing information source in brand choice decisions. The contribution of this research is twofold. First, this study unravels the role of recent brand consumption on subsequent brand choice decision-making, while controlling for purchase history. To the best of our knowledge, we are the first to consider both prior purchase and recent consumption behavior in an empirical setting, a combination that helps us better understand the consumers' brand choice process. Beyond the well-established role of prior purchases (e.g., Ailawadi et al., 2007; Andrews & Currim, 2009; Gönül & Srinivasan; 1996), we find that recent brand consumption is also an important uncertainty-reducing information source that consumers rely on when making brand choice decisions.

Second, extant research indicates that the amount of experienced uncertainty may vary in a grocery context (Kaplan et al., 1974; Tsiros & Heilman, 2005), which implies that the role of recent brand consumption as an information source may also vary across shopping contexts. We account for characteristics typically changing consumers' experienced uncertainty (i.e., brand price, strictness of the household budget, and brand experience), and show how these factors alter the relationship between recent brand consumption and subsequent brand choices.

The rest of this paper is organized as follows. We first provide a theoretical background on the role of recent brand consumption as an uncertainty-reducing information source during brand choice decisions and introduce the conceptual framework and hypotheses. Next, we introduce the data and research method, followed by the results. We then discuss the theoretical and managerial implications and lay out future research directions.

[2] https://apnews.com/article/poll-cost-living-groceries-expense-stress-worrycd183c59f034f6e87525675f3ca04864.

2. Theoretical background

In their *decision-making under uncertainty framework*, Erdem and Keane (1996) argue that consumers' information about a brand and its characteristics is limited and imperfect, which, in turn, leads to uncertainty while making choices (Ching, Erdem, & Keane, 2013, 2017; Erdem & Keane, 1996). This is especially true in consumer goods markets such as grocery retailing, in which brands are constantly adapted or new brands and SKUs are regularly introduced to meet consumers' heterogeneous tastes (Erdem & Keane, 1996; van Ewijk, Gijsbrechts, & Steenkamp, 2022). Extant research establishes that uncertainty can arise because consumers often find it hard to estimate product quality (van Ewijk, Gijsbrechts, & Steenkamp, 2022), creating uncertainty about the product's ability to meet expectations and satisfy needs. Moreover, consumers generally purchase and consume brands in a sequential order rather than simultaneously, which impedes effective brand comparisons and learning (Warlop et al., 2005). Thus, consumers can only gradually resolve their uncertainty over time (Ching et al., 2013; Erdem, 1998). In the longer run, uncertainty remains even for established brands, because not all category users (frequently) consume all brands. Moreover, existing users forget about their experiences and new users (without brand experiences) may also enter the product category (van Ewijk, Gijsbrechts, & Steenkamp, 2022).

Consumers are generally risk averse, meaning that they prefer situations in which they experience a minimal amount of uncertainty (Tsiros & Heilman, 2005; Zhang et al., 2014). Uncertainty creates negative emotions such as worry and fear (Grant & Tybout, 2008). Because consumers dislike these negative emotions, they engage in uncertainty-reducing mechanisms of which searching and processing information are prominent (Grant & Tybout, 2008; He & Rucker, 2023), especially in the context of brand choice decisions (Dowling & Staelin, 1994; Sun, Keh, & Lee, 2012; Tsiros & Heilman, 2005). The tendency to rely on information as a coping mechanism to reduce uncertainty is stronger if the extent of experienced uncertainty is higher (Babutsidze, 2012; Hoch, 2002; Smith, R.E., & Swinyard, 1983; Tversky & Kahneman, 1991), resulting in even more thorough information processing of already available information (Dowling & Staelin, 1994; Sun, Keh, & Lee, 2012; Tsiros & Heilman, 2005).

When searching and processing information in an attempt to reduce uncertainty, consumers tend to focus on already available information because it is perceived reliable (Grant & Tybout, 2008; He & Rucker, 2023). Moreover, consumers consider internal information sources, such as personal experiences, as more credible than external sources of information. Indeed, internal information sources are perceived as not staged or influenced by an external party (Babutsidze, 2012; Hoch, 2002; Smith, R.E., & Swinyard, 1983). Furthermore, consumers can be seduced by their own experiences because these are more engaging and can be interpreted in a suitable way (Babutsidze, 2012; Hoch, 2002; Smith, R.E., & Swinyard, 1983). Taken together, consumers tend to rely on their own, personal experiences during grocery shopping (Hoch, 2002; van Ewijk, Gijsbrechts, & Steenkamp, 2022; Verschooren & Egner, 2023).

Prior research has shown that personal experiences in the form of a consumer's purchase history play a vital role during current purchase decisions (Ching, Erdem, & Keane, 2013, 2017; Erdem & Keane, 1996; Lattin & McAlister, 1985). Previous research also concludes that consumers take prior brand choices into account when making current brand choices (e.g., Russel, 2014). Guadagni and Little (1983) introduced the brand loyalty variable, which captures past brand choice behavior, and showed its pivotal role in decision making. Apart from a consumer's purchase history, experimental research has shown that consumers also rely on other types of personal experiences. Specifically, evidence is presented that consumers, when making grocery purchase decisions, often rely on prior category experiences rather than engaging in in-store decision-making based on contextual information (Hoyer, 1984). For instance, Lemon, White, and Winer (2002) show that consumers rely on information regarding category experience to determine whether they want to keep or drop a service.

While the impact of purchase history (e.g., brand loyalty) has been extensively researched, the effect of recent brand consumption remains to be empirically determined. Studies that try to incorporate recent consumption (e.g., Erdem, Keane, & Sun, 2008; Szymanowski & Gijsbrechts, 2012) are limited in terms of data. Indeed, these studies often use purchase data as a proxy for consumption. However, conceptually, information retrieved from purchases is different than information retrieved from consumption. While purchases tend to provide information about search attributes (e.g., price), recent consumption provides information about experience attributes (e.g., taste, quality) (Chandon & Wansink, 2012; Degeratu et al., 2000; Higgs & Donohoe, 2011; Steenkamp, 1986). These differences can change the way consumers search for and process information, and hence both types of information may be useful in a brand choice decision.

Recent brand consumption and brand choice

Literature on the retrievability of information corroborates the fact that consumers rely on recent brand consumption as an information source (Schwarz et al., 1991; Wänke, 2013). Because consumers can only process a limited amount of information at a time (Raue & Scholl, 2018; Tversky & Kahneman, 1974), consumers often make decisions based on the retrievability of information (Schwarz et al., 1991; Wänke, 2013). Retrievability is driven by the vividness of available information. Vivid information, as compared to non-vivid information, creates more images in the consumers' mind, making the experience detailed and clear (Keller & Block, 1997; Nisbett & Ross, 1980). Because brand consumption activates the use of senses, the level of vividness and thus retrievability increases.

Thus, during brand choice decisions, information inherent to recent brand consumption is vivid (i.e., detailed and clear in the consumer's mind) and easily retrievable (Higgs & Donohoe, 2011; Nisbett & Ross, 1980; Seguias & Tapper, 2018), which will help the consumer to reduce the experienced uncertainty (Lemon, White, & Winer, 2002). This is important because consumers are generally risk averse (Tsiros & Heilman, 2005; Zhang et al., 2014). As such, recent brand consumption will positively affect brand choice likelihood. We hypothesize:

H1: Recent brand consumption increases the likelihood of brand choice.

Uncertainty

Uncertainty during shopping can stem from different sources (Kaplan et al., 1974; Tsiros & Heilman, 2005). Specifically, we can

categorize uncertainty as follows: performance, physical, psychological, social, and financial uncertainty (Kaplan et al., 1974; Tsiros & Heilman, 2005). Performance uncertainty means that consumers are uncertain about the quality standards, physical uncertainty refers to safety concerns in using the product, psychological uncertainty means that a choice can harm a consumer's ego, social risk relates to potential embarrassment towards friends and family, and financial uncertainty refers to potential financial losses when buying a product (Kaplan et al., 1974; Tsiros & Heilman, 2005). These types of uncertainty are unlikely to play an equivalent role during brand choice decisions in a grocery context. Prior literature shows that performance and financial uncertainty prevail in a grocery setting (Dunn, Murphy, & Skelly, 1986). Therefore, this study will focus on these two types of uncertainty.

We argue that different levels of performance or financial uncertainty affect the role of recent brand consumption in brand choice decisions. Therefore, we include brand price, strictness of the household budget, and brand experience – variables that conceptually tie closely with performance and/or financial uncertainty – as moderating variables.

Brand price. Brand prices can impact uncertainty during grocery shopping in multiple ways. First, brand prices could influence the impact of recent brand consumption on brand choices through financial uncertainty. One could argue that consumers experience more financial uncertainty for higher (versus lower) priced brands, making consumers more reliant on recent brand consumption as an information source. Consumers face more uncertainty for higher priced brands because the question arises whether these brands are worth their price, as higher prices imply a higher, potential financial loss (Kaplan et al., 1974; Tsiros & Heilman, 2005). Thus, the impact of recent brand consumption on brand choice will be stronger for higher, as compared to lower, priced brands (Kaplan et al., 1974; Tsiros & Heilman, 2005).

Second, the role of recent brand consumption can also be altered through performance uncertainty. Because the quality of a brand is often unknown by consumers (Erdem & Keane, 1996; Erdem, Keane, & Sun, 2008), they often use price as an indicator for quality (Erdem, Keane, & Sun, 2008). Higher brand prices are associated with higher quality brands (Erdem et al., 2008; Wolinsky, 1983). This higher perceived quality will decrease performance uncertainty (Kaplan et al., 1974; Tsiros & Heilman, 2005), which should attenuate consumers' tendency to engage in searching for and processing information. Consequently, the impact of recent brand consumption on brand choice will be weaker for higher, as compared to lower, priced brands (Dowling & Staelin, 1994; Grant & Tybout, 2008; He & Rucker, 2023; Tsiros & Heilman, 2005).

In sum, higher (versus lower) brand prices may increase financial uncertainty but decrease performance uncertainty. While consumers have the tendency to use recent brand consumption as an information source to reduce financial uncertainty, this tendency is attenuated in case of performance uncertainty. In light of these contrasting arguments, we posit the following contrasting hypotheses:

H2a: The impact of recent brand consumption on the likelihood of brand choice is stronger for brands with a higher (vis-à-vis a lower) price.

H2b: The impact of recent brand consumption on the likelihood of brand choice is weaker for brands with a higher (vis-à-vis a lower) price.

Strictness of the household budget. When consumers live by a strict budget, they face resource scarcity and enter the grocery store with a limited budget (Hamilton et al., 2019a). To stay within budget, these consumers must know how much they are spending, and these estimates directly determine how much they spend. A study by Van Ittersum, Pennings, and Wansink (2010) shows that consumers consistently underestimate shopping basket spending, which puts them at risk for spending more than they budgeted. In turn, household budgets sometimes need to be reallocated, which may trigger a chain of budget and spending decisions that could cause substantial financial uncertainty for consumers (Van Ittersum, Pennings, & Wansink, 2010). As budget-constrained households also lack financial slack, i.e., excess resources that can be deployed in times of need, they do not have a buffer against financial distress, further increasing financial uncertainty. Moreover, budget-constrained households face higher stakes if costs deviate from expectations, amplifying the uncertainty tied to financial planning and decision-making. Because consumers often recognize that another purchase need is on the horizon (Jones, Camp, & Fairhurst, 2015), budget-constrained households may think more about opportunity costs and tradeoffs (Hamilton et al., 2019a). Indeed, they realize that money saved on the current purchase may forestall any potential negative impact of (un)anticipated future purchases (Jones, Camp, & Fairhurst, 2015). The fact that strict budgets steer consumers' attention to money (cf. Hamilton et al., 2019b) may imply that consumers feel cognitively taxed, which encourages them to become more efficient with their resources (Hamilton et al., 2019a). As a result, consumers living by a strict budget tend to rely on internal information sources, of which recent brand consumption is most prevalent. Recent brand consumption experiences are vivid and, as a result, more easily retrievable, which is cognitively less of a burden than other information sources. We hypothesize:

*H3: The impact of recent brand consumption on the likelihood of brand choice is stronger for households with stricter (*versus *more generous) budgets.*

Brand experience. Over time, while purchasing and consuming products, consumers gain brand experience (Ching et al., 2013, 2017; Tsiros & Heilman, 2005). When consumers have more brand experience, they are better able to estimate product quality, and performance uncertainty is reduced (Kaplan et al., 1974; Tsiros & Heilman, 2005). Consequently, consumers that have high (versus low) levels of brand experience do not feel the need for searching and processing information (Dowling & Staelin, 1994; Grant & Tybout, 2008; He & Rucker, 2023; Tsiros & Heilman, 2005), which lowers the role of recent brand consumption when making brand choices.

In contrast, if consumers do not have a lot of experience with a brand, they tend to feel uncertain about its attributes (Aylott & Mitchell, 1998; Tsiros & Heilman, 2005; Van Ewijk et al., 2022). In this case, consumers encounter difficulties in predicting the product's quality as they did not acquire sufficient knowledge (Aylott & Mitchell, 1998; Tsiros & Heilman, 2005; Van Ewijk et al., 2022). Performance uncertainty is thus present, which triggers consumers to search and process information, making the role of recent brand consumption more prominent. Therefore:

H4: The impact of recent brand consumption on the likelihood of brand choice is weaker for households with more (compared to less) brand experience.

Fig. 1 shows the conceptual framework. Next to determining the role of recent brand consumption in brand choice decisions (above

and beyond the effect of prior purchases), we also seek to determine to what extent the role of recent brand consumption changes when the perceived performance and financial uncertainty vary. Therefore, we argue that brand price, the households' budget strictness, and brand experience – three conceptually-related factors of performance and/or financial uncertainty – change the role of recent brand consumption in brand choice decisions. Based on existing research, we also control for certain factors that have an important impact on brand choices (Andrews & Currim, 2009; Erdem & Keane, 1996; Guadagni & Little, 1983).

3. Methodology

To test our predictions regarding the relationship between recent brand consumption and brand choice likelihood and how this relationship is moderated by factors related to performance and financial uncertainty, we model brand choice conditional on category purchase (Swaminathan, Fox, & Reddy, 2001). Because brand choices are nested within a category, we use a nested logit model (e.g., Ailawadi et al., 2007; Andrews & Currim, 2009; Dubé, Hitsch, & Rossi, 2010; Holtrop et al. 2025; Kamakura & Russell, 1989; Train 2009). This specification allows us to model two stages of the purchase process i.e., the brand choice decision (conditional on category incidence) and the category incidence decision.

Brand choice decision

The probability that household h chooses brand b (among the k brands present in a category) during a shopping trip where category c is purchased on day t is given by the multinomial logit model:

$$P(purchase_{bcht}|categoryincidence) = \frac{\exp(U_{bcht})}{\sum_k \exp(U_{kcht})}, \tag{1}$$

where the deterministic part of the utility of household h for brand b belonging to category c on day t is given by the following equation:

$$\begin{aligned} U_{bcht} = {} & \beta_{bc} + \beta_{1h} RecentBrandConsumption_{bcht} + \beta_{2h} BrandPrice_{bcht} * RecentBrandConsumption_{bcht} \\ & + \beta_{3h} StrictBudget_{ht} * RecentBrandConsumption_{bcht} + \beta_{4h} BrandExperience_{bcht} * RecentBrandConsumption_{bcht} \\ & + \beta_{5h} LastPurchased_{bcht} + \beta_{6h} BrandLoyalty_{bch} + \beta_{7h} BrandPrice_{bcht} + \beta_{8h} BrandExperience_{bcht} + \beta_{9h} Promotion_{bcht} \\ & + \beta_{10h} TimeSinceLastPurchase_{bcht}. \end{aligned} \tag{2}$$

β_{bc} represents the vector of the category-brand specific intercepts,[3] the variable $RecentBrandConsumption_{bcht}$ represents the previous consumption incidences of brand b belonging to category c for household h at a shopping trip on day t. In line with the typical adstock specification (Broadbent, 1979), we account for past consumption by calculating a stock variable as follows:

$$BrandConStock_{bcht} = \lambda_h * BrandConsumption_{bch,t-1} + (1 - \lambda_h) * BrandConStock_{bch,t-1}. \tag{3}$$

In this equation, $BrandConStock_{bcht}$ represents the retrievability of consumption in the minds of the consumer on day t. $BrandConsumption_{bch,t-1}$ is a dichotomous variable equal to one if consumption of the focal brand occurred on day t-1, and zero otherwise. λ_h is a household-specific decay parameter, which we estimate in our model (e.g., Doganoglu & Klapper, 2006). We consider potential brand consumption incidences until seven days prior to the current day t. To capture the moderating effects of brand price, strictness of the household budget, and brand experience, we add interaction effects to equation (2). $BrandPrice_{bcht}$ is the brand price for brand b in category c in the chain that household h visits on day t. $StrictBudget_{ht}$ captures the extent to which household h perceives that it has to deal with strict budgets during grocery shopping on day t.[4] $BrandExperience_{bcht}$ captures the number of times household h has purchased brand b in category c during one year prior to the current brand choice on day t.

We also add control variables to the model. Brand purchase history is represented by $LastPurchased_{bcht}$, a dummy variable equal to one if brand b in category c was purchased during the previous category purchase by household h, and zero otherwise. $BrandLoyalty_{bch}$ is the market share of brand b in category c for household h in the initialization period. $Promotion_{bcht}$ is a dummy variable that reflects whether brand b belonging to category c is on price promotion in the chain that household h visits on day t. $TimeSinceLastePurchase_{bcht}$ is the number of days between day t and the previous time that household h bought brand b in category c. Details on the operationalization of all variables can be found in the Data section.

Brand price and promotion are under managerial control, and thus the usage of these instruments could depend on (past) demand or unobserved market factors (e.g., competition or consumer preferences). We follow prior research and implement the control function approach (Petrin & Train, 2010), which is the preferred approach when instruments are available (Andrews & Ebbes, 2014). As instruments we use store-mean corrected price and promotion variables (cf. Andrews & Currim, 2009; Andrews & Ebbes, 2014). Our brand price instruments for household h in category c for brand b in retail chain s at time t are $Z^s_{bct,\ price} = (BrandPrice^s_{bcht} - \overline{BrandPrice}_{bct})$, where $\overline{BrandPrice}_{bct}$ is the average brand price of brand b in category c on day t in other chains. Similarly, our promotion instruments are $Z^s_{bct,\ promotion} = (Promotion^s_{bcht} - \overline{Promotion}_{bct})$. As shown by Andrews and Ebbes (2014), these instruments are preferred over other, theoretically derived instruments, as they are generally stronger than such instruments. In Web Appendix A we show that

[3] We include category-specific intercepts for private labels as well, as we pool private label brands within a category (see Data section).

[4] *Strictbudget* is observed on a yearly basis. The main effect of *Strictbudget* is not identified in the brand choice model as it is the same across brand choice options, and hence it is included in the category incidence model. We thank an anonymous reviewer for this suggestion.

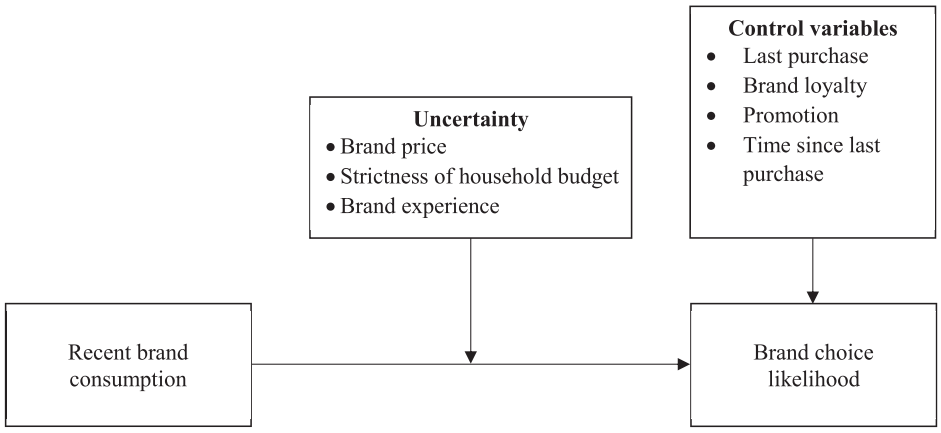


Fig. 1. Conceptual framework.

these instruments are strong for our application.

Category incidence decision

We model the probability that category c is bought by household h during a shopping trip on day t using a binary logit specification:

$$P(categoryincidence_{hct}) = \frac{\exp(V_{hct})}{1+\exp(V_{hct})}, \tag{4}$$

where the deterministic part of the utility of household h buying category c on day t is given by the following equation:

$$V_{hct} = \alpha_{0h} + \alpha_{1h} PurchaseRate_{hc} + \alpha_{2h} CategoryInventory_{hct} + \alpha_{3h} CategoryValue_{hct} + \alpha_{4h} StrictBudget_{ht} + \alpha_{5h} CategoryConsumption_{hct}, \tag{5}$$

where α_{0h} is the overall household-specific intercept. We follow prior research (e.g., Ailawadi & Neslin, 1998; Ailawadi et al., 2007; Holtrop et al., 2025) and add $PurchaseRate_{hc}$ and $CategoryInventory_{hct}$ as explanatory variables of category incidence. The variable $PurchaseRate_{hc}$ represents the average daily volume of category c, calculated as the average daily product volume that household h buys of category c during the initialization period. $CategoryInventory_{hct}$ is calculated recursively following Ailawadi and Neslin (1998). We provide more details in the Data section. $CategoryValue_{hct}$ represents the attractiveness of category c on day t for household h in a nested logit specification. It is calculated as the log of the denominator of the brand choice model (see equation (1)). Consequently, the variables affecting the brand choice decision also influence the category incidence decision indirectly through this term. $CategoryConsumption_{hct}$ represents the recent consumption incidences of category c for household h at a shopping trip on day t. In line with the typical adstock specification (Broadbent, 1979), we specify:

$$CategoryConStock_{cht} = \kappa_h * CategoryConsumption_{ch,t-1} + (1-\kappa_h) * CategoryConstock_{ch,t-1}. \tag{6}$$

In this equation, $CategoryConStock_{cht}$ represents the retrievability of consumption in the category in the minds of the consumer on day t. $CategoryConsumption_{ch,\ t\text{-}1}$ is a dichotomous variable equal to one if consumption in the category occurred on day t-1, and zero otherwise. κ_h is a household-specific decay parameter, which we estimate in our model (e.g., Doganoglu & Klapper, 2006). We consider potential category consumption incidences until seven days prior to the current day.

Estimation

We jointly estimate the brand choice and category incidence models in a Bayesian framework to accommodate heterogeneity in the parameters and to allow for correlation between incidence and choice model parameters (Andrews & Currim, 2009). This, in combination with the inclusion of the category value variable in the incidence model, ensures that both submodels are connected. Parameters for both models are stacked and modeled using a joint covariance matrix for maximum flexibility, such that $(\alpha_h, \beta_h) \sim N((\alpha,\beta), \Sigma_{\alpha,\beta})$. For further details on prior specifications and the joint model likelihood, we refer to Web Appendix B. We implement the joint model in the STAN package (STAN Development Team, 2024) and estimate the model using four chains of 5,000 HMC draws (2,500 burn-in draws) each. Convergence across chains was assessed using the modified split $\widehat{R}$ statistic (Vehtari et al., 2021) and was achieved for all models with $\widehat{R} < 1.0$. Nested models are compared using the LOOIC and WAIC criteria (Vehtari, Gelman, & Gabry, 2017), the likelihood ratio index (Train 2009, p. 68), and the in-sample predicted incidence and choice probabilities (Andrews and Currim, 2009, p. 201).

4. Data

To test the conceptual framework, we use two different datasets collected by Kantar UK from 2014 until 2017. We split both datasets into an initialization period (2014) and an estimation period (2015–2017). The first dataset is a purchase scanner dataset,

including data on the purchases made by a panel of households (gross panel size = 25,000) in 20 different grocery chains across the UK. This dataset includes daily information on the products purchased, including quantities and prices, by a specific household. Furthermore, we have information on product characteristics.

The second dataset is based on consumption diaries of 3,770 households from the same panel of households in the aforementioned dataset and includes information on product consumption. For each household, we observe daily consumption incidences of products during multiple fourteen-day period diaries, which are interrupted during the observation window. On average, each household participates in three consumption diaries per year. This implies that over the estimation period of 2015–2017, we observe consumption behavior during, on average, nine two-week diary periods per household. On a yearly basis, we observe on average 612 product consumption incidences by a household across the different diary windows. Categories are consumed on average 9,647 times on a yearly basis. The consumption dataset also provides information on product characteristics related to the consumed product. Finally, the data is enriched by yearly survey data on the household level. We use these data to measure $StrictBudget_{ht}$.

To link the purchase and consumption datasets, we first apply some selection procedures. First, we select the households that are part of both the consumption and the purchase scanner dataset and exclude all other households. Second, we focus on food and drink categories only since other categories are not included in the consumption dataset. Moreover, as we concentrate on brand choices, we exclude product categories for which the sales of unbranded products are higher than twenty percent of total category value sales in the initialization year. This leads to 178 product categories in the final dataset (which are listed in Web Appendix C).

Following previous research focusing on brand choices (e.g., Ailawadi et al., 2007), we focus on the top five brands purchased in each product category based on their total value sales during the initialization year. All private labels within one product category are grouped into one overall private label brand in the corresponding product category (see Chib et al., 2004; Ailawadi et al., 2007 for a similar practice). We focus only on purchases made during the second week of all the consumption diaries happening between 2015 until 2017 (i.e., the estimation period) which allows us to look at potential consumption incidences up to seven days before the purchase. Between consumption diary periods and in the first week of a diary, we have no information on recent consumption incidences. This means that we cannot determine how recent brand consumption influences brand choices in these weeks. Therefore, purchase observations of a household occurring between consumption diary periods of that household and purchases during the first week of diary periods are excluded.[5]

To control for the potential effect of outliers in our data, we use a similar approach as Kurt et al. (2021) and winsorize the continuous variables at the 1 percent and 99 percent levels. Moreover, we only keep observations without missing values for the explanatory variables. The final dataset contains 537,786 observations for the brand choice model, where one observation is a category shopping trip made by a household. During this particular category shopping trip happening on a certain day, the household chooses one of the (up to) five selected brands. Hence, these observations are conditional on category incidence and on one of the five most popular brands being chosen. For the category incidence model, we have 6,475,031 observations which represent the decision by a certain household to buy in a particular category conditional on a shopping trip.

Below, we discuss the operationalization of the variables in Table 1. Tables 2 and 3 provide correlations and summary statistics for the brand choice model and the category incidence model, respectively.

5. Results

To determine the impact of recent consumption on brand choice likelihood (conditional on category purchase) and category incidence, we estimate nested logit regressions as specified in the Methodology section. The results of these models are presented in Table 4. First, we estimate a model with only purchase history (model 1), which is commonly used in prior choice literature. Second, we specify a model in which we also include recent consumption (model 2), showing the extent to which recent consumption plays a role during brand choice decisions above and beyond prior purchases. To examine how the effect of recent brand consumption on brand choice likelihood changes contingent upon uncertainty, we expand model 2 by adding interaction effects between recent brand consumption and the factors that are conceptually related to performance and financial uncertainty (i.e., brand price, strictness of the household budget, and brand experience; model 3).

First, we discuss the results from the brand choice part of the model. We observe a WAIC (LOOIC) of 77,175 (76,811) for model 2, while the WAIC (LOOIC) for model 1 is equal to 79,801 (79,735), indicating that model 2 is a substantive improvement to model 1. The higher likelihood ratio index of model 2 (0.201) compared to model 1 (0.161) indicates a similar improvement, while there are marginal increases in predicted incidence and choice probabilities. Adding recent brand consumption thus improves the prediction of brand choice. Moreover, model 2 shows that recent brand consumption has a significant positive effect on brand choice ($\beta_{1,\ \text{model 2}} = 2.750$, $p < 0.05$). Thus, hypothesis 1 is confirmed.

Although not the focus of this research, the control variables are all significant and face-valid in both models. First, the last purchase variable is positively significant ($\beta_{5,\ \text{model 2}} = 1.562$, $p < 0.05$), which is in line with prior research (e.g., Ailawadi et al., 2007). Further, brand loyalty has a positive and significant impact on brand choice ($\beta_{6,\ \text{model 2}} = 1.016$, $p < 0.05$), indicating that consumers take prior brand purchases into account when making current brand choices (Guadagni & Little, 1983). Also, the results for the marketing mix-

[5] In Web Appendix I, we report the results of a model in which we include the purchase data of the full estimation window to estimate brand preferences for a limited number of categories. The results remain robust.

Table 1
operationalizations of the variables.

Variables	Operationalization
Brand choice model	
Dependent variable	
Brand choice	*Brand choice* is a categorical variable equal to a number between 1 and 5 that represents the brand that is chosen.
Independent variables	
Recent brand consumption	*Recent brand consumption* is a stock variable representing brand consumption retrievability in consumer minds. See Equation (3) for the specification of this variable and Web Appendix B for the prior specifications of the parameters.
Brand price	*Brand price* is the price of the brand in British Pence operationalized in a similar way as Hitsch et al. (2021). We first calculate the weekly price per volume unit for each SKU belonging to a brand within a category per chain. Then we use these weekly volume prices to calculate the weighted average weekly price of a brand belonging to a category per chain. As weights, we use the market share (value-based) of the SKU within a brand belonging to a certain category at the particular chain. These chain-specific weights are fixed and based on the data of 2014 (initialization period). Observations with missing values for brand prices were removed from the dataset.
Strictness of the household budget	Data on the *strictness of the household budget* were obtained through the yearly survey with all consumption panel households. This measure represents the perceived strictness of the overall household budget. It is measured by using the item "I work to a strict budget when buying groceries" on a 5-point Likert scale ranging from disagree strongly to agree strongly. For each household, the value of the strict budget measure corresponds to the value in the year in which the brand is bought.
Brand experience	*Brand experience* is operationalized as the number of times a brand is purchased by a household during the year preceding the current brand choice decision.
Control variables	
Last purchase	To account for state dependence in the data, we follow the approach of Ailawadi et al. (2007) and create a *last purchased* variable, which indicates whether a household purchased the considered brand during the last shopping trip in which the specific category was purchased.
Brand loyalty	To operationalize *brand loyalty*, we use a similar measure as Andrews and Currim (2009). It represents the value market share of the brand within the category for each household, calculated during the initialization period.
Price promotion	Following Keller et al. (2019), we assume that a brand is on price promotion in a chain if at least one SKU belonging to that brand in a product category was on promotion in that chain. An SKU is considered on promotion if the price of that SKU in a chain is two standard deviations lower than its average SKU price over the last thirty days. *Price promotion* of a brand is then operationalized on a daily level as a dummy variable equal to one if at least one SKU was on promotion in the chain, and zero otherwise (Keller et al., 2019).
Time since last purchase	The *time since last purchase* is the number of days since the brand was previously bought by the household.
Category incidence model	
Dependent variable	
Category incidence	*Category incidence* is a dummy variable that equals one if the category is purchased at the particular time, and zero otherwise.
Independent variables	
Purchase rate	The *purchase rate* represents the average daily volume and is calculated as the total volume that a household h has bought of a category c during the initialization period (2014), divided by 365 days (see Ailawadi and Neslin (1998) and Ailawadi et al. (2007) for a similar approach).
Category inventory	*Category inventory* is calculated using the approach of Ailawadi and Neslin (1998). For each household h, we recursively calculate the inventory of category c on a specific day t, using the following formula: where $\text{volumepurchased}_{cht}$ represents the total volume purchased by household h in category c at day t, $\text{dayslastpurchase}_{cht}$ represents the number of days since the last purchase in category c by household h, and purchaserate_{ch} is the average daily purchase volume in category c by household h. Note that we cannot use the consumption data to infer the rate of consumption for the household because of the interrupted time windows of the consumption diaries and the fact that these diaries do not include information on consumption quantity. Therefore, we estimate purchaserate_{ch} from the purchase data in the initialization year 2014, as the total volume purchased during that year divided by the number of days in 2014 (see Ailawadi and Neslin (1998) for a similar practice). (1) $\text{Inventory}_{cht} = \text{inventory}_{ch,t-1} + \text{volumepurchased}_{cht} - \text{dayslastpurchase}_{cht} * \text{purchaserate}_{ch}$
Category value	*Category value* represents the attractiveness of the category in a nested logit specification. It is calculated as the log of the denominator of the brand choice model (see equation (1) in the methodology section). See Ailawadi et al. (2007) and Andrews and Currim (2009) for a similar approach.
Recent category consumption	*Recent category consumption* is a stock variable representing category consumption retrievability in consumer minds. See Equation (6) for the specification of this variable and Web Appendix B for the prior specifications of the parameters.

Table 2
Summary statistics and correlation matrix brand choice variables.

Variable	Mean	Min.	Max.	1.	2.	3.	4.	5.	6.	7.	8.
1. Recent brand consumption	0.03	0	0.52	1	0.42	0.15	−0.01	−0.00	0.40	0.01	−0.28
2. Last Purchased	0.10	0	1		1	0.08	−0.00	−0.00	0.45	0.01	−0.30
3. Brand Loyalty	0.06	0	1			1	−0.02	−0.01	0.11	−0.01	−0.00
4. Brand price	1.17	0.01	89.97				1	−0.00	−0.02	0.00	−0.01
5. Strictness of household budget	2.05	1	5					1	0.00	0.01	−0.01
6. Brand experience	4.45	0	182						1	0.02	−0.18
7. Promotion	0.02	0	1							1	0.00
8. Time since last purchase	26.33	1	364								1

Table 3
Summary statistics and correlation matrix category incidence variables.

Variable	Mean	Min.	Max.	1.	2.	3.	4.	5.
1. Category incidence	0.04	0	1	1	0.22	0.21	0.22	0.03
2. Recent category consumption	0.03	0	0.52		1	0.11	0.31	0.00
3. Category inventory	42.49	0	9081.90			1	0.14	0.01
4. Purchase rate	11.06	0	161.619				1	0.01
5. Strictness of household budget	1.75	1	5					1

related variables are in line with what we should expect. Brand price is significantly negative ($\beta_{7,\ \text{model 2}} = -0.017$, $p < 0.05$), while promotion has a positive impact on brand choice ($\beta_{9,\ \text{model 2}} = 0.286$, $p < 0.05$).[6] Moreover, the time since the last purchase has a significant negative effect ($\beta_{10,\ \text{model 2}} = -0.527$, $p < 0.05$).

In model 3, we include the interaction effects which decreases the WAIC and LOOIC further (when compared to models 1 and 2), which implies an improvement in model fit. The higher likelihood ratio index and predicted brand choice probabilities similarly support this improvement. The effect of recent brand consumption on brand choice remains significantly positive ($\beta_{1,\ \text{model 3}} = 2.315$, $p < 0.05$), providing further support for hypothesis 1. The interaction effect between recent brand consumption and brand price is significantly positive ($\beta_{2,\ \text{model 3}} = 0.227$, $p < 0.05$), in support of hypothesis 2a. This implies that financial uncertainty prevails and that recent brand consumption plays a more important role during brand choice decisions for higher (as compared to lower) priced brands. Further, the interaction effect between recent brand consumption and strictness of the household budget is significantly positive ($\beta_{3,\ \text{model 3}} = 0.674$, $p <= 0.05$). Hence, in support of hypothesis 3, we find evidence that brand consumption is especially valuable as a source of information for households with larger budget constraints.

Finally, we also find support for hypothesis 4. We observe a negative and significant interaction effect between brand experience and recent brand consumption ($\beta_{4,\ \text{model 3}} = -0.118$, $p < 0.05$), indicating that recent brand consumption is less important for brand choices when households have more (vis-à-vis less) experience with the brand. Note that this negative interaction effect implies that the effect of recent brand consumption becomes negative if the household has bought the brand in the preceding year more than 19 times which occurs only seldomly in our observation window (i.e., only eight percent of our observations).[7] While the effect of recent brand consumption is thus mostly positive, in line with our argumentation that consumers are risk averse and use recent brand consumption to reduce uncertainties, the effect of recent brand consumption becomes negative in extreme cases of brand experience which may be due to a tendency to seek variety.

While the focus of our paper is on the impact of recent brand consumption on brand choices, the results from the category incidence model indicate that recent category consumption has a significant positive impact on category incidence ($\alpha_{4,\ \text{model 2}} = 2.960$, $p < 0.05$). Interestingly, we observe this effect of recent category consumption, even while controlling for the effect of category inventory in model 2 ($\alpha_{2,\ \text{model 2}} = 0.004$, $p < 0.05$). Stockpiling can be considered as an important mechanism explaining repurchasing behavior after recent consumption, as consumers would need to repurchase if inventory is low because of the recent consumption. However, our results show that stockpiling is not the only mechanism at play, as recent category consumption has an effect above and beyond inventory.

6. Robustness checks

To verify the robustness of the results, we ran various additional analyses. The results are reported in the Web Appendix.

First, in our focal models we follow prior research regarding how to incorporate purchase feedback (i.e., the impact of past purchases on current preferences) in the brand choice model (Ailawadi, Gedenk, & Neslin, 1999). In detail, purchase feedback is modeled

[6] The large difference in size of the coefficients of price and price promotions are due to the large difference in average values of these variables (1.17 for price and 0.02 for promotion).

[7] Calculated on the basis of the coefficients from model 3 in the brand choice models in Table 4, while setting the other interaction effects to their average.

Table 4
Results brand choice and category incidence model.

Variable	Parameter estimates [95% HPD] **Model 1**		Parameter estimates [95% HPD] **Model 2**		Parameter estimates [95% HPD] **Model 3**	
	M	SD	M	SD	M	SD
Brand choice						
Recent brand consumption			**2.750** [2.40; 3.10]	**0.037** 0[.00; 0.14]	**2.315** [1.84; 2.80]	**0.114** 0[.00; 0.46]
Brand price * recent brand consumption					**0.227** 0[.06; 0.68]	**0.023** 0[.00; 0.11]
Strictness household budget * Recent brand consumption					**0.674** 0[.37; 0.99]	**0.022** 0[.00; 0.09]
Brand experience * Recent brand consumption					**−0.118** [-0.33; −0.09]	**0.439** 0[.28; 0.63]
Control variables						
Last purchased	**2.331** [2.12; 2.60]	**0.052** 0[.01; 0.13]	**1.562** [1.45; 1.77]	**0.008** 0[.00; 0.03]	**1.530** [1.35; 1.17]	**0.031** 0[.00; 0.11]
Brand loyalty	**2.980** [2.72; 3.34]	**0.023** 0[.01; 0.08]	**1.016** 0[.85; 1.17]	**0.017** 0[.00; 0.07]	**1.350** [1.17; 1.52]	**0.029** 0[.00; 0.12]
Brand price	**−0.014** [-0.19; −0.09]	**0.002** 0[.00; 0.01]	**−0.017** [-0.03; −0.01]	**0.000** 0[.00; 0.00]	**−0.043** [-0.083; −0.01]	**0.001** 0[.00; 0.003]
Brand experience					**0.337** 0[.31; 0.37]	**0.155** 0[.12; 0.19]
Promotion	**0.330** 0[.09; 0.78]	**0.032** 0[.00;.01]	**0.286** 0[.06; 0.51]	**0.007** 0[.00; 0.03]	0.186 [-0.11; 0.47]	**0.028** 0[.00; 0.12]
Time since last purchase	**−0.801** [-0.87; −0.73]	**0.024** 0[.00; 0.11]	**−0.527** [-1.09; −0.13]	**0.005** 0[.00; 0.01]	**−1.090** [-1.55; −0.73]	**0.014** 0[.00; 0.058]
Control function price	***−0.012*** [-0.04;.02]	**0.004** 0[.00;.01]	***−0.016*** [-0.04; 0.00]	**0.000** 0[.00; 0.001]	***−0.030*** [-0.12; 0.07]	**0.004** 0[.000; 0.02]
Control function promotion	−0.207 [-0.38; 0.85]	**0.010** 0[.00; 0.04]	−0.073 [-0.52; 0.35]	**0.003** 0[.00; 0.00]	−0.132 [-0.69; 0.42]	**0.023** 0[.00; 0.111]
Decay coefficient brand consumption stock (α)			**0.260** 0[.23; 0.31]	**0.039** 0[.02; 0.05]	**0.370** 0[.31; 0.47]	**0.073** 0[.05; 0.10]
Category incidence						
Intercept	**−4.780** [-4.88; −4.60]	**1.090** 0[.85; 1.44]	**−5.130** [-5.54; −5.01]	**0.813** 0[.56; 1.02]	**−5.061** [-5.47; −4.98]	**0.764** 0[.55; 0.99]
Purchase rate	**0.011** 0[.01; 0.01]	**0.000** 0[.00; 0.00]	**0.011** 0[.01; 0.01]	**0.000** 0[.00; 0.00]	**0.012** 0[.01; 0.01]	**0.000** 0[.00; 0.00]
Category inventory	**0.004** 0[.00; 0.01]	**0.000** 0[.00; 0.00]	**0.004** 0[.00; 0.00]	**0.000** 0[.00; 0.00]	**0.004** 0[.00; 0.00]	**0.000** 0[.00; 0.00]
Strictness household budget	**0.323** 0[.21; 0.43]	**0.002** 0[.00; 0.01]	0.151 [-0.13; 0.28]	**0.006** 0[.00; 0.01]	0.139 [-0.14; 0.30]	**0.005** 0[.00; 0.01]
Category value	**0.160** 0[.04; 0.24]	**0.015** 0[.00; 0.04]	**0.067** 0[.05; 0.07]	**0.005** 0[.00; 0.01]	**0.127** 0[.04; 0.21]	**0.007** 0[.00; 0.01]
Category consumption			**2.960** [2.60; 3.44]	**0.410** 0[.05; 1.00]	**3.012** [2.83; 3.59]	**0.423** 0[.07; 0.99]
Decay coefficient category consumption stock (α)			**0.639** 0[.18; 0.94]	**0.805** 0[.55;1.01]	**0.547** 0[.16; 0.90]	**0.762** 0[.47;1.00]
Brand-category specific intercepts	Yes		Yes		Yes	
Number of choice observations	537,786		537,786		537,786	
Number of incidence observations	6,475,031		6,475,031		6,475,031	
Number of households	3,770		3,770		3,770	
Number of categories	157		157		157	
WAIC	79801.2 (669.9)		77175.2 (725.7)		74261.2 (681.3)	
LOOIC	79735.4 (663.7)		76810.9 (660.6)		73692.7 (661.2)	
Likelihood ratio index	0.161		0.201		0.247	
P(Inc)	0.859		0.867		0.871	
P(Choice)	0.897		0.898		0.929	

Notes: Bolded numbers indicate that the 95% HPD does not include zero, bolded and italic numbers indicate that the 90% HPD does not include zero. P(Inc) and P (Choice) are the average predicted actual incidence and choice probabilities (Andrews and Currim 2009, p. 201).

using two separate constructs: the last purchased variable and a brand loyalty variable. The last purchased variable is a dummy variable indicating whether a brand was purchased during the last category-shopping trip (e.g., Bell & Lattin, 1998; Bucklin & Gupta, 1992). The loyalty variable is operationalized as the average value market share of the brand in the category during the initialization period. However, it is interesting to assess whether the results hold up if we operationalize prior purchases more in line with the operationalization of recent brand consumption, i.e., with a stock type specification. Hence, we ran a robustness check in which we operationalize both the last purchased and recent brand consumption variable in a similar fashion as the adstock specification based on Broadbent (1979). The results remained robust (see Web Appendix D).

Second, we assumed that the impact of recent brand consumption on brand choice diminishes over time following a pre-defined distribution, similar to an adstock specification (Broadbent, 1979). An alternative is to use a lag structure, which allows to model the impact of recent brand consumption more flexibly. Specifically, we re-estimate model 2 but model the effect of recent brand consumption by using seven lags (representing the seven days prior to the brand choice occasion). The results replicate the important impact of recent brand consumption on brand choice decisions above and beyond the impact of purchase history (see Web Appendix E). Specifically, the impact of the first lag is the most important, but consumption in earlier days still has a significant positive impact on brand choice.

Third, when faced with uncertainty, consumers might rely on other internal sources of information next to consumption, such as their own (past) purchases. To investigate the extent to which consumption and past purchases explain the reduction of uncertainty, we estimated a model where we included interaction terms with our last purchase variable to our model 3. We find that all three consumption interaction terms remain significant, but also two last-purchase interaction terms (with brand price and brand experience) are significant (see Web Appendix F). To assess which effect is stronger, we also computed elasticities for these interaction effects in line with extant literature (Ai & Norton, 2003; Holtrop et al., 2025; Train, 2009). We find that the consumption effects are on average significantly stronger than the last purchase effects, indicating that consumption has a larger influence in reducing uncertainty than own purchases.

Fourth, we used the control function approach with instrumental variables to control for potential endogeneity of our marketing stimuli (i.e., brand price and promotion). As a robustness check, we also ran the three models without control functions. The results remain the same, showing a positive impact of recent brand consumption on brand choice decisions and the same, significant directions for all interaction effects (see Web Appendix G). Note that the effect of brand price becomes positive when the control function is deleted from the model, which seems to suggest that an endogeneity correction for brand price is necessary.

Fifth, we also look at the purchase quantity decision. As the consumption dataset does not include information on consumption quantities, we could not include this information. However, the purchase quantity decision is also part of the overall purchase decision. Hence, we look at purchase quantity as an additional dependent variable in a robustness check. We use a zero-truncated Poisson model to study how the volume purchased by a household (conditional on brand choice) is influenced by the same variables as included in the brand choice model (cf., Ailawadi et al., 2007; Andrews & Currim, 2009). We find that recent brand consumption also positively affects the quantity decision and that it leads to an increase in model fit (see Web Appendix H).

Finally, our consumption data is limited to, on average, nine two-week periods per household. Our main results are thus obtained using a relatively limited observation period per household, potentially biasing our estimates. To remedy this, we re-estimated the main effects model for the five most sold categories (in volume in 2014) using the full three-year data (2015–2017) for all variables except consumption, which we treat as missing for non-diary periods. We report the results in Web Appendix I where we show two sets of results. In the first column, we replicate the main model based on the diary periods only for the five most sold categories. In the second column, we show the results for the same set of five categories based on the full observation window of three years. These results show that the impact of consumption remains positive and significant. It is interesting to note that including more purchase information decreases the impact of the last purchase variable, while the effect of brand loyalty is much stronger. These estimates align in size and direction with earlier research on brand choice (e.g., Andrews and Currim 2009), indicating that brand loyalty impacts brand choice more than state-dependence.

7. Discussion

During grocery shopping, consumers may experience substantial uncertainty because they often have insufficient and imperfect information about a brand (van Ewijk, Gijsbrechts, & Steenkamp, 2022). Especially in times of high financial uncertainty and constrained budgets, uncertainty is further amplified. To decrease the extent of experienced uncertainty, consumers use information from different sources. Literature shows that consumers mainly rely on personal experiences when faced with uncertainty. However, prior empirical research mainly focuses on the role of purchase history in subsequent brand choices (e.g., Ailawadi et al, 2007; Andrews & Currim, 2009; Ching, Erdem, & Keane, 2013, 2017; Gönül & Srinivasan, 1996), while the consumer behavior literature suggests that consumers' recent brand consumption may also influence these decisions (Hoch, 2002; Lemon, White, & Winer, 2002; Schwarz et al., 1991). This suggestion is further corroborated by the nature of recent brand consumption itself, as its information is easily retrievable from memory (Roggeveen, Grewal, Townsend, & Krishnan, 2015; Wänke, 2013).

By leveraging a unique dataset combining purchase and consumption data over several years, we provide a better understanding on how consumers use personal experiences during grocery purchase decisions. While prior research on brand choice decisions mainly focused on the impact of purchase history (e.g., Ailawadi et al., 2007; Andrews & Currim, 2009), we expand the knowledge of the use of personal experiences by also including recent brand consumption as an information source. To the best of our knowledge, this study is the first to empirically examine the impact of recent brand consumption on brand choice.

Compared to existing literature, we show that consumers do not only rely on brand purchase history (e.g., Ailawadi et al., 2007;

Andrews & Currim, 2009), but also on recent brand consumption during brand choice decisions. Indeed, when we compare a traditional purchase history model with a model that includes recent brand consumption as an additional predictor, we notice a substantial increase in fit of the choice model. Our results indicate that both prior purchases and recent consumption experiences have an important influence on subsequent brand choices, which seems to indicate that the information retrieved from both sources is indeed different. Prior research provides a theoretical reasoning for this difference in type of information: while information from past purchases is believed to be based on search attributes (Degeratu et al., 2000; Steenkamp, 1986), consumption-related information is believed to be based on experience attributes (Chandon & Wansink, 2012; Higgs & Donohoe, 2011). To the best of our knowledge, we are the first to empirically demonstrate that both types of information help consumers in making brand choices. We show that this is also true for the decision as to whether or not to make a purchase in the category.

Additionally, we examine the role of performance and financial uncertainty during grocery shopping, showing that the effect of recent brand consumption on brand choice likelihood varies across shopping contexts. In particular, we identify factors that potentially affect the extent to which uncertainty is experienced during grocery shopping (Dowling & Staelin, 1994; Erdem, Keane, & Sun, 2008; Tsiros & Heilman, 2005), which, in turn, may alter the importance of recent brand consumption during brand choice decisions. First, we observe that recent brand consumption is more important for brand choice decisions of higher (as compared to lower) priced brands. Prior research shows that consumers experience more financial uncertainty for higher priced brands (Rao, 2005; Tsiros & Heilman, 2005; Jacoby and Kaplan, 1972), and are, as such, surrounded by higher levels of uncertainty. Lower-priced brands, on the other hand, are associated with lower levels of perceived financial uncertainty. Interestingly, our results are not in line with the alternative performance uncertainty mechanism that we outlined which would predict a stronger effect of recent brand consumption in case of lower priced brands. The financial uncertainty mechanism thus dominates the performance uncertainty mechanism, which may be the case because we only consider the five most important brands in the category for which performance uncertainty may be limited.

Second, we find that the impact of recent brand consumption is stronger for households with stricter budgets. These households are likely to experience more financial uncertainty (Van Ittersum, Pennings, & Wansink, 2010), which steers their attention to money and increases their tendency to think more about opportunity costs and tradeoffs (Hamilton et al., 2019a). This implies that households with stricter budgets feel cognitively taxed, and to relieve this burden, they rely on internal information sources. Recent brand consumption turns out an especially important source of information for budget-constrained households because it is vivid, and thus easily retrievable, which lowers cognitive load.

Finally, we find that households who have more (less) experience with a brand tend to rely less (more) on recent brand consumption during brand choice decisions. This is in line with previous research (e.g., Ching et al., 2013, 2017; Tsiros & Heilman, 2005), showing that consumers learn over time and have less need for searching and processing information when they get more product experience. Specifically, consumers who have more brand experience possess more knowledge, perceive less uncertainty, and hence have a lower need for information such as recent brand consumption.

As an additional analysis, we gauged the relative impact of recent consumption and associated factors on brand choice. Specifically, we computed the change in brand choice probabilities in response to a one standard deviation increase in either variable compared to a baseline scenario where all variables are at their mean value. This analysis reveals that: (i) a one standard deviation increase in recent brand consumption increases average choice probabilities by 10.2%, (ii) a one standard deviation increase in price decreases[8] average choice probabilities by 6.4%, (iii) a one standard deviation increase in budget constraint decreases average choice probabilities by 4.7%, and (iv) a one standard deviation increase in brand experience increases choice probabilities by 8.3%. Thus, recent brand consumption has the largest (absolute) effect on brand choice probabilities, followed by brand experience.

Practical implications

Apart from the substantive theoretical insights, our research also has important implications for managers. First, we highlight the importance of recent brand consumption towards brand managers. Indeed, this research shows that brand managers should try to nudge consumers towards actual consumption of their brand next to only purchasing it, as this positively affects subsequent brand choice decisions. Brand managers should not simply make the assumption that purchased products are automatically consumed, as food waste shows quite the opposite. Specifically, the European Commission estimates that around 53 percent of food waste in the EU stems from households, indicating that a lot of purchased products are not consumed (European Commission, 2023). This underscores the importance of stimulating consumption next to the purchase of brands. Chandon and Wansink (2012) provide a good overview of how brand managers can positively affect food intake with food marketing. For instance, the authors show that temporary price reductions such as promotions can positively affect food intake (Chandon & Wansink, 2012). Defoor (2024) also provides guidance in stimulating consumption probability. For instance, the author concludes that products bought at a higher price are more likely to be consumed (Defoor, 2024), which suggests that the likelihood of buying higher priced brands in the future increases. Retail managers can also actively prime consumers to consume a brand by using in-store advertising. Indeed, prior research already established that using food samples as in-store advertisements can stimulate consumption (Minton, Cornwell, & Kahle, 2017; Steinberg & Yalch, 1978). This stimulation can increase brand choice likelihood in the future.

Our research also shows that in uncertain situations the role of recent brand consumption becomes even more prominent, which is especially relevant in times consumers are experiencing a lot of uncertainty because of, for example, inflation, potential tax increases,

[8] An average decrease might seem surprising given the positive sign for the interaction effect, but the magnitude of interaction effects in non-linear models varies over values of the moderators such that both positive and negative predicted values can occur even when the interaction coefficient is positive (Ai & Norton, 2003, in particular Fig. 2). When computing the mean over these predictions, this leads to a decrease on average.

or political instability. In these uncertain situations, brand managers should be aware that recent brand consumption plays a more important role during brand choice decisions and should, therefore, employ effective nudge strategies toward consumption. For instance, we show that the role of recent brand consumption is more important for higher (versus lower) priced brands. For retailers it is, however, more difficult to nudge consumers towards actual consumption of higher versus lower-priced products because these products carry greater financial risk. Because financial risk is more prominent than performance uncertainty, using free in-store sampling tends to be a valuable nudge strategy for retailers. In-store sampling may provide confidence in the value of the product, which is especially relevant when consumers sense financial uncertainty.

Further, we show that the role of recent brand consumption is also more important for households that have a stricter budget. Because households with stricter budgets tend to shift their attention to money (i.e., the resource that is scarce) (Hamilton et al., 2019b), retailers are encouraged to use nudge strategies that are focused on reducing costs or increasing value for money, such as discounts or bundling. Finally, the role of recent brand consumption is also more important for households that do not have a lot of (versus households that do have a lot of) experience with a brand. To estimate brand experience, retailers can use, for example, data gathered through loyalty cards. Via these loyalty cards, retailers can nudge consumers toward consumption by offering loyalty rewards.

Limitations and future research directions.

While we provide unique insights into the effect of recent brand consumption on brand choice decisions during grocery shopping, our research contains certain limitations which create interesting avenues for future research. First, the consumption diary data only include information on whether a household consumes a certain product but not how much of the product is consumed. Future research could include consumption quantity as an explanatory variable, as larger quantities can potentially lead to a satiety effect (Cornill, 2017), reducing brand choice likelihood. The short diary periods (i.e., 14 days) also prohibit us to investigate the long-term impacts of brand consumption (beyond the first choice occasion). Future research could address this limitation by running longer diary studies to observe multiple choice and consumption occasions.

Second, while we use uncertainty as a mechanism to explain how the relationship between recent brand consumption and brand choice decisions is moderated by brand price, the households' budget strictness, and brand experience, the data did not allow us to measure uncertainty directly. Although there are ample indications that uncertainty plays a key role, future research could confirm this by utilizing survey data to measure uncertainty underlying different grocery contexts. Furthermore, other mechanisms, such as brand beliefs, can be examined. Brand beliefs are defined as the overall evaluations of a brand (Keller, 1993), and can be functional, symbolic, and experiential. Extant research argues that past consumer purchase and recent consumption of a product are confounding factors in the relationship between brand beliefs and brand choice behavior (e.g., Szymanowski & Gijsbrechts, 2012), which warrants future research attention.

Third, we do not have information regarding the valence of the consumption experience. While we show that prior consumption reinforces subsequent brand choices based on the risk aversion of consumers, we are unable to make a distinction between positive and negative consumption experiences, which could have a different impact on subsequent behavior. Future research could focus on differences in valence regarding how consumption experience affects subsequent purchase behavior. Such research might also focus on other factors that impact prior consumption experiences, such as perishability (Tsiros & Heilman, 2005).

Fourth, we add to the brand choice literature that until now only considered the role of prior brand purchases on subsequent brand decisions. However, we did not model the full dynamic interplay between consumption and purchases including mechanisms as state dependence and learning (see Dubé, Hitsch, & Rossi, 2010; Kamakura & Russell, 1989; Levine & Seiler, 2023; Seetharaman, Ainslie, & Chintagunta, 1999) and some of our variables, such as purchase rate are static, providing fruitful avenues for future research.

Fifth, an interesting empirical observation is that the decay parameter for category consumption is much larger than that of brand consumption (0.639 vs. 0.260 in Model 2), indicating that brand consumption incidences are retained more in memory than category consumption incidences. There is no clear theoretical explanation for this finding, which we hope future research can provide.

Finally, we only consider the grocery shopping setting, which leaves open the opportunity for future researchers to consider other settings. For instance, in the service context or the durables sector, uncertainty could play an even more prominent role. Despite these limitations, our findings provide unique insights into the impact of recent brand consumption on brand choice decisions and the role of uncertainty herein.

CRediT authorship contribution statement

Kathleen Cleeren: Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Néomie Raassens:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Niels Holtrop:** Writing – review & editing, Validation, Software, Methodology, Formal analysis. **J.Jeffrey Inman:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Formal analysis, Conceptualization. **Henri Defoor:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijresmar.2026.01.003.

Data availability

The authors do not have permission to share data.

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