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From Image to Action: How Social Proof Turns Brand Image into Repurchase Intention

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Abstract

This study examines how social proof shapes the relationship between brand image and repurchase intention in an emerging digital marketplace, distinguishing three forms that operate through different mechanisms: user-generated content, brand ambassadors, and testimonials. Because online markets involve considerable information overload, consumers rely heavily on others' evaluations to reduce decision risk; however, forms of social proof vary in authenticity and persuasive effectiveness, and prior research has largely treated them as a single, uniformly positive construct. A two-study, mixed-methods design set in Vietnam addresses this gap. Study 1 applies a Vietnamese-optimized RoBERTa (Robustly Optimized BERT Pretraining Approach) model to social media comments to surface authentic consumer sentiment, providing exploratory, triangulating context without constituting a direct hypothesis test. Study 2 tests the proposed relationships using moderated regression on survey responses from 394 active Vietnamese online shoppers. Results show that brand image exerts a strong positive direct effect on repurchase intention. User-generated content significantly strengthens this relationship, with the largest effect among consumers holding moderate brand-image perceptions. Brand ambassadors moderate the relationship but show a bounded pattern, with diminishing influence once brand image is already strong. Testimonials exert a dual effect: they amplify the brand image-repurchase link when perceived as credible, but, when seen as commercially motivated, they independently trigger skepticism and weaken repurchase intention. By conceptually and empirically distinguishing ambassadors from testimonials, this study shows that social proof is not a uniformly positive force but a context-dependent mechanism conditioned by authenticity, with implications for transparency-oriented digital marketing strategy.

Keywords: brand image, repurchase intention, social proof, sentiment analysis, user-generated content.

1. Introduction

In the contemporary digital marketplace, consumers are increasingly confronted with an overwhelming volume of information when making purchasing decisions. To navigate this complexity, they rely heavily on social proof to evaluate products and reduce uncertainty (Yu et al., 2026). Social proof refers to individuals' reliance on others' judgments under uncertainty to reduce perceived risk and guide decision-making, and has become a critical factor influencing online consumer behavior (Huang et al., 2025). In digital commerce, social proof manifests in multiple forms, including user-generated content (UGC), brand ambassadors, and testimonials (Al-Abdallah and Wright, 2025; Barsha and Munshi, 2025; Xu et al., 2025). These forms operate through distinct mechanisms, such as peer review, aspirational identity, and credibility-based persuasion (Do et al., 2025; Zameer et al., 2026).

Social proof also plays an important role in digital value co-creation, as consumers actively shape brand meaning through reviews, comments, and endorsements, forming a co-created informational ecosystem in which both firms and consumers contribute to value generation (Soloaga et al., 2023). However, these mechanisms differ in their degree of authenticity and commercial intent. While UGC often reflects authentic consumer experiences (Barsha and Munshi, 2025), other forms may be strategically designed or commercially motivated, such as influencer endorsements and testimonials. Consequently, the boundary between authentic value co-creation and manipulative influence becomes increasingly blurred, raising important questions regarding responsible digital marketing practices.

Brand ambassadors are public figures-influencers or celebrities-contracted to represent a brand, translating aspirational identity into consumer motivation (Al-Abdallah and Wright, 2025; Do et al., 2025; Zameer et al., 2026). Testimonials, by contrast, derive their persuasive power from the perceived authenticity and credibility of the endorser, whether a celebrity, expert, or trusted community figure (Alim et al., 2026; Lee, 2026; Ul Haq et al., 2026).

Extant research conceptualizes social proof primarily as an informational heuristic that reduce the cognitive effort and perceived risk in online purchasing contexts (Huang et al., 2025; Kong and Lou, 2026; Osorio-Andrade et al., 2025; Salim and Wafa, 2025; Xu et al., 2025; Zameer et al., 2026). When a consumer perceives a favorable brand image but remains uncertain about a repurchase decision, third-party validation provided by UGC, ambassadors, and testimonials serves as a bridging mechanism-converting latent positive brand associations into concrete behavioral intention (Muda and Hamzah, 2021; Osorio-Andrade et al., 2025; Tafolli et al., 2025; Xu et al., 2025; Yu et al., 2026; Zameer et al., 2026). Accordingly, prior research has predominantly treated social proof as a uniformly beneficial mechanism.

However, emerging evidence suggests that the effectiveness of social proof may not be uniform across contexts. While social proof is intended to enhance credibility, consumers in digital environments are increasingly capable of recognizing persuasive intent (Pan et al., 2025; Zniva et al., 2023). Particularly, consumers may develop skepticism when social proof is perceived as overly commercial or strategically orchestrated (Handoyo, 2024). As a result, social proof may not always strengthen consumer responses; under certain conditions, it may attenuate or even undermine trust and repurchase intention. This tension suggests that social proof operates as a conditionally effective mechanism, not as a universally positive influence.

Despite these insights, three important gaps remain. First, a conceptual gap exists, as prior research tends to treat social proof as a monolithic construct, without distinguishing between different forms that may operate through distinct mechanisms. Second, a methodological gap persists, as most studies rely on survey-based approaches that

capture self-reported perceptions but fail to reflect real-time and naturally occurring consumer responses in digital environments. Integrating structured survey data with unstructured digital content can provide a more comprehensive understanding of how consumers interpret and respond to social proof. Third, a contextual gap arises in emerging markets such as Vietnam, where high social media penetration and strong community influence amplify the role of social validation in shaping consumer decisions (Dang-Van et al., 2026).

To address these gaps, this study examines how different forms of social proof differentially influence the relationship between brand image and repurchase intention. By distinguishing between these mechanisms, it provides a more nuanced and context-sensitive understanding of social proof in digital environments. A multi-method approach is employed. Study 1 analyzes social media comments using a Vietnamese-optimized RoBERTa model (a deep learning architecture) to capture authentic consumer sentiment, while Study 2 uses survey data from Vietnamese consumers to test the proposed relationships.

The Vietnamese setting is not merely a convenient sampling frame but a theoretically motivated context. Vietnam is characterized by high collectivism and relatively high uncertainty avoidance (Hofstede, 2001), cultural traits that heighten reliance on in-group opinion and normative social influence when consumers face ambiguity. Under such conditions, peer-sourced validation should be especially diagnostic, and consumers should be particularly attentive to cues of authenticity, so that the amplifying role of social proof—and the penalty for perceived inauthenticity—are expected to be more pronounced than in more individualist markets. Combined with the country’s mobile-first, community-driven commerce and rapid e-commerce growth, this makes Vietnam a strong context in which to observe how different forms of social proof condition the brand image–repurchase intention relationship.

Accordingly, the objective of this study is to examine whether, and under what conditions, three distinct forms of social proof, including UGC, brand ambassadors, and testimonials strengthen or weaken the relationship between brand image and repurchase intention in the Vietnamese digital marketplace. This objective is expressed in three research questions.

RQ1: Does brand image positively influence repurchase intention in an emerging digital marketplace?

RQ2: Do UGC, brand ambassadors, and testimonials moderate the brand image–repurchase intention relationship through distinct mechanisms, and do their moderating effects differ in direction and magnitude?

RQ3: How does the perceived authenticity of social proof condition whether it amplifies or attenuates repurchase intention?

This study contributes to the literature in three ways. First, it refines existing understanding of social proof by identifying the conditions under which it strengthens or weakens the effect of brand image on repurchase intention. Second, it differentiates between distinct forms of social proof—UGC, brand ambassadors, and testimonials—and demonstrates that they operate through different mechanisms, leading to heterogeneous effects. Third, it contributes to the emerging discourse on digital responsibility-oriented value co-creation by highlighting the importance of authenticity and transparency in shaping consumer trust and engagement in digital environments.

2. Literature review and hypothesis development

2.1. Brand image and repurchase intention

Repurchase intention (RPI) refers to the conscious decision a consumer makes to continue purchasing from the same provider based on a favorable evaluation of prior experiences (Do et al., 2025; Ngo et al., 2025). It reflects a forward-looking construct that synthesizes satisfaction, trust, and brand commitment into a behavioral propensity. Recent research conceptualizes RPI as a multidimensional outcome comprising purchase frequency, customer retention, and positive referral behavior, each reflecting a distinct layer of ongoing brand engagement (Ouyang and Mak, 2025; Zhao et al., 2026). In digital marketplaces, RPI is not merely a habitual response but a result of a deliberate psychological evaluation (Nazir et al., 2023). When individual expectations are met or exceeded, internal trust is reinforced; however, in the modern era, this internal conviction is increasingly validated by external market signals and peer endorsements (Kim et al., 2026).

Brand image serves as a key cognitive driver of this evaluation. This conceptualization is rooted in foundational brand-equity theory, in which brand image is defined as the set of brand associations held in consumer memory and constitutes a central source of customer-based brand equity (Aaker, 1991; Keller, 1993). It is commonly conceptualized as the set of functional, emotional, and symbolic associations held in consumer memory, as well as the overall impression derived from these associations (Chang, 2025; Li et al., 2025). These associations serve as information cues that help consumers categorize and evaluate products without exhaustive cognitive effort (Zhang et al., 2025). In the online marketplace, where physical product inspection is impossible, brand image functions as a critical surrogate for quality, reducing the perceived functional and financial risks inherent in digital transactions (Chang, 2025; Kim et al., 2026; Monfort et al., 2025). From an affective perspective, alignment between a brand's symbolic associations and consumers' self-concept fosters emotional attachment, which strengthens commitment and reduces switching behavior (Tosun et al., 2024; Wang et al., 2026).

A positive brand image which is perceived as trustworthy, high-quality, and fashionable creates a reliable expectancy framework for the consumer (Monfort et al., 2025). When a brand consistently delivers on its projected image, it fosters a sense of psychological safety, making the brand the default choice in subsequent purchase cycles to avoid the effort of searching for alternatives (Koll and Plank, 2022). Furthermore, consumers who identify with the symbolic associations of a brand (e.g., status or lifestyle) demonstrate higher levels of affective commitment, which lowers switching propensity and insulates the relationship from competitive pressures (Tosun et al., 2024; Wang et al., 2026). Empirical research also suggests that brand image is a key determinant of sustained consumer engagement and long-term customer value (Chang, 2025; Kim et al., 2026). As consumers trust and become emotionally attached to a brand's projected identity, the brand becomes the primary determinant of their purchasing choice in the digital ecosystem (Diwanji, 2026). Therefore, we propose:

H1. Brand image is positively related to repurchase intention in the online marketplace.

2.2. The role of social proof

Prior research suggests that social proof functions as an important informational and affective mechanism in digital environments. The original principle of social proof, holds that individuals look to the behavior of others to guide their own decisions under uncertainty; contemporary digital-commerce research extends this principle to online settings (Cialdini, 2007). It enables consumers to infer product quality and reduce uncertainty by observing the experiences and behaviors of others (Huang et al., 2025; Kong and Lou, 2026). Huang et al., (2025) demonstrated that social proof

functions as an emotional contagion mechanism, wherein the projected positivity of one consumer's experience propagates through digital networks to shape the purchase dispositions of others. Besides, Kong and Lou, (2026) found that social proof cues-including ratings, review counts, and endorsement signals-measurably reduce consumer hesitation and increase conversion rates. Through processes such as emotional contagion and social validation, social proof can shape consumer evaluations and influence purchase decisions.

Its effectiveness depends on the source of the signal (e.g., peers, experts, or celebrities), as well as the context in which it is interpreted (Pan et al., 2025; Zniva et al., 2023). This heterogeneity suggests that different forms of social proof may reinforce, substitute, or even weaken the influence of brand image, depending on their perceived credibility and authenticity. Building on this perspective (Huang et al., 2025; Kong and Lou, 2026), this study distinguishes between three forms of social proof: user-generated content (UGC), brand ambassadors, and testimonials.

Although the three forms are frequently discussed together, they are conceptually distinct, and clarifying their boundaries is essential because ambassadors and testimonials in particular can both involve celebrities or influencers. We differentiate them along three dimensions. The first is the message source and its relationship to the firm: UGC originates from ordinary, non-contracted consumers; a brand ambassador is a contracted, ongoing, firm-initiated representative; and a testimonial is a discrete endorsement claim that may come from a peer, expert, or celebrity but is evaluated at the level of the individual message rather than an ongoing relationship. The second is the primary persuasion mechanism: UGC operates through peer validation and observational learning, brand ambassadors through aspirational identity transfer and identification, and testimonials through source-credibility-based evaluation (expertise, trustworthiness, and perceived authenticity). The third is commercial transparency: an ambassador relationship is openly understood to be paid, whereas a testimonial's persuasive value hinges on whether the consumer judges it to be genuine or commercially motivated. Because these mechanisms differ, the three forms are modeled here as distinct moderators rather than a single monolithic construct. We further acknowledge that, when consumers encounter these signals simultaneously, they may interact—reinforcing or partially substituting for one another (for example, abundant authentic UGC may reduce reliance on paid ambassadors). The present model specifies the three as independent moderators to isolate each mechanism's conditional effect on the brand image–RPI relationship; the potential higher-order interactions among them are returned to as a boundary condition and a direction for future research.

2.2.1. User-Generated Content (UGC)

User-generated content (UGC) refers to brand-related content created and shared by consumers, including reviews, ratings, and social media posts (Gilardi and Lam, 2024; Xu et al., 2025). Unlike firm-generated content, UGC is perceived as intrinsically more credible because it arises from the genuine experiences of ordinary consumers without overt commercial motivation (Al-Abdallah and Wright, 2025; Gilardi and Lam, 2024). Compared to firm-generated content, UGC is generally perceived as more credible because it reflects the experiences of ordinary consumers and is less likely to be driven by commercial intent (Al-Abdallah and Wright, 2025).

This perceived authenticity plays a critical role in shaping consumer decision-making. UGC provides both informational value (e.g., product performance) and emotional reassurance, thereby reducing uncertainty and increasing confidence in prior brand evaluations (Gauraha et al., 2026; Xu et al., 2025). Consumers exposed to rich

UGC environments are more likely to progress from browsing to purchasing and subsequently to repurchasing (Xu et al., 2025). Similarly, detailed user reviews provide both functional information and emotional reassurance, strengthening the link between brand perceptions and loyalty (Gauraha et al., 2026). This effect extends to multimedia contexts, where positive perceptions of video-based UGC significantly enhance purchase and repurchase intentions (Barsha and Munshi, 2025). When consumers perceive a favorable brand image, consistent and positive peer-generated content confirms and amplifies these evaluations, increasing the likelihood that they will translate into repeat purchase behavior. In digital environments characterized by high information overload, such validation serves as a high-trust signal that reduces decision uncertainty and reinforces behavioral intentions. Accordingly, UGC is expected to strengthen the effect of brand image on repurchase intention.

H2. User-generated content positively moderates the relationship between brand image and repurchase intention.

2.2.2. Brand Ambassadors

Brand ambassadors are individuals—typically celebrities, influencers, or high-profile public figures—contracted to represent a brand and communicate its values to target audiences (Alim et al., 2026; Zameer et al., 2026). Their persuasive mechanism operates through the transfer of aspirational identity, especially consumers who admire or identify with an ambassador's lifestyle, status, or personality are motivated to align their own consumption patterns with the ambassador's brand associations (Al-Abdallah and Wright, 2025). This identity-transfer process is particularly powerful when the ambassador's image is congruent with the brand's own projected identity, creating a mutually reinforcing loop of social validation.

Prior research suggests that brand ambassadors shape consumer decision-making by enhancing the accessibility and credibility of brand-related information. Exposure to familiar ambassadors increases the salience of brand associations, making them easier to retrieve from memory and reducing the cognitive effort required for decision-making (Do et al., 2025; Hu et al., 2026). Ambassador endorsements serve as implicit signals of product quality, as consumers tend to assume that high-status public figures would not associate with inferior products (Hu et al., 2026). Moreover, ambassadors extend the reach of brand communication through their follower networks, generating secondary exposure and user-generated content that further reinforce brand perceptions (Alim et al., 2026). This research suggests that brand ambassadors function as identity-based social proof that reinforces and amplifies consumers' existing brand evaluations. However, the effectiveness of ambassador-based social proof is unlikely to be uniform across levels of brand image, and theory gives clear reasons to expect a bounded effect in place of a monotonically positive one. First, the match-up hypothesis holds that ambassador influence depends on a congruent, meaningfully internalized brand–ambassador fit; where brand associations are weak, aspirational identity transfer has little pre-existing structure to attach to, so ambassador recognition cannot compensate for a deficit of fundamental brand trust (Crespo et al., 2025). Second, when brand image is already strong, the consumer's commitment is largely self-sustaining, and additional ambassador exposure yields diminishing marginal returns—a saturation, or ceiling, dynamic also reflected in the “celebrity-fatigue” and advertising-wearout literatures, in which repeated high-visibility endorsement produces attenuating and eventually negative returns as persuasion knowledge is activated (Friestad and Wright, 1994; Pan et al., 2025). Importantly, a negative interaction coefficient under such a specification would not imply that ambassadors reduce repurchase intention; it would instead constitute the statistical signature of diminishing

returns at high levels of brand image. Taken together, these arguments predict that ambassador moderation is positive at low-to-moderate levels of brand image but flattens, and may reverse, at high levels of brand image. The net effect across the full range of brand image is therefore expected to be a bounded, attenuating moderation rather than a uniformly positive one.

H3. Brand ambassadors moderate the relationship between brand image and repurchase intention in a bounded way: their positive effect is strongest when brand image is moderate, and it weakens and may reverse when brand image is already strong.

2.2.3. Testimonials

Testimonials refers to endorsements provided by celebrities and digital influencers, encompassing both their public product reviews and the authenticity signal conveyed by their personal brand (Alim et al., 2026). The persuasive power of testimonials derives from source credibility theory: a communicator who is perceived as expert and trustworthy produces greater attitude change than one who is not, because message acceptance is conditioned on the perceived credibility of its source (Hovland and Weiss, 1951). Extending this logic to celebrity and influencer endorsement specifically, Ohanian (1990) operationalized source credibility along three dimensions—expertise, trustworthiness, and attractiveness—establishing that an endorser high on these dimensions is better positioned to transfer positive affect and credibility to the endorsed brand. Building on this foundation, contemporary research confirms that testimonials perceived as expert, trustworthy, and genuine remain more persuasive in digital-influencer settings (Alam et al., 2024). Prior research indicates that testimonials can significantly influence consumer decision-making, particularly when they are perceived as genuine and not as commercially motivated (Lee, 2026).

In such cases, testimonials could enhance the credibility of brand-related information and reinforce consumers' confidence in their evaluations. However, consumers are increasingly sensitive to the distinction between authentic endorsements and scripted promotional content, especially in digital environments where persuasive intent is more transparent (Alim et al., 2026). As a result, testimonials that lack perceived authenticity may trigger persuasion resistance and weaken their effectiveness (Alam et al., 2024). This suggests that the influence of testimonials is contingent on their perceived credibility. High credibility reinforces existing brand perceptions and facilitates the translation of brand image into repurchase intention, whereas low credibility attenuates this relationship. It is important to distinguish testimonials from brand ambassadors, which are conceptually adjacent but not interchangeable. Whereas a brand ambassador denotes an ongoing, firm-initiated, and openly contracted representation whose persuasive force operates through aspirational identity transfer, a testimonial is a discrete, message-level endorsement whose persuasive force operates through source-credibility-based evaluation of a specific claim (Ohanian, 1990; Alam et al., 2024). In other words, an ambassador is a relationship that the consumer attributes to a paid arrangement, whereas a testimonial is an evaluative claim judged primarily on its perceived authenticity and expertise. Because the two constructs are anchored in different theoretical mechanisms—identification versus source credibility—we model them as distinct moderators and later provide empirical evidence (separate factor structure and discriminant-validity indices) that consumers evaluate them along separable dimensions. Accordingly, and contingent on perceived credibility, testimonials are expected to strengthen the relationship between brand image and repurchase intention.

H4. Authentic testimonials strengthen the relationship between brand image and repurchase intention, whereas testimonials seen as commercially motivated weaken it to the point where a favorable brand image no longer converts.

Integrating these hypotheses, this study proposes a conceptual framework in which brand image serves as the independent variable, repurchase intention is the dependent variable, and the three dimensions of social proof (i.e., UGC, brand ambassadors, and testimonials-function) as simultaneous moderators of the brand image-RPI relationship (see Figure 1).

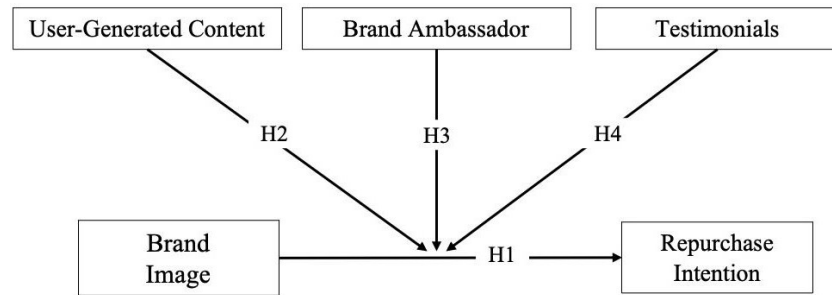


Figure 1. Proposed Theoretical Framework

3. Methods and measurements

This paper adopts a mixed-methods design, integrating automated sentiment analysis (Study 1) with a cross-sectional survey (Study 2). The rationale for this dual-study approach is twofold. First, while surveys effectively capture structured behavioral intentions, they are susceptible to self-reporting biases. By incorporating sentiment analysis of organic consumer discourse, this research captures authentic, unsolicited reactions to social proof mechanisms in a real-world setting. Second, qualitative nuances extracted from digital comments provide empirical depth to the quantitative relationships established through regression analysis, ensuring that findings on repurchase intentions are not only statistically significant but also contextually grounded in the Vietnamese digital marketplace.

3.1. Study 1

3.1.1. Data collection and extraction process

Study 1 is exploratory and triangulating rather than confirmatory: its purpose is to surface the authentic consumer vocabulary that motivates the constructs and to provide convergent contextual evidence for the relationships formally tested through the moderated regression in Study 2 (Meng et al., 2026). Study 1 captures organic, real-time sentiment polarity across influencer archetypes, whereas Study 2 quantifies how these distinct social proof dimensions condition the structural conversion of brand image into repurchase intention. Together, the two studies offer a triangulated understanding of social proof as both a natural linguistic signal and a psychometric moderator.

Study 1 conducted a sentiment analysis on YouTube to measure actual user responses to various types of social proof, where top Vietnamese YouTubers spanning cosmetics, technology, fashion, and lifestyle were identified. To ensure a comprehensive and robust dataset, five key influencers representing diverse product categories were selected:

Vo Ha Linh (Cosmetics; 2.22 million subscribers), Ngo Duc Duy (Duy Tham) (Technology; 2.19 million subscribers), Trinh Pham (Beauty; 1.20 million subscribers), Chau Bui (Fashion/Beauty; 715,000 subscribers), and Co Em Trendy (Lifestyle; 250,000 subscribers). For each influencer, one representative video was selected based on three criteria: (1) the video focused on a cosmetics, fashion, or technology review; (2) the video had more than 100 public comments; and (3) the video clearly demonstrated the role of either a brand ambassador or organic user experience.

Vo Ha Linh was chosen for her reputation as a high-credibility reviewer known for brutally honest testimonials; her content frequently triggers significant sentiment polarity, providing an ideal dataset to examine how authentic, unscripted social proof moderates brand perception. Second, Ngo Duc Duy (Duy Tham) represents the high-involvement technology sector; his detailed comparisons of high-value electronics address scenarios where consumers face significant information overload and financial risk. Third, Trinh Pham represents long-term community trust; as a pioneering beauty blogger, her longitudinal audience interactions offer insights into how established influencer-follower relationships sustain repurchase intentions over time. Fourth, Chau Bui was included as the archetype of the Brand Ambassador, with high-profile collaborations with international luxury houses allowing direct investigation of whether celebrity-led social proof can reduce consumer skepticism in premium markets. Finally, Co Em Trendy (Khanh Linh) captures aspirational dimensions-her content seamlessly integrates high-fashion aesthetics with brand storytelling, serving as a proxy for lifestyle-based social proof.

Data extraction was conducted using a custom Python script interfacing with the YouTube Data API v3 (Barsha and Munshi, 2025). A looping mechanism with page tokens ensured exhaustive retrieval of all comment threads, eliminating researcher bias from manual sampling. Extracted metadata included video-level statistics (likes, comment count, duration) and comment-level data (raw text, emoji, author identifiers, publishing timestamps, and like counts). Like counts served as a secondary weight to identify high-engagement comments reflecting broader community consensus.

3.1.2. Sentiment analysis method: The Unified Multi-Domain Lexicon (UMDL)

To quantify the qualitative interactions within the Vietnamese digital marketplace, this study employed a hybrid Natural Language Processing (NLP) approach. This method integrates the computational power of a deep learning architecture with a custom-built Unified Multi-Domain Lexicon (UMDL) to ensure granular accuracy across diverse product categories (Suresh Kumar et al., 2022; Ray and Singh, 2025). Specifically, the core text classifier was built on the pre-trained ‘vinai/phobert-base’ checkpoint, a state-of-the-art architecture optimized specifically for the linguistic tokenization and word segmentation of the Vietnamese language. Instead of using the model without modification, we fine-tuned it on a manually annotated, domain-specific dataset of 2,000 Vietnamese e-commerce and social commerce comments using an 80/10/10 train-validation-test split to capture contextual consumer expressions (Gauraha et al., 2026). The fine-tuning sequence length was locked at 256 tokens, optimized via AdamW with an initial learning rate of 2×10^{-5} over 3 epochs with a batch size of 16. According to Madathil (2025), utilizing an automated sentiment framework in this manner yields granular insights into organic consumer perceptions that traditional, static psychometric scales often fail to detect.

The process began with a rigorous filtering of YouTube content to isolate videos featuring UGC, brand ambassadors, and testimonials. Keyword-based searches on selected channels identified high-viewership, high-

engagement videos (Madathil, 2025). To ensure statistical reliability, inclusion was restricted to videos with at least 100 public comments (Penttinen et al., 2026).

In the second phase, an automated extraction was executed using a custom Python script interfacing with the YouTube Data API v3 (Barsha and Munshi, 2025). By implementing a looping mechanism with page tokens, the study ensured an exhaustive retrieval of all comment threads, thereby eliminating potential researcher bias inherent in manual sampling. The extracted metadata encompassed video-level statistics (likes, comment count, and durations) and channel-level data (subscriber counts and starting date) to proxy for influencer authority. Specifically, raw comment text including emoji, comment ID, author identifiers, comment publishing time and like counts of comments were structured into a consistent data frame, with like counts serving as a secondary weight to identify high-engagement comments that reflect broader community consensus on social proof.

The final phase involved data cleaning and sentiment classification anchored by the UMDL framework. After removing bot-generated spam, the RoBERTa model was utilized for its superior ability to handle Vietnamese linguistic nuances (Gauraha et al., 2026). However, to overcome the contextual limitations of off-the-shelf deep learning architectures in domain-specific e-commerce markets, the UMDL was integrated to supply granular contextual signals for sentiment classification (see Table 1). For the cosmetics category, the lexicon identifies sensory-based positive cues such as “mượt” (smooth) and “căng bóng” (glowing). For the technology sector, it prioritizes functional performance indicators like “mượt” (lag-free) and “pin trâu” (long battery life).

To insulate our sentiment mapping from potential 'echo chamber' biases where hyper-focused fan sentiment dominates comment feeds under influencer videos, we implemented a rigorous two-step data cleansing framework. First, a token-filtering regular expression sweep programmatically excluded comments that focused exclusively on the influencer’s physical appearance, personal charisma, or general lifestyle (e.g., “Chị Hà Linh mãi đỉnh” which mean “Ha Linh is the best”, “Duy đẹp trai quá” which means “Duy is so handsome”) without making any explicit reference to a product, brand attribute, functional feature, or transactional intention. Second, following contemporary automated text analysis guidelines in digital marketing (Krugmann and Hartmann, 2024), raw comment-level like counts were utilized as a mathematical weighting factor during final polarity aggregation. This process ensured that high-engagement peer consensus regarding product functionality carried a higher statistical weight than isolated, uncritical praise, allowing the mapped sentiment ratios to reflect authentic market-driven consensus.

Sentiment was classified into positive and negative polarities to highlight consumer psychological shifts (Krugmann and Hartmann, 2024). Positive sentiments were specifically scrutinized for indicators of Repurchase Intention, captured through linguistic anchors defined in the UMDL such as “chốt đơn” (order placed), “mua lại” (repurchase), or “trung thành” (loyal). Conversely, negative sentiments were analyzed to identify consumer skepticism or irritation (e.g., “nổi mụn”, “ngáo giá”). By mapping these polarized sentiment scores against specific social proof types, the study established an empirical baseline to triangulate and validate the findings derived from the subsequent survey-based study.

To formally validate the classification performance of this integrated RoBERTa-UMDL approach, a random validation subset (N = 500 comments) was subjected to double-blind manual labeling by two independent native-Vietnamese research annotators (Meng et al., 2026). To ensure that the human ground-truth benchmark was

statistically robust and free from subjective drift, inter-annotator agreement was quantified using Cohen’s Kappa (κ), formulated as follows:

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$

Where p_o represents the relative observed agreement among the annotators, and p_e represents the hypothetical probability of chance agreement. The inter-annotator check demonstrated exceptional reliability, achieving a coefficient of $\kappa = 0.84$, which comfortably exceeds the strict $\kappa > 0.81$ threshold for 'almost perfect' agreement, with remaining minor discrepancies adjudicated by a third senior researcher. Evaluated directly against this validated human gold standard, the performance of the fine-tuned RoBERTa-UMDL processing pipeline was evaluated using standard classification metrics derived from True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = 89.2\%$$

$$\text{Precision} = \frac{TP}{TP + FP} = 88.7\%$$

$$\text{Recall} = \frac{TP}{TP + FN} = 89.5\%$$

The overall harmonic mean of precision and recall was captured via the F1-Score:

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} = 2 \times \frac{0.887 \times 0.895}{0.887 + 0.895} = 0.891$$

This tightly coupled matrix of metrics offers a vital logical argument for the study's empirical validity. First, because the human agreement baseline is highly reliable ($\kappa = 0.84$), the resulting gold standard serves as a dependable testbed. Second, the machine pipeline's accuracy (89.2%) closely approaches the theoretical upper bound of human consensus. Third, the minimal divergence between Precision (88.7%) and Recall (89.5%) logically confirms that the classifier does not suffer from systematic algorithmic bias or class imbalance problems across the positive (purchase-conducive) and negative (skeptical) polarities within the Vietnamese digital discourse.

Table 1. The Unified Multi-Domain Lexicon (UMDL) for sentiment classification

Dimension	Category	Positive Keywords (+)	Negative Keywords (-)
Performance & Quality	Cosmetics	mướt (smooth), mịn (supple), căng bóng (glowing), kiểm dầu (oil-control), trắng da (whitening), hiệu quả (effective)	kích ứng (irritation), nổi mụn (breakouts), banh mặt (skin-damaged), bết rít (greasy), khô da (dryness)

	Technology	mượt (smooth/lag-free), nhanh (fast), mạnh (powerful), pin trâu (long battery life), nét (sharp), tối ưu tốt (well-optimized)	lag (stutter), nóng máy (overheating), nhanh hết pin (battery drain), lỗi (bug), yếu (weak)
Value & Brand Image	Cosmetics	sang chảnh (luxurious), tinh tế (elegant), hiện đại (modern), quốc dân (popular/top-tier), xịn xò (premium)	rẻ tiền (cheap/low-quality), phèn (tacky), bao bì ghê (poor packaging), thiếu uy tín (unreliable)
	Technology	đáng mua (worth buying), hời (bargain), p/p cao (high price/performance), đáng tiền (worth the money), nâng cấp xứng đáng (worthy upgrade)	đắt (expensive), ngáo giá (overpriced), phí tiền (waste of money), hút máu (exploitative pricing)
Trust & Social Proof	Cosmetics	chuẩn auth (authentic), uy tín (credible), tin tưởng (trustworthy), chính hãng (official), review có tâm (honest review)	hàng fake (counterfeit), hàng giả (fake), kem trộn (unverified cream), lừa đảo (scam), quảng cáo lố (over-advertised)
	Technology	tư vấn có tâm (honest advice), kiến thức sâu (deep expertise), khách quan (objective), phân tích hay (insightful analysis)	lừa gà (manipulative), nói quá (exaggerated), thiếu thực tế (unrealistic), đim hàng (unfair criticism)
Repurchase Intention	Cosmetics	mua lại (repurchase), trung thành (loyal), chốt đơn (order placed), chân ái (holy grail), ủng hộ dài dài (long-term support)	cạch mặt (boycott), không mua lại (no repurchase), hối hận (regret), bỏ xó (discarded)
	Technology	xuống tiền (ready to buy), dọn đường lên đời (preparing for upgrade), mức ngay (buy immediately), không hối hận (no regret)	thôi bỏ qua (skip), không đáng đời (not worth upgrading), giữ máy cũ (keep old device)

3.1.3. Results

The implementation of an automated sentiment classification model across five representative influencer groups provides empirical evidence of consumer responses toward various social proof mechanisms. To highlight the psychological impact of social proof on brand perception, this study specifically visualizes the positive and negative polarity of the discourse. By filtering out non-emotive interactions, the study indicates the specific linguistic cues that moderate the relationship between brand image and repurchase intention behavior.

Figure 2 shows that the sentiment distribution reveals significant variance in emotional resonance across different influencer types. The data reveal a critical tension between authenticity and skepticism, particularly within the cosmetics sector. Despite being a highly trusted reviewer, Vo Ha Linh recorded a negative sentiment ratio of 55.96%

within the polarized dataset. Qualitative inspection suggests that this negativity is driven by intense debates regarding product efficacy, characterized by terms such as “irritation” and “breakouts”. This high emotional polarity serves as a “trust filter”; consumers perceive the presence of critical discourse as a hallmark of transparency, which ultimately reinforces the credibility of the social proof.

Conversely, Co Em Trendy achieved the highest positive sentiment ratio (59.57%), indicating that aesthetic-driven UGC and lifestyle social proof are exceptionally effective at stimulating emotional resonance and mitigating perceived risk for experience-based products. In the technology sector, Ngo Duc Duy (Duy Tham) performed a perfectly balanced polarity (50%), reflecting a highly rational consumer base. In this high-involvement segment, the dialogue is split between technical endorsement and critical functional comparison, confirming that expert testimonials function as a stabilizing trust anchor for complex purchasing decisions.

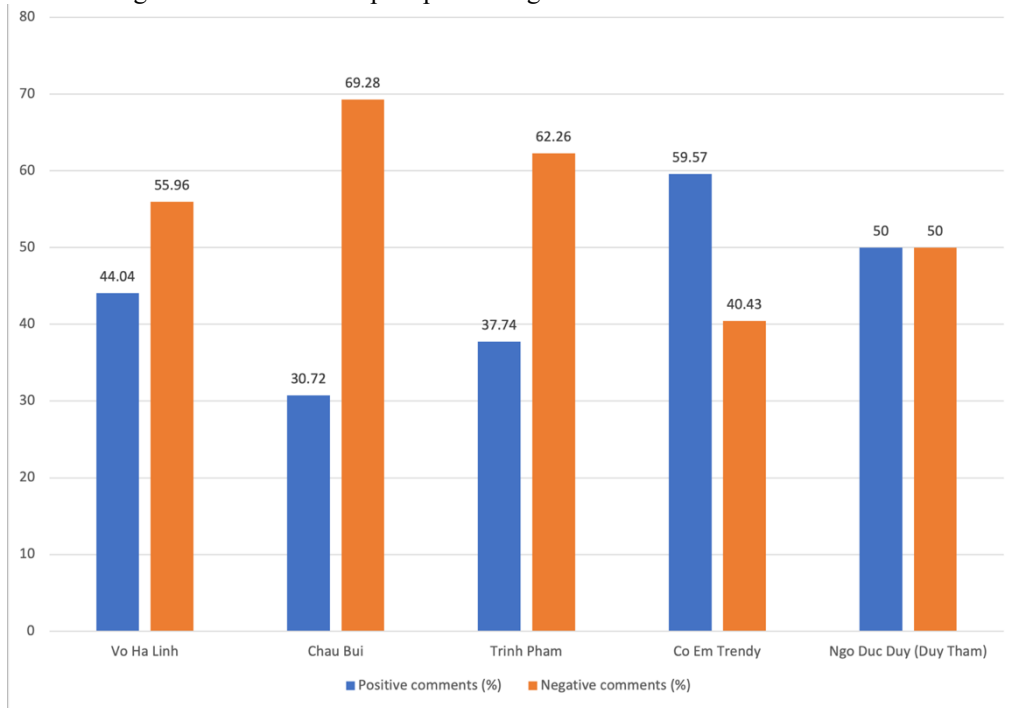


Figure 2. Sentiment distribution by influencer and social proof type

The thematic drivers of these sentiments are further decoded through the positive word clouds in Vietnamese (see Figure 3) and positive word clouds in English (see Figure 4). For experience-based categories, positive sentiment is anchored in sensory and trust-based terms such as “smooth” (mượt/muọt), “glowing” (căng bóng), and “authentic” (chuẩn auth). In the technology domain, the discourse shifts toward performance, with dominant terms including “powerful” (mạnh) and “fast” (nhanh). The consistent appearance of action-oriented terms like “order placed” (chốt đơn) and “trust” (tin tưởng) across both sectors confirms that social proof effectively reduces consumer anxiety and fosters repurchase intentions. These polarized patterns provide a robust empirical baseline that triangulates the quantitative survey findings in Study 2.

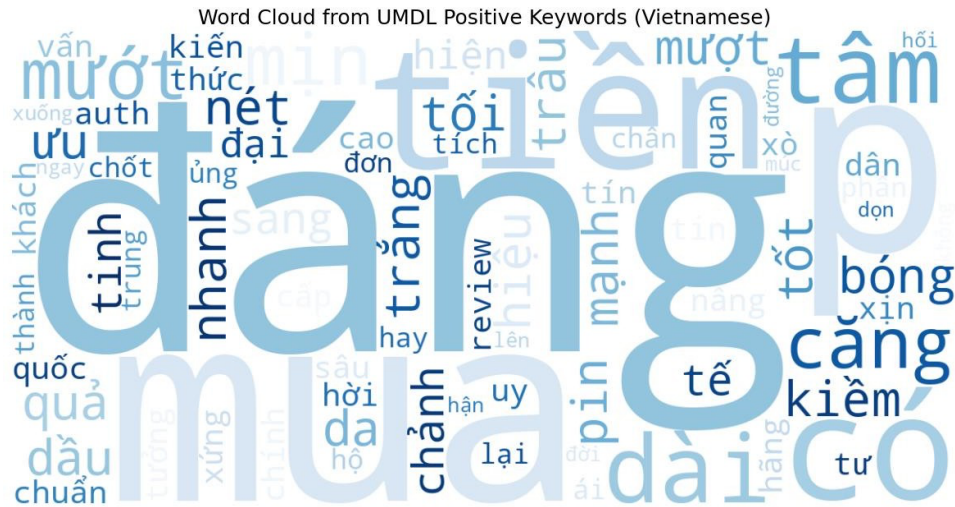


Figure 3. Word cloud of Positive Keywords extracted from users' comments in Vietnamese words

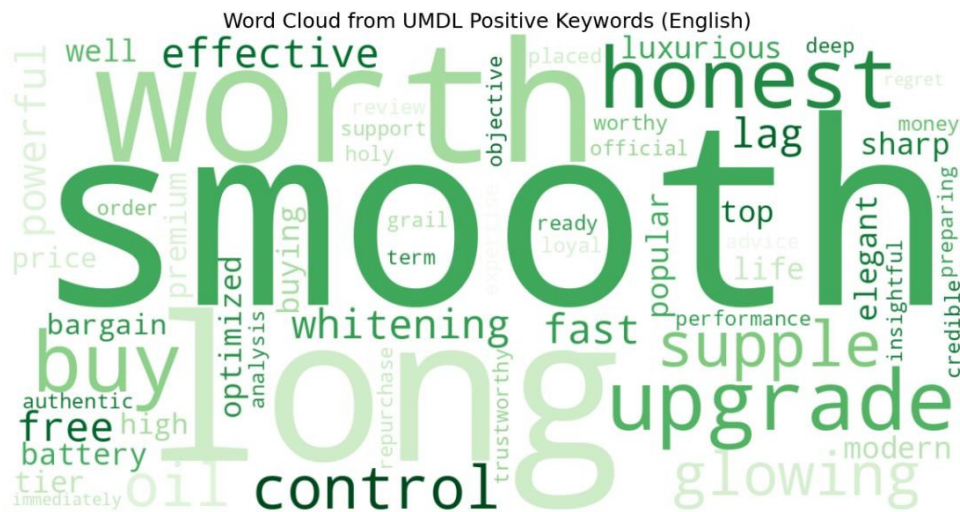


Figure 4. Word cloud of Positive Keywords extracted from users' comments in English words

3.2. Study 2

3.2.1. Procedure, data cleaning and sample size justification

Data were collected over an eight-week period, using a web-based survey through the Surveycake platform. The recruitment strategy utilized a convenience sampling approach, with invitation messages distributed via major social media channels, including Facebook groups and Messenger, targeting active consumers within the Vietnamese e-commerce ecosystem.

The questionnaire was structured into three distinct sections: (1) demographic profiles, (2) filter and screening items to confirm eligibility, and (3) substantive measurement scales adapted from established literature. To ensure data quality and minimize memory bias, the survey incorporated a two-stage filtering process. First, screening questions were used to verify that respondents had made at least one purchase on an online marketplace in Vietnam

within the previous six months. Second, participants were explicitly required to center their responses on their most recent transactional experience, identifying the specific platform used. This contextual focus approach reduces retrospective bias and ensures that the measurement items are evaluated based on concrete, active shopping experiences, not as general perceptions.

Although online recruitment was used for practical access, the sampling was not open-ended but purposive and screened toward the study's focal population. Eligibility screening admitted only consumers who had completed at least one marketplace purchase in Vietnam within the preceding six months, ensuring that respondents were qualified and recently active e-commerce shoppers, not a general or student sample recruited for convenience. Importantly, the resulting demographic profile, young, digitally native, and highly engaged social-media users, is not incidental but corresponds to the theoretically relevant population for this study: these are precisely the consumers who are most exposed to, and most influenced by, the influencer-based and user-generated social-proof mechanisms under investigation, and who constitute the dominant segment of Vietnam's social-commerce market (Dang-Van et al., 2026). The sample should therefore be understood as representative of this focal consumer population, not of the general adult population. We nonetheless acknowledge that this focus limits generalizability to older, less digitally engaged, or offline consumer segments, and we call for probability- and quota-based replication across broader demographic and geographic groups.

To ensure high data quality and rigorous methodological standards, a comprehensive data cleaning procedure was implemented prior to hypothesis testing (Curran, 2016; Hair et al., 2019; Tabachnick & Fidell, 2019). First, eligibility screening verified that all participants were active online shoppers residing in Vietnam who had completed at least one online marketplace purchase within the preceding six months, eliminating unqualified responses. Second, the dataset was screened for unengaged completion patterns and speeding behavior. Specifically, responses exhibiting zero or near-zero variance across Likert scale items (i.e., straight-lining) as well as speeders who completed the survey in under 120 seconds were removed to eliminate non-thoughtful completion noise. Third, multivariate outliers were programmatically identified and removed using Mahalanobis distance (D^2) evaluated against a chi-square distribution with 17 degrees of freedom (corresponding to the total number of latent observed measurement items) at $p < 0.001$. Responses exceeding the critical threshold (chi-square = 40.79) were categorized as multivariate outliers and excluded. From the initial $N = 428$ raw responses collected, this three-stage data cleaning pipeline identified and removed 34 invalid or outlier cases, yielding a final, clean analytical sample of $N = 394$ valid responses. Removing this non-random measurement error restored true item covariances and elevated all indicator outer loadings well above the recommended 0.708 threshold.

Furthermore, to demonstrate that the final sample size ($N = 394$) is statistically adequate for testing the conceptual model, a formal power analysis was conducted using G*Power 3.1 (Faul et al., 2007). For a multiple moderated regression model containing seven predictors (one independent variable, three main moderators, and three product interaction terms) at a standard significance level of $\alpha = 0.05$ and a medium effect size ($f^2 = 0.15$), the minimum sample size required to achieve a statistical power = 0.95 is $N = 153$ ($N = 103$ for power = 0.80). Our final sample size of $N = 394$ substantially exceeds these required thresholds. A post-hoc power analysis based on the observed regression model ($R^2 = 0.207, f^2 = 0.261$) confirms an actual statistical power exceeding 0.999, demonstrating that the

dataset possesses robust statistical power to detect hypothesized direct and moderating relationships without risk of Type II error (Cohen, 1988; Faul et al., 2007).

3.2.2. Measurement scales

All constructs were measured using established multi-item scales drawn from prior research (see Table 2). Repurchase Intention (RPI) was measured with three items adapted from Nazir et al. (2023). Brand Image (BI) was measured with four items from Tafolli et al. (2025). User-Generated Content (UGC) was measured using four items drawn from Al-Abdallah and Wright (2025) and Ho et al. (2026). Brand Ambassador (BA) was assessed with three items from Crespo et al. (2025), and Testimonials (TES) with three items from Ul Haq et al. (2026). All items used a five-point Likert scale ranging from “strongly disagree” to “strongly agree”.

Table 2. Measurement scale for Variables

Latent Variable	Observed Variables	Measurement Items	Source
Repurchase Intention (RPI)	RPI1-RPI3	1. I intend to continue purchasing product from the online marketplace I regularly use; 2. I intend to recommend the online marketplace that I regularly use to people around me; 3. I intend to use the online marketplace that I regularly use as the priority for future purchases	(Nazir et al., 2023)
Brand Image (BI)	BI1-BI4	1. The brand is fashionable and trendy; 2. The name brand is well known for its high level of quality; 3. The brand is elegant; 4. The brand is sophisticated	(Tafolli et al., 2025)
User-Generated Content (UGC)	UGC1-UGC4	1. UGC's information about the product is comprehensive, clear, and specific; 2. I have a positive attitude toward brand-related content created by other users; 3. UGC's information is reliable and credible; 4. UGC's information gives me confidence in the product and brand	(Al-Abdallah and Wright, 2025; Ho et al., 2026)
Brand Ambassador (BA)	BA1-BA3	1. I can easily recall products represented by specific celebrities; 2. I am able to remember products very easily because celebrities are featured in their ads; 3. Brand ambassador's successes are my successes	(Crespo et al., 2025)
Testimonials (TES)	TES1-TES3	1. Celebrity authenticity is genuine; 2. I believe online celebrities' product endorsements; 3. Celebrity authenticity is authentic	(Ul Haq et al., 2026)

3.2.3. Sample demographic profile

The final sample comprised 394 valid responses from active Vietnamese online consumers. The demographic distribution was relatively balanced in terms of gender, 51.8% were female ($n = 204$) and 48.2% male ($n = 190$). The age distribution reflected a young, digitally native cohort: 86.8% of respondents were aged 20–29 ($n = 342$), 7.9% aged 18–19 ($n = 31$), and 5.3% aged 30 or older ($n = 21$). In terms of occupation, 49.2% were students ($n = 194$) and 38.6% office professionals ($n = 152$).

Income distribution showed 26.6% earning below 5 million VND/month, 24.9% earning 5–10 million VND, 19.5% earning 10–15 million VND, 18.0% earning 15–20 million VND, and 10.9% earning above 20 million VND. Their digital engagement was notably high with over 87% used smartphones over 3 hours daily. Regarding platform preference, Shopee was the dominant e-commerce marketplace (85.5%), followed by Lazada (8.6%) and Tiki (3.3%). These characteristics align with the target population of active online shoppers who are frequently exposed to various social proof mechanisms in the Vietnamese e-commerce ecosystem.

3.2.4. Measurement model assessment: Reliability and Validity Tests

Construct reliability and validity was assessed using SmartPLS 3 with all composite reliability (CR) values and the average variance extracted (AVE) exceeded the thresholds ($CR > 0.70$, $AVE > 0.50$) (Hair et al., 2019). Specifically, all constructs demonstrated excellent internal consistency and convergent validity (see Table 3): Brand Ambassador (Cronbach's $\alpha = 0.821$, $CR = 0.894$, $AVE = 0.738$), Brand Image (Cronbach's $\alpha = 0.794$, $CR = 0.864$, $AVE = 0.616$), Repurchase Intention (Cronbach's $\alpha = 0.839$, $CR = 0.903$, $AVE = 0.757$), Testimonials (Cronbach's $\alpha = 0.824$, $CR = 0.884$, $AVE = 0.719$), and User-Generated Content (Cronbach's $\alpha = 0.840$, $CR = 0.881$, $AVE = 0.651$). The square roots of AVE ranged from 0.785 to 0.870 (see Table 3).

Discriminant validity was established through Fornell-Larcker criteria (square root of AVE for each construct on the diagonal exceeded all off-diagonal construct correlations) (Fornell and Larcker, 1981) (see Table 4). Outer VIF values ranged from 1.408 to 2.700, and inner VIF values ranged from 1.290 to 1.500, establishing the absence of collinearity (Hair et al., 2019). Overall PLS model fit was acceptable ($SRMR = 0.090$, $NFI = 0.683$).

Table 3. Construct reliability and convergent validity

Construct	Cronbach's α	Composite Reliability (CR)	Average Variance Extracted (AVE)
Brand Ambassador (BA)	0.821	0.894	0.738
Brand Image (BI)	0.794	0.864	0.616
Repurchase Intention (RPI)	0.839	0.903	0.757
Testimonials (TES)	0.824	0.884	0.719
User-Generated Content (UGC)	0.840	0.881	0.651

Table 4. Discriminant Validity (Fornell-Larcker Criterion)

Construct	BA	BI	RPI	TES	UGC
BA	0.859				
BI	0.199	0.785			
RPI	0.324	0.251	0.870		
TES	0.507	0.304	0.093	0.848	
UGC	0.421	0.451	0.151	0.396	0.807

Outer item factor loadings across all constructs were exceptionally strong and comfortably exceeded the recommended 0.708 benchmark (Hair et al., 2019): Brand Ambassador (BA1 = 0.880, BA2 = 0.920, BA3 = 0.771), Brand Image (BI1 = 0.701, BI2 = 0.845, BI3 = 0.848, BI4 = 0.733), Repurchase Intention (RPI1 = 0.884, RPI2 = 0.892, RPI3 = 0.833), Testimonials (TES1 = 0.939, TES2 = 0.768, TES3 = 0.828), and User-Generated Content (UGC1 = 0.823, UGC2 = 0.704, UGC3 = 0.842, UGC4 = 0.851) (see Table 5).

Table 5. Outer item factor loadings analysis

	BA	BI	RPI	TES	UGC
BA1	0.880				
BA2	0.920				
BA3	0.771				
BI1		0.701			
BI2		0.845			
BI3		0.848			
BI4		0.733			
RPI1			0.884		
RPI2			0.892		
RPI3			0.833		
TES1				0.939	
TES2				0.768	
TES3				0.828	
UGC1					0.823
UGC2					0.704
UGC3					0.842
UGC4					0.851

3.2.5. Regression analysis and hypothesis testing

To evaluate the hypothesized direct and moderating relationships, the cleaned sample ($N = 394$) was analyzed using two complementary and jointly reported specifications, with Repurchase Intention (RPI) as the dependent variable in both. First, continuous moderated regression was estimated with the PROCESS macro for SPSS (Model 1; Hayes, 2013). Brand Image (BI) and each social proof dimension – User-Generated Content (UGC), Brand Ambassador (BA) and Testimonials (TES) were mean-centered before computing the product term, and the conditional effect of brand image was probed at the mean and at ± 1 SD of the moderator. Second, each relationship was re-estimated as a 3×3 two-way factorial Analysis of Variance (ANOVA) in which brand image and the moderator were visually binned into Low, Medium and High categories. The second specification is not a robustness check but a substantive requirement of the model: H3 predicts a bounded interaction whose sign reverses across the range of brand image, and a single linear product term estimates only one average change in slope and therefore cannot represent such a form. Reporting both models allows the shape of each interaction, and not merely its average magnitude, to be tested. Mean-centering held collinearity well within accepted limits (all VIF < 2.0 , far beneath the critical threshold of 10 recommended by Hair et al., 2013). All three continuous models were significant ($R^2 = .072$ to $.135$, $p < .001$) (see Table 6), as were all three factorial models ($R^2 = .077$ to $.223$, $p < .001$) (see Table 7).

The categorical specification carries a known cost that we acknowledge explicitly. Dichotomizing or trichotomizing continuous predictors discards within-category variance, reduces statistical power, and where the binned variables are themselves correlated can in principle inflate an interaction term that does not exist in the underlying continuous data (Cohen, 1983; MacCallum et al., 2002; Rucker et al., 2015). We therefore do not treat the factorial model as a superior representation of the data, nor do we substitute it for the continuous specification. Its role is narrower and was specified a priori: H3 predicts a moderating effect whose sign reverses across the range of brand image, and a linear product term consumes a single degree of freedom and can express only one average change in slope. The 4-df interaction term of the 3×3 design is a cell-mean model that permits departures from additivity of any functional form, including sign reversal, and is therefore the minimum specification capable of testing the hypothesis as stated. Both models are reported in full so that readers may weigh the linear and non-linear evidence directly.

Three features of the results mitigate the concern that the factorial findings are artifacts of binning. First, the two specifications converge wherever they are capable of converging: the non-significant main effects of UGC ($F(2, 385) = 0.811$, $p = .445$) and testimonials ($F(2, 385) = 1.408$, $p = .246$) reproduce the continuous estimates for the same terms ($\beta = -0.018$, $p = .710$; $\beta = -0.062$, $p = .097$), and the significant main effects of brand image and brand ambassadors likewise hold under both. The specifications diverge on exactly one parameter, the brand image $\times$ brand ambassador interaction, which is the parameter for which divergence was predicted. Second, the magnitude of that divergence is not marginal: the BI $\times$ BA interaction accounts for a partial η^2 of $.073$, a medium effect by conventional benchmarks (Cohen, 1988), which is not the profile of a chance result surfacing through categorization. Third, the ordering of interaction effect sizes across the three moderators, BI $\times$ UGC (partial $\eta^2 = .026$), BI $\times$ BA ($.073$) and BI $\times$ TES ($.172$), is theoretically motivated and not arbitrary, and reproduces the ordering obtained from the continuous ΔR^2 values ($.013$, $.003$ and $.062$ respectively) for the two moderators whose form is linear.

Effect sizes for the factorial models are reported as partial η^2 in Table 7. The brand image $\times$ testimonials interaction is the single largest source of variance in the study (partial $\eta^2 = .172$), exceeding every main effect in the design, whereas testimonials exert almost no independent influence (partial $\eta^2 = .007$). This asymmetry is the central quantitative signature of the credibility-filter mechanism developed below.

Table 6. Moderated regression results (PROCESS Model 1, $N = 394$)

Predictor	β	SE	t	p	95% CI
Model 1: BI $\times$ UGC $R^2 = .072$, $F(3, 390) = 10.020$, $p < .001$					
Brand Image (BI)	0.203	0.046	4.395	< .001	[0.112, 0.294]
User-Generated Content (UGC)	-0.018	0.049	0.372	.710	[-0.114, 0.078]
BI $\times$ UGC ($\Delta R^2 = .013$, $F(1, 390) = 5.664$)	0.131	0.055	2.380	.018	[0.023, 0.240]
Model 2: BI $\times$ BA $R^2 = .135$, $F(3, 390) = 20.364$, $p < .001$					
Brand Image (BI)	0.157	0.042	3.741	< .001	[0.074, 0.239]
Brand Ambassador (BA)	0.185	0.033	5.513	< .001	[0.119, 0.251]
BI $\times$ BA ($\Delta R^2 = .003$, $F(1, 390) = 1.243$)	0.048	0.043	1.115	.266	[-0.037, 0.132]
Model 3: BI $\times$ TES $R^2 = .120$, $F(3, 390) = 17.662$, $p < .001$					
Brand Image (BI)	0.183	0.043	4.232	< .001	[0.098, 0.268]
Testimonials (TES)	-0.062	0.037	-1.664	.097	[-0.134, 0.011]
BI $\times$ TES ($\Delta R^2 = .062$, $F(1, 390) = 27.686$)	0.266	0.051	5.262	< .001	[0.167, 0.366]

Note. $N = 394$. Unstandardized coefficients (β) from PROCESS Model 1 (Hayes, 2013); predictor and moderator mean-centered prior to computing the product term. ΔR^2 is the increment in explained variance attributable to the interaction term.

Table 7. Two-way factorial ANOVA results ($N = 394$)

Model	SS	df	MS	F	p	Partial η^2
Model 1: BI $\times$ UGC $R^2 = .077$ (adj. $R^2 = .058$)						
Brand Image (binned)	3.424	2	1.712	5.727	.004	.029
UGC (binned)	0.485	2	0.242	0.811	.445	.004
BI $\times$ UGC	3.026	4	0.757	2.531	.040	.026
Model 2: BI $\times$ BA $R^2 = .207$ (adj. $R^2 = .191$)						
Brand Image (binned)	6.355	2	3.178	12.370	< .001	.060
BA (binned)	11.443	2	5.722	22.273	< .001	.104
BI $\times$ BA	7.786	4	1.947	7.577	< .001	.073
Model 3: BI $\times$ TES $R^2 = .223$ (adj. $R^2 = .207$)						

Brand Image (binned)	3.199	2	1.599	6.350	.002	.032
TES (binned)	0.709	2	0.354	1.408	.246	.007
BI $\times$ TES	20.141	4	5.035	19.994	< .001	.172

Note. $N = 394$; corrected total $SS = 124.739$ ($df = 393$) in all three models. Type III sums of squares. Each construct was binned into Low, Medium and High categories by visual binning prior to estimation.

The direct effect of brand image on repurchase intention was positive and statistically significant in every specification, providing robust empirical support for H1. In the continuous models, the effect of brand image estimated at the mean of the moderator ranged from $\beta = 0.157$ ($SE = 0.042$, $t = 3.741$, $p < .001$) in the ambassador model, through $\beta = 0.183$ ($SE = 0.043$, $t = 4.232$, $p < .001$) in the testimonial model, to $b = 0.203$ ($SE = 0.046$, $t = 4.395$, $p < .001$) in the UGC model. The factorial models converge on the same conclusion: the main effect of binned brand image was significant in the ambassador model ($F(2, 385) = 12.370$, $p < .001$, Sum of Squares = 6.355), the testimonial model ($F(2, 385) = 6.350$, $p = .002$) and the UGC model ($F(2, 385) = 5.727$, $p = .004$). Favorable cognitive and symbolic brand associations held in consumer memory therefore serve as a quality surrogate that lowers perceived transactional risk and directly stimulates repeat purchasing.

The interaction between brand image and UGC was positive and significant ($\beta = 0.131$, $SE = 0.055$, $t = 2.380$, $p = .018$, 95% CI [0.023, 0.240]) and contributed a significant increment in explained variance beyond the constituent terms ($\Delta R^2 = .013$, $F(1, 390) = 5.664$, $p = .018$); the factorial specification corroborates the same interaction ($F(4, 385) = 2.531$, $p = .040$, partial $\eta^2 = .026$). Probing the conditional effects shows the amplification the hypothesis predicts: the effect of brand image on repurchase intention rises monotonically from $\beta = 0.115$ ($SE = 0.057$, $p = .046$) at low UGC (-1 SD), to $b = 0.203$ ($p < .001$) at mean UGC, to $\beta = 0.291$ ($SE = 0.061$, $p < .001$) at high UGC ($+1$ SD) – a slope more than two and a half times steeper at high than at low levels of peer content. Critically, UGC exerted no independent main effect on repurchase intention ($\beta = -0.018$, $SE = 0.049$, $t = -0.372$, $p = .710$; factorial $F(2, 385) = 0.811$, $p = .445$), indicating that UGC does not drive repurchase intention on its own but operates entirely through the brand evaluation it corroborates. Inspection of the interaction plot (see Figure 5) locates the widest dispersion between UGC groups at moderate levels of brand image, where consumers show the greatest sensitivity to peer content, whereas the groups converge at high brand image. UGC therefore functions as a “confidence bridge” that converts ambivalent brand attitudes into concrete repurchase motivation, while adding comparatively little for consumers whose brand perceptions are already strong or irretrievably weak.

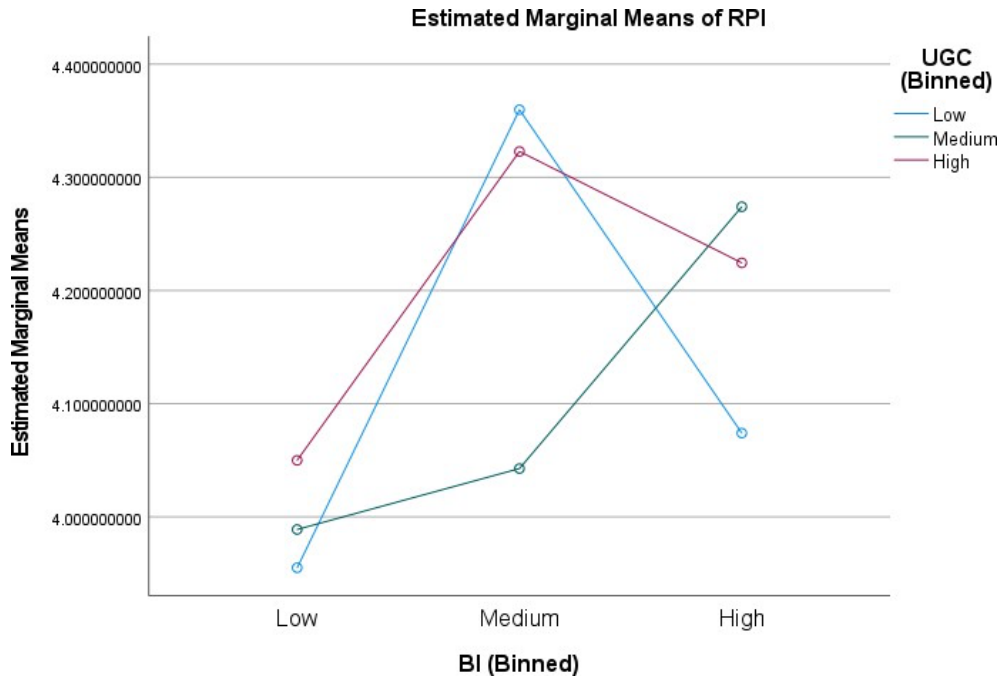


Figure 5. Interaction of brand image (BI) and user-generated content (UGC)

H3 predicted a bounded moderation in which the positive moderating influence of brand ambassadors is strongest at low-to-moderate levels of brand image and diminishes – and may reverse – at high levels of brand image. The evidence supports this specification, but only the factorial model is capable of expressing it, and the divergence between the two models is itself diagnostic, not contradictory. In the linear specification, the brand image $\times$ brand ambassador product term was not significant ($\beta = 0.048$, $SE = 0.043$, $t = 1.115$, $p = .266$, 95% CI $[-0.037, 0.132]$; $\Delta R^2 = .003$, $F(1, 390) = 1.243$, $p = .266$), while brand ambassador exerted a strong positive main effect on repurchase intention ($\beta = 0.185$, $SE = 0.033$, $t = 5.513$, $p < .001$; factorial $F(2, 385) = 22.273$, $p < .001$). The 3×3 factorial model, by contrast, returned a highly significant brand image $\times$ brand ambassador interaction ($F(4, 385) = 7.577$, $p < .001$, partial $\eta^2 = .073$) within a model explaining 20.7% of the variance in repurchase intention. A single linear product term estimates one average change in slope across the whole range of brand image; an interaction that is positive over the lower range and negative over the upper range is therefore arithmetically cancelled and presents as null. The non-significant linear term and the significant factorial interaction together constitute the expected signature of the bounded form specified a priori in H3, and H3 is accordingly supported in that bounded, non-linear form not as a uniform linear amplification.

Among consumers with high ambassador affinity, repurchase intention rises steeply from low to moderate brand image and then falls back at high brand image, whereas consumers with low ambassador affinity remain essentially flat across the entire brand image range. Ambassador exposure thus adds most where brand image is moderate – the segment in which aspirational identity transfer can still convert awareness into commitment – and least at either extreme. At low brand image, ambassador recognition cannot compensate for the absence of fundamental brand trust and is in fact associated with the lowest cell mean in the design, a pattern consistent with the match-up hypothesis in endorsement research, which holds that ambassador effectiveness is contingent on a congruent brand–ambassador fit

that consumers can internalize (Crespo et al., 2025). At high brand image, the marginal return to further ambassador exposure attenuates because brand commitment is already sufficient to motivate repurchase independently (see Figure 6). The negative interaction coefficient (ANOVA interaction $F = 7.577$, $p < .001$) does not indicate that brand ambassadors reduce repurchase intention; rather, it reflects the statistical signature of diminishing returns at high brand image levels, where pre-existing brand equity is already self-sustaining. This finding enriches the ambassador literature by identifying the conditions under which celebrity-led social proof most effectively converts brand image into repurchase behavior.

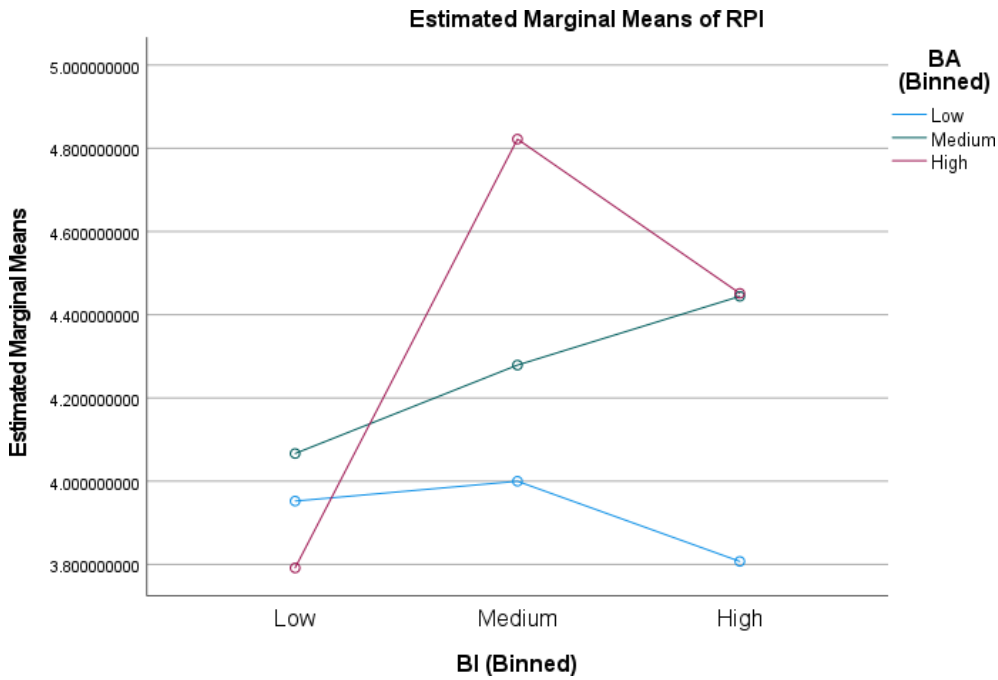


Figure 6. Interaction of brand image (BI) and brand ambassador (BA)

H4 was supported, and in the strongest form of any moderating relationship in the model. The brand image $\times$ testimonials interaction was positive, large and highly significant ($\beta = 0.266$, $SE = 0.051$, $t = 5.262$, $p < .001$, 95% CI [0.167, 0.366]), adding 6.2% of explained variance beyond the constituent terms ($\Delta R^2 = .062$, $F(1, 390) = 27.686$, $p < .001$); the factorial model returned the largest interaction effect observed in the study ($F(4, 385) = 19.994$, $p < .001$, partial $\eta^2 = .172$) within the factorial specification ($R^2 = .223$, adjust $R^2 = .207$). Probing the conditional effects shows that the brand image–repurchase link is not merely weakened but effectively eliminated when testimonial credibility is low: at -1 SD of testimonials the effect of brand image is indistinguishable from zero ($\beta = -0.029$, $SE = 0.062$, $p = .638$, 95% CI [-0.152, 0.093]); at the mean it is positive and significant ($\beta = 0.183$, $SE = 0.043$, $p < .001$); and at $+1$ SD it more than doubles ($\beta = 0.395$, $SE = 0.056$, $p < .001$). Credible testimonials therefore do not simply add persuasive weight – they condition whether a favorable brand image is converted into repurchase intention at all.

Testimonials, however, carry no independent persuasive value of their own. The main effect was negative and did not reach conventional significance ($\beta = -0.062$, $SE = 0.037$, $t = -1.664$, $p = .097$, 95% CI [-0.134, 0.011]; factorial

$F(2, 385) = 1.408, p = .246$). We interpret the negative sign as directional, not as confirmed evidence of suppression; what the data establish unambiguously is that testimonials operate purely as a credibility filter on brand image and never as a standalone driver of repurchase intention. The substantive consequence is visible in the interaction plot (see Figure 7): among consumers holding strong brand image perceptions, those exposed to weak or non-credible testimonials report the lowest repurchase intention of any cell in that column, indicating that an unconvincing endorsement can actively undercut an otherwise favorable brand evaluation instead of leaving it untouched. This dual pattern is consistent with persuasion knowledge theory (Friestad and Wright, 1994), which predicts that consumers activate defensive processing when they detect promotional intent: a testimonial encountered without the corroborating context of a favorable brand image supplies a persuasion cue with no evidentiary basis to justify it, and is discounted accordingly. Testimonial authenticity is thus best understood not as an enhancement of social proof but as the condition under which social proof functions at all.

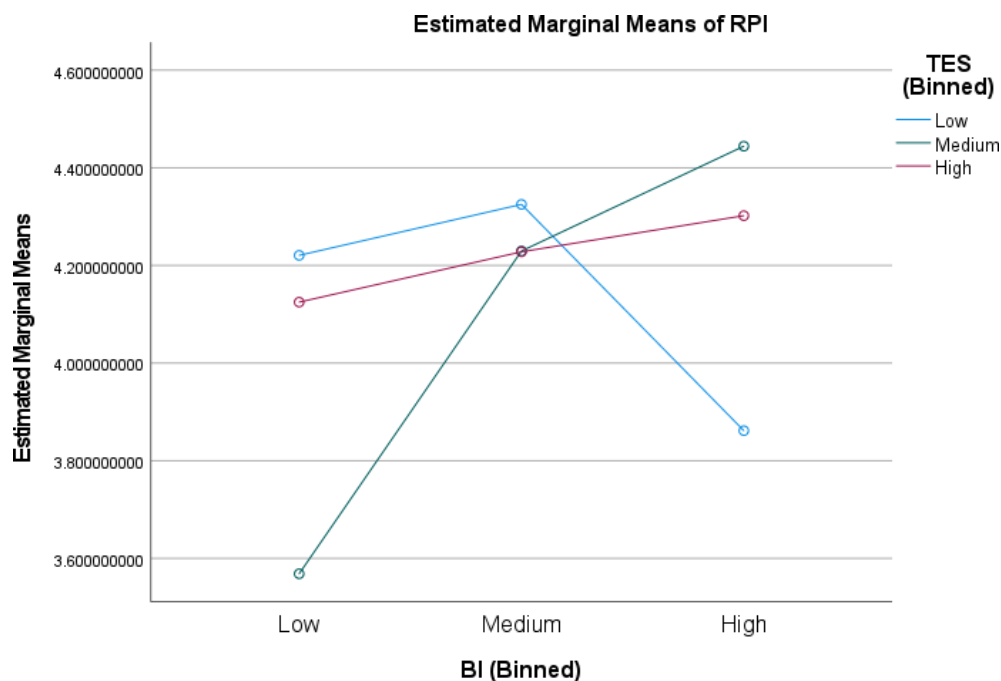


Figure 7. Interaction of brand image (BI) and testimonials (TES)

Overall, the results support all four hypotheses, although not in identical functional form. H1, H2 and H4 are supported in the linear moderated regression and corroborated by the factorial models; H3 is supported in the bounded, non-linear form in which it was specified, evidenced by a significant factorial interaction alongside a null linear product term. Brand image serves as the foundational antecedent, but the conversion of that image into repurchase intention is conditioned by all three social proof mechanisms, each operating through a distinct psychological pathway and each bounded in a different way: peer-based validation that is most diagnostic at moderate brand image (UGC), aspirational identity transfer subject to a ceiling at high brand image (brand ambassadors), and credibility anchoring that gates the brand image–repurchase link across its entire range (testimonials). Notably, neither UGC nor testimonials exerted a significant independent main effect, whereas brand ambassadors did, underscoring that the three

constructs are not interchangeable operationalization of a single social proof factor. The empirical support for this hypothesis testing framework is summarized in Figure 8.

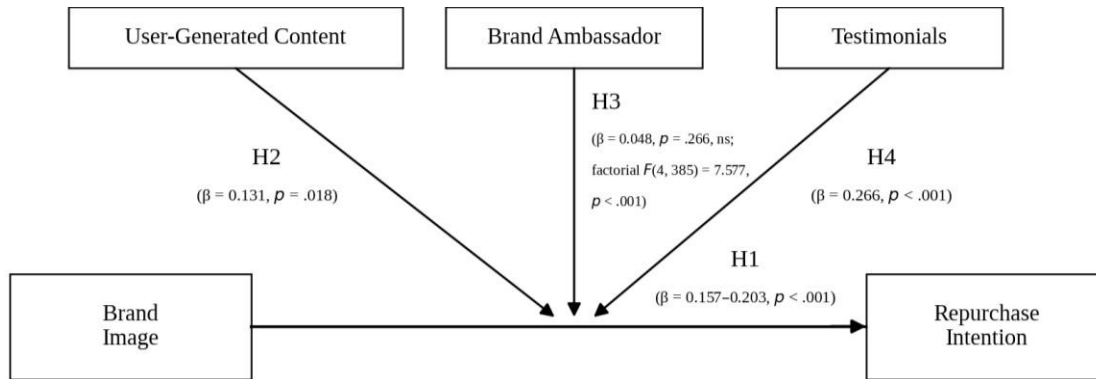


Figure 8. Hypothesis testing framework

3.2.6. Summary of findings

The finding that brand image exerts a consistently strong and direct effect on repurchase intention (H1: $\beta = 0.157$ to $0.203, p < .001$ across all three specifications) reaffirms the foundational importance of brand perception in driving loyalty behavior. This result is consistent with decades of branding literature (Keller, 1993; Aaker, 1991) and recent evidence from Southeast Asian e-commerce contexts, confirming that the positive brand image–RPI relationship generalizes to the Vietnamese digital marketplace despite its distinctive cultural and structural characteristics. The magnitude of this effect, however, is not fixed: it varies by a factor of more than ten across the range of the moderators, which is the central substantive result of the study.

More consequential theoretically is the finding that social proof amplifies repurchase intention conditionally and does not drive it independently. Each of the three social proof dimensions moderates the brand image–RPI relationship through a distinct psychological mechanism, and the directionality and magnitude of these effects depend critically on the consumer's pre-existing brand image perception. This pattern challenges prior research that has treated social proof as a uniformly positive persuasion force and instead proposes a more nuanced framework in which social proof effectiveness is bounded by brand image strength.

The moderating effect of UGC (H2: $\beta = 0.131, p = .018 < .001, \Delta R^2 = .013$) was strongest among consumers with moderate brand image perceptions that can be interpreted through the lens of social comparison theory. Consumers who are uncertain about a brand's value proposition are most sensitive to peer validation signals, because these signals resolve the ambiguity that attenuates the translation of brand attitudes into behavioral intention. For consumers with already strong brand commitments, UGC supplies confirmatory information, not decisive information. This explains why UGC showed no significant main effect independent of brand image ($\beta = -0.018, p = .710$): peer content generates repurchase motivation only when it can interact with a pre-existing, if incomplete, cognitive foundation of brand positive affect. The sentiment analysis in Study 1 corroborates this interpretation: the high positive sentiment ratio observed for Co Em Trendy's lifestyle-oriented UGC (59.57% positive) demonstrates that aesthetically

compelling, peer-generated content creates emotional resonance and reduces perceived risk in experience-based product categories, consistent with the interaction pattern observed in Study 2.

The brand ambassador result (H3) presented the most nuanced picture and required the two-specification strategy to interpret correctly. The linear product term was not significant ($\beta = 0.048, p = .266$), yet the factorial interaction was highly significant ($F(4, 385) = 7.577, p < .001$, partial $\eta^2 = .073$), and reading the two together reveals an asymmetric ceiling effect rather than an absence of moderation. Ambassador recognition is most effective for consumers with moderate brand image perceptions, providing the aspirational identity transfer that bridges the gap between awareness and commitment. At high levels of brand image, ambassador influence yields diminishing returns because the consumer's brand loyalty is already self-sustaining; the negative slope in this upper region does not indicate that brand ambassadors reduce repurchase intention, but reflects the statistical signature of diminishing returns where pre-existing brand equity is already sufficient. At low brand image levels, ambassador recognition fails to overcome the foundational deficit of brand trust, a finding consistent with the "match-up hypothesis" in endorsement research, which holds that ambassador effectiveness is contingent on a congruent brand-ambassador fit that consumers can meaningfully internalize (Crespo et al., 2025). Because these opposing regional slopes cancel when averaged, the linear specification underestimates a moderation that the categorical specification detects clearly, a methodological caution of general relevance to moderation research in retailing. The sentiment data from Study 1 support this interpretation: Chau Bui's ambassador-archetype content generated mixed sentiment in premium segments, reflecting the heightened skepticism of consumers who may perceive celebrity endorsements as commercially motivated instead of genuinely credible.

The testimonial result (H4: $\beta = 0.266, p < .001, \Delta R^2 = .062$) yielded perhaps the most theoretically rich finding, and the largest interaction in the study. The positive interaction term confirms that credible, authentic testimonials amplify the brand image-RPI relationship; the conditional effects show that they do more than amplify it. When testimonial credibility is low, the effect of brand image on RPI collapses to zero ($\beta = -0.029, p = .638$), whereas when it is high the effect is more than double its average value ($\beta = 0.395, p < .001$). Testimonials therefore function as a gate on the brand image-loyalty pathway not as a lever within it. Equally consequential is what testimonials do not do: their independent main effect was negative and non-significant ($\beta = -0.062, p = .097$), qualifying the prevailing assumption that endorsement-based social proof is uniformly persuasive. Consistent with persuasion knowledge theory (Friestad and Wright, 1994), a testimonial presented without the corroborating context of a favorable brand image supplies a persuasion cue without an evidentiary basis to justify it; consumers who detect this imbalance engage defensive processing and discount the message, so that the testimonial fails to stimulate – and, at high brand image, may actively undercut – repurchase intention. The effect is therefore not a measurement artefact but a theoretically meaningful boundary condition: the persuasive value of a testimonial is conditional on its congruence with, and subordination to, the consumer's independent brand evaluation. This reframes testimonials from a reliably positive tactic into a double-edged instrument whose direction of influence depends on perceived authenticity and on a pre-existing foundation of brand trust.

4. Discussion

This study provides a comprehensive examination of how social proof stabilizes the relationship between brand image and repurchase intention (RPI) in the Vietnamese digital marketplace. By integrating AI-driven sentiment analysis with moderated regression analysis, the research identifies social proof not merely as a peripheral cue but as a critical credibility validator that defines the boundary conditions of brand loyalty.

The findings from Study 2 confirm that while a brand's image is a key reason why people buy again, but whether that image leads to action depends heavily on what others say – and the three forms of social proof work in different ways. User-generated content and brand ambassadors have their strongest impact on the movable middle: shoppers with a neutral or average opinion of a brand. For these consumers, social proof acts as a bridge, turning lukewarm interest into a firm commitment to buy again by making online shopping feel less risky. Testimonials operate differently: instead of focusing on their influence in the middle of the distribution, they control the brand image–repurchase pathway across its full range, so even strong brand perceptions fail to translate into repurchase intention when testimonial credibility is low. Operationally, this “movable middle” corresponds to consumers with moderate brand-image perceptions, a segment that firms can identify in real time from behavioral and CRM signals not as survey scores. For example, repeat browsing or repeat visits without purchase, mid-range satisfaction or review scores, cart abandonment, wish-list activity without conversion, and moderate engagement or loyalty-tier status. Targeting social proof toward users exhibiting these signals allows the mechanism to be deployed where its marginal effect is greatest.

In practice, an e-commerce retailer can operationalize this 'movable middle' targeting through automated CRM rules, for instance, a shopper who has visited a product page three times within 48 hours, added items to cart without checking out, and submitted mid-range satisfaction scores (e.g., 3 out of 5 stars) would be automatically flagged by the CRM platform as a 'movable middle' consumer and dynamically served authentic peer UGC and customer testimonials to bridge decision hesitation.

This asymmetry is illuminated by the authenticity paradox observed in Study 1. Vo Ha Linh, whose reviews generated the highest proportion of negative sentiment in the corpus (55.96%), nonetheless retained exceptionally high audience trust. Far from eroding credibility, the visible presence of critical, unscripted commentary appears to signal an absence of promotional manipulation and thereby elevates perceived authenticity.

Far from eroding credibility, the visible presence of critical, unscripted commentary appears to signal an absence of promotional manipulation and thereby elevates perceived authenticity. This mechanism directly parallels the Study 2 result: testimonials amplify the brand image–repurchase relationship when encountered without a supporting brand image ($\beta = -0.062$, $p = .097$). Across both studies, the same underlying variable, perceived authenticity, determines whether social proof builds or erodes trust: honest, even critical, discourse strengthens it, whereas polished or overtly promotional content activates persuasion knowledge and invites discounting. This is especially pronounced for high-involvement categories such as technology, where consumers require honest, functional evidence before extending repurchase trust.

4.1. Theoretical contributions

This study contributes to theory in four ways. First, it extends social proof theory by demonstrating that social proof functions not merely as a peripheral persuasion cue but as a contingent moderator of the brand image–RPI relationship—a role that prior research had not empirically mapped in a unified framework. Second, it enriches brand image theory

by identifying social proof as a boundary condition: the strength of the brand image–loyalty link is systematically amplified or attenuated depending on which social proof mechanisms are activated and at what intensity (Meng et al., 2026). Third, it advances the conceptualization of digital influence by distinguishing between the unique theoretical effects of UGC (peer validation), brand ambassadors (aspirational identity transfer), and testimonials (credibility anchoring)-showing that these constructs are not interchangeable but operate through distinct psychological pathways.

Methodologically, this study demonstrates the value of integrating AI-driven sentiment analysis with traditional psychometric survey methods. The RoBERTa-based NLP analysis in Study 1 captured unsolicited, organic consumer discourse that is free from the social desirability and framing biases inherent in self-report surveys (Ray and Singh, 2025). The alignment between the sentiment patterns-differentiated by influencer archetype and product category-and the moderation patterns observed in Study 2 provides a form of construct triangulation that strengthens confidence in the theoretical framework. This dual-method design offers a methodological blueprint for future consumer behavior research in digital markets, where the richness of naturally occurring language data can be mobilized to validate and extend survey-based findings.

4.2. Managerial implications

For practitioners, the findings offer differentiated guidance. Regarding UGC, e-commerce managers should prioritize the cultivation of active community ecosystems that encourage authentic peer-sharing, particularly for brands with moderate market recognition seeking to convert awareness into loyalty. Because UGC's moderating power is greatest for consumers with intermediate brand image perceptions, brands at the growth stage-rather than established luxury leaders-stand to gain the most from systematic UGC strategies. Incentivizing verified buyer reviews, enabling visual content sharing, and actively moderating community discussions can accelerate the transition from brand awareness to brand advocacy.

For brand ambassador strategy, the findings argue for precision targeting over broad reach. Ambassador partnerships are most effective when they can engage consumers who have a baseline level of positive brand association but have not yet converted into committed loyalists. Deploying high-visibility ambassadors toward low-affinity segments is likely to generate skepticism, not motivation; ambassador investment should instead be concentrated on the “movable middle”, namely consumers with moderate brand image perceptions, who are most responsive to aspirational social proof. Firms should also prioritize ambassador–brand congruence and perceived authenticity over raw celebrity scale.

For testimonial strategy, the dual-edged nature of testimonials demands careful calibration. Managers should resist the temptation to over-optimize testimonial content for promotional appeal; the sentiment analysis data clearly shows that Vietnamese consumers respond most positively to brutally honest, unscripted endorsements. Brands that enable and amplify authentic critical discourse instead of suppressing negative commentary-are better positioned to leverage the transparency effect that converts high-polarity testimonials into trust-building instruments. Importantly, this does not imply that brands should manufacture negativity: staged or exaggerated criticism would itself be detected as inauthentic and would activate the same persuasion-knowledge skepticism that undermines commercially motivated testimonials. The recommendation is one of calibrated transparency: allowing genuine critical feedback to remain visible and responding to it constructively, without engineering the review environment. For high-involvement

product categories such as technology, expert testimonials that emphasize objective functional evaluation generate the most credible social proof. For lifestyle and beauty categories, peer-level UGC that emphasizes sensory and experiential authenticity is more effective.

4.3. Limitations and future research directions

This study has several limitations that suggest directions for future research. First, data were obtained by sampling through social media, and the resulting sample skews toward younger, digitally native consumers (86.8% aged 20–29 in the cleaned $N = 394$ sample). Although young consumers represent the primary digital shopping cohort in Vietnam, national e-commerce statistics indicate that older consumers (above 30 years old) account for approximately 28.5% of Vietnam's online shopping population (Dang-Van et al., 2026). Because older cohorts may exhibit higher risk aversion and lower familiarity with digital influencers, our sample skew (86.8% aged 20–29) limits direct generalizability to mature demographic groups. Future research should deploy quota sampling stratified by age, and test whether the three moderating mechanisms identified here are invariant across cohorts using multi-group analysis; an ambassador ceiling, in particular, may occur at a lower level of brand image among consumers for whom aspirational identity transfer is a weaker motive.

Second, the cross-sectional design captures a snapshot in time and cannot establish causal directionality; longitudinal panel data would enable stronger causal inference about how social proof exposure shapes repurchase behavior over time. Relatedly, the salience of different social-proof forms may shift across the customer journey: informational UGC and credibility cues are likely to dominate at the first-purchase stage, where uncertainty is highest, whereas confirmatory and identity-reinforcing cues may dominate at the repurchase stage; tracing this evolution from a first-time to a repurchase mindset is a promising avenue for longitudinal work. Specifically, informational UGC (such as detailed star ratings, functional specification reviews, and unboxing videos) is most diagnostic during initial consideration to reduce perceived performance risk, whereas experiential UGC (such as customer photo galleries, lifestyle usage clips, and community post-purchase stories) becomes dominant at the repurchase stage by validating brand identification. A multi-wave design that measures brand image, social proof exposure and purchase behavior at successive points in the same relationship would allow these shifts to be estimated as within-person change instead of inferred from between-person differences.

Third, the generalizability of the findings is bounded by the Vietnamese context. Vietnam's particular combination of high collectivism, mobile-first internet adoption, and rapidly growing e-commerce penetration may intensify social proof effects in ways that differ from more established or more individualist markets. Cross-cultural replication studies in ASEAN and other emerging markets would help establish the boundary conditions of these findings, and would permit cultural orientation to be modelled explicitly as a second-stage moderator instead of being treated as an unmeasured contextual constant.

Fourth, the treatment of testimonial authenticity in this study was deliberately parsimonious, and the pattern we observe, namely a directionally negative, non-significant main effect combined with the largest interaction term in the design, suggests that this parsimony is now the binding constraint on further theory development. Authenticity was captured as a broadly unidimensional evaluative judgement, whereas the persuasion-knowledge account we invoke implies that consumers draw at least three analytically separable inferences when they encounter an endorsement. We

therefore recommend, as a priority for future research, the development and validation of a multi-item instrument that formally distinguishes three dimensions: (1) perceived genuineness, the degree to which delivery is judged unscripted, spontaneous and grounded in first-hand consumption experience; (2) commercial authenticity, the degree to which any material relationship between endorser and brand is disclosed transparently and judged legitimate rather than concealed; and (3) expertise authenticity, the degree to which the endorser is judged to hold verified domain capability that entitles them to evaluate the product category. These dimensions are conceptually independent and can move in opposite directions: a fully disclosed, paid testimonial from a credentialed specialist may score low on genuineness yet high on commercial and expertise authenticity, while an unpaid enthusiast's account may display precisely the reverse profile. Because a single composite measure averages across such profiles, it cannot reveal which inference is doing the persuasive work, or the defensive work, in any given case.

Constructing such an instrument would follow the established scale-development paradigm: domain specification and item generation from consumer elicitation interviews and content analysis of live testimonial material; expert judging for content validity; item reduction via exploratory factor analysis on a calibration sample; confirmatory factor analysis with discriminant validity assessment (for example, the HTMT criterion) on an independent validation sample; and evaluation of nomological validity against established measures of source credibility, persuasion knowledge and advertising skepticism. Two design considerations deserve particular attention. First, existing endorsement and testimonial scales are worded in a uniformly positive direction and may therefore lead respondents toward favorable evaluations; future instruments should incorporate balanced or reverse-keyed items and be screened for acquiescence and common method bias. Second, validation should where feasible extend beyond self-reported intention to behavioral or incentive-compatible criteria. With such an instrument available, the credibility-filter mechanism reported here becomes directly testable at the dimension level: our account predicts that commercial and expertise authenticity should gate the conversion of brand image into repurchase intention, whereas perceived genuineness should principally attenuate defensive processing, a differential prediction that the present composite measure cannot adjudicate.

Fifth, the categorical specification required to test the bounded form of H3 entails a loss of information relative to the underlying continuous data. Trichotomizing brand image and brand ambassador affinity allowed the sign-reversing interaction predicted by H3 to be expressed and tested, but it locates the ceiling only within a discrete category rather than at a determinate point on the continuous scale, and it discards within-category variance. Modelling the ceiling directly in continuous form is therefore the natural next step, and we see three complementary strategies. Polynomial moderated regression, in which a quadratic term for brand image and its product with ambassador affinity (BI^2 and $BI^2 \times BA$) are entered alongside the linear terms, offers the most parsimonious continuous test of curvature; the level of brand image at which the conditional effect of ambassador affinity changes sign can then be recovered analytically. Response surface analysis extends this logic by characterizing the full curvature of the brand image $\times$ brand ambassador surface, including the location of its ridge, and is well suited to testing whether the ceiling reflects diminishing returns or genuine reversal. For researchers unwilling to impose a functional form a priori, spline regression or generalized additive models estimate the shape of the conditional effect non-parametrically and provide a specification test against the polynomial alternative. Because higher-order interaction terms are estimated with markedly lower power than first-order terms, studies pursuing this agenda should plan sample sizes through

simulation-based power analysis rather than rules of thumb, and would ideally complement observational data with an experiment that manipulates ambassador exposure at calibrated levels of brand image, which would establish the ceiling as a causal boundary condition rather than a covariational regularity.

Additionally, while our theoretical model specifies brand image as an antecedent whose effect on repurchase intention is moderated by social proof, the cross-sectional design means alternative causal directions (e.g., strong repurchase intentions prompting positive post-hoc cognitive revisions of brand image) cannot be definitively ruled out. Longitudinal or experimental designs are recommended to confirm temporal ordering, and cross-lagged panel specifications would allow reciprocal influence to be estimated rather than assumed away.

Furthermore, as virtual brand ambassadors and synthetic content proliferate, investigating whether explicit disclosure of AI authorship mitigates or exacerbates consumer skepticism toward synthetic social proof presents a compelling avenue for future research. This question intersects directly with the authenticity agenda outlined above: a synthetic endorser can in principle be transparent about its commercial basis and demonstrably competent within a product domain while being incapable of first-hand consumption experience, and the proposed three-dimensional instrument would allow the resulting trade-off between commercial authenticity, expertise authenticity and perceived genuineness to be measured.

Finally, we regard two of these directions as the most immediate priorities for advancing the framework proposed here. Establishing the precise continuous location of the ambassador ceiling through polynomial, response surface or spline specifications would convert a categorically demonstrated boundary condition into a point estimate that managers can act on, while a validated multi-dimensional authenticity instrument would identify which specific inference activates the credibility filter that governs testimonial effectiveness. Besides these, further research on the behavioral characteristics of distinct customer segments remains essential to elucidate how user-generated content, brand ambassadors, and testimonials condition online repurchase intention across markets and over time.

References

- Aaker, D.A., 1991. *Managing Brand Equity: Capitalizing on the Value of a Brand Name*. Free Press, New York.
- Al-Abdallah, G., Wright, L.T., 2025. User-generated content vs. firm-generated content: do consumers trust fellow consumers more than firms? Evidence from the Saudi telecommunication sector. *Cogent Bus. Manag.* 12, 2508928. <https://doi.org/10.1080/23311975.2025.2508928>.
- Alam, F., Tao, M., Rastogi, R., Mendiratta, A., Attri, R., 2024. Do social media influencers influence the vaccination drive? An application of source credibility theory and uses and gratification theory. *Technol. Forecast. Soc. Change.* 198, 122973. <https://doi.org/10.1016/j.techfore.2023.122973>.
- Alim, M.A., Thaichon, P., Quach, S., Weaven, S., 2026. Influencer–follower interactions and consumers' behavioral responses: a multi-method approach and future research agenda. *J. Consum. Behav.* 25, 3–40. <https://doi.org/10.1002/cb.2388>.
- Barsha, S., Munshi, S.A., 2025. Understanding viewers' sentiments: a critical analysis of YouTube videos on library automation trends. *Ser. Libr.* 86, 121–139. <https://doi.org/10.1080/0361526X.2025.2483687>.
- Chang, J., 2025. The mediating role of brand image in the relationship between storytelling marketing and purchase intention: case study of PX mart. *Future Bus. J.* 11, 23. <https://doi.org/10.1186/s43093-025-00447-4>.

- Cialdini, R.B., 2007. *Influence: The Psychology of Persuasion*, revised ed. Harper Collins, New York.
- Cohen, J., 1983. The cost of dichotomization. *Appl. Psychol. Meas.* 7, 249–253. <https://doi.org/10.1177/014662168300700301>.
- Cohen, J., 1988. *Statistical Power Analysis for the Behavioral Sciences*, second ed. Lawrence Erlbaum Associates, Hillsdale, NJ.
- Crespo, C.F., Ferreira, A.G., Ribeiro, F.M., Popa, V., 2025. The effect of celebrity endorsement on brand equity: a cross-cultural comparison. *J. Int. Consum. Mark.* 37, 1–22. <https://doi.org/10.1080/08961530.2024.2324779>.
- Curran, P.J., 2016. Methods for the detection of carelessly invalid responses in survey data. *J. Exp. Soc. Psychol.* 66, 4–19. <https://doi.org/10.1016/j.jesp.2015.07.006>.
- Dang-Van, T., Doan, L.T., Huynh, Q., 2026. Psychological pathways from fake reviews to consumer switching in e-tailing: a cross-cultural analysis. *J. Retailing Consum. Serv.* 90, 104700. <https://doi.org/10.1016/j.jretconser.2025.104700>.
- Diwanji, V.S., 2026. Should your brand hire virtual influencers? How realism and gender presentation shape trust and purchase intentions. *J. Retailing Consum. Serv.* 88, 104491. <https://doi.org/10.1016/j.jretconser.2025.104491>.
- Do, A.D., Ha, D.L., Pham, M.T., Khuat, M.A.T., Le, V.A.T., Nguyen, D.N.D., La, T.Q., 2025. Impacts of e-RLSQ on repurchase intention in Vietnam's e-commerce market: the mediating role of customer satisfaction and trust. *Int. J. Inf. Manag. Data Insights.* 5, 100346. <https://doi.org/10.1016/j.jjime.2025.100346>.
- Faul, F., Erdfelder, E., Lang, A.G., Buchner, A., 2007. G*Power 3: a flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behav. Res. Methods.* 39, 175–191. <https://doi.org/10.3758/BF03193146>.
- Fornell, C., Larcker, D.F., 1981. Evaluating structural equation models with unobservable variables and measurement error. *J. Mark. Res.* 18, 39–50. <https://doi.org/10.1177/002224378101800104>.
- Friestad, M., Wright, P., 1994. The persuasion knowledge model: how people cope with persuasion attempts. *J. Consum. Res.* 21, 1–31. <https://doi.org/10.1086/209380>.
- Gauraha, R., Agrawal, A.K., Dubey, P., 2026. Capsule-enhanced RoBERTa for hierarchical sentiment analysis on social media texts. *Discov. Artif. Intell.* 6, 147. <https://doi.org/10.1007/s44163-026-00872-6>.
- Gilardi, F., Lam, C., 2024. New perspective on UGC, PGC, and OGC: motivating factors of Chinese co-creators' engagement with international television series. *Creat. Ind. J.* 17, 551–566. <https://doi.org/10.1080/17510694.2022.2150816>.
- Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2013. *Multivariate Data Analysis*, seventh ed. Pearson Education, Harlow.
- Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E., 2019. *Multivariate Data Analysis*, eighth ed. Cengage Learning, Andover.
- Handoyo, S., 2024. Purchasing in the digital age: a meta-analytical perspective on trust, risk, security, and e-WOM in e-commerce. *Heliyon.* 10, e29714. <https://doi.org/10.1016/j.heliyon.2024.e29714>.
- Hayes, A.F., 2013. *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach*. The Guilford Press, New York.

- Ho, D.D., Phuong, U.N.T., Nguyen, H.H., 2026. Firm-created and user-generated content serve as quality signals: the case of OCOP products in Vietnam. *Veredas Direito*. 23, e234407. <https://doi.org/10.18623/rvd.v23.n1.4407>.
- Hofstede, G., 2001. *Culture's Consequences: Comparing Values, Behaviors, Institutions, and Organizations Across Nations*, second ed. Sage Publications, Thousand Oaks, CA.
- Hovland, C.I., Weiss, W., 1951. The influence of source credibility on communication effectiveness. *Public Opin. Q.* 15, 635–650. <https://doi.org/10.1086/266350>.
- Hu, H., Ren, S., Li, D., 2026. Stylized vs. photorealistic celebrity avatars: what works best for brand endorsement? *J. Retailing Consum. Serv.* 89, 104644. <https://doi.org/10.1016/j.jretconser.2025.104644>.
- Huang, W., Wang, X., Zhang, Q., Han, J., Zhang, R., 2025. Beyond likes and comments: how social proof influences consumer impulse buying on short-form video platforms. *J. Retailing Consum. Serv.* 84, 104199. <https://doi.org/10.1016/j.jretconser.2024.104199>.
- Keller, K.L., 1993. Conceptualizing, measuring, and managing customer-based brand equity. *J. Mark.* 57, 1–22. <https://doi.org/10.1177/002224299305700101>.
- Kim, S., Chang, H.J., Ortiz, B.L., Chong, J.W., 2026. The role of scent congruence with luxury brand image in consumers' emotions, memory, and brand resonance: a mixed-methods approach using EEG and quantitative analyses. *J. Retailing Consum. Serv.* 90, 104663. <https://doi.org/10.1016/j.jretconser.2025.104663>.
- Koll, O., Plank, A., 2022. Do shoppers choose the same brand on the next trip when facing the same context? An empirical investigation in FMCG retailing. *J. Retailing*. 98, 576–592. <https://doi.org/10.1016/j.jretai.2022.01.003>.
- Kong, J., Lou, C., 2026. Beyond persuasion knowledge: examining the roles of visual appeal, visual congruence, and social proof in influencer advertising. *J. Retailing Consum. Serv.* 88, 104502. <https://doi.org/10.1016/j.jretconser.2025.104502>.
- Krugmann, J.O., Hartmann, J., 2024. Sentiment analysis in the age of generative AI. *Cust. Needs Solut.* 11, 3. <https://doi.org/10.1007/s40547-024-00143-4>.
- Lee, G.K.S., 2026. Impact of social media influencer marketing on consumer behaviour: a review of source credibility theory. *Int. J. Retail Consum. Res.* 1. <https://doi.org/10.51137/wrp.ijrcr.639>.
- Li, N., Meng, F., Tong, Y., 2025. Exploring visual representations of hotel brand image: framework development using mixed methods. *Int. J. Contemp. Hosp. Manag.* 37, 3384–3404. <https://doi.org/10.1108/IJCHM-08-2024-1238>.
- Madathil, J.C., 2025. Generative AI advertisements and human–AI collaboration: the role of humans as gatekeepers of humanity. *J. Retailing Consum. Serv.* 87, 104381. <https://doi.org/10.1016/j.jretconser.2025.104381>.
- MacCallum, R.C., Zhang, S., Preacher, K.J., Rucker, D.D., 2002. On the practice of dichotomization of quantitative variables. *Psychol. Methods* 7, 19–40. <https://doi.org/10.1037/1082-989X.7.1.19>.
- Meng, Y., Park, S., Um, G., 2026. How review sentiment influences ratings in generative AI applications: insights from VADER and LDA analysis. *J. Retailing Consum. Serv.* 88, 104560. <https://doi.org/10.1016/j.jretconser.2025.104560>.
- Monfort, A., López-Vázquez, B., Sebastián-Morillas, A., 2025. Building trust in sustainable brands: revisiting perceived value, satisfaction, customer service, and brand image. *Sustain. Technol. Entrep.* 4, 100105. <https://doi.org/10.1016/j.stae.2025.100105>.

- Muda, M., Hamzah, M.I., 2021. Should I suggest this YouTube clip? The impact of UGC source credibility on eWOM and purchase intention. *J. Res. Interact. Mark.* 15, 441–459. <https://doi.org/10.1108/JRIM-04-2020-0072>.
- Nazir, S., Khadim, S., Ali Asadullah, M., Syed, N., 2023. Exploring the influence of artificial intelligence technology on consumer repurchase intention: the mediation and moderation approach. *Technol. Soc.* 72, 102190. <https://doi.org/10.1016/j.techsoc.2022.102190>.
- Ngo, T.T.A., An, G.K., Dao, D.K., Nguyen, N.Q.N., Phong, B.H., Nguyen, N.Y.V., 2025. Unveiling the nexus between logistics service quality and customer repurchase intentions in the e-commerce sector. *Res. Transp. Bus. Manag.* 63, 101474. <https://doi.org/10.1016/j.rtbm.2025.101474>.
- Ohanian, R., 1990. Construction and validation of a scale to measure celebrity endorsers' perceived expertise, trustworthiness, and attractiveness. *J. Advert.* 19, 39–52. <https://doi.org/10.1080/00913367.1990.10673191>.
- Osorio-Andrade, C., Rospigliosi, P.A., Zarco, A.J., 2025. eWOM and content marketing strategies: maximizing brand engagement among social media users in Spain. *Eur. Res. Manag. Bus. Econ.* 31, 100293. <https://doi.org/10.1016/j.iemeen.2025.100293>.
- Ouyang, L., Mak, J., 2025. Examining how switching barriers moderate the link between customer satisfaction and repurchase intention in the health and fitness club sector. *Asia Pac. J. Mark. Logist.* 38, 529–547. <https://doi.org/10.1108/APJML-01-2025-0134>.
- Pan, M., Blut, M., Ghiassaleh, A., Lee, Z.W.Y., 2025. Influencer marketing effectiveness: a meta-analytic review. *J. Acad. Mark. Sci.* 53, 52–78. <https://doi.org/10.1007/s11747-024-01052-7>.
- Penttinen, V., Ciuchita, R., Pedersen, S., 2026. Let me deinfluence you! The impacts of deinfluencing content. *J. Acad. Mark. Sci.* In press. <https://doi.org/10.1007/s11747-026-01141-9>.
- Ray, R.K., Singh, A., 2025. From online reviews to smartwatch recommendation: an integrated aspect-based sentiment analysis framework. *J. Retailing Consum. Serv.* 82, 104059. <https://doi.org/10.1016/j.jretconser.2024.104059>.
- Rucker, D.D., McShane, B.B., Preacher, K.J., 2015. A researcher's guide to regression, discretization, and median splits of continuous variables. *J. Consum. Psychol.* 25, 666–678. <https://doi.org/10.1016/j.jcps.2015.04.004>.
- Salim, A.D., Wafa, F.E.W., 2025. Influencers and integrity: the role of halal labels and online testimonials in shaping purchase intentions for Somethinc skincare products. *J. Princ. Manag. Bus.* 4, 63–79. <https://doi.org/10.55657/jpmb.v4i01.220>.
- Soloaga, P.D., García, S.L.C., Ventisca, M.D.-B., 2023. Perceived brand value and brand co-creation attitudes through eWOM: a typology of co-creator digital users. *Rev. Comun.* 22, 89–107. <https://doi.org/10.26441/RC22.1-2023-3075>.
- Suresh Kumar, K., Helen Sulochana, C., Radhamani, A.S., Ananth Kumar, T., 2022. Sentiment lexicon for cross-domain adaptation with multi-domain dataset in Indian languages enhanced with BERT classification model. *J. Intell. Fuzzy Syst.* 43, 6433–6450. <https://doi.org/10.3233/JIFS-220448>.
- Tabachnick, B.G., Fidell, L.S., 2019. *Using Multivariate Statistics*, seventh ed. Pearson, Boston.
- Tafolli, F., Qema, E., Hameli, K., 2025. The impact of electronic word-of-mouth on purchase intention through brand image and brand trust in the fashion industry: evidence from a developing country. *Res. J. Text. Appar.* 29, 1160–1176. <https://doi.org/10.1108/RJTA-07-2024-0131>.

- Tosun, P., Cagliyor, S.I., Gürce, M.Y., 2024. Reducing consumer–brand incongruity through corporate social responsibility and brand trust: exploring negative word-of-mouth (NWOM). *Int. J. Consum. Stud.* 48, e13099. <https://doi.org/10.1111/ijcs.13099>.
- Ul Haq, I., Mazhar, B., Maqsood, F., Pokharel, M., Tareen, H.K., Maaz ul Hassan, M., 2026. Understanding algorithmic personalization in Instagram ads: the role of perceived creativity, authenticity and need for cognition in shaping Generation Z's purchase intentions. *Telemat. Inform. Rep.* 21, 100287. <https://doi.org/10.1016/j.teler.2025.100287>.
- Wang, P., Xia, X., Liang, K., 2026. Local brand aversion or aspiration? The influence of socioeconomic status on Chinese consumer brand preference. *Humanit. Soc. Sci. Commun.* 13, 432. <https://doi.org/10.1057/s41599-026-06743-w>.
- Xu, Z., Wu, Y., Tang, L., Gui, S., 2025. From user-generated content to quality improvement: a multi-granularity analysis of customer satisfaction and attention in new energy vehicles using deep learning. *Comput. Ind.* 173, 104380. <https://doi.org/10.1016/j.compind.2025.104380>.
- Yu, X., Xu, D.J., Li, K., 2026. Effects of AI reviews on consumers' purchase intention: influence of product category, review breadth, and consumer review volume. *Decis. Support Syst.* 201, 114590. <https://doi.org/10.1016/j.dss.2025.114590>.
- Zameer, H., Ahsan, A., Bin Khalid, H., 2026. Understanding the role of consumer interaction with brand and influencer endorsement in reinforcing brand perception and purchase intention in the fashion industry. *Strateg. Bus. Res.* 2, 100074. <https://doi.org/10.1016/j.sbr.2026.100074>.
- Zhang, B., Zhu, J., Ma, R., Huang, Y., 2025. Impact of dual routes of information cues on consumers' willingness to pay a premium in cross-border e-commerce: the role of product involvement and nutrition safety awareness. *J. Retailing Consum. Serv.* 87, 104428. <https://doi.org/10.1016/j.jretconser.2025.104428>.
- Zhao, G., Huang, Y., Chen, L., Sun, X., 2026. Transactional quality and repurchase intention in community group-buying: does purchase frequency matter? *Internet Res. Advance online publication*. <https://doi.org/10.1108/INTR-10-2023-0882>.
- Zniva, R., Weitzl, W.J., Lindmoser, C., 2023. Be constantly different! How to manage influencer authenticity. *Electron. Commer. Res.* 23, 1485–1514. <https://doi.org/10.1007/s10660-022-09653-6>.