Consumer-Brand Relationship in the Age of Recommender Systems: Knowledge, Legacy and Guilt

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Abstract
Recommender systems (RS) are essential tools that support consumers in their online purchasing process by filtering products that strongly align with their needs and preferences. Moreover, they draw attention to novel items by highlighting core attributes relevant to quality evaluation. While their effectiveness in improving decision quality has been widely studied, the impact of RS on the consumer-brand relationship has received limited attention. This study adopts a qualitative approach, using Grounded Theory to analyse data from semi-structured, in-depth interviews. It investigates how recommender systems influence consumer decision-making, particularly the choice between known and lesser-known brands, by examining three key variables: breadth of knowledge, legacy, and guilt. Results suggest that consumers expand their consideration set by including unfamiliar brands, particularly for experience goods, low-involvement products and when category knowledge is limited or recommendations are perceived as repetitive and unsatisfactory. However, known brands remain particularly relevant for high-involvement products and when consumers have a strong knowledge of the category. User-based content emerges as the primary driver of choice, alongside preference matching and transparency. The effectiveness of guilt-framed recommendations is contingent upon consumers' internalisation of norms, perceived credibility and individual sensitivity. Effective recommender systems then build trust by combining personalisation with transparency, while carefully balancing familiar and novel brands. These findings help managers understand how to use recommender systems to boost brand visibility, customer trust, and long-term reputation in online markets.

Keywords: Recommender Systems, Personalisation, Transparency, Brand Preference, Trust.

Introduction

In an increasingly digitalised world, consumers risk experiencing "information overload", where having too many options can be confusing and discouraging (Jangid & Kumar, 2024) and impact decision-making, productivity, and well-being (Shahrzadi et al., 2024). In e-commerce, Recommender Systems (RS) identify relevant items aligned with consumers' interests and needs through interactions with the platform or similar users' profiles, making the selection process easier and personalised (Ghanem et al., 2022; Xiao & Benbasat, 2007; Molaie & Lee, 2022), thus mitigating information overload. Extant research demonstrates the effectiveness of RS in facilitating product choices and decision efficiency (e.g. Adomavicius et al., 2018; Senecal & Nantel, 2004); this shift may reduce reliance on brand names (Hoyer et al., 2020) as alternatives perceived to deliver greater value can stimulate switching behaviour (Van Trijp et al., 1996). RS influence product diversity (Yi et al., 2022), either by helping consumers discover niche and lesser-known products (Oestreicher-Singer & Sundararajan, 2012) or by restricting it to popular items (Yi et al., 2022). When it comes to product selection, the trust and quality assurance associated with reputable brands (Yaqub et al., 2020; Wuestefeld et al., 2012) may instead derive from other e-commerce mechanisms, such as user-generated content (Xu et al., 2023; Maslowska et al., 2017). Lastly, emotions strongly influence decision-making and can impact the perceived desirability of a product (Peng et al., 2023). Guilt emerges as a powerful motivator (Chatterjee et al., 2022), and it is frequently used to persuade through guilt appeals (Peng et al., 2023); therefore, guilt-framed recommendations may influence acceptance.

Building on this, this study explores how RS influence the brand-consumer relationship, particularly whether exposure to new or more valuable products may trigger switching from established to less known alternatives. It does so by including breadth of knowledge (expansion of consumers' consideration set), legacy (trust and credibility attached to the brand), and guilt (emotional framing of recommendations) as key factors shaping RS' influence.

This research contributes to the research streams of online search and choice behaviour in personalised contexts, applying well-established concepts to the contemporary digital shopping environment within an integrated framework, offering both theoretical enrichment and practical insights to managers seeking to maintain strong brand relevance in the RS context.

Theoretical framework

Maintaining relevance to consumers and ensuring continued use requires RS to offer diverse product options, balancing novelty with familiarity and "breadth" with "depth" (Baccelloni et al., 2025a; Celma, 2010; Matt et al., 2019). As extant research shows that RS shape the range of products consumers are exposed to (Yi et al., 2022), this study includes breadth of knowledge as a key factor, positing that RS may redirect attention to unfamiliar but highly tailored products. If so, unfamiliar items may take precedence over established ones. According to supporters of the *long-tail view*, RS facilitate the discovery of niche and unknown items (Oestreicher-Singer & Sundararajan, 2012; Yi et al., 2022) and allow for comparison until a better match is found by reducing search costs (Rothschild, 1974). Contrarily, proponents of the *rich-get-richer view* argue that RS enhance the popularity of already popular products, creating "popularity bias" (Brynjolfsson et al., 2011; Yi et al., 2022). This disagreement may be due to several, often subjective, factors influencing how RS affect the breadth of knowledge. First, accuracy alone is insufficient (McNee et al., 2006): repeated exposure to the same or similar items may diminish engagement (Burke et al., 2023)

and create boredom with already purchased or disliked items (McNee et al., 2006). Eventually, this can prompt consumers to seek novelty (Kapoor et al., 2015). Product type is also important: while search goods are easier to evaluate due to their objective, measurable features (Xiao & Benbasat, 2007; Yi et al., 2022), consumers search more thoroughly for experience goods because of their subjective attributes (Xiao & Benbasat, 2007), even if they trust algorithms less for this type of goods (Mazzù et al., 2024). Purchase involvement also plays a role (Park & Milla, 1985): for high-involvement products, consumers tend to remain loyal to familiar brands to minimise the risk of making a wrong choice (Mitchell, 1991), thereby narrowing their consideration set (Konstantoulaki et al., 2020). By contrast, low-involvement products may trigger variety-seeking behaviour (Van Trijp et al., 1996), although this tendency is moderated by the type of perceived risk (e.g. psychological, financial) (Xiao & Benbasat, 2007). Finally, consumers' expertise affects decision-making. While expert consumers more readily select products that are in line with their needs (Clarkson et al., 2013) and are less likely to rely on RS' preference-matching methods (Xiao & Benbasat, 2007), novice consumers with low category knowledge typically compare multiple options to find distinguishing features (Wang & Jin, 2022).

Familiarity and credibility are central to purchasing decisions: brand awareness serves as a decision-making shortcut (Macdonald & Sharp, 1996), and reputable brands are generally more trusted (Erdem & Swait, 2004). Known brands with a strong reputation are often associated with trustworthiness, credibility and reliability (Yaqub et al., 2020) and ensure constant quality (Wuestefeld et al., 2012). However, other signals, like e-Wom, can play a role in building confidence and quality assurance in e-commerce (Xu et al., 2023). This study examines conditions under which those signals may outweigh familiarity, making an unfamiliar option appear more valuable. The effectiveness of RS largely depends, in fact, on their ability to meet consumer needs (i.e. recommendation precision) (Gretzel et al., 2006), with personalisation enhancing engagement (Adomavicius et al., 2018) and acceptance (Senecal & Nantel, 2004).

Finally, emotions also shape product desirability (Peng et al., 2023), with guilt being a particularly strong motivator (Chatterjee et al., 2022). Guilt arises when actions or inaction conflict with personal, moral or social standards (O'Keefe, 2000) and often elicits reparative behaviour (Antonetti & Baines, 2014). For this reason, it is a common persuasive tool in marketing through guilt appeals (Peng et al., 2023). Therefore, this study explores whether guilt-evoking recommendations for unfamiliar products can be more persuasive than familiar options.

Building on this, the study examines how RS, by influencing breadth of knowledge, legacy and by leveraging guilt, affect consumers' choice between familiar and unfamiliar brands. The central question follows:

RQ1: "How do recommender systems influence consumers' product selection between unfamiliar and familiar brands through breadth of knowledge, legacy and guilt?
RQ2: What other factors shape decision-making when evaluating recommended products?"

Methodology

We employed a qualitative research design, particularly suited to capture openness and explore individuals' experiences and perceptions (Lim, 2025; Agius, 2013). Data were collected from 15 participants (46% females, 54% males; M=24.5, Var=1.84, SD=1.36) and sampling was continued until saturation was reached (Glaser & Strauss, 1967). Purposive sampling was used to ensure the relevance of insights (Stratton, 2024), as this demographic is familiar with online shopping and frequently exposed to digital environments. Before

interviews, participants confirmed their understanding of e-commerce recommendation dynamics.

Semi-structured, in-depth interviews with open-ended questions allowed flexibility to adapt or add questions as needed. The interview guide reflected the main themes identified in the literature review; for guilt, visual stimuli were employed. Anticipatory guilt was examined by providing complementary information after the first selection to evaluate changes in choices. Reactive guilt was tested by using both high and low-intensity appeals.

Data were analysed using Grounded Theory, appropriate when existing literature does not fully explain the phenomenon (Lim, 2025). The process followed three main steps: data collection, coding and comparison (Glaser & Strauss, 1967). Subcategories were used to collect open codes sharing synergies, subsequently grouped in two layers of axial codes and finally into selective codes (*Table 1; Table 2*). *Figure 1* depicts the final coding structure.
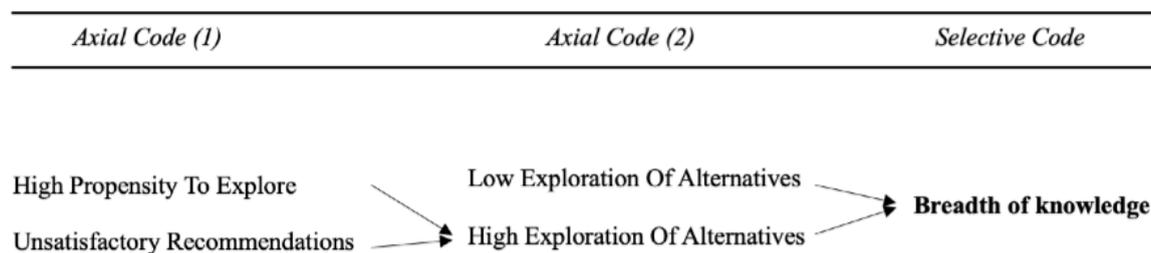
A flexible approach, collecting extra data when needed, peer debriefing with mentors and member checking ensured validity.
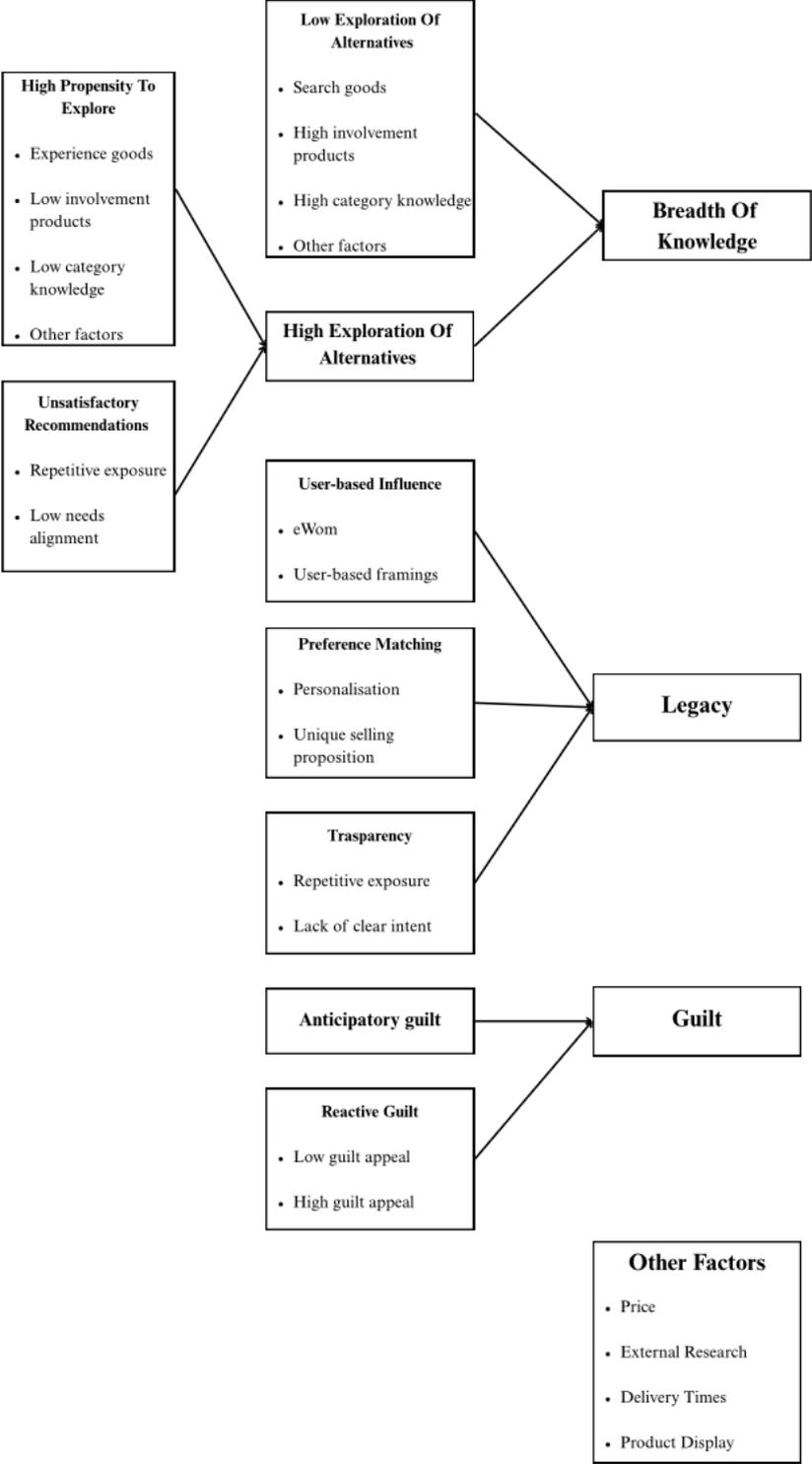
Draft of the coding structure

Table 1

Open codes	Subcategory	Axial code (2)	Selective code
Reviews ➔ selection method (10) Reviews ➔ choice validation (8) Reviews ➔ product quality (9) Reviews ➔ more important than brand (10) Reviews ➔ less important than brand (2) Reviews > brand ➔ contextual= prior knowledge (3) Reviews ➔ more important than personalisation (8) Reviews ➔ less important than personalisation (5) Reviews > personalisation ➔ contextual= functional goods only (2)	eWom	User-based influence	**Legacy**

Table 2

Axial Code (1)	Axial Code (2)	Selective Code

High Propensity To Explore → Low Exploration Of Alternatives

Unsatisfactory Recommendations → High Exploration Of Alternatives → **Breadth of knowledge**

Figure 1 – Visual representation of the coding structure

Results

All participants acknowledged that RS increase their awareness of alternative brands and products. The selective code *Breadth of knowledge* comprises: High Exploration of Alternatives and Low Exploration of Alternatives.

High exploration was primarily observed for experience goods, described as difficult to assess and more subjective. Exploration was also common for low-involvement products, with reviews, price or product features used to evaluate unfamiliar brands. Low category knowledge boosted exploration, as consumers cited a lack of information and difficulty identifying the best option. Curiosity, the attractiveness of recommended items, and purchase uncertainty were additional motivators. Half of the sample argued that personalisation doesn't prevent exploration. When suggestions were unsatisfactory, consumers searched beyond them. Respondents consistently ignored repetitive exposure to the same or similar items, while poor alignment with needs was often mentioned as driving them away from recommendations.

Conversely, most consumers reported prioritising less time-consuming searches for search goods, and some relied on popularity labels. For high-involvement products, consumers tended to consider fewer options, often sticking to familiar brands that they associated with quality and lower risk. Risk was most often tied to high costs, but also to purchases seen as important (e.g., technology, health, skin care). In all cases, high category knowledge limited exploration to well-known brands. Other factors discouraging exploration included prior positive brand experiences, certainty about the purchase, and personalisation

The selective code *Legacy* includes the axial codes *User-based Influence*, *Preference Matching* and *Transparency*. E-Wom, specifically reviews, was a recurring theme: consumers used them to select the best product, validate choices or assess quality and functionality. Ten participants favoured an unfamiliar brand with stronger reviews over a well-known brand. For half the sample, reviews outweighed preference-matching, while a minority noted that this applied more to functional than aesthetic items. User-based framings were also mentioned as decision cues.

While low personalisation or poor need alignment prompted exploration, one third valued preference-matching above brand and reviews. The uniqueness of offers matters too, and price was a decisive factor if products are not easily distinguishable.

Regarding transparency, all participants reported avoiding repeatedly recommended items, with some switching retailers in such cases. While half the participants found repetitive exposure frustrating, two-thirds stated it doesn't affect their brand perception. Nonetheless, most expressed frustration when recommendations lacked a clear rationale.

The selective code *Guilt* includes Reactive Guilt and Anticipatory Guilt. For anticipatory guilt, norm internalisation is key: sustainability claims were mostly effective on sustainability-attentive consumers. As additional information was shared, many participants reconsidered their initial choice. For reactive guilt, credibility was necessary to evoke guilt: only participants perceiving the stimuli as credible felt motivated, whereas the others based their choice on different factors, with some noting that the appeal may still work for others. The intensity also mattered, as the high guilt appeal was often viewed as frustrating or manipulative, even when credible, while the low guilt appeal was generally accepted.

Lastly, additional decision drivers emerged as price, delivery times, and product display.

Discussions

This study investigated how RS affect consumers' preference between familiar and unfamiliar brands through three key variables, namely breadth of knowledge, legacy and guilt, as well as potential additional factors. Results confirm that RS expand consumers' consideration set (Oestreicher-Singer & Sundararajan, 2012; Yi et al., 2022). More alternatives are explored for experience than search goods, as such choices are based on tastes and time-consuming (Xiao & Benbasat, 2007). Although findings in the literature are mixed, low-involvement products generally encourage exploration of unfamiliar brands (Van Trijp et al., 1996), while high-involvement purchases reinforce reliance on familiar brands to minimise risk (Mitchell, 1991). Low category knowledge encourages discovery (Wang & Jin, 2022) while high category knowledge narrows choices to familiar products (Clarkson et al., 2013).

Repeated and unsatisfactory recommendations foster disengagement (Baccelloni et al., 2025), independent search (Kapoor et al., 2015) and resistance (Zhao et al., 2025).

Product uncertainty and attractive recommendations encourage exploration, while product certainty, prior good experiences, and brand specialisation reduce it, suggesting the importance of quality experiences to remain competitive.

Exposure to alternatives may not always pose a threat to well-known brands. Still, other drivers, eWom in particular, are crucial: reviews often outweigh preference-matching, and highly rated unfamiliar products are preferred over familiar ones (Gai et al., 2019). Moreover, reviews are frequently used to assess the product quality (Xu et al., 2023) and to select the best option.

While being valued, personalisation can reduce search (Fong, 2016; Chandra et al., 2022) but doesn't necessarily prevent exploration and is not preferred over a well-established brand (though many exceptions emerged).

A unique selling proposition is important to avoid the substitution effect (Van Trijp et al., 1996) while minimal differences foster substitutability, comparison and reconsideration (Yan et al., 2016; Zhang et al., 2025).

While repetitive exposure is not always frustrating or manipulative (Zhao et al., 2025) and generally doesn't damage the brand (Cotte et al., 2005), many participants considered the absence of a clear rationale irritating (Burke et al., 2023; McNee et al., 2006).

Finally, guilt-framed recommendations influenced participants' decisions by promoting ethical consumption (e.g. eco-guilt) (Chatterjee et al., 2022; Unger-Plasek et al., 2024) and by offering a way to cope with past behaviours in unrelated contexts, such as purchases in self-improvement categories (Allard et al., 2015; Antonetti & Maklan, 2014).

Credibility and norm internalisation are necessary, though not sufficient, to evoke guilt (Cotte et al., 2005; Hibbert et al., 2007; Antonetti & Maklan, 2014). However, sharing additional information influenced decisions, suggesting that certain messages can outweigh brand relevance (Antonetti & Maklan, 2014; Osterhus,1997) and affect choices. Nonetheless, the effectiveness of guilt-based framings remains subjective (Mazzù et al., 2023), signalling the importance of precise targeting. While effective on some, guilt appeals provoked annoyance, manipulation, or resistance in others (Lwin et al., 2008; Hibbert et al., 2007; O'Keefe, 2000), especially for high-intensity appeals (Coulter & Pinto, 1995).

Limitations, future research and contribution

The study's main limitation is its generalizability, as participants shared a similar cultural background (all lived in Italy) and the sample was not random; hence, findings may not be applicable in other contexts where cultural norms may shape purchasing behaviour differently. Age (23-30) is another limitation, as younger consumers tend to be more technologically confident and may interact with RS differently from less digitally experienced groups. Moreover, economic background was not considered, focusing on behavioural responses rather than purchasing power.

Qualitative research often involves small groups, which limits representativeness (Lim, 2025), while researchers' subjectivity may cause biases in data interpretation. Future research could overcome such limitations, explore emerged factors and investigate the interaction between variables.

This research has contributed to the current literature by offering a multidimensional understanding of how RS influence online purchasing dynamics and addressing some of the main situational and behavioural drivers of decision-making in such a context. Moreover, it offers a unified framework of well-studied concepts in marketing and applies them to digital shopping environments, also favouring the rise of weak-ties marketing (Baccelloni et al, 2025b).

The study presents key insights to managers willing to build or maintain brand relevance and reputation in the RS context. First, providing diverse recommendations and distinguishable items prevents the substitution effect. Right targeting reduces disengagement with the product and the platform by limiting repetitive and misaligned recommendations and recognising that novice vs expert consumers may benefit from broader or accurate recommendations, while terms like "recommended" act as expertise cues for novice consumers (Packard & Berger, 2016). Evaluating consumers' subjectivity is important when using guilt appeals to prevent backfiring. Finally, delivering high-quality products and involving consumers also through storytelling (Giorgino & Mazzù, 2024) supports relevance through positive reviews and a strong online presence.

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