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Are brand preferences inherent, constructed, or a mixture of both? A memory-based dual-process model

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Abstract
Understanding whether consumer preferences are inherent or constructed has profound implications for a range of marketing and economic issues, such as demand estimation, consumer education and information, market design and competition. The literature reveals a formidable divide between inherent versus constructed preferences, underscoring a long-standing debate regarding the nature of consumer preferences. In this research, we develop a dual-process structural learning model rooted in cognitive theories, enabling empirical estimation of the extent to which preferences are inherent versus constructed. Our results show that brand preferences are largely constructed, with 76% of brand evaluations across all studied brands being formed at the time of purchase. This finding helps to reconcile the enduring divide that has shaped the field's evolution. In addition, our analysis reveals that the mode of evaluation significantly influences market competitive dynamics, with 60% of brand-switching resulted from constructed preferences. Furthermore, we also find mode of evaluation has asymmetric impacts on established versus new brands. These findings open up novel avenues for shaping competitive landscapes by strategically altering (e.g., through nudges) consumer's mode of evaluation, becoming extremely relevant in the digital economy characterized by overwhelming and rapid information exchange.

Keywords Inherent preference · Constructed preference · Quality learning · Memory -based choice · Dual-process model

JEL CODES D83 Search · Learning · Information and Knowledge · Communication · Belief · Unawareness

1 Introduction

Consider a consumer who is buying diapers for her[1] baby at a typical supermarket. Choosing a brand from the vast array of available options is a daunting task even for an experienced user. How will the consumer choose a particular brand?

[1] We refer to the representative consumer as a female for ease of writing, but any observation is generalizable to the male consumer as well.

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Rationality-based arguments suggest that the consumer will examine her preferences for the various brands and their prices to select the one that yields the highest quality per unit price (Allenby and Rossi 1991; Chiang 1991; Chintagunta 1993). However, the important question is where these brand preferences come from: does the consumer arrive at the supermarket with a pre-existing preference structure, or does she construct her preferences at the time of purchase?

The classical economic theory of consumer demand (Houthakker 1950; Samuelson 1964; Richter 1966) posits that a choice made by the consumer, who is a utility maximizer, should yield her the highest utility from the available options. The consumer is assumed to have a master list of the values for all the product alternatives in her choice set. In this sense, preferences are inherent, i.e., they are known, well defined, and readily available to the consumer (McFadden 1999). These preferences are also assumed to be complete and consistent[2] (Slovic 1995).

However, behavioral scientists disagree with this view of pre-existing preferences. They assert that "preferences for objects of any complexity are constructed – not merely revealed – while generating a response to a judgment or choice task" (Payne et al. 1992). Accumulating behavioral evidence has corroborated this theory by showing situations in which the inherent-preference argument fails (Tversky and Kahneman 1981; Thaler 1985; Simonson and Tversky 1992; Bettman et al. 1998). For example, the pervasiveness of preference reversal (Tversky and Kahneman 1981; Tversky et al. 1990; Slovic 1995) demonstrates that people do not use the precomputed valuations for their maximization problem, but rather construct new valuations given the available choices. This suggests that preferences are constructed, incomplete, and unstable. In other words, when making a choice, consumers construct preferences by combining information stored in their memory.

Behavioral scientists treat preferences as primitives of analysis, and believe that conventional economic research does not give enough importance to the process of preference formation. However, economists do not think that such neglect threatens the fundamentals of the rational economic agent theory. As mentioned by McFadden (1999), the behavioral anomalies established in various experiments cannot fault the robustness of the rational agent model. This view is also supported by Simonson (2008); he suggests that Behavioral Decision Theory research has overstated the constructionist viewpoint. He also points out that conclusions made in carefully engineered experimental environments might lose external and ecological validity.

To reconcile both sides of the debate, Kivetz et al. (2008) suggest that a good approach is to accept the partial truths of each view while rejecting their purity. They propose using real-world field experiments or secondary data analyses to provide more evidence to settle the discussion. Thus, instead of asking whether consumers recall inherent preferences or construct new preferences at the time of choice, one should ask *the extent to which* consumers construct their preferences. Therefore, the primary goal of this paper is to propose a dual-process experiential

[2] Completeness means that there should be a complete order relation between the options that enables the consumer to determine the optimal option in the light of available choice alternatives. Consistency of preferences means that the order relation of preferences is context invariant, i.e., preferences should not change with the way choice options are described, or with the way the evaluation or judgment is elicited.

quality learning model that allows consumers to either recall inherent preferences or construct new preferences while making a choice. Such model enables us to empirically estimate, with readily available data, the proportion of revealed versus constructed preferences, thus reconciling the age-old debate regarding the nature of consumer preferences.

We calibrate the proposed model on scanner panel data in the diaper category. We find that preferences are largely constructed – 76% of all the brand evaluations across both purchased and non-purchased brands are constructed. However, when we only focus on the purchased brands, the percentage of constructed brand evaluations drops to 38%. We find that consumer preferences revealed in their brand choices are relatively stable. Even though a significant portion of brand evaluations is newly formed, it does not lead to brand switching because the newly formed brand evaluations conform to the inherent brand evaluations. Thus, stable preferences are the consequence of two different underlying behavioral processes: one is due to the recall of stable brand evaluations, and the other arises from the constructed brand evaluations conforming to the same brand choices.

We also find the mode of evaluation, inherent versus constructed preferences, has an impact on brand switching. After splitting purchases into switched and non-switched cases, 60% of the 745 switched purchases are made with constructed preferences, while 70% of the 1879 non-switched purchases are based on inherent purchases. Though preferences are stable in general, it seems that constructing a preference is more likely to induce a brand switch. In our counterfactual analysis, forcing all the consumers to rely solely on inherent preferences increases the market share for well-known brands. Conversely, when directing all the consumers to construct new preferences, the market share for less recognized brands increases. Our results indicate that constructing a new preference not only enhances the likelihood to switch, but also tends to benefit less-recognized brands.

Our research has both theoretical and managerial implications. First, it attempts to reconcile the fundamental question "are brand preferences inherent or constructed?" by empirically estimating the proportions of brand preferences that are constructed versus inherent. Second, it brings new insights into state dependence literature; With our findings, we believe that the "state" might be better interpreted not as the last choice, but as the last consumption experience. A last consumption experience signals high quality leads to positive state dependence, while a last consumption experience with low quality leads to negative state dependence. Finally, this research also sheds light on how market shares of different brands respond to changes in consumers' mode of evaluations. Hence, firms should customize their media efforts to elicit the right mode of evaluation from their targeted consumers.

Our paper is organized into the following sections. In Section 2, we introduced the memory-based judgment theory, a foundational framework serves as the basis for our dual process model. Section 3 is devoted to the development of our model from both a consumer's and an econometrician's perspectives. In Section 4, we describe our data set in detail, and show model-free evidence that allows us to separately identify the two modes of brand evaluations. Section 5 involves estimation of competing models and a discussion of the results. Section 6 concludes the paper and suggests directions for future research.

2 Memory foundations

Whether a consumer recalls a pre-existing preference or constructs a new preference with recalled information, we cannot properly discuss our model without looking into the underlying cognitive processes, especially the memory foundations. It is well established that human memory can be divided into sensory memory, short-term memory and long-term memory (Atkinson & Shiffrin 1968; Squire 2004). A major strand of cognitive psychology literature views long-memory as consisting of both implicit and explicit memory, where implicit memory is subconscious and explicit memory is conscious (Squire 1986). In the context of memory-based judgment, explicit memory is the relevant memory component for this study. In his work (Tulving 1972, 1983), Tulving proposed and proved experimentally that the explicit memory can be further divided into two distinct memory systems: the episodic memory (events) and the semantic memory (facts). This proposition has latter been proved with clinic and anatomy evidences (Aggleton and Brown 1999; Mishkin et al. 1997) that each of the two memory systems is supported by different parts of the brains. Tulving's memory theory has caused a paradigm shift in memory research and remains widely accepted as a foundation for understanding of memory structure to this day (Renoult and Rugg 2020).

Episodic memory is a more or less accurate record of a person's experience. Therefore, every "item" in episodic memory represents the experience of an episode or event. Recalling from episodic memory is like traveling back in time to re-experience past events. In contrast, semantic memory does not store any personally experienced unique episodes. Rather, it stores organized knowledge using concepts and relations. In other words, semantic memory is "knowledge," while episodic memory is "memory." The two memory systems also differ in the rate of memory decay; compared to semantic memory, episodic memory has been proven to be more susceptible to recall error (Craik and Lockhart 1972; Tulving 1983; Johnson and Anderson 2004; Wingfield and Byrnes 2013).

To understand the distinction between episodic and semantic memories in the context of brand evaluation, let us revisit the diaper case. A consumer may have prior consumption experiences with certain brands. For example, she might remember that the diaper was effective in preventing leaking. She might also recall that on a road trip, the baby was uncomfortable after wearing it for two hours. These are examples of vivid recalls from episodic memory. Alternatively, she may recall her "overall evaluation", such as "Pampers is usually a good choice" or "the baby was comfortable with Pampers". These are examples of recall from semantic memory. Note that while "overall brand evaluation" is a mental construct built on prior consumption experiences, it is the distilled brand knowledge possessed by the consumer based on multiple consumption experiences and stored in the semantic memory.

The concept of "quality learning" was introduced and modelled by Erdem and Keane (1996) to the marketing literature. Unlike the previous consumer choice models where the brand quality is static, Erdem and Keane (1996) modeled a process where the brand quality needs to be learnt and updated with every consumption experience. The need to learn a brand's quality can be attributed to two types of uncertainty, the inherent product variability and consumer's idiosyncratic errors. Inherent product variability is especially common in agriculture products and service industry that a consumer can randomly get a 'lemon' or a 'windfall'. Consumer's idiosyncratic errors describe situations where the quality of a product largely depends on the ability or methods to use the product. In the quality learning literature (Erdem and Keane 1996; Mehta et al. 2003, 2004), a consumer has a mental construct – namely, a brand quality – and the rules for updating this construct –the Bayesian updating rule – in their semantic memory. During the consumption occasion, as quality signals based on consumption episodes arrive, the consumer updates his/her brand quality and stores this revised value in their semantic memory. At the purchase occasion, this new brand quality is recalled by the consumer for the choice decision. From this angle, the extant learning model is a pure reflection of inherent preferences, since consumers in such a model are not allowed to construct any new evaluations at the time of choice.

Based on current learning models that only allow recalling brand quality from semantic memory, we build an experiential quality learning model that allows consumers to either use pre-existing evaluations (inherent preferences) or construct new preferences at every purchase occasion. In this way, a consumer in our model is depicted more authentic, who are allowed to engage both memory systems at the time of purchase. We achieve this by recognizing the fact that memory decay is different across these two memory systems and can lead to different brand evaluations.

3 Model development

In this section, we discuss the modeling details of the choice decision by a consumer who may use either inherent or constructed preferences. In Section 3.1, we discuss the model primitives. In Section 3.2, we lay out the dual-process model from the perspective of a consumer, who is assumed to have perfect memory, before relaxing our assumption and allowing the consumer to have imperfect memory in Section 3.3. In Section 3.4, we discuss the model from an econometrician's perspective, i.e., how an econometrician is able to infer values that are only observable to the consumer. Finally, we present the unconditional choice probability in Section 3.5.

3.1 Model primitives

Consider a product category with J brands. A consumer learns about the brand quality through their consumption experiences. At the t-th consumption occasion, the consumer receives a quality cue $\lambda_{j,t}$. Since consumption experience is inherently "ambiguous" (Hoch et al. 1986) due to perceptual errors, inherent variability in product quality, and context specific factors, the quality signal received by a consumer will be the true quality along with these 'noises.'

$$\lambda_{j,t} = q_j + \eta_{j,t} \tag{1}$$

where q_j is the true quality of brand j, and $\eta_{j,t} \sim N(0, \sigma_\lambda^2)$ stands for the distortion in quality due to noises. This means that the quality distortion can happen on both sides and even after multiple consumptions, the consumer would still be uncertain about the true quality as each consumption experience brings them only a 'noisy' signal about the true quality. Hence, as far as the consumer is concerned, the quality-specific component $\lambda_{j,t}$ is a random variable from the normal distribution $\lambda_{j,t} \sim N\left(q_j, \sigma_\lambda^2\right)$.

At the beginning of the purchase history, the consumer's initial belief about product quality is $q_{j,0} \sim N\left(\omega_o, \psi_0^2\right)\forall j$, where ω_0 is her expected brand quality and ψ_0^2 is her uncertainty about brand quality. As she purchases more, she receives more quality signals from consumption, which she uses to update her initial belief. We refer to these realized quality signals as $\hat{\lambda}_{j,t}$. At purchase occasion t, a consumer uses her latest quality belief, $q_{j,t-1} \sim N\left(\omega_{j,t-1}, \psi_{j,t-1}^2\right)$, to form her utility function. Since the consumer is assumed to be risk neutral, she will use expected utility to make her brand choice.

$$E_t U_{j,t} = E\left(q_{j,t-1}\right) - \theta p_{j,t} \tag{2}$$

where $p_{j,t}$ is the price of brand j and θ is the price coefficient.

3.2 A consumer's model with perfect memory

Here, we lay out the model from the perspective of a consumer, who is assumed to have perfect memory. We call the reader's attention to two different time occasions: (i) the consumption occasion, when the consumer uses consumption experience to update her quality belief, and (ii) the purchase occasion, where the consumer decides whether to use inherent preferences or construct a new preference.

3.2.1 At the consumption occasion

The consumer learns about the product quality through consumption experiences. At consumption occasion t–1, after using product j, the consumer receives a quality signal $\hat{\lambda}_{j,t-1}$. She uses this quality signal to update her prior belief into posterior belief $q_{j,t-1} \sim N\left(\omega_{j,t-1}, \psi_{j,t-1}^2\right)$ as described in Eq. (3).

$$\omega_{j,t-1} = \frac{\frac{\omega_{j,t-2}}{\psi_{j,t-2}^2} + d_{j,t-1} \cdot \frac{\hat{\lambda}_{j,t-1}}{\sigma_\lambda^2}}{\frac{1}{\psi_{j,t-2}^2} + d_{j,t-1} \cdot \frac{1}{\sigma_\lambda^2}}; \; \frac{1}{\psi_{j,t-1}^2} = \frac{1}{\psi_{j,t-2}^2} + d_{j,t-1} \cdot \frac{1}{\sigma_\lambda^2} \tag{3}$$

where $d_{j,t\text{-}1}$ is a purchase indicator if brand j is chosen for purchase occasion t-1. Since this posterior belief $q_{j,t-1} \sim N\left(\omega_{j,t-1}, \psi_{j,t-1}^2\right)$ is an overall evaluation, it is stored in the consumer's semantic memory. On the other hand, $\hat{\lambda}_{j,t-1}$ is instantaneously stored in her episodic memory along with the contextual details.

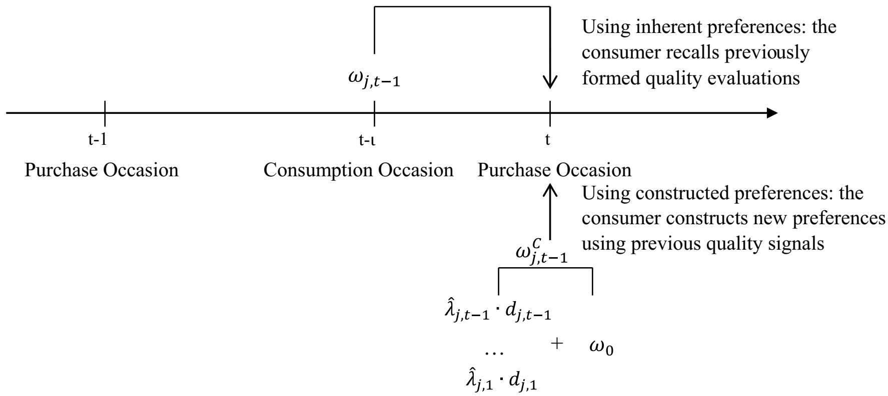

Fig. 1 Inherent versus constructed preference for brand j

3.2.2 At the purchase occasion

During the purchase occasion, the consumer might either recall her inherent preferences or construct new preferences. If she uses her inherent preferences, she will recall the recently updated quality belief from her semantic memory and use the posterior mean, $\omega_{j,t-1}$, as the brand quality evaluation. This is shown in Eq. (2). Since ι, the time gap between consumption and the purchase occasion, is assumed to be infinitesimally small, the posterior $\omega_{j,t-1}$ formed as a result of consumption at ι before t can be recalled perfectly at purchase occasion t. This is similar to previous learning models (Erdem and Keane 1996; Mehta et al. 2003, 2004) where the consumer always recalls a belief from their semantic memory rather than forming any new beliefs. To better demonstrate this process, we use the upper part of Fig. 1 to illustrate the situation where a consumer uses inherent preferences for brand evaluation.

If the consumer does not have a well-defined prior brand evaluation, or if the environmental cues (Huber et al. 1982; Simonson 1989; Palos-Sanchez, et al 2021) force him/her to actively reconsider the preferences, he/she may opt to construct a new quality evaluation with past consumption experiences recalled from episodic memory (Motta-Filho 2021). Since we assume the consumer has perfect memory, she can retrieve all her past consumption experiences with no recall errors. She uses her initial prior and realized sequence of quality signals, as shown in the bottom half of Fig. 1, to obtain a new brand evaluation. In Fig. 1, $\omega^{C}_{j,t-1}$ is the constructed brand evaluation; we use superscript C to indicate values that are constructed.

Equation (4) shows how a brand evaluation is constructed at the time of purchase. Here the consumer recalls all her past consumption experiences from her episodic memory and recalls the prior and the law of Bayesian updating (Bayes and Price 1763) from her semantic memory.

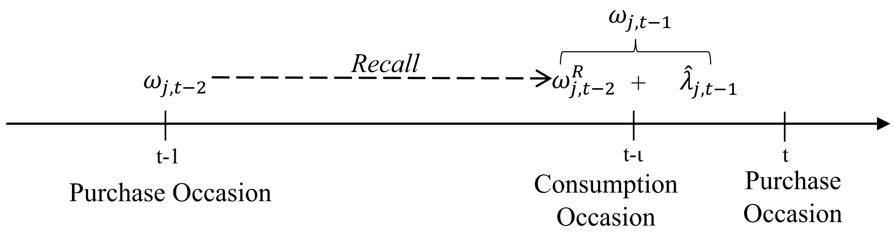

Fig. 2 Updating quality belief for brand j with recalled prior

$$\omega^c_{j,t-1} = \frac{\frac{\omega_0}{\psi_0^2} + \sum_{\tau=1}^{t-1} \frac{\hat{\lambda}_{j,\tau}}{\sigma_\lambda^2} \cdot d_{j,\tau}}{\frac{1}{\psi_0^2} + \sum_{\tau=1}^{t-1} \frac{d_{j,\tau}}{\sigma_\lambda^2}}; \quad \frac{1}{\left(\psi^c_{j,t-1}\right)^2} = \frac{1}{\psi_0^2} + \sum_{\tau=1}^{t-1} \frac{d_{j,\tau}}{\sigma_\lambda^2} \tag{4}$$

Therefore, Eqs. (3) and (4) represent two different underlying behaviors when the consumer makes a judgment. However, mathematically, these two equations are equivalent.[3] This is because the same set of quality signals (consumption experiences) is used to update the consumer's perception of brand quality. Since the consumer is assumed to have perfect memory, whether the quality signals are incorporated into the updating process sequentially, as in the case of Eq. (3), or used all at once, as in the case of Eq. (4), does not lead to different outcomes. Therefore, with perfect memory, the two scenarios of inherent versus constructed preferences are not separately identifiable.

3.3 A consumer's model with imperfect memory

In reality, however, people forget. As a result, consumers will recall different quality beliefs from what is stored in their memory. To account for this, a consumer with imperfect memory is portrayed in this section. We discuss how memory decay due to forgetting can affect the recall process, and, consequently, the formation of brand evaluations along the purchase and consumption history.

3.3.1 At the consumption occasion

At the consumption occasion, the consumer uses the newly received quality signal to update her quality belief. To do so, she needs to recall the quality belief from her semantic memory, as shown in Fig. 2. Since there is a time gap (in absolute calendar days) between purchase occasion *t*-1 and *t*, the prior $\omega_{j,t-2}$ is retrieved with a recall error. We use superscript R to denote values that are recalled, i.e., $\omega^R_{j,t-2} \neq \omega_{j,t-2}$. Note that since updating happens immediately after the consumption experience, the perceived consumption experience $\hat{\lambda}_{j,t-1}$ is not affected. Both $\omega^R_{j,t-2}$ and $\hat{\lambda}_{j,t-1}$ are used

[3] Equation (3) can be written as Eq. (4) if we follow the law of motion and recursively replace the posterior as the function of its prior and the newly received signal.

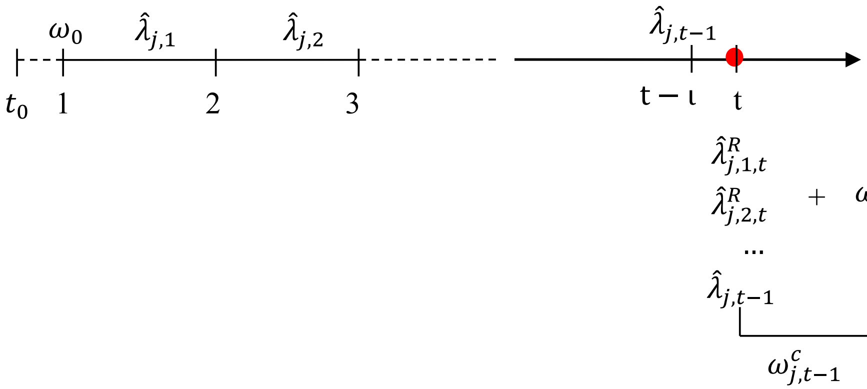

Fig. 3 Construction of quality belief

to form $\omega_{j,t-1}$, as shown in Fig. 2. In addition, the consumer is aware that she might recall a value that is different from what was originally stored, but does not know the exact magnitude of the recall error or she would have corrected it. This leads to higher uncertainty associated with recalled quality, i.e., $\left(\psi^R_{j,t-2}\right)^2 \geq \left(\psi_{j,t-2}\right)^2$.

3.3.2 At the purchase occasion

In the purchase occasion, the consumer can either recall a recently updated evaluation or construct a new brand evaluation. If the consumer is to use an inherent preference, no recall error is incurred as the time lapse ι between the consumption occasion and purchase occasion is infinitesimally small, i.e., $\omega^R_{j,t-1} = \omega_{j,t-1}$. However, if in the immediate prior period, the consumer had not purchased and thus consumed brand j, such an evaluation needs to be recalled where $t - \tau$ is the period during which the last consumption of brand j occurred.

If the consumer is constructing a new preference, she will recall her past consumption experiences from the episodic memory. These recalled consumption experiences will thus contain forgetting errors, i.e., $\hat{\lambda}^R_{j,\tau,t} \neq \hat{\lambda}_{j,\tau}$. $\hat{\lambda}_{j,\tau}$ is the realized quality signal that was received in period τ and $\hat{\lambda}^R_{j,\tau,t}$ is the recall of that signal at purchase occasion t. Since the consumer is aware that she may be forgetting, her uncertainty associated with the recalled experiences increases thus $(\sigma^R_{j,\tau,t})^2 \geq \sigma^2_{\lambda}$. Note that the only quality signal that does not get distorted is the one received at time period $t-1$. The newly constructed quality belief is then denoted as $\omega^C_{j,t-1}$. Figure 3 illustrates the construction of belief using previously received quality signals.

3.4 The econometrician's model

In the consumer's model, a consumer (1) observes the actual quality signals, (2) knows the recalled values, and (3) is aware of whether an inherent preference is recalled or a new preference is constructed. However, these are not observable to an econometrician. As such, when modeling a consumer's decision process, an econometrician has to make probabilistic inferences about these unobservables. This gives rise to the econometrician's model, which addresses this information asymmetry.

3.4.1 The quality signals

While the consumer uses the product and has full access to the consumption experiences, $\widehat{\lambda}_{j,t}$, the econometrician does not observe the consumer's realized quality signals. However, he[4] knows the distribution from which these quality signals are drawn from, i.e., $\lambda_{j,t} \sim N(q_j, \sigma_\lambda^2)$ as in Eq. (1). As such, he uses random draws from the distribution $N(q_j, \sigma_\lambda^2)$ to simulate the actual realizations received by the consumer (Erdem and Keane 1996; Mehta et al. 2003, 2004).

3.4.2 The recalled values

Unlike the consumer, the econometrician does not observe the value recalled by the consumer. However, he knows that the recalled value is merely the original value with recall errors. To infer the values recalled by the consumer, he needs to gauge the size of the recall errors.

The monumental work by Ebbinghaus (1885) explores the relationship between memory retention and time. In his research, Ebbinghaus uses an exponential function to describe how information is lost with the passage of time. Mehta et al. (2004) employ the theory of the forgetting curve, and use time lapse to gauge the size of a forgetting error – the longer the time lapses, the larger the recall errors are. In this paper, we model the forgetting error in a similar fashion. Thus, the econometrician models the recall of a previously formed quality evaluation $\omega_{j,t-2}$ as $\omega^R_{j,t-2}$, where

$$\omega^R_{j,t-2} = \omega_{j,t-2} + v_{j,t-2}\varphi_{j,t-2} \tag{5}$$

In Eq. (5), the forgetting error is $v_{j,t-2}\varphi_{j,t-2}$, where $v_{j,t} \sim N(0,1)$ is a random draw from a standard normal distribution. $\varphi_{j,t-2}$ is the scale of the forgetting error that is modeled as an exponential function of the time lapse between when the value is received and when it is recalled.

$$\varphi^2_{j,t-2} = \psi^2_{j,t-2}\left(e^{B^S w_{t-1}} - 1\right) \tag{6}$$

where $\psi^2_{j,t-2}$ is the posterior variance of the consumer's belief in period t-1, w_{t-1} is the inter-purchase time between t and period t-1, and B^S ($B^S \geq 0$) measures the consumer's tendency to forget. We use superscript S to indicate that the recall is from semantic memory in this situation. With Eqs. (5) and (6), the recalled value equals the original value received when (i) there is no time lapse in between ($w_{t-1} = 0$) and (ii) the memory is perfect ($B^S = 0$). Hence, the recalled belief about the brand quality can be written as

[4] We will be referring to the econometrician as a male to differentiate him from the consumer.

$$q^R_{j,t-2} \sim N\left(\frac{\omega_{j,t-2} + v_{j,t-2}\psi_{j,t-2}\sqrt{e^{B^s w_{t-1}} - 1}}{\omega^R_{j,t-2}}, \frac{\psi^2_{j,t-2} e^{B^S w_{t-1}}}{\left(\psi^R_{j,t-2}\right)^2}\right) \tag{7}$$

As a result, $q^R_{j,t-2} \sim N\left(\omega^R_{j,t-2}, \left(\psi^R_{j,t-2}\right)^2\right)$ is the recalled belief by the consumer from the econometrician's perspective.

Similarly, the econometrician infers the recall of the quality signal as follows:

$$\lambda^R_{j,\tau,t} = \lambda_{j,\tau} + v_{j,t}\phi_{j,\tau,t} \tag{8}$$

where $\lambda^R_{j,\tau,t}$ is the value of brand j's quality signal that is received at consumption occasion τ and recalled at purchase occasion t. $\lambda_{j,\tau}$ is the original value of the quality signal received at period τ. $v_{j,t} \sim N(0, 1)$ and $v_{j,t}\phi_{j,\tau,t}$ is the recall error. The additional uncertainty caused by forgetting, $\phi^2_{j,\tau,t}$, is therefore

$$\phi^2_{j,\tau,t} = \sigma^2_\lambda(e^{B^E W_{\tau,t}} - 1) \tag{9}$$

where $W_{\tau,t}$ is the actual time in weeks between purchase occasion τ and purchase occasion t. $B^E(B^E \geq 0, B^E \neq B^S)$ is the consumer's tendency to forget. We use the superscript E to indicate that the retrieval is from episodic memory. We allow different decay rates as it is well documented in cognitive science literature that episodic memory is generally more prone to memory decay than semantic memory (Craik and Lockhart 1972; Tulving 1983; Johnson and Anderson 2004; Wingfield and Byrnes 2013). Hence, $\lambda^R_{j,\tau,t}$ is specified as

$$\lambda^R_{j,\tau,t} \sim N\left(\lambda_{j,\tau} + v_{j,t}\phi_{j,\tau,t}, \phi^2_{j,\tau,t}\right) \tag{10}$$

i.e., $\lambda^R_{j,\tau,t} \sim N\left(q_j + v_{j,t}\phi_{j,\tau,t}, (\sigma^R_{j,t,\tau})^2\right)$, where $(\sigma^R_{j,t,\tau})^2 = \sigma^2_\lambda e^{B^E W_{\tau,t}}$. Once the econometrician has these recalled values, he can update brand quality as the consumer does, per Eqs. (11) and (12). To differentiate between the modes of evaluation, we use superscript *I* for inherent preferences and superscript *C* for constructed preferences.

$$\omega^I_{j,t-1} = \frac{\frac{\omega^R_{j,t-2}}{\left(\psi^R_{j,t-2}\right)^2} + \frac{\lambda_{j,t-1}}{\sigma^2_\lambda}\cdot d_{j,t-1}}{\frac{1}{\left(\psi^R_{j,t-2}\right)^2} + \frac{1}{\sigma^2_\lambda}\cdot d_{j,t-1}}; \quad \frac{1}{\left(\psi^I_{j,t-2}\right)^2} = \frac{1}{\left(\psi^R_{j,t-2}\right)^2} + \frac{d_{j,t-1}}{\sigma^2_\lambda} \tag{11}$$

$$\omega^C_{j,t-1} = \frac{\frac{\omega^R_0}{\left(\psi^R_0\right)^2} + \sum_{\tau=1}^{t-2}\frac{\lambda^R_{j,\tau,t}}{\left(\sigma^R_\lambda\right)^2} + \frac{\lambda_{j,t-1}}{\sigma^2_\lambda}\cdot d_{j,t-1}}{\frac{1}{\left(\psi^R_0\right)^2} + \sum_{\tau=1}^{t-2}\frac{\lambda^R_{j,\tau,t}}{\left(\sigma^R_\lambda\right)^2} + \frac{1}{\sigma^2_\lambda}\cdot d_{j,t-1}}; \quad \frac{1}{\left(\psi^C_{j,t-2}\right)^2} = \frac{1}{\left(\psi^R_0\right)^2} + \sum_{\tau=1}^{t-2}\frac{\lambda^R_{j,\tau,t}}{\left(\sigma^R_\lambda\right)^2} + \frac{1}{\sigma^2_\lambda}\cdot d_{j,t-1} \tag{12}$$

3.5 3.5 Choice probability

The consumer can deterministically make her choice decision by selecting a brand that maximizes her surplus. The econometrician uses similar utility maximization as the consumer by following Eq. (13).

$$E_t U_{i,j,t} = E\left(q_{i,j,t-1}\right) - \theta p_{i,j,t} + \varepsilon_{i,j,t} \tag{13}$$

where $\varepsilon_{i,j,t}$ is the unobserved random component and assumed to be a type-I extreme value distribution for a random error that is i.i.d. across all consumers, brands, and purchase occasions. Hence, the econometrician can define the consumer's choice probability for each brand conditioned on the mode of processing as

$$\begin{aligned} Pr\left[d_{i,j,t} = 1|I\right] &= \frac{exp(\omega^{I}_{i,j,t-1} - \theta \cdot p_{i,j,t})}{\sum_{l \in J} exp(\omega^{I}_{i,l,t-1} - \theta \cdot p_{i,l,t})} \\ \Pr\left[d_{i,j,t} = 1|C\right] &= \frac{\exp(\omega^{C}_{i,j,t-1} - \theta \cdot p_{i,j,t})}{\sum_{l \in J} \exp(\omega^{C}_{i,l,t-1} - \theta \cdot p_{i,l,t})} \end{aligned} \tag{14}$$

At purchase occasion t, the consumer knows for certain whether she has recalled inherent preferences or has constructed a new preference, but the econometrician does not. Hence, he needs to make a probabilistic assumption about the consumer's tendency to use inherent versus constructed preferences. Equation (15) shows the probability that the consumer will use inherent preferences.

$$Pr_i[I] = \frac{\exp\left(\alpha_i + X\beta\right)}{1 + \exp\left(\alpha_i + X\beta\right)} \tag{15}$$

Simonson (2008) has shown that using inherent or constructed preferences may or may not be obvious, and that it is more often a latent tendency. Hence, $\alpha_i \sim N(\alpha, \sigma^2_\alpha)$ in Eq. (15) is an individual's intrinsic tendency to use inherent versus constructed preferences. In addition, both occasion-specific and non-occasion-specific factors, such as motivation for accuracy (Chaiken 1980; Chen et al. 1996), time constraints (Suri and Monroe 2003), and mental capacity (Barret et al. 2004), have been identified in prior literature to explain a consumer's choice between the two types of preferences. X is a vector of such explanatory variables. In this study, we only use variables that are available in our data set (gender, age, and product knowledge).

The probability of the consumer using constructed preferences is $Pr_i[C] = 1 - Pr_i[I]$. Therefore, the probability that an individual i will choose brand j at purchase occasion t can be represented as

$$\Pr\left[d_{i,j,t} = 1|\Lambda_{i,t-1}, V_{i,t-1}, \alpha_i, \Delta\right] = Pr_i[I] \cdot \Pr\left[d_{i,j,t} = 1|\mathrm{I}\right] + Pr_i[C] \cdot \Pr\left[d_{i,j,t} = 1|\mathrm{C}\right] \tag{16}$$

where $\Lambda_{i,t_i} \equiv \left\{\lambda_{i,1,s} d_{i,1,s}, \ldots \lambda_{i,j,s} d_{i,J,s}\right\}_{s=1}^{t-1}$ represents the string of signals that are received by the consumer till purchase occasion t, and $V_{i,t_i} \equiv \left\{v_{i,1,s}, \ldots, v_{i,j,s}\right\}_{s-1}^{t-2}$ is a matrix of $J \times t_i$ i.i.d. standard normal random errors. Δ is the vector of population parameters $\{\beta, \theta, q_1 \ldots q_J, \sigma_\lambda, \sigma_\alpha\}$. Equation (16) shows as far as an econometrician is concerned, the choice probability is an expected value of the both processes.

Table 1 Descriptive statistics for the diaper category

Brand	Market share (%)	Mean (US$ per piece) price (Std. dev.)	Mean inter-purchase time (weeks)
Huggies	28.01	0.293 (0.028)	7.72
Pampers	36.85	0.287 (0.028)	7.66
LUVs	19.44	0.234 (0.027)	7.48
Other Brands	15.70	0.211 (0.027)	7.38

To understand how the posterior quality belief evolves across these two processes, we study and compare the asymptotic properties of posterior belief distribution. We found with the presence of forgetting, even after infinite times of consumption, consumers can never be certain about the true quality. We refer the readers to see the detailed derivation of the asymptotic properties of the posterior belief in Technical Appendix I.

4 Data and model-free evidence

4.1 Data

For the model calibration and analysis, we use the diaper purchases from the IRI scanner panel data from USA. The brands included in the analysis are Huggies, Pampers, LUVs, and other brands, with national brands accounting for a total of 84% of the market share. The diaper data set has a total of 195 (44 male and 151 female) panelists, who have made at least eight purchases during the five years. We randomly selected 39 (8 male and 31 female) panelists as our holdout sample with 665 observations, leaving an estimation sample of 156 panelists (36 male and 120 female) with 2,624 observations. The average number of purchases is 16.82 in the estimation sample and 17.05 in the holdout sample. The overall average inter-purchase time is 7.56 weeks for the estimation sample and 7.00 weeks for the holdout sample. The summary statistics for the different brands are given in Table 1. While our structural econometric model is tested on a single product category, given the broadly applied behavioral assumptions, our model should be applicable to other categories and shopping contexts, provided the decision-makers conform to the behavioral assumptions outlined by our model."

4.2 Model-free evidence

In this section, we provide some model-free evidence to show that the data has both the learning effect and the forgetting effect, without which we would not be able to identify the two modes of evaluations.

Table 2 Percentage (%) of switches in the early and late stages of the purchase history

	First 3 purchases	First 4 purchases	First 5 purchases	First 6 purchases	First 7 purchases	First 8 purchases
$\overline{\mathrm{S_E}}$	36.86	35.26	33.97	33.46	33.33	32.51
$\overline{\mathrm{S_L}}$	24.96	22.35	20.28	17.93	15.29	13.06

4.2.1 Learning effect

Consumers obtain signals of product quality when they consume a product, and are able to infer the true product quality through sufficient consumption experiences. If a consumer learns about a brand's quality, we should observe more switches during the beginning of the consumer's purchase history and fewer switches during the later stages of the purchase history. This is because in the early stage, the consumer has limited knowledge to differentiate among the brands in a product category, thus price dictates their choices. However, when the consumer is better informed about the quality differences among the brands, the brands will be more differentiated, and larger price differences will be needed to induce brand switching. As such, we should observe fewer switches during the later stage than the early stage of a consumer's purchase history. To examine this effect, we construct a variable called "switching" in the following fashion:

$$S_{it}\begin{cases} = 0 if d_{it} = d_{i,t-1} \\ \\ = 1 if d_{it} \neq d_{i,t-1} \end{cases}$$

where d_{it} is consumer i's choice at purchase occasion t. Let $\sum_{t=2}^{E} S_{it}$ be the total number of switches made by a consumer in the early stage of her purchase history and $\sum_{t=E+1}^{L} S_{it}$ be the total number of switches made in the later stage of the purchase history. We start from the second purchase as we do not observe whether the first purchase is or is not a switch. The capital E stands for the number of purchases that are considered as early-stage purchases, and L stands for the total number of purchases. In our data set, a consumer's number of purchases ranges from 8 to 40 times, and we use different thresholds (different values of E) to define early stage and the results exhibit consistent patterns.

Since different consumers have different lengths of purchase history, instead of using the absolute number of switches, we use the percentage of switching against the total number of purchases as our comparison statistics. In other words, $S_E = \frac{\sum_{t=2}^{E} S_{it}}{E-1}$ and $S_L = \frac{\sum_{t=E+1}^{L} S_{it}}{L-E}$. As shown in Table 2, we use different values for E as the early stage of the purchase history. $\overline{\mathrm{S_E}}$ and $\overline{\mathrm{S_L}}$ are the mean percentages of switches in the early and late stages of purchase history for all the panel subjects.

Table 3 Average inter-purchase time for switched or non-switched purchases (weeks)

	Switch (weeks)	Non-switch (weeks)
With all switches	11.58	6.26
With only non-price-induced switches	9.21	6.26

From Table 2, we see that (1) the percentage of switches in the early stage is much higher than in the later stage ($\overline{S_E} > \overline{S_L}$), and (2) with the increase of early-stage purchases, $\overline{S_E}$ and $\overline{S_L}$ both decrease. This means that the later the purchase history, the fewer the switches. If there is no learning, the percentage of switches should be distributed evenly throughout a consumer's purchase history.

4.2.2 Forgetting effect

The time lapse between two purchases is a major contributor to forgetting in the context of our research. The longer the time lapse, the more the consumer forgets. This in turn, leads to decreases in learning efficiency; brands become less vertically differentiated in consumers' minds. Thus, the longer the inter-purchase time, the larger the number of switches as consumers are more likely to forget. To test this theory, we compare the inter-purchase times for both switching and non-switching occasions, with the first purchase excluded from the comparison. Table 3 compares the mean inter-purchase times for purchases where there is switching and where there is no switching. For purchases where switching occurs, the inter-purchase time is longer (11.58 weeks) than for purchases where switching does not occur (6.26 weeks).

An alternative explanation for this pattern is stockpiling as a result of price promotion. When a competing brand is undergoing price promotion, the consumer switches to said brand due to the price cut and may also stockpile. The stockpiling behavior is reflected by a longer post-promotion inter-purchase time. At the next purchase occasion, the customer will switch back to the brand they originally preferred. To exclude the possibility of such alternative explanations, we define any price that is at least 5% lower than the mean price as a price-promotion occasion, and delete any switches associated with such promotions. We then check if switches are still associated with longer inter-purchase time. As shown in the second row of Table 3, the average inter-purchase time for purchases where switching occurs (after deleting data points that indicate possible stockpiling behavior) is now reduced to 9.21 weeks. However, this is still significantly longer than the inter-purchase time where there is no switching (6.26 weeks). This shows that stockpiling behavior alone cannot explain why switches are associated with longer inter-purchase time. We also refer readers to Technical Appendix II for discussion on model identification.

5 Results and discussion

5.1 Estimates and model performance

We estimate our model using the diaper data set. The estimates are mostly statistically significant. We compare the goodness-of-fit and the predictive power of the proposed model (Model IV) with three other competing specifications:

Model I is a learning model that assumes the consumer has perfect memory, like in Erdem and Keane (1996). In Model II, the consumer is assumed to have imperfect memory, but only recalls her inherent preference or her previously formed brand evaluation, like in Mehta et al. (2004). In Model III, the consumer is forgetful, similar to Model II, but constructs new preferences or brand evaluations at every purchase occasion. Model IV, our proposed model, allows the consumer with imperfect memory to either recall a previously formed preference or construct a new preference at every purchase occasion. The results of all the model estimates are given below in Table 4. We can see that the estimates of all the common variables, the true quality of brands ($q_{Huggies}$, $q_{Pampers}$, q_{LUVs}), signal variance (σ_λ), and price (θ), are significant across all the models.

We use a log-likelihood ratio test to inspect the goodness-of-fit for the models which are nested. The log-likelihood values for all models in the estimated sample are reported at the bottom of Table 4. In total, we run four log-likelihood ratio tests using either Model I or Model III as the null model. The test statistics show that Model II is not significantly superior to Model I. This is because B^S, though statistically significant, is extremely small (3.685E-09), making Model II almost identical to Model I. We find that both Model III (274.25) and Model IV (418.40) are superior to Model I. The test statistics also show that Model IV, our proposed model, is significantly better than Model III (144.14). Hence, our proposed model is the best representation of the consumer choice decision among all four models.

In terms of predictive power, we examine hit rates in both the estimation sample and the holdout sample. As shown in Table 5, Model IV has the highest hit rates among all the models for both the estimated and holdout samples. Thus, we conclude that Model IV is the best model to predict an individual consumer's choice decision.

5.2 Discussions and implications of the results

We summarize our findings under four broad substantive topics:

Inherent versus Constructed Preferences: The main objective of this research is to empirically investigate whether preferences are inherent or constructed in a choice decision. In the model for econometricians, we use $Pr[I]$ (Eq. 15) to infer the likelihood that the consumer will use inherent preferences over constructed preferences. The intercept α measures a consumer's mean tendency to use inherent preferences. Our estimate of α (= -5.081) implies that the population under study tends to construct preferences (whose coefficient is normalized to zero). We find that

Table 4 Parameter estimates for competing models

Parameter	Explanation	Model I	Model II	Model III	Model IV
$q_{Huggies}$	True quality of Huggies	**4.392 (0.179)**	**4.392 (0.186)**	**5.138 (0.265)**	**7.375 (0.412)**
$q_{Pampers}$	True quality of Pampers	**4.535 (0.167)**	**4.535 (0.174)**	**5.003 (0.243)**	**7.667 (0.429)**
q_{LUVs}	True quality of LUVs	**3.192 (0.157)**	**3.192 (0.162)**	**3.536 (0.218)**	**6.096 (0.410)**
$\sqrt{\sigma_\lambda}$	Standard deviation for quality signals	**0.500 (0.050)**	**1.284 (0.033)**	**1.214 (0.109)**	**1.495 (0.039)**
$\ln B^S$	Forgetting rate for semantic retrieval		**−19.419 (0.144)**	**0.176 (0.068)**	**−33.056 (0.021)**
$\ln B^E$	Forgetting rate for episodic retrieval				**4.636 (1.349)**
α	Tendency to use semantic retrieval				**−5.081 (0.945)**
$\sqrt{\sigma_\alpha}$	Standard deviation of $\boldsymbol{\alpha}$				**0.708 (0.192)**
θ	Price coefficient	**12.389 (0.760)**	**12.389 (0.694)**	**12.407 (0.717)**	**10.909 (0.760)**
β_{gender}	Gender coefficient				−0.265 (0.521)
β_{age}	Age coefficient				0.753 (0.521)
β_{pk}	Product knowledge coefficient				**7.959 (1.343)**
Log-likelihood		−2516.219	−2516.220	−2379.092	−2307.021
$-2\log(\Lambda)$	Model I as the Null Model		0.003	**274.254**	**418.398**
$-2\log(\Lambda)$	Model III as the Null Model				**144.142**

* Standard errors are in parentheses. The numbers in bold are significant at the 0.05 level

Table 5 Hit Rates (%) in both estimation and holdout samples

	Model I	Model III	Model IV
Estimation Sample	62.88	55.37	63.38
Holdout Sample	57.14	49.02	58.35

Table 6 Percentage of evaluations made with inherent preferences

	Inherent preference	Constructed preference
All Brands	23.85%	76.15%
Purchased Brands	61.51%	38.49%
Non-Purchased Brands	11.29%	88.71%

demographic characteristics such as gender and age are not significant in explaining a consumer's mode of evaluation. For product knowledge, we use cumulative purchases till date as a measure. The estimate of product knowledge, 7.959, is significant at the 5% level; the more a consumer purchases a brand, the more likely they are going to recall a pre-existing evaluation for their choice decision. This result is in line with Dimofte and Yalch (2010), who have shown that with more accumulated product knowledge, consumers are more likely to use inherent preferences.

With the estimates above, we can finally answer our main research question: to what extent do consumers use inherent versus constructed preferences? There are 2,624 purchases. For each purchase, a consumer evaluates four brands, leading to a total of 10,496 brand evaluations. We use a 0.5 cut-off value to determine whether each consumer is using inherent or constructed preferences at each purchase occasion for each brand under consideration. Ultimately, consumers use inherent preferences only 24% of the time. From this perspective, preferences are largely constructed, as argued by Payne et al. (1992). Interestingly, when focusing on brands that were actually purchased, 61% of them are made with inherent preferences and 39% are based on constructed preferences. On the other hand, for brands not purchased, a whopping 89% of the brand evaluations stem from constructed preferences, leaving a mere 11% attributed to inherent preferences as shown in Table 6.

Forgetting and state dependence As previously mentioned, the process of forgetting acts differently across the two different evaluation processes, which allows us to identify which process a consumer is using. As shown in Table 4, the rate of memory decay for semantic memory ($lnB^S = -33.056$) is significantly lower than that for episodic memory ($lnB^E = 4.636$). This is substantiated by literature that has found that episodic memory is more vulnerable to recall errors. As captured in Eqs. (9) and (11), a large forgetting error in semantic memory still leads to an almost perfect recall of a previously stored brand evaluation. On the other hand, a large recall error in episodic memory implies that the recalled consumption experiences are associated with larger errors. As such, it does not contribute much to belief updating in our model setting; the larger the recall error associated with a particular quality

Table 7 Brand switching and mode of brand evaluation

	Inherent Preferences		Constructed Preferences		Total	
	#	%	#	%	#	%
Switched Purchases	301	40.40	444	59.60	745	100.00
Non-switched Purchases	1,313	69.88	566	30.12	1,879	100.00
Total	1,614	61.51	1,010	38.49	2,624	100.00

signal, the less weight it has on the posterior belief. Thus, our estimates indicate that although some people use general impressions (inherent preference) for brand evaluation, most use the last consumption experience to construct a brand evaluation (constructed preference). Our data shows that around 76% of brand evaluations are made through constructed evaluations, which reveals that the majority of brand evaluations are dependent on a consumer's last consumption experience. In Dubè et al. (2010), state dependence is defined as the loyalty effect of a past brand choice on the current brand choice. In this paper, we are able to further enrich the meaning of state dependence by clarifying that state might be better interpreted not as the last choice, but rather as the last consumption experience. Our model provides a clear identification of what drives the phenomenon of state dependence.

Preference stability Bronnenberg et al. (2012) investigate the evolution of brand preferences for packaged goods. They find that the relative brand share stayed stable even after consumers migrated to different states in the U.S., and conclude that brand preferences are rather stable once formed. Our data also suggests stable consumer choices. As shown in Table 7, there are 2,624 purchases in total, with 745 switched purchases and 1,879 non-switched purchases. Of the 745 switched purchases, 354 were switched price-cuts, and the rest may have included switches back to the original brands. This means that consumer choices are more or less stable since there are very few real brand switches in our data. Table 7 also shows that of the 1879 non-switched purchases, 70% are based on inherent preferences and 30% are made with constructed preferences. Thus, stable preferences are the consequence of two different underlying behavioral processes: one is due to the recall of stable brand evaluations, and the other is due to the fact that the constructed evaluations lead to the same brand choices.

Mode of evaluation and market share We also find the mode of evaluation, inherent versus constructed preferences, affects brand switching. After dividing purchases into switched and non-switched cases as shown in Table 7, 60% of the switched purchases are made with constructed preferences, while 70% of the non-switched purchases are based on inherent purchases. Though preferences are in general stable, it seems that constructing a preference is more likely to induce a brand switch. To evaluate the impact of mode of evaluation on market share, we conducted two counterfactual analyses. Counterfactual analysis, a methodological approach rooted in thought experiments, seeks to answer hypothetical "what-if" questions. According

Table 8 Predicted market share (%)

	Huggies	Pampers	LUVs	Other brands
Using inherent preferences only *(counterfactual analysis)*	27.92	40.44	21.99	9.60
Using constructed preferences only *(counterfactual analysis)*	20.85	31.25	24.12	23.78
Using both preferences *(model prediction)*	26.37	37.42	23.93	12.27
Observed	28.01	36.85	19.44	15.70

to Lewis (1973), the essence of counterfactual analysis can be encapsulated in the question, "If A occurred, what would have happened to C?" This analytical framework has been widely adopted in empirical marketing research to explore various hypothetical scenarios and their potential outcomes (Zhao et al. 2013; Li and Srinivasan, 2019; Zhang and Chung 2020). In our study, we specifically examined the market share dynamics for each brand under two distinct scenarios: one where all consumers of a brand base their preferences on constructed preferences, and another where preferences are inferred. This approach allowed us to assess how different modes of evaluation influence a brand's market share, providing insights into consumer behavior and preference formation.

The results are shown in Table 8 along with the market share predicted by our dual-process model and the observed market share. We find that leading brands such as Huggies and Pampers would have a larger market share if all the consumers relied on inherent preferences for brand evaluation. On the other hand, if all the brand evaluations were made with constructed preferences, the market shares of the well-known brands (Huggies and Pampers) drop significantly. The reasoning behind this is that established brands have a strong presence in the market, often due to significant advertising spending. When consumers recall these evaluations, the well-known brands typically perform well. However, when consumers are prompted to form new preferences, it diminishes the advantage these well-known brands hold.

One implication of the findings above is that firms can customize their marketing efforts to alter consumers' mode of brand evaluation (Henseler et al. 2021). For example, the literature suggests that there are two types of advertising formats: argument-based and drama-based (Deighton et al. 1989). Argument-based ads have their content read out by a narrator, with usually no character or storyline. They persuade a viewer with evidence and reasoning. For well-known brands, this type of ads is more effective since the ads make the overall brand perception very salient, leading consumers to use inherent preference for brand evaluation. Conversely, when the reputation of the well-known brands has been firmly established in the market, using argumentative ads with direct and overt statements might be less impactful. Drama-based ads engage viewers using vivid stories, experiences, and feelings of characters. Research shows that these ads might even dilute the original memory or implant false memories in consumers' minds about their consumption experiences (Braun 1999). Hence, for less established brands, using drama-based ads might induce a particular experience in the consumer's mind and trigger a construction of preferences. This, in turn, could lead to an enhanced brand evaluation for less established brands. Nonetheless, this hypothesis stems exclusively from our results and the characterization of the two different ads formats. We encourage advertising researchers to conduct further studies to rigorously ascertain and validate this effect.

6 Conclusions and future research

In this paper, we build a memory-based dual-process model that allows the consumer to either recall an inherent preference or construct a new preference at the time of choice, and thereby aims to reconcile the conflicting views regarding the formation of preferences. It enables us to empirically estimate the extent to which preferences are constructed. We find that preferences are largely constructed as 76% of all brand evaluations are formed at the time of choice decision. However, when we only focus on the purchased brands, the percentage of constructed brand evaluations drops to 38%.

Our findings provide a new explanation of the underlying source of state dependence. The model directly measures to what extent the current choice is affected by previous consumption experiences. It also shows that construction of preferences does not necessarily lead to consumers switching brand. In fact, even after constructing preferences, consumers often continue to purchase the brand they originally preferred. Finally, we also explain how our findings can be used by firms to customize advertising using the right ad format, which can cause consumers to change their mode of evaluation, leading to an increase in market share.

This research is not without its limitations. Since we focus on a memory-based choice model, when modeling constructed preferences, consumption experiences are the most frequently used diagnostic inputs. However, in-store products, advertising stimulus, previous media exposure, word of mouth, etc. could all contribute to preference construction too. Due to data availability, these were not incorporated into our model; however, they could be easily incorporated should the data be available. It would be interesting to see how these factors impact the formation of consumer preferences in future studies. Moreover, in this research we use episodic versus semantic memory as the foundation on which we build our model. We do not observe the activation of each type of memory, but use different rates of memory decay to separate the two evaluation processes. A more robust way to test memory-based preference construction would be to run a lab-based experiment where fMRI is used to identify the activation of the hippocampus (a brain region responsible for episodic memory) when subjects are presented with a choice task. This would precisely identify whether past consumption experiences are recalled in any choice decision. Finally, in this model, we weigh the earlier consumption experiences less than the more recently received consumption experiences. However, this may not always be an accurate reflection of reality. A way to adjust for this would be to model a signal's salience relative to all other signals received to date. We leave these for future research to explore.

In this study, we adopt the structural econometrical modelling approach. Our model is based on three behavioural assumptions: rational agent assumption, Bayesian learning assumption and episodic versus semantic memory assumption. The first assumption pertains to the objectives of a decision-maker that consumers are utility maximiser. This assumption has been a basic premise deployed by numerous empirical economic research (Houthakker 1950; Samuelson 1964; Richter 1966; Slovic 1995; McFadden 1999; Simonson 2008). The second details the methods a decision-maker employs to utilize information that decision makers use new information to update their prior knowledge as a learning paradigm. Bayesian learner assumption has been adopted widely adopted in various learning literature including, consumer learning (Erdem and Keane 1996; Mehta et al. 2003, 2004), machine learning (Tipping 2001; Barber 2012; Theodoridis 2015), neural networks (Barber and Bishop 1998; Neal 2012) and etc. The third assumption outlines the storage of information within the memory system that there exist two distinct long term memory systems. Tulving's memory model has been adopted as a foundational framework for memory related cognitive research (Renoult and Rugg 2020). The three assumptions are extensively used in economic, learning, and cognitive research. Therefore, as long as the decision-maker (consumer) is a rational (utility maximiser) learner (information updater) with access to both memory systems, our model remains valid over time, product categories and shopping environment (online or offline). To further strengthen the generalizability and robustness of our model, we encourage additional studies to replicate our approach across various product or service categories to explore and define its boundary conditions.

7 Technical appendix I: Asymptotic property of posterior belief

Before proceeding to the estimation, it is important to understand the mechanics of how the evaluations from each of the processes differ from each other. This is important especially since the consumer receives only one set of quality cues, which are used differently in each of the adopted behavior processes. Hence, any difference in choice can be attributed to the fact that the inputs are recalled differently under each of the processes.

To see how the posterior quality belief evolves across these two processes, we study and compare the asymptotic properties of posterior belief distribution. In particular, we ask: given infinite consumptions, does the posterior belief converge to true quality under either of these processes in the presence of forgetting? If not, which mode leads to larger deviation from the true quality?

To facilitate this discussion, we set the inter-purchase time between any two consecutive purchases as W, and the forgetting error ν as a constant across all purchase occasions. In addition, we also assume equal forgetting rates ($B^S = B^E = b$) across the two memories for a fair comparison.

Proposition 1: *With the presence of forgetting, consumers can never be certain about their mean posterior quality even after infinite consumptions. However, their uncertainty does approach a certain constant level:. In addition, at each period,*

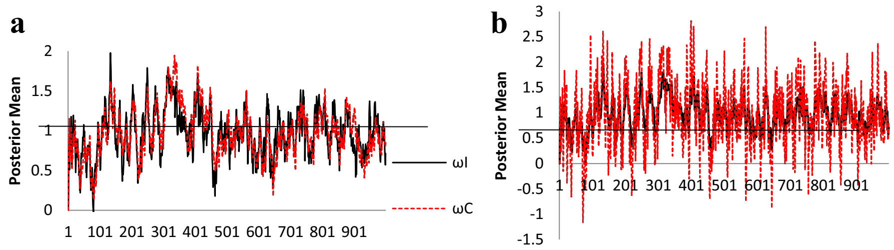

Fig. 4 **a** Evolution of posterior mean for both processes ($B^s = B^E = 0.1$). **b** Evolution of posterior mean for both processes ($B^s = 0.1; B^E = 0.5$)

$\left(\psi_N^I\right)^2 = \left(\psi_N^C\right)^2 = \frac{e^{bW}-1}{e^{bW}}\sigma_\lambda^2 \left(\psi_N^I\right)^2 = \left(\psi_N^C\right)^2$ (please refer to the Technical Appendix for proof).

It is interesting to see that even with infinite consumptions, the posterior variance never decreases to zero, but approaches a limiting value. This is because, in the case of perfect recall, every quality signal takes the same weight when updating the posterior belief. Thus, each signal has the same impact on the consumer's uncertainty about the true quality. In the presence of imperfect memory, the earlier signals have less impact in reducing uncertainty than the later signals. Therefore, with forgetting, the consumer's uncertainty is never completely resolved. This proposition contrasts Dubè et al. (2010), who argue that with sufficient learning, the posterior quality distribution should tighten up, and the consumers should eventually behave in accordance with the standard learning model, as if there is no uncertainty.

Proposition 2: *With the existence of forgetting, the posterior mean of both inherent and constructed preferences will never converge to the true quality even after infinite consumptions. The recall errors are larger for constructed preferences even when the rate of memory decay is the same across the two memory systems.*

(please refer to the Technical Appendix for proof).

Despite the same information set (i.e., the initial quality belief and the quality signals) being received, the limiting posterior belief evolves in a different fashion, as forgetting occurs differently in the two processes. In the case of an inherent preference, the forgetting error in a prior belief gets attenuated from one period to the next (see equation II in the Technical Appendix). However, in the case of constructed preference, the recall error impacts the posterior belief directly. Therefore, even though more cognitive resources are used when constructing a new evaluation, the newly constructed quality evaluation is not better than a quality evaluation that comes from inherent preferences.

However, note that the propositions above are derived from two assumptions: 1) equal tendencies to forget in different memory systems, i.e., $B^S = B^E$, and 2) equal inter-purchase time between purchases, which facilitates the discussion of the convergence property of the posterior mean and variance. We performed a simulation with 1000 purchase incidents to illustrate the evolution of posterior means for both processes, where the true mean q = 1 and the initial prior mean $q_0 = 0$. We can see that when the forgetting parameters are the same, the evolution trajectories of the posterior means are fairly similar to each other (Fig. 4a). However, when the

Table 9 Sum of squared errors between posterior mean and true mean

	Inherent Preference	Constructed Preference
$B^S = B^E = 0.1$	93.48	96.39
$B^S = 0.1$, $B^E = 0.5$	93.48	417.61

forgetting rate is larger because the consumer is recalling from episodic memory, the posterior mean is much more volatile in the case of constructed preferences than in the case of inherent preferences (Fig. 4b). We report the sum of the squared errors between the posterior mean and the true mean for both modes in Table 9. This supports Proposition 1; the deviation from true quality is larger when preferences are constructed (96.39) than when preferences are recalled (93.48). However, when the forgetting rate is larger for episodic memory, the deviation from true quality becomes much larger (417.61).

8 Appendix II: Model identification

In our model, we have the following parameters to estimate: $\{q_1, q_2, q_3, \ldots, q_J, \sigma_\lambda, B^S, B^E, \alpha, \sigma_\alpha, \beta\}$. To facilitate the discussion, we reiterate the meaning of the parameters here. $\{q_1, q_2, q_3, \ldots, q_J\}$ represents the set of mean qualities of the brands under analysis, and σ_λ describes the noise size of the consumption signals. The reader may refer to various Bayesian consumer learning papers (Erdem and Keane 1996; Mehta et al. 2004) for the identification of these brand quality parameters.

B^S and B^E are the rates of forgetting of semantic and episodic memory, respectively. We do not have identification issues for B^S and B^E since we assume that the forgetting error is an exponential function of the time lapse between the stored and recalled information. Since the time lapses associated with B^S and B^E are different (refer to Eqs. (6) and (9)), they can be separately identified.

α and σ_α are the heterogeneity parameters for the consumer's intrinsic tendency to use inherent versus constructed preferences, whereas the β's are the demographic and purchase-specific parameters that help explain the usage of inherent versus constructed preferences. Since researchers do not observe which mode of evaluation is employed by a consumer, we will focus our discussion on how the two modes of evaluation can be separately identified from our data, namely the identification of $N(\alpha, \sigma_\alpha^2)$.

As previously mentioned, if the consumer has perfect memory, the two behaviorally different processes are mathematically equivalent. It is forgetting that allows us to identify these two processes. As shown in Appendix II, the two modes of evaluation differ in terms of how forgetting errors accumulate, leading to a different brand evaluation (posterior mean) under each process, and, thus, potentially different choices. For example, if the inherent preference results in a choice of brand 1 but the constructed preference predicts a choice of brand 2, and the actual choice is brand 2, more weight will be attributed to the constructed preference (Eq. 15). Since

α stands for the population mean tendency to recall an inherent preference, then in the case above, a negative α fits the model. As such, we can look at our model as an *occasion-specific latent class model*, where at each purchase occasion the consumer falls into one of two behaviorally different segments, and either employs constructed or inherent preferences. Here, the α stands for the time-invariant factor that determines the size of each segment.

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Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

Aggleton JP, Brown MW (1999) Episodic memory, amnesia and the hippocampal-anterior thalamic axis. Behav Brain Sci 22:425–44

Allenby GM, Rossi PE (1991) Quality perceptions and asymmetric switching between brand. Market Sci 10(3):185–204

Atkinson RC, Shiffrin RM (1968) Huamn Memory: A proposed system and its control process. Psychol Learn Motiv 2:89–195

Barber D (2012) Bayesian reasoning and machine learning. Cambridge University Press

Barber D, Bishop CM (1998) Ensemble learning in Bayesian neural networks. Nato ASI Ser F Comput Syst Sci 168:215–238

Barret LF, Tugade MM, Engle RW (2004) Individual differences in working memory capacity and dual-process theories of the mind. Psychol Bull 130(4):553–573

Bayes T, Price R (1763) An essay towards solving a problem in the doctrine of chance. By the late Rev. Mr. Bayes, communicated by Mr. Price, in a letter to John Canton, A.M.F.R.S. Philos Trans R Soc Lond 53:370–418

Bettman JR, Luce MF, Payne JW (1998) Constructive consumer choice processes. J Consum Res 25(3):187–217

Braun KA (1999) Postexperience advertising effects on consumer memory. J Consum Res 25(4):319–334

Bronnenberg BJ, Dubé JP, Gentzkow M (2012) The evolution of brand preferences: Evidence from consumer packaged goods. Am Econ Rev 102(6):2472–2508

Chaiken S (1980) Heuristic versus systematic information processing and the use of source versus message cues in persuasion. J Pers Soc Psychol 39(5):752–756

Chen S, David S, Chaiken S (1996) Getting at the truth or getting along: accuracy-versus impression motivated heuristic and systematic processing. J Pers Soc Psychol 71(2):262–275

Chiang J (1991) A simultaneous approach to the whether, what and how much to buy questions. Mark Sci 10(4):297–315

Chintagunta PK (1993) Investigating purchase incidence, brand choice and purchase quantity decisions of households. Mark Sci 12(2):184–208

Craik FIM, Lockhart RS (1972) Levels of processing: a framework for memory research. J Verbal Learn Verbal Behav 11(6):671–684

Deighton J, Romer D, McQueen J (1989) Using drama to persuade. J Consum Res 16(3):335–343

Dimofte CV, Yalch RF (2010) The role of frequency of experience with a product category and temporal orientation in self-referent advertising. J Consum Psychol 20(3):343–354

Dubé JP, Hitsch G, Rossi P (2010) State dependence and alternative explanations for consumer inertia. Rand J Econ 41(3):417–445

Ebbinghaus H (1885) Memory: a contribution to experimental psychology. Dover, New York

Erdem T, Keane M (1996) Decision making under uncertainty: capturing dynamic brand choice processes in turbulent consumer goods markets. Mark Sci 15(1):1–20

Henseler J, Guerreiro M, de Matos N (2021) The interplay of marketing and design. RMS 15:1129–1137

Hoch SJ, Ha YW (1986) Consumer learning: Advertising and the ambiguity of product experience. J Consum Res 13(2):221–233
Houthakker HS (1950) Revealed preference and the utility function. Econ New Ser 17(66):159–174
Huber J, Payne J, Puto C (1982) Adding asymmetrically dominated alternatives: violations of regularity and the similarity hypothesis. J Consum Res 9(1):90–98
Johnson SK, Anderson MC (2004) The role of inhibitory control in forgetting semantic knowledge. Psychol Sci 15(7):448–453
Kivetz R, Netzer O, Schrift R (2008) The synthesis of preferences: bridging behavioral decision research and marketing science. J Consum Psychol 18:179–186
Lewis D (1973) Counterfactuals and Comparative Possibility. In: Harper WL, Stalnaker R, Pearce G (eds) IFS. The University of Western Ontario Series in Philosophy of Science, vol 15. Springer, Dordrecht. https://doi.org/10.1007/978-94-009-9117-0_3
Li H, Srinivasan K (2019) Competitive dynamics in the sharing economy: An analysis in the context of Airbnband hotels. Mark Sci 38(3):365–391
Mcfadden DL (1999) Rationality for economists. J Risk Uncertain 19(1/3):73–105
Mehta N, Rajiv S, Srinivasan K (2003) Price uncertainty and consumer search: a structural model of consideration set formation. Mark Sci 22(1):58–84
Mehta N, Rajiv S, Srinivasan K (2004) Role of forgetting in memory-based choice decisions: a structural model. Quant Mark Econ 2:107–140
Mishkin M, Suzuki WA, Gadian DG, VarghaKhadem F (1997) Hierarchical organization of cognitive memory. Philos Trans r Soc London B 352:1461–1467
Motta-Filho MA (2021) Brand experience manual: bridging the gap between brand strategy and customer experience. RMS 15:1173–1204
Neal RM (2012) Bayesian learning for neural networks, vol 118. Springer Science & Business Media
Palos-Sanchez P, Saura JR, Correia MB (2021) Do tourism application's' quality and user experience influence its acceptance by tourists. RMS 15:1205–1241
Payne JW, Bettman JR, Coupey E, Johnson EJ (1992) A Constructive process view of decision making: multiple strategies in judgment and choice. Acta Psychol 80(1–3):107–141
Renoult L, Rugg MD (2020) An historical perspective on Endel Tulving's episodic-semantic distinction. Neuropsychologia 139:107366
Richter M (1966) Revealed preference theory. Econometrica 34(3):635–645
Samuelson P (1964) Economics: An Introductory Analysis, 6th edn. MacGraw-Hill, New York
Simonson I (1989) Choice based on reasons: the case of attraction and compromise effects. J Consum Res 16(2):158–174
Simonson I (2008) Will I like a 'medium' pillow? Another look at constructed and inherent preferences. J Consum Psychol 18(3):155–169
Simonson I, Tversky A (1992) Choice in context: tradeoff contrast and extremeness aversion. J Mark Res 29(3):231–295
Slovic P (1995) The construction of preference. Am Psychol 50(5):364–371
Squire LR (1986) Mechanisms of memory. Science 232(4758):1612–1619
Squire LR (2004) Memory systems of the brain: a brief history and current perspective. Neurobiol Learn Mem 82(3):171–177
Suri R, Monroe KB (2003) The effects of time constraints on consumers' judgments of prices and products. J Consum Res 30(1):92–104
Thaler RH (1985) Mental accounting and consumer choice. Mark Sci 4(3):199–214
Theodoridis S (2015) Machine learning: a Bayesian and optimization perspective. Academic press
Tipping ME (2001) Sparse Bayesian learning and the relevance vector machine. J Mach Learn Res 1(Jun):211–244
Tulving E (1972) Episodic and semantic memory. In: Tulving E, Donaldson W (eds) Organization of memory. Academic Press, New York, pp 381–403
Tulving E (1983) Elements of episodic memory. Oxford University Press, New York
Tversky A, Kahneman D (1981) The framing of decisions and the psychology of choice. Science 211:453–458
Tversky A, Slovic P, Kahneman D (1990) The causes of preference reversal. Am Econ Rev 80(1):204–217
Wingfield A, Byrnes DL (2013) The psychology of human memory. Academic Press Inc., New York
Zhang L, Chung DJ (2020) Price bargaining and competition in online platforms: An empirical analysis of thedaily deal market. Mark Sci 39(4):687–706

Zhao Y, Yang S, Narayan V, Zhao Y (2013) Modeling consumer learning from online product reviews. Mark Sci 32(1):153–169

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