The Variant Similarity Sweet Spot: How Word-of-Mouth Moderates New Product Launch in E-Commerce

ABSTRACT

Effective management of product variants is critical for success in e-commerce, where categories commonly feature numerous options in colors, styles, and other attributes. While the strategic introduction of new variants is a key managerial lever, there remains a limited theoretical understanding of its effectiveness in online retailing. This study addresses this gap by examining how retailers should introduce new product variants, focusing on the impact of variant similarity on sales performance and the moderating role of word-of-mouth (WoM). Analyzing data from an online retailer on a leading e-commerce platform, we find that the similarity between new and existing variants exhibits an inverted U-shaped relationship with the sales of both the new and existing variants. Furthermore, WoM moderates these relationships by intensifying the curvilinear effects. These findings offer actionable insights for online retailers' variant introduction strategies and contribute to the literature on e-commerce category management, new product launch, and WoM.

Keywords:

Variant Similarity; Word-of-mouth; Product Variant; New Product Launch; Product Category Management.

INTRODUCTION

In e-commerce platforms, retailers typically enrich their product category by offering multiple variants with differences in color, style, and other attributes to satisfy diverse consumer preferences (Sethuraman et al., 2022). Effectively managing these product variants, particularly the strategy of introducing new variants, is crucial for online retailers' success (Ren et al., 2011; Gopalakrishnan et al., 2023). To illustrate this concept, Figure 1 presents a fashion category with three existing variants and a new one, while Figure 2 depicts a similar expansion for mugs. Faced with rapidly changing market demands and increasingly intense competitive environments, retailers must continuously update and optimize their product (Bertsimas and Mišic, 2015). However, when introducing new variants, retailers face a key challenge: how to determine the optimal variant similarity level between new and existing variants, or in other words, the degree of differentiation. Excessive variant similarity may lead to intensified internal competition and cannibalization of existing variant sales (Aurier and Mejía, 2020), while insufficient variant similarity might deviate from target customer preferences and affect brand recognition consistency (Ton and Raman, 2010).

Existing research has extensively examined product category management, primarily focusing on how category size affects retail performance. Some studies suggest that expanding category size can improve performance by providing more choices and increasing consumer satisfaction (Briesch et al., 2009; Ma, 2016). However, other research indicates that excessive category size may lead to information overload, causing consumer confusion and reducing retail performance (Beneke et al., 2013; Boatwright and Nunes, 2001). These contradictory findings suggest that the impact of

Figure 1
Example of a Fashion Product Category with Existing Variants and Introduction of a New Variant

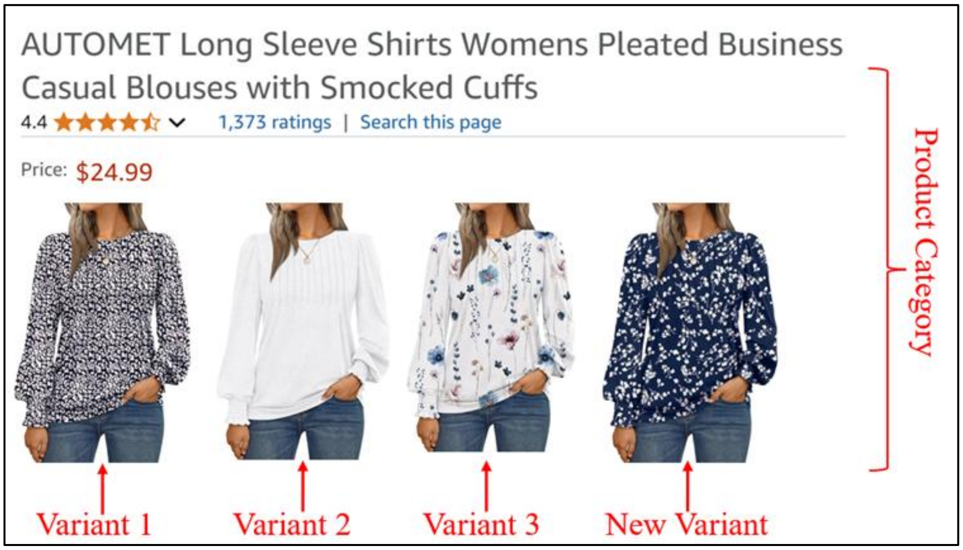


Figure 2
Example of a Mug Product Category with Existing Variants and Introduction of a New Variant

category size on retail performance may be moderated by other factors, such as channel characteristics (Ma, 2016), product type (Argouslidis et al., 2018), and consumer characteristics (G ázquez-Abad et al., 2021). These studies mainly focus on the static relationship between category size and retail performance, overlooking the dynamic aspects of category management, particularly how retailers should introduce new product variants into existing categories.

Variant similarity refers to the degree of resemblance between new variants and existing variants within the product category in terms of features, design, and appearance (Park et al., 1991; Holcombe 2009; Li and Xie, 2013) that plays a crucial role in introducing new variants. Existing research on new product launches suggests that launch success largely depends on product innovativeness (Cooper, 2019; Matikainen et al., 2015). However, compared to conventional new product launches, introducing product variants within a category faces different challenges—retailers need to balance maintaining relevance to existing products while achieving differentiated innovation (McNally et al., 2010; Ton and Raman, 2010). Viewed through the lens of Optimal Distinctiveness Theory (ODT), retailers must navigate a strategic trade-off: they need to maintain sufficient similarity to ensure legitimacy and trigger the "familiarity effect," while simultaneously achieving enough distinctiveness to minimize internal competition (Brewer, 1991; Deephouse, 1999). Yet, how this "legitimate distinctiveness" (Navis and Glynn, 2011) affects new variants' market performance lacks systematic investigation. Notably, the introduction of new variants not only affects their own sales but may also impact existing variants' sales through mechanisms such as attention spillover or demand cannibalization (Bayus et al., 2003). Therefore, understanding how variant similarity between new and existing variants affects sales performance of both is significant for retailers' product category management. This forms our first research question:

Research Question 1: How does variant similarity affect the sales of new and existing variants *in e-commerce platforms?*

Beyond variant similarity, category-level characteristics may also influence the success of new variant introductions. Previous research has found that environmental factors (such as market competition intensity and demand uncertainty) significantly moderate the effects of new product launches (Cui et al., 2011; Tang and Zhu, 2020). In the unique context of e-commerce platforms, the WoM information system constitutes a key environmental characteristic (Donthu et al., 2021). Unlike traditional retail channels, e-commerce platforms provide consumers with rich WoM information, including ratings, review volume, and review content, which can reduce purchase uncertainty and influence product choice (Chevalier and Mayzlin, 2006; Al-Adwan et al., 2022). While existing research has extensively examined the impact of WoM on product sales in e-commerce platforms, how it moderates the relationship between variant similarity and new variant launch success remains unclear. To fill this research gap, we propose our second research question:

Research Question 2: How does WoM of product category moderate the effect of variant similarity on the sales of new and existing variants?

To address these research questions, we conducted an empirical analysis using a unique dataset from a fashion retailer on a leading U.S. e-commerce platform, comprising 258 new variant introductions over a two-year period. By employing deep learning-based computer vision techniques to quantify visual similarity, we uncover compelling evidence of inverted U-shaped relationships between new-existing variant similarity and the sales performance of both the new and existing variants. Furthermore, our results demonstrate that category-level Word-of-Mouth (WoM) acts as a critical moderator, intensifying these curvilinear effects.

This study makes distinct theoretical and practical contributions. Theoretically, we advance the literature in four ways. First, we contribute to product category management research by shifting the focus from static category size effects to the dynamic optimization of variant similarity, offering a new perspective on how to successfully expand categories without triggering choice overload. Second, we enrich the new product launch literature by distinguishing variant introduction from conventional new product launches, highlighting the unique challenge of balancing differentiation with brand consistency in existing categories. Third, drawing on Optimal Distinctiveness Theory (ODT), we provide a theoretical framework that explicates the dual mechanisms — balancing the familiarity effect and attention spillover against the internal competition effect—that drive the inverted U-shaped sales outcomes. Fourth, we extend the e-commerce literature by identifying WoM as a contextual boundary condition that amplifies consumer responses to similarity signals. Practically, we provide online retailers with actionable guidelines for managing product categories, offering specific insights into the "similarity sweet spot" and how to tailor launch strategies based on the category's reputation.

In the following sections, we provide a comprehensive literature review and identify research gaps in Section 2. Section 3 presents four hypotheses, followed by a detailed methodology discussion. Section 5 presents the analytical results. Finally, we discuss implications and limitations.

LITERATURE REVIEW

Product Category Management

A product category refers to a collection of products that satisfy similar consumer needs or serve similar usage scenarios (Sethuraman et al., 2022). In product category management, category size is a core concept, defined as the total number of different options available to consumers within a specific product category, which can manifest as different brands, stock keeping units (SKUs), or product features such as different colors or packaging formats (Ma, 2016). Changes in category size can influence consumer behavior. From a positive perspective, expanding category size can enhance consumer choice satisfaction, decision confidence, and freedom, thereby increasing purchase intention, sales, and profits (Gao and Simonson, 2016). However, excessive category size may also produce negative effects, such as information overload, increased cognitive burden, and heightened choice uncertainty, ultimately leading to choice avoidance behavior among consumers (Kahn et al., 2013). This dual effect makes the impact of category size on retail performance uncertain.

Existing research has extensively examined the relationship between category size and retail performance. Many studies have found that larger category size leads to better retail performance. For instance, Briesch et al. (2009) found that the number of brands offered by retailers shows a significant positive correlation with consumer store choice. Ma's (2016) research indicates that online retailers can significantly increase their revenue by offering larger product assortments. However, other studies have reached different conclusions. Beneke et al. (2013) found that retail managers can reduce category size by eliminating low-selling items without affecting retail performance and may even improve consumer satisfaction. Similarly, Boatwright and Nunes (2001), through studying an online grocery store, discovered that sales increased rather than decreased after reducing the number of SKUs in the category.

These seemingly contradictory research findings suggest that the impact of category size on retail performance may be moderated by other variables. Specifically, existing research has identified several important moderating variables: First, channel characteristics play a crucial moderating role, with Ma (2016) finding that online channels can better accommodate large category sizes compared to offline channels. Second, product type is an important moderating variable, with Argouslidis et al. (2018) discovering that hedonic product categories are more suitable for category size expansion than utilitarian ones. Additionally, consumer characteristics play a significant moderating role, with factors such as education level (Gázquez-Abad et al., 2021), psychological distance (Goodman and Malkoc, 2012), and thinking style (Benoit and Miller, 2017) all affecting consumer responses to category size.

While existing research has provided rich theoretical guidance for category size optimization decisions, two key gaps remain in the literature. First, previous research has primarily focused on product category depth (i.e., assortment size) as a quantitative and static determinant of retail performance (Briesch et al., 2009; Ma, 2016). However, focusing solely on depth—the number of variants—overlooks the relational nature of category expansion. Two categories with the same depth can have vastly different internal structures depending on how similar the variants are to one another. Therefore, a mere count of SKUs fails to capture the strategic nuances of how retailers should introduce new variants relative to existing ones. Second, although variant introduction is prevalent in e-commerce platforms, our understanding of how such introductions affect the sales performance of both new and existing variants remains limited. Unlike the static measure of category depth, variant introduction is a distinct event that triggers consumer comparison processes. Given the increasingly dynamic e-commerce environment, these research gaps are particularly significant as effective variant introduction strategies are crucial for retailers' competitive advantage. Addressing these gaps will provide valuable insights for retailers to develop more effective category management strategies that go beyond simply managing the number of offerings.

New Product Launch

Research on the success factors of new product launches primarily revolves around three dimensions: product characteristics, external environment, and launch strategies (Cooper, 2019; Salmen, 2021). Existing research has largely focused on the market introduction of entirely new products (Fraenkel et al., 2016), while relatively limited attention has been paid to the introduction of new variants within existing product categories. Given the prevalence and importance of variant management in e-commerce practice (Ma, 2016), understanding the success mechanisms of variant introduction carries significant implications.

At the product level, innovativeness and advantage are viewed as key success elements (Cooper, 2019; Matikainen et al., 2015). Product advantages can be manifested in functionality (McNally et al., 2010), user value (Kurt, 2010), and price-performance ratio (Li et al., 2019). However, the relationship between innovativeness and market success is complex: moderate innovation can bring competitive advantages (McNally et al., 2010), but excessive innovation may increase consumers' cognitive burden (Alexander et al., 2008; Aurier and Mejía 2020). Compared to conventional new product launches, introducing variants within a product category faces distinct challenges - how to achieve effective differentiation while maintaining brand consistency, an issue that has not received sufficient attention in existing research.

Environmental factors play important moderating roles between product characteristics and launch performance. Extant research has primarily focused on factors such as market competition intensity (Su and Rao, 2011), demand uncertainty (Hitsch, 2006; Negahban and Smith, 2016), and consumer heterogeneity (Tang and Zhu, 2020). However, the e-commerce platform environment possesses unique characteristics: user reviews and electronic WoM influence purchase decisions through immediate feedback (Hu et al., 2014; Verma and Yadav, 2021), while dynamic pricing (Lei et al., 2018) and other features have altered traditional competition rules. How these platform characteristics, particularly WoM, influence new product launch success, especially in the context of product variant introduction, requires further investigation.

Launch strategies have direct impacts on new product launch success, encompassing three core dimensions: launch timing, pricing strategy, and marketing strategy (Di, 1999; Cooper, 2019). Launch timing strategy focuses on market entry sequence (Lieberman and Montgomery, 2013), seasonality factors (Luan and Sudhir, 2009), and competitive conditions (Su and Rao, 2011). Appropriate timing selection can reduce market uncertainty and capture market opportunities (Su and Rao, 2011). Regarding pricing strategy, retailers need to balance between skimming and penetration pricing (Liu et al., 2019), while dynamic pricing mechanisms in e-commerce environments further increase strategy complexity (Bauer and Jannach, 2018). Marketing strategy includes not only traditional promotional and channel decisions (Ernst et al., 2010) but also needs to consider e-commerce platform-specific marketing tools, such as search engine optimization (SEO) (Gruner et al., 2019), content marketing (Winata et al., 2021), live streaming commerce (Chen et al., 2023), and algorithmic recommendation mechanisms (Li and Karahanna, 2015).

Despite valuable insights from existing research, three key gaps remain in new product launch research within the e-commerce environment. First, existing research has primarily focused on completely innovative new products, while lacking in-depth investigation of new variant introductions within existing product categories - variants need to achieve differentiated positioning while maintaining brand recognition. Second, variant similarity between new and existing products, as a core characteristic, has not been systematically examined in terms of its impact mechanism on launch success. Third, e-commerce platform-specific characteristics, such as the review and rating system, may moderate the effects of variant similarity, but this moderating effect has not been thoroughly studied.

By focusing on product variant introduction in e-commerce platforms, particularly examining the mechanism of variant similarity between new and existing variants, and the moderating effects of platform characteristics (such as WoM), this research extends the theoretical boundaries of new product launch research. This study not only fills the gap in product category management research but also provides theoretical guidance for new product launch practices in e-commerce environments.

Optimal Distinctiveness and New Variant Launch

Optimal Distinctiveness Theory (ODT), initially proposed by social psychologist Brewer (1991) to explain the psychological motivation of individuals to simultaneously seek a sense of belonging and uniqueness within social groups, was later introduced into the field of strategic management by scholars such as Deephouse (1999). They argued that firms face a similar strategic trade-off between legitimacy and competitive differentiation. According to the central tenet of ODT, for any organization to excel in a complex competitive landscape, it must strike a delicate balance between two opposing forces. On one hand is the pursuit of legitimacy, which involves gaining stakeholder approval by conforming to established norms and market expectations (Suchman, 1995). On the other hand is the pursuit of distinctiveness, which involves building competitive barriers through differentiation to avoid homogenous competition (Porter, 1980). The core insight of ODT is that peak organizational performance is achieved not at the extremes of complete conformity or radical differentiation, but at an "optimal point" that satisfies both needs. This typically manifests as a classic inverted U-shaped relationship between distinctiveness and performance (Deephouse, 1999; Zhao et al., 2017).

In strategic management and organization theory research, the logic of ODT has been widely applied to explain core issues such as product innovation, market categorization, and consumer evaluation. Scholars have found that a product's market performance heavily depends on how external audiences (e.g., consumers, critics) perceive and categorize it. A key finding is that when products are ambiguous and difficult to classify, they often suffer an "illegitimacy discount," meaning they are overlooked or undervalued by the market (Zuckerman, 1999). Therefore, a product must adhere to existing categorical "codes" or prototypes to some extent to ensure it is comprehensible and acceptable. For instance, a study of French haute cuisine demonstrated that the success of restaurants attempting to introduce new elements depended on whether key stakeholders perceived these innovations as "retaining the code" rather than "violating the code" (Durand et al., 2007). This indicates that even in innovation-driven fields, established boundaries of legitimacy must be respected. Consequently, scholars have proposed the concept of "legitimate distinctiveness," emphasizing that successful innovation involves differentiation that is grounded in maintaining category identity (Navis and Glynn, 2011). These studies collectively reveal that successful product positioning is not about maximizing innovation, but about a deliberate trade-off between category fit and novelty.

Applying the ODT framework to the domain of new product launches provides a profound theoretical basis for understanding the complex relationship between product innovation and market acceptance. While traditional product innovation literature often posits "innovativeness" as a key driver of product success (Cooper, 2019), the ODT perspective reveals the "double-edged sword" effect of innovativeness. Whereas moderate innovation can confer a significant competitive advantage upon a new product (McNally et al., 2010), excessive innovation (i.e., overly high distinctiveness) can lead to evaluation difficulties by deviating from consumers' established cognitive frameworks for a category, potentially resulting in market rejection (Alexander et al., 2008). Thus, the success of a new product largely depends on its ability to achieve a precise strategic calibration between the distinctiveness afforded by innovation and the similarity required for category belonging. This theoretical tension maps directly onto our study's central construct of "variant similarity."

The theoretical tension of ODT becomes particularly salient in the context of introducing a product variant. Unlike disruptive innovations, a product variant is an incremental innovation within an existing brand and category-cognition system, and its positioning strategy directly affects the health of the entire product line. In this context, ODT's pursuits of legitimacy and distinctiveness can be deconstructed into micro-level mechanisms that influence consumer behavior and category dynamics. On one hand, the pursuit of legitimacy requires a new variant to maintain a degree of similarity with the category prototype. This activates consumers' cognitive fluency and facilitates the transfer of trust and goodwill from the existing brand to the new product (Aaker & Keller, 1990; Erdem, 1998)—a mechanism we term the "familiarity effect." On the other hand, the pursuit of distinctiveness demands that the new variant be differentiated from existing members to avoid the "internal competition effect" and demand cannibalization that arise from high substitutability (Moorthy & Png, 1992; Mason & Milne, 2013). Furthermore, the introduction of a new variant has systemic effects on other members of the category; for example, through an "attention spillover effect," market attention drawn by the new product can diffuse to existing products, potentially creating positive externalities (Balachander & Ghose, 2003). The interplay and trade-offs among these three effects constitute the specific manifestation of ODT in the context of product variant launches and provide a robust theoretical foundation for this study's series of hypotheses regarding the inverted U-shaped relationships between variant similarity and the sales of both new and existing variants.

HYPOTHESIS FORMULATION

The Impact of Variant Similarity on New Variant Sales

We posit an inverted U-shaped relationship between the variant similarity of a new variant to existing variants and its sales performance. This curvilinear relationship stems from the core tension of Optimal Distinctiveness Theory (ODT), which argues that for any entity (such as a product) to achieve superior performance, it must balance two conflicting pressures: the pursuit of legitimacy and the demand for distinctiveness (Deephouse, 1999; Zhao et al., 2017).

On the one hand, as similarity increases from a low level, it yields significant legitimacy benefits that produce “**familiarity effect**”. According to prototype theory, consumers form a cognitive prototype of a product category based on their experiences with existing variants (Rosch, 1975). This prototype serves as their mental benchmark for evaluation (Loken & Ward, 1990). When a new variant maintains moderate similarity to this prototype, it enhances consumers' cognitive fluency through a mechanism of prototype matching. This fluency reduces consumers' cognitive load and perceived risk, as it allows them to leverage existing knowledge structures rather than constructing entirely new cognitive frameworks (Meyers-Levy & Tybout, 1989; Gregan-Paxton & John, 1997). This cognitive ease fosters a "familiarity effect," enabling the smooth transfer of positive affect and trust associated with the existing product line to the new variant, thereby enhancing its market acceptance and purchase intention (Aaker & Keller, 1990; Erdem, 1998). In essence, similarity at this stage serves as a signal of reliability and conformity, allowing the new variant to achieve a state of legitimacy in the minds of consumers (Suchman, 1995).

On the other hand, once similarity surpasses an optimal threshold, the costs arising from a lack of distinctiveness begin to dominate, leading to **internal competition effect** and therefore a decline in sales performance. Excessive similarity results in internal competition among variants, as the new variant becomes highly substitutable for existing ones in terms of function and value (Lancaster, 1990; Moorthy & Png, 1992). When variants are perceived as near-perfect substitutes, the new product struggles to communicate a clear and unique value proposition. This not only dilutes its competitive advantage but also leaves consumers with little reason to choose the new offering over an existing one (Mason & Milne, 2013; Shocker et al., 2004). Furthermore, in the information-rich e-commerce environment, a large number of highly similar options can trigger "choice overload," increasing decision difficulty, causing consumer confusion, and potentially leading to purchase postponement or abandonment (Iyengar & Lepper, 2000; Chernev et al., 2015; Huffman & Kahn, 1998). This internal cannibalization for attention and market share ultimately undermines the new variant's sales potential.

The interplay between the positive familiarity effect derived from legitimacy and the subsequent losses from internal competition dictates the existence of an optimal level of similarity, at which the marginal benefits of legitimacy are perfectly balanced by the marginal costs of insufficient differentiation. Therefore, we predict that new variant sales will first increase and then decrease as similarity increases, following an inverted U-shaped curve.

Hypothesis 1: There exists an inverted U-shaped relationship between new-existing variant similarity and new variant sales, such that as variant similarity increases, new variant sales first increase and then decrease.

The Moderating Effect of WoM on the Relationship between Variant Similarity and New Variant Sales

We further propose that category-level Word-of-Mouth (WoM) acts as a key contextual variable that strengthens the inverted U-shaped relationship between variant similarity and new variant sales. In the e-commerce environment, WoM, embodied by online ratings and reviews, is a powerful mechanism of social proof that effectively reduces consumer uncertainty and profoundly influences purchase decisions (Chevalier & Mayzlin, 2006; Donthu et al., 2021). A strong and positive WoM enhances consumer trust and elevates the product category's status in the market (Zhao et al., 2020; Kim et al., 2016).

Within the ODT framework, we argue that positive WoM primarily exerts its moderating effect by **amplifying the familiarity effect driven by legitimacy benefits**. When a product category enjoys high WoM, the cognitive prototype formed in consumers' minds becomes more than just a neutral set of features; it becomes a market-validated "template for success" (Loken & Ward, 1990). The abundance of positive evaluations from prior consumers sends a clear signal that conforming to this prototype is desirable and low-risk. Consequently, when a new variant matches this more credible prototype, the legitimacy signal it conveys becomes exceptionally strong. The process of trust transfer from the established brand is also smoother and more potent, as the brand's reputation has received broad social endorsement (Reast, 2005; Hem et al., 2003). This reinforced "halo effect" (Nisbett & Wilson, 1977) magnifies the positive outcomes of moderate similarity, such as enhanced cognitive fluency and risk reduction.

By enhancing the credibility of the category prototype and facilitating a stronger transfer of trust, high WoM significantly boosts the positive impact of the familiarity effect. This implies that at any given level of moderate similarity, the sales uplift will be more substantial in a high-WoM context. This amplification of the upward trend in the first half of the curve renders the entire inverted U-shaped relationship more sensitive to changes in similarity, thus making the curve steeper.

Hypothesis 2: WoM strengthens the inverted U-shaped relationship between new-existing variant similarity and new variant sales, such that the inverted U-shaped relationship becomes steeper as brand WoM improves.

The Impact of Variant Similarity on Existing Variant Sales

The introduction of a new variant generates systemic effects across the entire product category, thereby influencing the market performance of existing variants. Drawing on ODT's principles of systemic balance and interdependence (Zhao et al., 2017), we predict this impact also follows an inverted U-shaped pattern, driven by a trade-off between positive spillover effects and negative competitive effects.

Initially, moderate similarity between new and existing variants triggers positive legitimacy reinforcement and **attention spillover effect**. The launch of a successful new variant is, in itself, a signal of the brand's vitality and innovative capacity, which can enhance the perceived quality and appeal of the entire product line, thus reinforcing the category's overall legitimacy (Wernerfelt, 1988; Dacin & Smith, 1994). Marketing activities and consumer buzz surrounding the new product can create an attention spillover effect, attracting new or renewed interest to the entire category (Balachander & Ghose, 2003). As consumers' attentional resources are finite (Kahneman, 1973), attention directed toward a focal object (the new variant) tends to diffuse along associative networks to related items (the existing variants). Moderate similarity ensures this association is strong, thereby increasing the market salience and cognitive accessibility of existing variants, which may ultimately translate into sales growth.

However, as similarity becomes excessive, this synergistic relationship transforms into a competitive one, and the negative **internal competition effects** become prominent. High similarity positions the new variant as a direct substitute for existing ones, leading to demand cannibalization—the new product, with its novelty advantage, captures sales that would have otherwise gone to older products (Moorthy & Png, 1992; Mason & Milne, 2013). This zero-sum game for the same customer base directly erodes the sales of existing variants (Draganska & Jain, 2005). Furthermore, the addition of a highly similar member can dilute the unique positioning of existing products in the broader market, weakening their differentiation advantage (Shocker et al., 2004). This intensified intra-category competition can also induce consumer confusion and choice difficulty, potentially suppressing sales for the category as a whole (Huffman & Kahn, 1998).

Therefore, the net effect on the sales of existing variants depends on the balance between positive spillover effects and internal competition effect. An optimal level of similarity exists where the positive synergistic effects are maximized before destructive internal competition becomes dominant.

Hypothesis 3: There exists an inverted U-shaped relationship between new-existing variant similarity and existing variant sales, such that as variant similarity increases, existing variant sales first increase and then decrease.

The Moderating Effect of WoM on the Relationship between Variant Similarity and Existing Variant Sales

Finally, we propose that category-level WoM also strengthens the inverted U-shaped relationship between variant similarity and the sales of existing variants. This moderation occurs because **high WoM amplifies the positive attention spillover mechanism** that benefits existing variants.

When a product category has a strong reputation among consumers, it creates a powerful "trust halo" (Kim et al., 2016; Reast, 2005). Under this halo, consumers attracted by a new variant are more willing and motivated to explore other products belonging to the same trusted brand. Positive WoM essentially lowers the psychological barrier for consumers to extend their interest from a new product to established ones (Balachander & Ghose, 2003). Because the entire category is perceived as a guarantor of quality and satisfaction, the associative diffusion of attention from the new variant to existing ones becomes more efficient and widespread. In other words, high WoM acts as a catalyst, enabling the attention captured by a new variant to be more effectively converted into incremental interest and sales for the entire product line (Chen & Xie, 2008).

Consequently, in a high-WoM context, the positive attention spillover triggered by moderate similarity is significantly amplified. This causes the sales of existing variants to grow more rapidly and to a greater extent during the upward-sloping portion of the inverted U-shaped curve. By magnifying the potential benefits of introducing a moderately similar variant, high WoM makes the entire curvilinear relationship more pronounced.

Hypothesis 4: WoM strengthens the inverted U-shaped relationship between new-existing variant similarity and existing variant sales, such that the inverted U-shaped relationship becomes steeper as WoM improves.

METHODOLOGY

Data and Sample

The data for this study comes from a fashion retailer that manufactures in China and sells on a leading e-commerce platform in the United States. The retailer provided us with its complete operational data from June 2022 to June 2024. All financial metrics in the dataset, including price and advertising expenditure, are recorded in US Dollars (USD). This data was shared with the retailer's full consent and contains no personally identifiable information, ensuring our research adheres to privacy and ethical standards.

The fashion retail context is an excellent fit for our research, which examines how product design similarity affects sales during new variant launches in e-commerce. This context is ideal for three key reasons: First, fashion products experience highly frequent new product launches, providing abundant empirical data for observing variant launch effects. This contrasts sharply with high-complexity or high-cost categories (such as electronics or home appliances), where new variant releases are relatively infrequent and tend to emphasize internal specifications rather than design or appearance modifications. Second, in the fashion domain, product design (such as appearance, color, and style) serves as the dominant driver of consumer choice and sales performance (Hirschman and Holbrook, 1982; Park et al., 2012). In certain categories (such as home appliances), while appearance design matters, it is typically not the primary determinant. Third, fashion consumers frequently engage in repeat purchases of similar items (for instance, purchasing the same shirt in different colors), which not only elevates the importance of inter-variant similarity but also creates a dynamic interaction uncommon in one-time purchase categories. Consequently, the fashion category constitutes an ideal setting for examining the specific impact of variant similarity on the sales performance of both new and existing products.

The dataset consists of three main components: The first component is product category structure data, which records all product variants within each product category and their launch dates. After processing, we identified that during this two-year period, the retailer had 312 product categories and 258 of them have launched new product variants. The second component is product performance data, containing real-time sales data for all products. These data record key performance indicators for each product variant, including daily average sales, cumulative sales, and conversion rates. The third component is marketing data, which details the retailer's advertising activities for various products across different periods, including advertising expenditure, impressions, and click-through rates. The combination of these data enables us to comprehensively analyze new product variant introduction strategies and their market performance.

Measures

This study includes two dependent variables. The first dependent variable is new variant sales (NewSales), defined as the cumulative sales volume (in units) of the new product variant within 15 days after its launch. The second dependent variable is the change in existing variant sales (ExistSalesChange), used to measure the impact of new variant launches on existing variant sales, calculated as the difference between the total sales (in units) of existing variants during the 15 days after and before the new variant launch. This measurement method effectively captures the sales impact of new product variant introductions on the existing product line.

The core independent variable is the variant similarity (ranging from 0 to 1) between new and existing variants (SIM). We employed a deep learning-based computer vision method to quantify the degree of variant similarity between products. Specifically, we used a pre-trained ResNet-50 model (He et al., 2016) to extract visual feature vectors from product images and calculate the cosine variant similarity between feature vectors to measure the degree of variant similarity between product pairs. Considering that different existing variants have varying market importance, we used sales volume as weights to calculate the weighted average variant similarity:

$$Weighted\ Average\ Similarity = \sum w_j \times Sim_j \,/ \sum w_j$$

where Sim_j represents the image variant similarity between the new variant and the j^{th} existing variant, and w_j is the sales volume of that existing variant during the 15 days before the new variant launch. This weighted calculation method ensures that the variant similarity metric better reflects the relationship between new variants and market-leading products. To provide a tangible understanding of what different similarity scores represent, Table 1 presents illustrative examples from our dataset, showcasing products with high, medium, and low levels of visual similarity.

Table 1.
Illustrative Examples of Variant Similarity

Similarity level	Example Images			Calculated SIM Value
Low Similarity		vs		0.21
Medium Similarity		vs		0.52
High Similarity		vs		0.89

In this study, we examine the moderating effect of product category WoM and operationalize this key construct as the category's overall rating (measured on a scale of 0 to 50). This methodological choice is grounded in a solid theoretical foundation. Through the mechanism of aggregation, an overall rating crystallizes a multitude of disparate and subjective individual evaluations into a single, stable, and easily interpretable market signal, thereby intuitively reflecting the overall WoM performance of the product (Chevalier and Mayzlin, 2006; Hendrikx et al., 2015; Das and Kumar, 2023). This signal, in turn, serves as a highly influential heuristic cue for consumers in an information-overloaded environment, significantly simplifying their decision-making process and thus being widely relied upon (Cheung and Thadani, 2012; Lee and Hosanagar, 2021). Moreover, this approach is highly consistent with a large body of classic empirical research in the field. Indeed, operationalizing WoM through ratings has become a mature and validated research paradigm in the field, with many influential studies using ratings as a core variable to measure e-commerce WOM and validating its significant effect on market outcomes (Ye et al., 2009; Chintagunta et al., 2010; Babić Rosario et al., 2016; Qiu et al., 2025).

Multiple control variables were included to enhance analytical accuracy. First, we controlled for category-level baseline characteristics. Category sales (CategorySales) was measured by the total sales (in units) of the entire product category during the 15 days before the new variant launch, reflecting the basic market performance of the product category. Second, to isolate the effect of similarity from pricing strategies, we included price variables. New variant price (NewPrice) refers to the actual selling price (in USD) of the new product variant, while existing variant price (ExistPrice) was calculated using sales-weighted averaging, specifically using the sales volumes of existing variants during the 15 days before the new launch as weights to calculate their weighted average price. Third, we accounted for marketing investments. New variant advertising spend (NewAdSpend) measures the total ad expenditure (in USD) for the new variant in the 15-day postlaunch window, and existing variant advertising spend (ExistAdSpend) captures the aggregate ad expenditure for existing variants during the same period. Controlling for these promotional efforts is crucial for disentangling the impact of similarity from that of marketing-driven sales boosts.

Considering the structural characteristics of product categories, we included the number of existing variants (VarCount) as a control variable, specifically using the total number of variants in the product category before the new launch to measure category scale characteristics.

Descriptive statistics for the main variables are shown in Table 1, while Table 2 displays the coefficient correlation matrix between these variables. Overall, the correlation analysis results indicate no multicollinearity issues among the variables.

Table 1
Descriptive Statistics

	Mean	**SD**	**Min**	**Max**
Dependent Variables				
NewSales	5.236	2.286	0.000	11.000
ExistSalesChange	25.880	9.499	0.000	63.000
Independent Variables				
SIM	0.566	0.178	0.037	0.754
WoM	41.461	2.927	36.000	50.000
Control Variables				
CategorySales	350.295	742.318	0.000	3223.000
NewPrice	52.705	31.484	19.990	159.990
ExistPrice	50.913	22.625	31.994	178.327
NewAdSpend	41.851	121.500	0.000	650.390
ExistAdSpend	587.503	311.104	30.750	1927.725
VarCount	6.988	4.656	1.000	21.000

Abbreviations: NewSales, new variant sales; ExistSalesChange, change in total existing variant sales; SIM, weighted average variant similarity between new and existing variants; WoM, product category word-of-mouth rating; CategorySales, total category sales before launch; NewPrice, new variant price; ExistPrice, existing variants' weighted average price; NewAdSpend, new variant advertising spending; ExistAdSpend, existing variants' advertising spending; VarCount, number of existing variants.

Table 2
Correlation Matrix

	1	2	3	4	5	6	7	8	9	10
1.NewSales	1.000	-	-	-	-	-	-	-	-	-
2.ExistSalesChange	0.477	1.000	-	-	-	-	-	-	-	-
3.SIM	0.260	0.222	1.000	-	-	-	-	-	-	-
4.WoM	0.465	0.197	0.382	1.000	-	-	-	-	-	-
5.CategorySales	0.323	0.506	0.190	0.023	1.000	-	-	-	-	-
6.NewPrice	-0.212	-0.124	0.394	0.123	-0.360	1.000	-	-	-	-
7.ExistPrice	-0.039	0.001	0.317	0.340	-0.244	0.546	1.000	-	-	-
8.NewAdSpend	0.370	-0.359	0.072	0.156	0.134	-0.185	-0.117	1.000	-	-
9.ExistAdSpend	0.307	0.269	0.175	-0.027	0.523	-0.226	-0.130	0.322	1.000	-
10.VarCount	0.087	0.456	0.235	0.110	0.519	0.070	0.111	-0.240	0.248	1.000

Abbreviations: NewSales, new variant sales; ExistSalesChange, change in total existing variant sales; SIM, weighted average variant similarity between new and existing variants; WoM, product category word-of-mouth rating; CategorySales, total category sales before launch; NewPrice, new variant price; ExistPrice, existing variants' weighted average price; NewAdSpend, new variant advertising spending; ExistAdSpend, existing variants' advertising spending; VarCount, number of existing variants.

Model specification

To test our hypotheses, we employed multiple regression models with time fixed effects. Although our data is cross-sectional in nature, the new variant introductions occurred at different time points, necessitating the control of potential temporal effects.

To examine the impact of variant similarity on new variant sales and existing variant sales, as well as the moderating effect of WoM, we specified the following regression models:

$$
\begin{aligned}
NewSales_t = {} & \beta_0 + \beta_1 SIM_t + \beta_2 SIM_t^2 + \beta_3 WoM_t + \beta_4 SIM_t \times WoM_t + \beta_5 SIM_t^2 \times WoM_t \\
& + \beta_6 CategorySales_t + \beta_7 NewPrice_t + \beta_8 ExistPrice_t + \beta_9 NewAdSpend_t \\
& + \beta_{10} ExistAdSpend_t + \beta_{11} VarCount_t + Month_t E + \varepsilon_t \qquad (1)
\end{aligned}
$$

$$
\begin{aligned}
& ExistSalesChange_t \\
& = \beta_0 + \beta_1 SIM_t + \beta_2 SIM_t^2 + \beta_3 WoM_t + \beta_4 SIM_t \times WoM_t + \beta_5 SIM_t^2 \times WoM_t \\
& + \beta_6 CategorySales_t + \beta_7 NewPrice_t + \beta_8 ExistPrice_t + \beta_9 NewAdSpend_t \\
& + \beta_{10} ExistAdSpendCh_t + \beta_{11} VarCount_t + Month_t E + \varepsilon_t \qquad (2)
\end{aligned}
$$

where $NewSales_i$ represents the sales volume of the new variant in observation i, and

$ExistSalesChange_i$ represents the change in sales volume of existing variants. SIM_i and SIM_i^2 are the weighted average similarity between new and existing variants and its squared term, allowing us to test the hypothesized inverted U-shaped relationships. WoM_i represents the product category's word-of-mouth rating. The interaction terms $SIM_i \times WoM_i$ and $SIM_i \times WoM_i^2$ enable us to test the moderating effects of WoM on the curvilinear relationships. For control variables, $CategorySales_i$ captures baseline category performance, $NewPrice_i$ and $ExistPrice_i$ control for price effects, $NewAdSpend_i$ and $ExistAdSpend_i$ account for advertising investments, and $VarCount_i$ controls for category size effects. $MonthFE$ represents month fixed effects. ε_i is the error term.

For the regression on existing variants, we use $ExistSalesChange_i$ (the change in sales) rather than absolute sales volume as the dependent variable for two reasons. First, this approach helps control for pre-existing differences in baseline sales levels across product categories, allowing us to better isolate the impact of new variant introduction. Second, measuring changes in sales rather than absolute levels aligns with our research objective of understanding how new variant introductions affect existing variants' performance.

ANALYTICAL RESULTS

Regression on New Variants Sales

Table 3 presents the regression results for new variant sales. Model 1 includes only control variables. Model 2 adds the linear and quadratic terms of variant similarity (SIM). Model 3 introduces the WoM variable, and Model 4 incorporates the interaction terms between variant similarity and WoM.

Table 3

Regression Result of New Variant Sales

DV: NewSales	Model 1	Model 2	Model 3	Model 4
CategorySales	0.0004	0.0003	0.0004*	0.001**
NewPrice	-0.004	-0.0134**	-0.011**	-0.0126**
ExistPrice	0.009	0.011	-0.002	-0.001
NewAdSpend	0.008***	0.0061***	0.0031**	0.0023*
ExistAdSpend	0.001	0.001	0.001*	0.001**
VarCount	0.059	0.056	0.002	-0.0002
SIM	-	16.868***	16.477***	-160.410**
SIM^2	-	-15.822***	-16.964***	173.954**
WoM	-	-	0.331***	-0.550*
WoM*SIM	-	-	-	4.566***
WoM*SIM^2	-	-	-	-4.909***
MonthFE	YES	YES	YES	YES
Constant	3.770***	0.411	-11.989***	21.860*
Observations	258	258	258	258
Adj R^2	0.260	0.314	0.430	0.438
U shape test	-	p=0.030	p=0.002	-
95% Fieller interval for extreme point	-	[0.459, 0.710]	[0.427, 0.586]	-
Extreme point	-	0.533	0.486	-
Slopes when SIM=0.037	-	15.709***	15.234***	-
Slopes when SIM=0.754	-	-6.982**	-9.094**	-

Notes: *p<0.10, **p<0.05, ***p<0.01.

Abbreviations: NewSales, new variant sales; ExistSalesChange, change in total existing variant sales; SIM, weighted average similarity between new and existing variants; WoM, product category word-of-mouth rating; CategorySales, total category sales before launch; NewPrice, new variant price; ExistPrice, existing variants' weighted average price; NewAdSpend, new variant advertising spending; ExistAdSpend, existing variants' advertising spending; VarCount, number of existing variants; MonthFE, month fixed effects.

The results of Model 2 show that the coefficient for SIM is positive (16.868) and significant at the 1% level, while the coefficient for SIM^2 is negative (-15.822) and significant at the 1% level as well. The significance of both terms, combined with the negative coefficient of the squared term, indicates a non-linear relationship between variant similarity and new variant sales. To rigorously validate this inverted U-shaped relationship, we employed the three-step testing approach proposed by Haans et al. (2016).

First, we verified that the extreme point (0.533) falls within the observed range of variant similarity [0.037, 0.754], with a 95% confidence interval of [0.459, 0.710]. Second, we examined the slopes at both ends of the distribution: when SIM = 0.037, the slope is 15.709 and significant ($p < 0.001$); when SIM = 0.754, the slope is -6.982 and significant ($p < 0.05$). Third, the U-shape test yielded a p-value of 0.030, confirming the presence of an inverted U-shaped relationship. These results strongly support Hypothesis 1, which posits that variant similarity has an inverted U-shaped relationship with new variant sales. Figure 3 illustrates this relationship.

Figure 3
Inverted U-shaped Relationship between *SIM* and *NewSales*

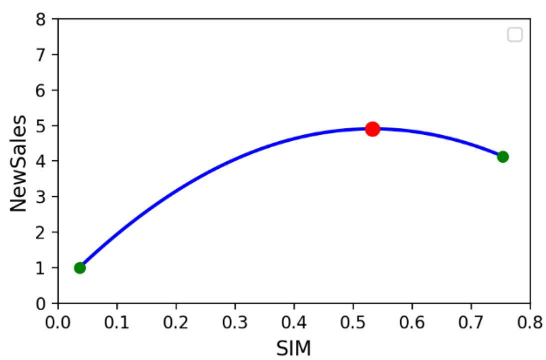
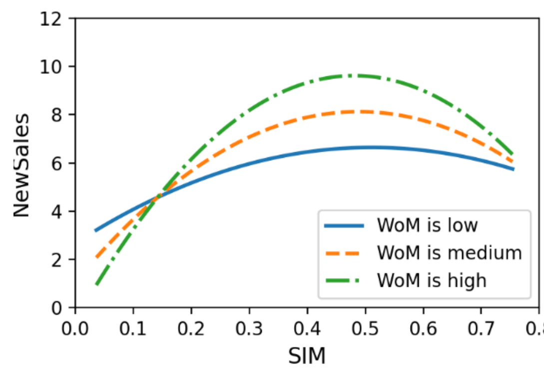


Figure 4
Moderating Effect of *WoM* on the Impact of *SIM* on *NewSales*



The moderating effect of WoM on this relationship is examined in Model 4. We noted that the coefficients for SIM and SIM^2 changed signs compared to Model 3. This is a mathematical artifact due to the inclusion of interaction terms with the non-centered WoM variable, where the main effects represent the curve at a hypothetical zero WoM (outside our observed range). Calculating the effective quadratic coefficient at the mean WoM level yields a negative value (-29.57), comparable in magnitude to Model 3 (-16.96). Furthermore, the turning point at the mean WoM (0.488) remains highly consistent with Model 3 (0.486), confirming the robustness of the inverted U-shaped relationship.

The interaction term between WoM and SIM^2 is negative (-4.909) and significant at the 1% level, indicating that WoM significantly influences the relationship between variant similarity and new variant sales. Specifically, the negative coefficient suggests that higher WoM steepens the inverted U-shaped relationship between variant similarity and new variant sales, supporting Hypothesis 2. Figure 4 visualizes this moderating effect by showing the relationship between variant similarity and new variant sales at different WoM levels (one standard deviation above and below the mean).

The previous analysis demonstrates that WoM can steepen the inverted U-shaped relationship between variant similarity and new variant sales. Additionally, the turning point of the inverted U-shaped curve between variant similarity and new variant sales may also be moderated by WoM. From the results presented in Model 4 of Table 3, we can observe that not only the interaction term between the squared variant similarity and WoM is significant, but also the interaction term between the linear term of variant similarity and WoM, which collectively affect the shift direction of the turning point as WoM changes. According to Haans et al. (2016)'s description, in a regression model in the form of formula (3), the direction of the shift in the turning point is determined by the sign of the numerator (4). If the numerator is positive, the turning point will shift to the right as the moderator increases. Conversely, if the numerator is negative, the turning point will shift to the left. According to the regression result of Model 4, we calculate the numerator for the moderator WoM, which turns out to be negative ($(-160.410 \times -4.909) - (173.954 \times 4.566) \approx -6.82$). Therefore, the turning point of the inverted U-shaped curve between variant similarity and new variant sales will shift to the left as WoM increases.

$$Y = \beta_0 + \beta_1 X + \beta_2 X^2 + \beta_3 XZ + \beta_4 X^2 Z + \beta_5 Z \quad (3)$$

$$\beta_1\beta_4 - \beta_2\beta_3 \quad (4)$$

These findings have important implications for retailers' new variant introduction strategies. The inverted U-shaped relationship suggests that moderate levels of variant similarity (around 0.533) optimize new variant sales. Moreover, this optimization becomes more critical in product categories with strong WoM, where the optimal similarity level shifts to the left. This implies that a strong reputation enables retailers to introduce variants with slightly lower similarity (i.e., higher distinctiveness) without sacrificing sales. In such categories, retailers should carefully consider how new variants align with established cognitive prototypes, as the impact of variant similarity on consumer acceptance is amplified by strong WoM.

Regression on Existing Variants Sales Change

Table 4 presents the regression results for changes in existing variant sales. Following the same analytical approach as new variant sales, we developed four models: Model 5 with control variables only, Model 6 adding variant similarity terms, Model 7 introducing WoM, and Model 8 incorporating interaction terms.

Table 4

Regression Result of Existing Variant Sales Change

DV: ExistSalesChange	Model 5	Model 6	Model 7	Model 8
CategorySales	0.005***	0.005***	0.005***	0.006***
NewPrice	0.005	-0.011	-0.006	-0.012
ExistPrice	0.026	0.032	0.002	0.006
NewAdSpend	-0.026***	-0.030***	-0.038***	-0.040***
ExistAdSpend	0.005**	0.005**	0.006***	0.006***
VarCount	0.307**	0.305**	0.172	0.165
SIM	-	45.109***	44.162***	-544.225**
SIM^2	-	-45.176***	-47.940***	594.353**

WoM	-	-	0.800***	-2.075
WoM*SIM	-	-	-	15.163**
WoM*SIM^2	-	-	-	-16.478**
MonthFE	YES	YES	YES	YES
Constant	18.778***	9.920***	-20.098***	90.474*
Observations	258	258	258	258
Adj R^2	0.484	0.500	0.537	0.542
U shape test	-	p=0.028	p=0.006	-
95% Fieller interval for extreme point	-	[0.422, 0.727]	[0.390, 0.591]	-
Extreme point	-	0.499	0.461	-
Slopes when SIM=0.037	-	41.799***	40.650***	-
Slopes when SIM=0.754	-	-22.991*	-28.105***	-

Notes: *p<0.10, **p<0.05, ***p<0.01.

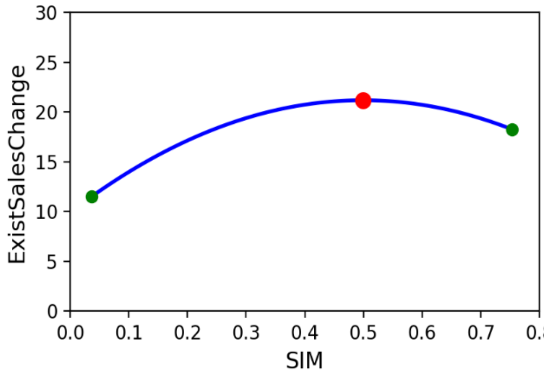
Abbreviations: NewSales, new variant sales; ExistSalesChange, change in total existing variant sales; SIM, weighted average similarity between new and existing variants; WoM, product category word-of-mouth rating; CategorySales, total category sales before launch; NewPrice, new variant price; ExistPrice, existing variants' weighted average price; NewAdSpend, new variant advertising spending; ExistAdSpend, existing variants' total advertising spending; VarCount, number of existing variants; MonthFE, month fixed effects.

In Model 6, the coefficient for SIM is positive (45.109) and significant at the 1% level, while the coefficient for SIM^2 is negative (-45.176) and also significant at the 1% level. To validate this inverted U-shaped relationship, we again employed the three-step testing approach (Haans et al., 2016). The analysis confirms that the extreme point (0.499) falls within the observed variant similarity range [0.037, 0.754], with a 95% confidence interval of [0.422, 0.727]. The slopes at both ends of the distribution are significant and opposite in sign: when SIM = 0.037, the slope is 41.799 and significant ($p < 0.001$); when SIM = 0.754, the slope is -22.991 and significant ($p < 0.10$). The U-shape test yielded a p-value of 0.028, providing strong support for Hypothesis 3, which posits an inverted U-shaped relationship between variant similarity and changes in existing variant sales. Figure 5 visualizes this relationship.

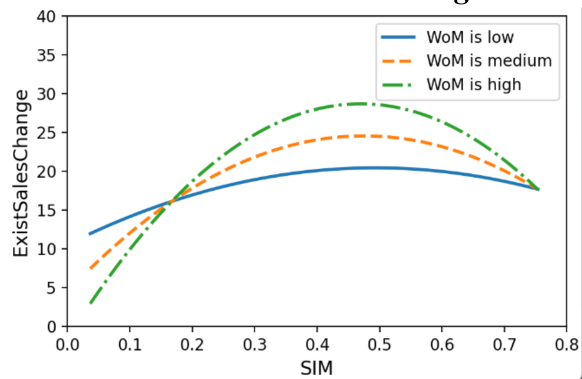
Figure 5
Inverted U-shaped Relationship between

Figure 6
Moderating Effect of *WoM* on the Impact

SIM* and *ExistSalesChange



of *SIM* on *ExistSalesChange*



Model 8 examines the moderating effect of WoM. Similar to the new variant model, the sign change in the main coefficients is due to zero-point extrapolation. At the mean WoM level, the effective quadratic coefficient is -88.82, which restores the negative sign and is consistent in magnitude with Model 7 (-47.94). The calculated turning point at the mean (0.475) also remains stable compared to Model 7 (0.461), validating the robustness of the results.

The interaction term between WoM and SIM^2 is negative (-16.478) and significant at the 5% level, supporting Hypothesis 4. The strengthening effect of WoM can be understood through its impact on the attention spillover effect. When WoM is high, consumers' overall trust and interest in the brand increases, making them more willing to pay attention to existing variants that share similarities with new variants. Therefore, at the same level of variant similarity, higher brand WoM strengthens the attention spillover effect from new variants to existing variants, leading to a more pronounced inverted U-shaped relationship. Figure 6 illustrates how WoM moderates this relationship at different levels (one standard deviation above and below the mean).

The turning point of the inverted U-shaped curve between variant similarity and existing variant sales change is also influenced by WoM. The interaction terms between WoM and the linear term of variant similarity, as well as the squared term of variant similarity, are both significant.

Similarly, here based on the regression result of Model 8, we calculated the numerator (4) of WoM and got a negative value. Therefore, with the increase of WoM, the turning point of the inverted U-shaped curve between variant similarity and existing variant sales change will shift to the left.

These findings provide important insights for retailers managing their product portfolios. The optimal variant similarity level for maximizing positive spillover effects on existing variant sales (around 0.499) is slightly lower than the optimal level for new variant sales (0.533). This difference suggests that retailers might need to balance these two objectives when introducing new variants. Furthermore, the strengthening effect of WoM indicates that in product categories with strong WoM, where the optimal similarity level shifts to the left, retailers should be particularly attentive to variant similarity levels. This implies that with strong reputation support, retailers can achieve maximum spillover benefits with slightly more differentiated variants, as their impact on existing variant sales becomes more pronounced.

Robustness Checks

To ensure the reliability of our findings, we conducted several robustness checks by examining alternative specifications and addressing potential endogeneity concerns.

Endogeneity Assessment Using Gaussian Copula Approach. A critical concern in our analysis is the potential endogeneity of variant similarity (SIM), as retailers might strategically choose similarity levels based on unobserved factors that also affect sales performance. To address this concern, we employed the Gaussian copula approach proposed by Eckert and Hohberger (2023), which can address endogeneity without requiring instrumental variables by adding control functions derived from the empirical distribution of the potentially endogenous variable. The SIM variable exhibits a skewness of -1.36, satisfying the condition for applying this method. The results are presented in Table 5. The endogeneity tests show no significant concerns for either model ($p = 0.539$ for new variant sales; $p = 0.624$ for existing variant sales change). For new variant sales, the inverted U-shaped relationship remains highly robust after correction, with both linear and quadratic terms maintaining strong statistical significance ($p < 0.01$) and the turning point shifting slightly from 0.486 to 0.544. For existing variant sales change, while the linear term loses significance after correction, the quadratic term remains marginally significant ($p < 0.10$), and the turning point shifts modestly from 0.461 to 0.490. The differential impact of the Gaussian copula correction suggests that the inverted U-shaped relationship is more robust for new variant sales than for existing variant sales change. Overall, the endogeneity analysis supports our main conclusions while providing nuanced insights into the relative stability of the relationships across different dependent variables.

Outlier Treatment. We addressed potential concerns about outliers by winsorizing both the dependent variables and the key independent variable (SIM) at the top and bottom 5% and re-estimating the models. The results after winsorization confirm our main findings remain robust. For new variant sales (Model 9), the linear coefficient of SIM is 19.809 ($p < 0.001$) and the quadratic coefficient is -20.348 ($p < 0.001$), with the inverted U-shaped relationship test being significant ($p = 0.004$) and an extreme point of 0.487. For existing variant sales change (Model 11), the linear coefficient of SIM is 61.711 ($p < 0.001$) and the quadratic coefficient is -64.989 ($p < 0.001$), with the inverted U-shaped relationship test also being significant ($p = 0.008$) and an extreme point of 0.475. Additionally, Models 10 and 12 examined the interaction effects between word-of-mouth rating (WoM) and variant similarity (SIM), and the results remain consistent with our main findings. These results confirm the robust inverted U-shaped relationships between variant similarity and sales performance, suggesting that our findings are not driven by extreme values.

Functional Form Verification. Third, to verify that the relationship between variant similarity and sales performance is indeed quadratic rather than cubic, we estimated models including cubic terms of SIM. The results show that the cubic terms are not statistically significant in either dependent variable model. Moreover, the inclusion of cubic terms does not meaningfully improve model fit, with the adjusted R^2 showing minimal changes. Additionally, when cubic terms are included, the linear and quadratic terms of variant similarity lose their statistical significance, suggesting that the cubic specification does not better capture the underlying relationship than our quadratic specification. This additional analysis provides further support for our theoretical framework that posits inverted U-shaped relationships between variant similarity and sales performance.

Alternative Similarity Measures. Fourth, we explored an alternative approach to calculating similarity measures. Our main analysis used sales-weighted average variant similarity between new and existing variants, where weights were determined by existing variants' sales volumes during the 15 days before new variant introduction. To test the robustness of this measurement, we reconstructed the variant similarity measure using simple arithmetic means of pairwise similarities between new and existing variants, rather than sales-weighted averages. The results using this alternative similarity calculation method demonstrate remarkable consistency with our main findings for the core inverted U-shaped relationships. For new variant sales (Model 17), the arithmetic mean similarity yields an optimal point at 0.485 with a significant inverted U-shaped relationship ($p = 0.002$), while for existing variant sales change (Model 19), the optimal point is at 0.461 with a significant relationship ($p = 0.006$). However, when interaction terms are included (Models 18 and 20), the moderating effects of WoM become statistically insignificant, unlike our main weighted-average approach where these interactions remain robust. This difference suggests that the arithmetic mean method introduces measurement noise by equally weighting all variants regardless of their market influence, thereby attenuating the detection of nuanced interaction effects. The loss of interaction significance actually validates the superiority of our sales-weighted approach, which better captures the competitive dynamics that consumers actually experience in the marketplace by emphasizing similarities with market-dominant variants.

Time Window Sensitivity. Finally, we examined the sensitivity of our results to different time windows. Our main analysis used a 15-day window for various measurements, including the calculation of new variant sales, existing variant sales changes (comparing 15 days before and after new variant introduction), and advertising expenditures for both new and existing variants. We tested alternative time windows of 7 days (model 21-24, table 9) and 30 days (model 25-28, table 10) to ensure our findings are robust across different temporal specifications. The results demonstrate notable consistency across these different time windows, confirming that our inverted U-shaped relationships are not artifacts of the chosen time period. For the 7-day window, the optimal similarity points are 0.504 for new variant sales and 0.450 for existing variant sales change. For the 30-day window, the optimal points are 0.489 and 0.460 respectively. These values remain very close to our main 15-day results (0.486 and 0.461), suggesting our findings capture fundamental market dynamics rather than temporal artifacts. However, for new variant sales, we observe some temporal sensitivity. While the U-test of the 30-day window yields results very similar to our main findings (optimal point: 0.489, p = 0.013), the 7-day window shows a weaker relationship with marginal significance (p = 0.060) and a confidence interval [0.411, 1.475] that extends beyond the theoretical range of similarity measures. This suggests that the immediate short-term effects on new variant sales may be more volatile and require a longer observation period to capture the full market dynamics. The temporal robustness for existing variant effects and the consistency in longer time windows (15-day and 30-day) for new variant effects validate the reliability of our theoretical framework while highlighting the importance of appropriate temporal measurement windows in dynamic e-commerce markets.

Table 5.
Endogeneity Test Results: Gaussian Copula Approach

Model	OLS Results			Gaussian Copula Corrected			Endogeneity Test (p-value)
	SIM Coef.	SIM² Coef.	Turning Point	SIM Coef.	SIM² Coef.	Turning Point	
NewSales	16.477*** (4.214)	-16.964*** (4.688)	0.486	22.159*** (8.096)	-20.357*** (7.642)	0.544	0.539
ExistSales Change	44.162*** (13.374)	-47.940*** (15.526)	0.461	33.809 (28.727)	-34.536* (19.083)	0.490	0.624

*Notes: *p<0.10, **p<0.05, **p<0.01. Standard errors in parentheses. The endogeneity test reports the p-value of the joint F-test for the Gaussian copula terms. A p-value > 0.05 indicates no significant endogeneity concern.
Abbreviations: NewSales, new variant sales; ExistSalesChange, change in total existing variant sales; SIM, weighted

average similarity between new and existing variants.

Table 6

Regression Results with Winsorized Data (5%)

DV	**NewSales**		**ExistSalesChange**	
	Model 9	**Model 10**	**Model 11**	**Model 12**
CategorySales	0.0004*	0.0004	0.005***	0.004***
NewPrice	-0.011*	-0.012**	-0.020	-0.022
ExistPrice	-0.001	-0.001	0.006	0.009
NewAdSpend	0.003**	0.005**	-0.032***	-0.065***
ExistAdSpend	0.001*	0.002*	0.005***	0.010***
VarCount	-0.005	-0.001	0.066	0.068
SIM	19.797***	-13.221	61.711***	11.387
SIM^2	-20.335***	16.784	-64.989***	7.280
WoM	0.334***	0.201**	0.824***	0.730**
WoM*SIM	-	0.638**	-	0.929
WoM*SIM^2	-	-0.732*	-	-1.448*
MonthFE	YES	YES	YES	YES
Constant	-12.831***	-5.855	-23.434***	-16.995
Observations	258	258	258	258
Adj R^2	0.421	0.431	0.470	0.471
U shape test	p=0.004	-	p=0.008	-
95% Fieller interval for extreme point	[0.434, 0.571]	-	[0.415, 0.582]	-
Extreme point	0.487	-	0.475	-
Slopes when SIM=0.037	12.282***	-	37.672***	-
Slopes when SIM=0.754	-9.088***	-	-30.583***	-

Notes: *p<0.10, **p<0.05, ***p<0.01.

Abbreviations: NewSales, new variant sales; ExistSalesChange, change in total existing variant sales; SIM, weighted average similarity between new and existing variants; WoM, product category word-of-mouth rating; CategorySales, total category sales before launch; NewPrice, new variant price; ExistPrice, existing variants' weighted average price; NewAdSpend, new variant advertising spending; ExistAdSpend, existing variants' total advertising spending; VarCount, number of existing variants; MonthFE, month fixed effects.

Table 7

Regression Results with Different Functional Form

DV	**NewSales**		**ExistSalesChange**	
	Model 13	**Model 14**	**Model 15**	**Model 16**
CategorySales	0.001*	0.001**	0.006***	0.006***

NewPrice	-0.012**	-0.013**	-0.009	-0.013
ExistPrice	-0.001	-0.0002	0.004	0.009
NewAdSpend	0.003**	0.002*	-0.039***	-0.041***
ExistAdSpend	0.001*	0.001**	0.006***	0.006***
VarCount	0.001	-0.001	0.169	0.162
SIM	9.963	-288.782	-3.659	-632.584
SIM^2	1.783	509.644	89.674	891.752
SIM^3	-15.513	-263.633	-113.874	-264.660
WoM	0.337***	-0.918	0.846***	-2.090
WoM*SIM	-	7.802	-	16.447
$WoM*SIM^2$	-	-13.301	-	-21.277
$WoM*SIM^3$	-	6.559	-	4.448
MonthFE	YES	YES	YES	YES
Constant	-11.626***	36.271	-17.434**	94.630
Observations	258	258	258	258
Adj R^2	0.428	0.426	0.444	0.453

Notes: *p<0.10, **p<0.05, ***p<0.01.

Abbreviations: NewSales, new variant sales; ExistSalesChange, change in total existing variant sales; SIM, weighted average similarity between new and existing variants; WoM, product category word-of-mouth rating; CategorySales, total category sales before launch; NewPrice, new variant price; ExistPrice, existing variants' weighted average price; NewAdSpend, new variant advertising spending; ExistAdSpend, existing variants' total advertising spending; VarCount, number of existing variants; MonthFE, month fixed effects.

Table 8

Regression Results with Alternative Similarity Measures

DV	**NewSales**		**ExistSalesChange**	
	Model 17	**Model 18**	**Model 19**	**Model 20**
CategorySales	0.0004*	0.0005*	0.005***	0.006***
NewPrice	-0.011*	-0.012**	-0.006	-0.008
ExistPrice	-0.002	-0.002	0.002	0.002
NewAdSpend	0.003**	0.003**	-0.038***	-0.038***
ExistAdSpend	0.001*	0.001*	0.006***	0.006***
VarCount	-0.001	0.003	0.165	0.180
SIM	16.266***	-21.303	43.116***	-66.006
SIM^2	-16.772***	17.671	-46.720***	64.253
WoM	0.333***	0.093	0.806***	0.186
WoM*SIM	-	1.008	-	2.908
$WoM*SIM^2$	-	-0.933	-	-2.961
MonthFE	YES	YES	YES	YES
Constant	-12.049***	-2.985	-20.140***	3.172

Observations	258	258	258	258
Adj R^2	0.430	0.429	0.537	0.535
U shape test	p=0.002	-	p=0.006	-
95% Fieller interval for extreme point	[0.425, 0.586]	-	[0.389, 0.599]	-
Extreme point	0.485	-	0.461	-
Slopes when SIM=0.040	14.933***	-	39.403***	-
Slopes when SIM=0.751	-8.940***	-	-27.095***	-

Notes: *p<0.10, **p<0.05, ***p<0.01.

Abbreviations: NewSales, new variant sales; ExistSalesChange, change in total existing variant sales; SIM, weighted average similarity between new and existing variants; WoM, product category word-of-mouth rating; CategorySales, total category sales before launch; NewPrice, new variant price; ExistPrice, existing variants' weighted average price; NewAdSpend, new variant advertising spending; ExistAdSpend, existing variants' total advertising spending; VarCount, number of existing variants; MonthFE, month fixed effects.

Table 9

Regression Results with Different Time Windows (7 days)

DV	**NewSales**		**ExistSalesChange**	
	Model 21	**Model 22**	**Model 23**	**Model 24**
CategorySales	0.0002	0.0002	0.003***	0.003***
NewPrice	-0.006	-0.006	-0.001	-0.003
ExistPrice	-0.004	-0.004	0.002	0.003
NewAdSpend	0.002	0.001	-0.039***	-0.041***
ExistAdSpend	0.001	0.001	0.006***	0.006***
VarCount	-0.018	-0.017	0.106	0.104
SIM	7.924**	-92.044*	26.132***	-277.636**
SIM^2	-7.865**	92.311	-29.016***	292.826**
WoM	0.185***	-0.371	0.382***	-1.175
WoM*SIM	-	2.608*	-	7.863**
WoM*SIM^2	-	-2.614*	-	-8.305**
MonthFE	YES	YES	YES	YES
Constant	-6.318***	14.969	-10.188***	49.624*
Observations	258	258	258	258
Adj R^2	0.228	0.234	0.529	0.534
U shape test	p=0.060	-	p=0.001	-
95% Fieller interval for extreme point	[0.411, 1.475]	-	[0.387, 0.537]	-
Extreme point	0.504	-	0.450	-
Slopes when SIM=0.037	7.347***	-	24.006***	-
Slopes when SIM=0.754	-3.933*	-	-17.608***	-

Notes: *p<0.10, **p<0.05, ***p<0.01.

Abbreviations: NewSales, new variant sales; ExistSalesChange, change in total existing variant sales; SIM, weighted average similarity between new and existing variants; WoM, product category word-of-mouth rating; CategorySales, total category sales before launch; NewPrice, new variant price; ExistPrice, existing variants' weighted average price; NewAdSpend, new variant advertising spending; ExistAdSpend, existing variants' total advertising spending; VarCount, number of existing variants; MonthFE, month fixed effects.

Table 10

Regression Results with Different Time Windows (30 days)

DV	NewSales		ExistSalesChange	
	Model 25	**Model 26**	**Model 27**	**Model 28**
CategorySales	0.001	0.001**	0.008***	0.008***
NewPrice	-0.020**	-0.023**	-0.004	-0.010
ExistPrice	-0.003	0.001	-0.008	0.0003
NewAdSpend	0.002**	0.001	-0.028***	-0.029***
ExistAdSpend	0.001**	0.001**	0.005***	0.005***
VarCount	0.041	0.035	0.294	0.282
SIM	21.655***	-366.273***	65.635***	-741.957*
SIM^2	-22.138***	407.538***	-71.267***	824.233*
WoM	0.514***	-1.335**	1.236***	-2.605
WoM*SIM	-	9.975***	-	20.762**
WoM*SIM^2	-	-10.993***	-	-22.906**
MonthFE	YES	YES	YES	YES
Constant	-18.304***	52.862***	-31.651***	116.226
Observations	258	258	258	258
Adj R^2	0.388	0.411	0.529	0.533
U shape test	p=0.013	-	p=0.006	-
95% Fieller interval for extreme point	[0.419, 0.664]	-	[0.389, 0.594]	-
Extreme point	0.489	-	0.460	-
Slopes when SIM=0.037	20.033***	-	60.413***	-
Slopes when SIM=0.754	-11.717**	-	-41.795***	-

Notes: *p<0.10, **p<0.05, ***p<0.01.

Abbreviations: NewSales, new variant sales; ExistSalesChange, change in total existing variant sales; SIM, weighted average similarity between new and existing variants; WoM, product category word-of-mouth rating; CategorySales, total category sales before launch; NewPrice, new variant price; ExistPrice, existing variants' weighted average price; NewAdSpend, new variant advertising spending; ExistAdSpend, existing variants' total advertising spending; VarCount, number of existing variants; MonthFE, month fixed effects.

Post-hoc analysis

In previous analysis, we have examined the moderating role of word-of-mouth on the relationship between similarity and sales. However, as one of the critical decision variables for retailers in the new product launching process, advertising expenditure on new variants and existing variants may also influence the relationship between similarity and sales performance of both new and existing variants. Therefore, here we conduct post-hoc analyses to explore how advertising expenditure on new variants (NewAdSpend) and existing variants (ExistAdSpend) moderates the effect of similarity on sales. Table 11 presents the analytical results after incorporating moderating variables related to NewAdSpend and ExistAdSpend.

Model 30 incorporates advertising-related moderating variables in the regression on new variant sales. The results show that the interaction term between new variant advertising spend and the squared term of similarity is significantly positive ($\beta = 2.112$, $p < 0.05$), indicating that advertising investment in new variants weakens the inverted U-shaped relationship between similarity and new variant sales. This can be understood through advertising's intervention in both the familiarity effect and the internal competition effect. At the low similarity end, new variants lack familiarity, but advertising can proactively convey product information, helping consumers establish cognitive matching and compensating for the insufficient familiarity effect. At the high similarity end, new variants face severe internal competition, but advertising investment can serve as a powerful persuasive tool, creating perceived differentiation for new variants by highlighting subtle new features, positioning the variant as the "latest" or "featured" option, or simply by commanding a higher share of voice. By mitigating disadvantages at both ends of the curve, new variant advertising investment makes the choice of similarity level less critical.

In contrast to NewAdSpend, the interaction term between ExistAdSpend and the squared term of similarity is significantly negative ($\beta = -0.126$, $p < 0.10$), indicating that ExistAdSpend strengthens the inverted U-shaped relationship between similarity and new variant sales. This can be understood through ExistAdSpend's dual amplification effect on both the familiarity effect and the internal competition effect. At moderate similarity levels, advertising investment in existing variants reinforces their status as the cognitive prototype for consumers, enhancing brand equity and mental share. This enables new variants to leverage the familiarity effect more effectively, establishing cognitive connections with a stronger prototype, accelerating consumer acceptance, and resulting in more pronounced sales increases. However, at high similarity levels, the stronger prototype status also intensifies the internal competition effect. Advertising reinforces consumers' preferences and loyalty toward existing variants, making it more difficult for highly similar new variants to capture market share from consumers, facing more intense substitution competition. By simultaneously amplifying both the benefits of the familiarity effect and the penalties of internal competition, existing variant advertising investment makes the inverted U-shaped relationship steeper, rendering the optimal choice of similarity more critical.

Model 32 presents the regression results for changes in existing variant sales. The interaction terms between new variant advertising spend and similarity are not significant, suggesting that NewAdSpend has a limited moderating effect on the relationship between similarity and existing variant sales. This may be because new variant advertising investment is relatively smaller in scale compared to existing variant advertising investment, primarily influencing consumers' evaluation and selection of the new variant itself, while the indirect impact on existing variant sales (whether through spillover effects or competition effects) is relatively weak.

In contrast, the interaction term between ExistAdSpend and the squared term is significantly positive ($\beta = 1.521$, $p < 0.01$), indicating that ExistAdSpend weakens the inverted U-shaped relationship between similarity and existing variants sales. This reflects advertising's buffering effect on the internal competition effect. Advertising investment in existing variants reinforces consumers' preferences, habits, and purchase inertia toward existing variants, effectively resisting the substitution threat from highly similar new variants. Even when new variants are highly similar to existing variants, sufficient advertising support enables existing variants to maintain their market share, mitigating the sales losses caused by internal competition. By providing protection at the high similarity end, existing variant advertising investment makes the curve flatter.

These findings provide important practical implications for retailers. Advertising investment can moderate the sensitivity of similarity decisions: when retailers invest heavily in advertising for new variants, the penalty for deviating from the optimal similarity level is reduced, allowing greater flexibility in product design; whereas when existing variant advertising investment is high, similarity decisions become more critical, requiring more precise calibration of the optimal similarity level. This implies that different similarity levels require differentiated advertising strategies. New variants with low similarity require increased new variant advertising spend to establish consumer awareness; new variants with high similarity can either break through internal competition by creating perceived differentiation through new variant advertising spend, or protect existing variant market share through existing variant advertising spend. Furthermore, advertising can serve as a remedial tool for similarity decisions. When the similarity choice at the product design stage is suboptimal, retailers can partially correct or buffer the adverse effects by adjusting advertising investment strategies, providing room for subsequent adjustments in managerial decision-making.

Table 11

Regression Results considering Advertising's Moderation

DV	NewSales		ExistSalesChange	
	Model 29	**Model 30**	**Model 31**	**Model 32**
CategorySales	0.0004*	0.002***	0.005***	0.005**
NewPrice	-0.011**	-0.0121***	-0.006	-0.011
ExistPrice	-0.002	-0.001	0.002	0.005
NewAdSpend	0.0031**	0.0019*	-0.038***	-0.039*
ExistAdSpend	0.001*	0.001*	0.006***	0.005***
VarCount	0.002	-0.0003	0.172	0.161
SIM	16.477***	-160.410*	44.162***	-467.254**
SIM^2	-16.964***	153.954**	-47.940***	436.453*
WoM	0.331***	-0.511**	0.800***	-2.054*
WoM*SIM	-	4.162*	-	16.161**
WoM*SIM^2	-	-4.203**	-	-15.423*
NewAdSpend* SIM	-	-0.344	-	0.111
NewAdSpend* SIM^2	-	2.112**	-	-0.449
ExistAdSpend* SIM	-	0.031*	-	-1.215*
ExistAdSpend* SIM^2	-	-0.126*	-	1.521***
MonthFE	YES	YES	YES	YES
Constant	-11.989***	11.581**	-20.098***	62.352**
Observations	258	258	258	258
Adj R^2	0.430	0.472	0.537	0.583
U shape test	p=0.002	-	p=0.006	-
95% Fieller interval for extreme point	[0.427, 0.586]	-	[0.390, 0.591]	-
Extreme point	0.486	-	0.461	-
Slopes when SIM=0.037	15.234***	-	40.650***	-
Slopes when SIM=0.754	-9.094**	-	-28.105***	-

Notes: *p<0.10, **p<0.05, ***p<0.01.

Abbreviations: NewSales, new variant sales; ExistSalesChange, change in total existing variant sales; SIM, weighted average similarity between new and existing variants; WoM, product category word-of-mouth rating; CategorySales, total category sales before launch; NewPrice, new variant price; ExistPrice, existing variants' weighted average price; NewAdSpend, new variant advertising spending; ExistAdSpend, existing variants' total advertising spending; VarCount, number of existing variants; MonthFE, month fixed effects.

DISCUSSION, IMPLICATIONS, AND LIMITATIONS

Discussion

This study aims to explore how variant similarity between new and existing variants affects sales performance in e-commerce product categories, and how WoM moderates these relationships. Our empirical analysis reveals several important findings that advance our understanding of product variant management in e-commerce contexts.

First, we discovered inverted U-shaped relationships between new-existing variant similarity and sales performance for both new and existing variants. For new variants, this relationship can be explained through the interplay between the familiarity effect and internal competition effect. The familiarity effect, grounded in prototype theory (Rosch, 1975), suggests that moderate variant similarity helps consumers match new variants with established cognitive prototypes, reducing cognitive load and enhancing product acceptance (Loken and Ward, 1990). However, when variant similarity becomes excessive, the internal competition effect dominates - according to substitution theory (Lancaster, 1990), higher variant similarity leads to stronger substitutability between variants, resulting in demand cannibalization and reduced differentiation advantages (Mason and Milne, 2013). For existing variants, we observed a similar inverted U-shaped relationship but driven by different mechanisms: the attention spillover effect and internal competition effect. The attention spillover effect, based on attention theory (Kumar and Krishnan, 2004), suggests that moderate variant similarity facilitates attention transfer from new to existing variants through associative mechanisms. However, as variant similarity increases further, the internal competition effect becomes dominant, leading to demand cannibalization between variants. Notably, we found different optimal variant similarity levels for new variants (0.533) and existing variants (0.499), suggesting that existing variants benefit from slightly lower variant similarity levels compared to new variants.

Second, we found that WoM strengthens both inverted U-shaped relationships, consistent with our theoretical predictions. For new variants, this strengthening effect can be understood through WoM's impact on the familiarity effect. According to prototype theory (Rosch, 1975), when a product category has high WoM, the prototype matching process is enhanced in two ways: First, high WoM indicates positive consumer evaluations of existing products, making prototypes formed based on existing variants more credible and valuable as references (Loken and Ward, 1990). Second, consumers transfer their overall trust in the brand to their evaluation of new products (Hem et al., 2003), increasing their willingness to engage in prototype matching. For existing variants, the strengthening effect operates through WoM's impact on the attention spillover effect. When WoM is high, consumers' overall trust and interest in the brand increases, making them more willing to pay attention to existing variants that share similarities with new variants (Kim et al., 2016). This enhanced attention spillover effect makes the relationship between variant similarity and existing variant sales more pronounced at higher levels of WoM.

Theoretical and practical implications

This study contributes to literature in three significant ways. First, this research contributes to product category management literature by examining the dynamic aspects of category expansion through new variant introductions. Previous research has primarily focused on the static relationship between category size and retail performance, with some studies suggesting that larger category size improves performance by providing more choices (Briesch et al., 2009; Ma, 2016), while others argue that excessive size may cause information overload (Beneke et al., 2013; Boatwright and Nunes, 2001). We extend this literature by investigating how retailers should strategically introduce new variants into existing categories, revealing that the relationship between new-existing variant similarity and sales performance follows an inverted U-shaped pattern. This finding extends the traditional category management perspective that focuses solely on size effects and provides new insights into the dynamic management of product categories.

Interestingly, in our analysis, the control variable for the number of existing variants (VarCount) had no significant effect on either new variant sales or the change in existing variant sales. We argue that this result does not directly contradict prior literature due to a fundamental difference in our research perspective. Traditional studies often focus on the macro-level impact of category size on overall category performance, whereas our study examines the micro-level effects on its internal components (i.e., new and existing variants). The drivers affecting the whole may not be the same as those affecting its parts. More importantly, this non-significant finding, especially when contrasted with the high significance of variant similarity (SIM), reveals a deeper mechanism: the impact of simply adding one more variant (i.e., category size +1) is not homogeneous; its effect largely depends on the "nature" of that new addition. When a new variant with moderate similarity is introduced, it can effectively meet new demands without causing confusion, potentially leading to the positive effects found in prior research. Conversely, when a highly similar variant is introduced, it only intensifies internal competition and consumer confusion, making the negative effects of "choice overload" more likely. Therefore, by shifting the focus from a pure "quantity" question (how many variants to offer) to a more strategic "relationship" question (what similarity to maintain), our study not only provides a new explanatory framework for the conflicting findings on category size effect but also underscores the primacy of optimizing similarity strategy in dynamic category management.

Second, this research advances new product launch literature by revealing the unique mechanisms of introducing variants within existing product categories. While previous research on new product launches has primarily focused on completely innovative products (Fraenkel et al., 2016) and emphasized innovativeness as a key success factor (Cooper, 2019; Matikainen et al., 2015), our study identifies distinct challenges in variant introductions where retailers must balance differentiation with brand consistency. Unlike traditional new product launches, variant introductions affect not only their own performance but also existing variants' sales. By integrating prototype theory, substitution theory, and attention theory, we develop a comprehensive framework that explains how variant similarity simultaneously influences both new and existing variants through distinct mechanisms - familiarity effect and internal competition effect for new variants, attention spillover effect and internal competition effect for existing variants. This dual-mechanism framework enriches our understanding of how to manage the complex interdependencies within product categories.

Third, this research enriches Optimal Distinctiveness Theory (ODT) by applying its core logic to the introduction of new product variants. While ODT traditionally explains how entities balance legitimacy and distinctiveness to succeed (Deephouse, 1999; Zhao et al., 2017), we show that this trade-off also governs the impact of variant similarity. Our findings support the concept of “legitimate distinctiveness” (Navis and Glynn, 2011): we find that moderate similarity achieves legitimacy by fostering the “familiarity effect” and trust transfer (Aaker and Keller, 1990; Erdem, 1998), whereas excessive similarity leads to negative “internal competition” and substitutability (Moorthy and Png, 1992). By verifying these dual mechanisms, we provide a micro-level explanation for how ODT shapes consumer choices in the e-commerce environment.

Fourth, this study extends research on WoM effects in e-commerce by identifying WoM as a critical moderator in variant introduction success. While previous research has examined how environmental factors such as market competition intensity and demand uncertainty moderate new product launch effects (Cui et al., 2011; Tang and Zhu, 2020), we highlight WoM as a unique e-commerce platform characteristic that influences variant introduction outcomes. By demonstrating that WoM strengthens both the positive and negative effects of variant similarity on sales performance through its impact on consumers' prototype matching and attention allocation processes, we provide new insights into how WoM shapes consumer responses to new variants in e-commerce contexts. This finding extends WoM literature beyond its direct effects on sales to show how it moderates the effectiveness of similarity-based product strategies.

Practically, our findings provide important implications for retailers managing product variants in e-commerce platforms. First, the inverted U-shaped relationships between variant similarity and sales performance suggest that retailers should carefully balance differentiation and consistency when introducing new variants. While moderate variant similarity (around 0.533) optimizes new variant sales by leveraging familiarity effects while avoiding excessive internal competition, a slightly lower variant similarity level (around 0.499) maximizes positive spillover effects on existing variant sales. These empirically derived benchmarks can guide retailers in determining appropriate levels of variant similarity when designing new variants for their product categories. To make these numerical benchmarks more intuitive and actionable for managers, we examined the characteristics of the new variants in our dataset that fall within this optimal "sweet spot" (i.e., similarity scores between 0.49 and 0.53). We found that these variants typically represent significant changes in aesthetic attributes such as color palettes, patterns, or prints, while maintaining the core silhouette and functional features of the existing product line. This insight provides a tangible design guideline for fashion retailers: to achieve optimal performance, new variants should feel familiar in form and function but appear refreshingly new in their visual presentation.

Second, our findings regarding WoM's moderating role suggest that retailers should adapt their variant introduction strategies according to their product categories' WoM levels. The strengthening effect of WoM indicates that in categories with strong WoM, variant similarity decisions become more consequential as they have amplified effects on both new and existing variant sales. This suggests that retailers should be particularly careful in managing variant similarity levels when introducing variants into high-WoM categories, as both the benefits of optimal variant similarity and the costs of suboptimal variant similarity are greater. Third, our empirical findings provide quantifiable insights that can be integrated into retailers' product portfolio management systems.

The identified relationships between variant similarity, WoM, and sales performance can inform decision support tools for new variant introductions, helping retailers make more data-driven decisions about product design features and launch timing. These insights are particularly valuable given the increasing importance of systematic category management in e-commerce environments.

Limitations and future research

While this study provides valuable insights into strategies of product category management and variant introduction in e-commerce contexts, several limitations should be noted that suggest directions for future research.

First, our empirical analysis is based on data from a fashion retailer on a single e-commerce platform. Given that different product types may have distinct characteristics affecting consumer responses to variant similarity and WoM (Taiminen and Karjaluoto 2015), future research should examine whether our findings generalize to other industries (e.g., electronics, home goods) and other e-commerce platforms. The optimal variant similarity levels we identified (0.533 for new variants and 0.499 for existing variants) may vary across different product contexts. Additionally, collecting data from multiple retailers would allow investigation of how retailer-specific factors (e.g., brand positioning, target market) influence the effectiveness of variant introduction strategies.

Second, our study measures variant similarity primarily through visual features using deep learning-based computer vision methods. While visual variant similarity is crucial in fashion products, future research could explore other dimensions of variant similarity, such as functional attributes, price positioning, or target consumer segments. A multi-dimensional approach to variant similarity measurement might provide more nuanced insights into how various aspects of variant similarity affect variant performance. Moreover, future studies could investigate how the relative importance of different variant similarity dimensions varies across product categories and consumer segments.

Third, we focused on sales volume as the key performance metric for both new and existing variants. While sales volume is a crucial indicator of market success, future research could examine other performance metrics such as profit margins, customer acquisition costs, and long-term customer value. Additionally, investigating how variant similarity affects non-financial metrics like brand perception and category perception could provide a more comprehensive understanding of variant introduction impacts.

Fourth, our aggregate data does not differentiate between new variants purchased by existing customers versus those purchased by entirely new customers. This prevents us from understanding whether variant similarity primarily drives customer retention (i.e., encouraging repeat purchases from loyal customers) or customer acquisition (i.e., broadening the customer base). Future research using customer-level data could explore, for instance, whether high similarity is more effective at generating sales from existing customers who appreciate familiar styles, while moderate similarity excels at attracting new customers by showcasing brand innovation. Disentangling these sales sources is essential for evaluating other critical performance metrics such as profit margins (given differing customer acquisition costs) and long-term customer value.

Fifth, our study focuses exclusively on the performance of new variants launched within existing product categories. We did not compare these outcomes against a control group of "entirely new products" launched independently of any existing line. This leaves an intriguing strategic question unanswered: would a product with low similarity to existing variants perform better if positioned as a completely new offering rather than a variant? Our findings show that low-similarity variants perform poorly, suggesting that the association with an existing line may not be beneficial when differentiation is too high. Future research can explore this boundary condition by comparing the efficacy of line extension strategies versus standalone new product launch strategies for products with varying degrees of distinctiveness.

Finally, while we examined WoM as a key moderator, future research could explore other potential moderators of the similarity-performance relationship. For instance, factors such as category competitive intensity, seasonal patterns, or platform-specific features might influence the optimal level of variant similarity. Additionally, investigating how the effectiveness of similarity-based strategies varies across different consumer segments (e.g., based on purchase history, browsing behavior, or demographic characteristics) could provide valuable insights for targeted variant introduction strategies.

These limitations and future research directions suggest that while our study provides important insights into variant introduction strategies, much remains to be learned about how retailers can optimize their product portfolio management in dynamic e-commerce environments.

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