

Drivers of Electronic Word-of-Mouth Adoption Among University Students: The Mediating Role of Brand Love

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Abstract

The present exploratory research identifies the factors that drive the adoption of electronic word-of-mouth (eWOM) among university students and examines their connection with brand love, emphasizing how this emotional bond shapes the acceptance of online reviews within social media. A questionnaire targeted at Facebook users guided data collection, and the dataset underwent analysis through a structural equation modeling approach (PLS-SEM), grounded in the Information Acceptance Model (IACM). The findings reveal that brand love plays a pivotal mediating role in the link between brand trust and eWOM adoption, as well as in co-creation intention. The results indicate that the emotional attachment to the brand channels trust into concrete actions of dissemination and co-creation on social networks. The study recommends that institutions develop marketing campaigns that strengthen social well-being and encourage socially responsible behaviors, integrating strategies that foster eWOM adoption among university students.

Keywords: Brand love, electronic word-of-mouth, social media.

Introduction

Consumer behavior shapes how and why individuals make their purchase decisions (Schiffman & Wisenblit, 2015). Word of mouth (WOM) provides one of the most influential mechanisms for guiding consumer behavior and functions as the most frequently used channel for obtaining information before, during, and after the consumption of a product or service (Yang, 2017). Researchers often recognize WOM as a highly impactful marketing outcome variable, exerting stronger influence on customers than advertising or firm-generated information (Rossmann et al., 2016). Consequently, electronic word of mouth (eWOM) has gained recognition as a major source of information for consumers (Le et al., 2022). As daily life accelerates and consumer attention spans diminish (Kotler et al., 2019), social media platforms increasingly replace traditional WOM with eWOM (Indrawati et al., 2023).

As more marketers embed social media within the promotional mix, rigorous research must examine the determinants that shape consumer actions (Chu & Kim, 2011). eWOM influences consumer behavioral intentions by shaping perceptions of credibility and usefulness across social networks and e-commerce platforms (Moradi & Zihagh, 2022). The distinctive nature of social media enables real-time interactions between consumers and brands, amplifying users' social responses to media content (Park & Kim, 2014). According to DataReportal (2024), Mexico hosts 107.3 million internet users, representing 83.2% of the national population. Among major social networks, 90 million individuals aged 18 or older maintain active accounts—equivalent to 98.1% of platform users and 84.1% of the total internet-using population.

Given this context, the present study aims to identify the factors that drive eWOM adoption among young Facebook users in Mexico and to examine its relationship with brand love across social media environments. Despite its relevance, eWOM has not received sufficient academic attention, particularly regarding how consumers engage with it (Rossmann et al., 2016; Wallace et al., 2022). Limited research examines the factors explaining eWOM adoption grounded in both cognitive and affective attitudes expressed on social networks (Aghakhani et al., 2018). Prior studies predominantly focus on the informational influence of eWOM while overlooking users' emotional and interpersonal dynamics within social media communities (Chu & Kim, 2011). Several scholars argue that social networks serve as valuable platforms for eWOM adoption, assuming that information adoption constitutes the first stage of consumers' online decision-making processes (Erkan & Evans, 2018; Khwaja & Zaman, 2020).

Drawing on the literature, the following hypothesis emerges: brand love shapes the adoption of eWOM among young Facebook users in Mexico. Identifying the factors that drive eWOM adoption and clarifying its connection to brand love enables a deeper understanding of this construct within the framework of the Information Adoption Model (IACM) developed by Erkan and Evans (2016). The study's findings enhance comprehension of eWOM adoption and reveal the effect of brand love on consumer behavior. Furthermore, they offer marketing departments relevant insights for designing social media strategies grounded in eWOM determinants, ultimately supporting consumer well-being and broader social welfare.

Theoretical framework

Background

Facebook usage currently reflects its relevance as one of the most widely used social media platforms among young people. According to DataReportal (2024), in Mexico, men (27.1%) and women (29.5%) aged 18 to 34 form the largest segment of the advertising-search audience across Facebook, Instagram, and Messenger. Among these platforms, Facebook remains the preferred option with 30.1%, followed by WhatsApp (26.7%) and TikTok (18%). Globally, Facebook leads the ranking of the most popular social networks, with more than three billion monthly active users (Statista, 2024). Within this context, Mexico occupies seventh place worldwide in social commerce participation, with at least 43% of users making purchases directly through social networks. Social media has evolved into the primary online channel for describing and searching for brands (Statista, 2023). Consequently, social networks allow organizations to capture customer attention through content that reflects brand identity (Kunja & GVRK, 2018). Platforms such as Facebook have reshaped how companies build brand image and manage online word of mouth (See-To & Ho, 2014). In Mexico, social media ranks first among website categories and application usage, reaching 99.2% of internet users (DataReportal, 2024).

Ngo et al. (2024) examined the impact of eWOM within Generation Z (ages 18–24), individuals born between 1997 and 2012 according to the Pew Research Center (2019). This cohort consists of young consumers who demonstrate high trust in technology and frequent engagement with social media. Likewise, university students represent a demanding consumer segment that facilitates the acceptance of social networks in an increasingly consumption-driven era (Mangold & Faulds, 2009). The distinctive nature of social media enables real-time interactions between consumers and brands, expanding users' responsiveness to media content (Park & Kim, 2014).

From WOM to eWOM

Traditional word of mouth (WOM) has long functioned as a key factor in consumer decision-making, since individuals often rely on informal or personal messages rather than formal or organizational sources when evaluating purchasing options (Bansal & Voyer, 2000). WOM stands as one of the most influential mechanisms shaping consumer behavior and as the primary channel used to gather information before, during, and after a consumption experience (Yang, 2017). A central difference lies in the fact that traditional WOM originates from a sender known to the recipient, strengthening message credibility (Cheung & Thadani, 2012). For this reason, WOM is considered one of the most powerful marketing outcome variables, often exerting greater influence than advertising or firm-generated information (Rossmann et al., 2016).

Traditional WOM has evolved through the internet into electronic word of mouth (eWOM), which has transformed consumer behavior as digital interactions proliferate (Lee et al., 2008; Yang, 2017). eWOM refers to any positive or negative statement, comment, or review made by potential, current, or former customers about a product or company, and made available to a wide audience through the internet (Hennig-Thurau et al., 2004). Beyond serving as a marketing

tool that enables firms to listen and converse with customers, eWOM also supports deeper understanding of consumer needs (Chan & Ngai, 2011). As a result, it functions as an important source of consumer information (Le et al., 2022), increasingly replacing traditional WOM (Indrawati et al., 2023).

A key difference between WOM and eWOM lies in the ease with which large volumes of messages can be retrieved and analyzed online, including their linguistic features such as message length (Cheung & Thadani, 2012). eWOM also unfolds in an asynchronous, anonymous, and high-speed environment (Davis & Khazanchi, 2008). These attributes turn eWOM into a vital tool within social media and marketing strategies, as consumers rely on it to reduce perceived risks when making decisions (Hussain et al., 2017).

Theoretical Models Applied to eWOM

The Elaboration Likelihood Model (ELM) explains consumer reactions to online reviews by focusing on information processing and the mechanisms that influence attitude change (Lee et al., 2008). Within the ELM framework, Bhattacharjee and Sanford (2006) identify peripheral cues such as the number of messages, number of sources, source likability, and credibility. Current research shows that consumers often rely on certain recommendations to guide their behavior, which in turn shapes their intentions (Moradi & Zihagh, 2022). Cultural background also affects eWOM message characteristics (Kusawat & Teerakapibal, 2024).

Moradi and Zihagh (2022), in their review of ELM-based eWOM literature, conclude that eWOM usefulness and credibility influence behavioral intentions, with eWOM adoption mediating these relationships. Similarly, Le et al. (2022) emphasize the need to conceptualize eWOM factors from an information-processing perspective. According to the ELM, argument quality and peripheral cues integrated into a message drive acceptance decisions (Bhattacharjee & Sanford, 2006).

The Information Adoption Model (IAM) explains how individuals adopt information through computer-mediated contexts, making it suitable for studying eWOM because it describes how users interact with online communication platforms (Erkan & Evans, 2016). The IAM integrates concepts from ELM and includes four elements: information usefulness, information adoption, source credibility (peripheral route), and argument quality (central route) (Sussman & Siegal, 2003). These authors reinterpret the internalization phase of knowledge processing and refer to this process as knowledge adoption. Adoption plays a crucial role in transferring ideas and shaping informational influence, thereby explaining how individuals adopt new ideas (Bhattacharjee & Sanford, 2006).

Both IAM and ELM clarify the initial stages of intention formation toward a message; however, neither model was designed to capture the full process of influence (Sussman & Siegal, 2003). Several studies have assessed the impact of eWOM on purchase intention using the IAM (Erkan & Evans, 2016; Leong et al., 2022; Indrawati et al., 2023). Although the IAM does not fully explain peripheral processes, it contributes key insights into information usefulness as a driver of influence in computer-mediated communication contexts (Sussman & Siegal, 2003). IAM posits that information usefulness, eWOM credibility, and information adoption remain theoretically linked (Cheung & Thadani, 2012).

Dual-processing theories, such as the ELM and the Heuristic–Systematic Model (HSM), offer valid frameworks to explain the individual-level impact of online reviews (Cheung & Thadani, 2012). These theories propose that highly motivated individuals tend to process information through the central route (Chaiken, 1980). Cheung and Thadani (2012) further demonstrate that receiver characteristics shape elaboration likelihood and moderate the effect of eWOM messages on consumer purchase decisions.

Information Acceptance Model (IACM)

Building on the IAM, Erkan and Evans (2016) developed the Information Acceptance Model (IACM), which incorporates consumer behaviors related to information usage. The IACM argues that consumer behavior toward eWOM influences its adoption on social networks by considering not only information attributes but also consumer-based behavioral components (Ngo et al., 2024). Consequently, the IACM offers a suitable framework for examining how brand love affects eWOM acceptance, as it enables analysis of both information characteristics and consumer attitudes.

Although numerous studies have evaluated eWOM impacts on purchase intention, further research must clarify how eWOM shapes customer perceptions and preferences, as well as the motivations of both senders and receivers (Chan & Ngai, 2011). Identifying the factors that drive eWOM adoption and understanding its connection to brand love becomes central when the IACM functions as the guiding theoretical framework (Erkan & Evans, 2016). Therefore, the study's findings enhance understanding of eWOM adoption and highlight the role of brand love in consumer behavior, reinforcing the relevance of the IACM for analyzing eWOM in social media environments.

Trust-Based Adoption Model (TBAM)

The Trust-Based Adoption Model (TBAM), developed by Komiak and Benbasat (2006), originates from the Theory of Reasoned Action (TRA) (Ajzen, 1985). This model depends on consumers' trust in recommendations and demonstrates that emotional trust develops from cognitive trust, subsequently influencing online purchase intention. TBAM adopts a dual perspective that integrates cognitive and emotional trust to examine the adoption of recommendation agents. Trust in online purchasing contexts has consistently appeared as one of the most critical factors (Zhang et al., 2014). Adoption intention refers to the degree to which a customer remains willing to allow eWOM to narrow the options that they will later evaluate during the purchase decision process (Komiak & Benbasat, 2006).

Methodology

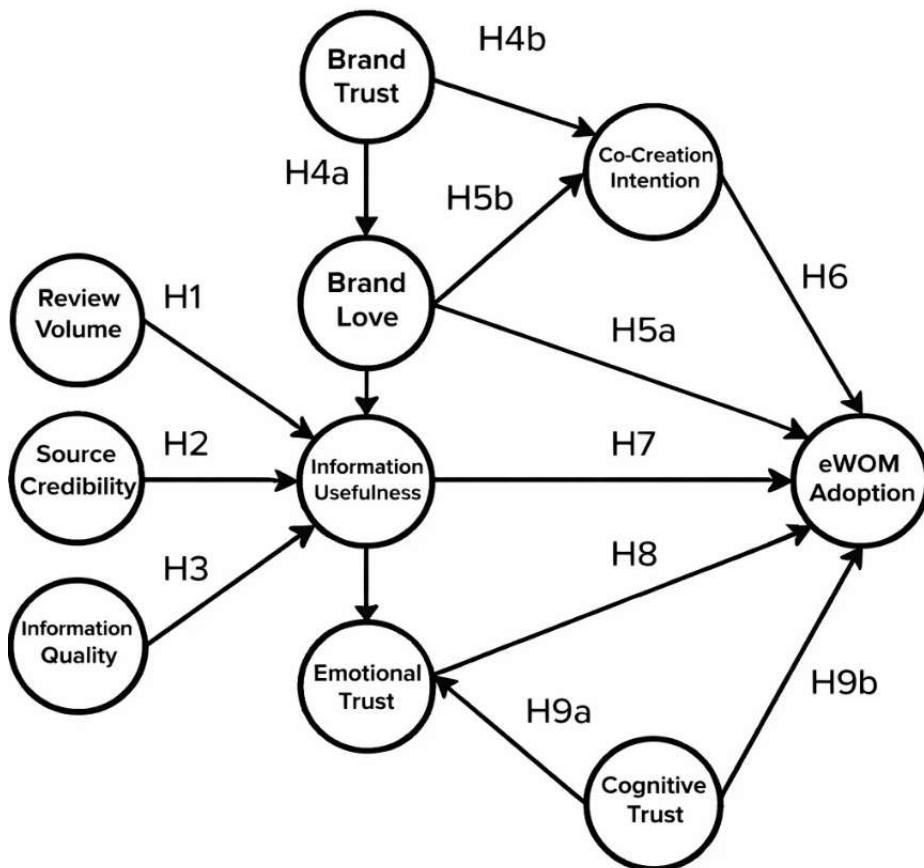
The theoretical foundation of the research model draws on the Information Acceptance Model (IACM), developed as an extension of the Information Adoption Model (IAM). This framework incorporates concepts from the Elaboration Likelihood Model (ELM) and the Trust-Based Adoption Model (TBAM), which in turn derives from the Theory of Reasoned Action (TRA). The present study focuses on the voluntary use of eWOM by users with direct experience on Facebook; therefore, the research model prioritizes the intention to adopt eWOM rather than

subjective norms. Accordingly, the study examines intentions toward eWOM adoption and identifies the factors that increase individuals' reliance on such adoption, without addressing the final stage of decision-making that leads to purchasing a given product or service.

A quantitative approach guided the analysis of correlations among the information-related elements involved in eWOM adoption. To this end, the study employed a conclusive research design aimed at testing specific hypotheses and examining targeted relationships. Using a simple cross-sectional design, the research team collected data from a single sample drawn from the population at one point in time. Information technology acceptance relies on central and peripheral processing routes, which influence perceived usefulness and attitudes, and consequently shape constructs such as argument quality and source credibility (Bhattacharjee & Sanford, 2006).

The research model emerged from an integrative review of relevant literature and the formulation of hypotheses. The model evaluates the effects of information quality, source credibility, quantity of reviews, information usefulness, brand trust, emotional trust, cognitive trust, co-creation intention, brand love, and eWOM adoption (see Figure 1).

Figure 1. Proposed Research Model



Note. Author's elaboration (2025).

According to the literature, several studies highlight source credibility as a key factor for explaining eWOM characteristics (Cheung & Thadani, 2012). Information usefulness, credibility, and eWOM adoption maintain theoretical interconnections that the IAM helps clarify, as this model explains how individuals come to adopt information disseminated in technology-mediated environments (Sussman & Siegal, 2003). The validity of the instrument aligned with the proposed theoretical model draws on the contributions of the authors listed in Table 1.

Table 1. Model Background

Code	Construct	Source
CC	Cognitive Trust	Komiak & Benbasat (2006)
CE	Affective or Emotional Trust	Komiak & Benbasat (2006)
CF	Source Credibility	Bhattacharjee & Sanford (2006)
CI	Information Quality	Bhattacharjee & Sanford (2006)
CR	Review Volume	Zhang, Zhao, et al. (2014)
UI	Information Usefulness	Bailey & Pearson (1983)
CM	Brand Trust	Gurviez & Korchia (2002)
AM	Brand Love	Carroll & Ahuvia (2006)
ICC	Co-Creation Intention	Tajvidi et al. (2021)
AE	eWOM Adoption	Cheung et al. (2009)

Note. Author's elaboration (2025) based on the literature review.

To determine the minimum sample size for exploratory studies, an initial rapid estimation relied on the “10-times rule” (Hair et al., 2011). This rule requires counting the number of predictors influencing the most heavily loaded construct and multiplying that number by 10. In this case, the construct with the highest number of predictors—eWOM Adoption (AE)—included four predictors, yielding a minimum sample size of 40. In addition, the study employed G*Power 3.1 as a complementary procedure using the following criteria: Type of power analysis (A priori), Test family (F tests), Statistical test (Linear multiple regression: Fixed model, R² deviation from zero). Input parameters included effect size ($f^2 = 0.35$), error probability (0.05), power ($1 - \beta = 0.80$), and four predictors, corresponding to the number of arrows pointing to the most heavily loaded dependent construct. The statistical power of the sample met the recommended minimum threshold of 0.80, along with the large effect size of 0.35 suggested for exploratory models (Hair et al., 2011). The study reported a sampling error of $\pm 15.1\%$. Given the exploratory nature of the research and the characteristics of PLS-SEM, this level remains acceptable. However, the study acknowledges this as a limitation and recommends replicating the model with larger samples and broader geographic dispersion across universities, as well as reducing the structural model or testing alternative specifications to obtain more precise estimates in future studies.

Data analysis relied on partial least squares structural equation modeling (PLS-SEM), a technique recommended for small samples due to its predictive orientation and its flexibility regarding non-normal data distributions (Hair et al., 2019). Therefore, a sample size of 40 or more proved suitable for exploratory assessment of the research model. SmartPLS Version 4.1.1.6 facilitated

both the measurement evaluation and the testing of the proposed structural model. The exploratory approach used to construct the theoretical model through PLS-SEM enabled the identification of significant relationships among constructs without requiring assumptions of normality or large sample sizes.

A non-probabilistic convenience sampling method guided participant selection, focusing on individuals who were readily accessible. The sample consisted of university students from the Instituto Tecnológico de Sonora (ITSON), a population that offered adequate accessibility for data collection. Facebook served as the representative social network for the study due to its popularity and its relevance as a communication channel between users and brands (Park & Kim, 2014). To qualify for participation, respondents needed to have used Facebook and followed one or more brands on the platform. Erkan and Evans (2018) also relied on university students to examine the influence of friend recommendations and anonymous website reviews on online purchase intention. Similarly, Wallace et al. (2022) studied young consumers from Generations Y and Z in Portugal who follow brands on social media. For this reason, the study considered a sample of university students aged 18 to 34 as appropriate.

Product or service involvement affects the degree to which consumers seek information (Adjei et al., 2010), strengthening their engagement with a brand's social network. In this regard, online reviews or eWOM function as a key source of information capable of influencing purchase decisions (Zhang, Cheung, et al., 2014). Participants in the present study identified the brands they followed on Facebook and responded with a specific brand in mind, given that consumer identification and attitudes vary across brands (Wallace et al., 2022). The questionnaire included minor adjustments to ensure respondents reflected on a favorite brand—one they followed or had “liked.” A survey collected the data from participants who had interacted with Facebook brand pages. The measurement items underwent refinement and minor modifications to align them with the study context. All constructs within the research model were measured with multi-item scales adapted from prior studies, using a five-point Likert-type scale.

The questionnaire first asked participants to answer general questions about their Facebook usage and sociodemographic information. The data analysis included only respondents with an active Facebook account who had given a “like” to at least one brand page. Participants then accessed their profile to report how many brand pages they followed and to identify the categories of the associated products or services. Afterward, they selected and indicated their favorite brand page on Facebook, which guided their responses for the remainder of the questionnaire. Carroll and Ahuvia (2006) note that many such brands tend to fall within hedonic or self-expressive categories (e.g., fashion or entertainment), which typically generate stronger brand love and higher levels of engagement than utilitarian brands.

The measurement model demonstrated adequate convergent and discriminant validity, reflected in Cronbach's alpha values exceeding the recommended 0.70 threshold and an average variance extracted (AVE) above 0.50 (see Table 2). These results indicate that the instrument achieved reliable performance and that its items correlated well internally, ensuring construct consistency. Cronbach's alpha values between 0.70 and 0.90 generally represent satisfactory internal reliability (Hair et al., 2019).

Table 2. Construct Reliability and Validity – SmartPLS

	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
AE	0.941	0.944	0.955	0.810
AM	0.910	0.961	0.937	0.635
CC	0.819	0.831	0.874	0.582
CE	0.947	0.947	0.966	0.905
CF	0.842	0.849	0.895	0.681
CI	0.904	0.919	0.933	0.779
CM	0.965	0.967	0.973	0.877
CR	0.886	0.898	0.929	0.813
ICC	0.921	0.945	0.950	0.864
UI	0.921	0.921	0.950	0.863

Note. Author's elaboration (2025) based on PLS-SEM model results.

The data collection instrument consisted of a 45-item questionnaire measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire was designed in Google Forms due to its ease of distribution and accessibility for university students. The analysis excluded all incomplete responses and any entries from individuals who did not use social media, did not have a Facebook profile, or had not “liked” a brand page. Out of 57 respondents, 2 reported not using social media and 13 did not have a Facebook account nor had they liked any brand page. As a result, 15 cases were removed, leaving 42 valid questionnaires—a number that meets the minimum required sample size of 40.

Data analysis employed the partial least squares (PLS) technique within the structural equation modeling (SEM) framework. This method was selected for its flexibility, limited distributional assumptions, and suitability for small samples and exploratory studies (Cheung, 2014). The use of PLS-SEM enabled the evaluation of the instrument's validity and reliability, the testing of the proposed hypotheses, and the examination of the significance of relationships between constructs, particularly the impact of eWOM information on behavioral intentions (Abedi et al., 2020). The method also aligns well with the research model, as it allows simultaneous estimation of both the measurement and structural components without imposing distributional constraints (Hair et al., 2019).

The analysis relied on SmartPLS Version 4.1.1.6, which facilitated the assessment of the measurement model and the structural model, enabling the identification of significant relationships among constructs without requiring normal data distributions or large sample sizes (Cheung, 2014).

Results

Among the 57 respondents, 59.65% identified as female and 40.35% as male. Regarding age, the largest segment corresponded to individuals between 18 and 25 years (60%), followed by those aged 26 to 35 (19%). In total, participants aged 18 to 34 represented 79% of the sample, while the segments aged 36 to 45 (11%) and 46 to 55 (11%) reported lower participation. In terms of occupation, more than half were students (54.39%), followed by employees (28.07%), students

who also worked (15.79%), and unemployed participants (1.75%). Overall, the sample reflected a predominantly student population (70.18%), consistent with the age distribution.

The social media platforms most frequently used to search for reviews, opinions, or comments included YouTube and TikTok (20% each), followed by Facebook (18%), Instagram (16%), Pinterest (9%), X (Twitter) (7%), and WhatsApp (7%). The platforms with the lowest usage (1% each) were Facebook Messenger, Telegram, and LinkedIn. Additionally, 76.3% of respondents reported having a Facebook account and having “liked” a brand page.

The most frequently consulted categories for product or service reviews on social media were “Food and Beverages” (16%), “Music and Entertainment” (15%), “Restaurants” (14%), “Clothing and Footwear” (11%), “Personal Care and Cosmetics” (10%), “Technology Services or Products” (9%), “Professional Services” (8%), “Accommodation and Lodging” (5%), “Home Goods” (4%), “Tourism” (4%), and “Vehicles or Auto Parts” (3%). Consequently, the analysis focused on 42 users who actively participated on Facebook, the platform chosen as the reference social network for the study.

Hypothesis testing

Hypotheses were tested using the Partial Least Squares (PLS) approach in SmartPLS. To assess hypothesis significance in PLS-SEM, the statistical relevance of path coefficients was examined through bootstrapping, a procedure that generates confidence intervals and p-values for each coefficient (Hair et al., 2019). The study employed a bootstrapping process with 5,000 iterations to evaluate the significance of path coefficients. A significance level of 0.05—corresponding to a 95% confidence interval—guided the analysis. When the confidence interval excluded zero and the p-value fell below 0.05, the hypothesis was considered supported.

The hypotheses evaluated in the study were as follows:

H1: The Quantity of Reviews (CR) positively influences information usefulness (UI).

H2: Source credibility (CF) positively affects information usefulness (UI).

H3: Information quality (CI) positively influences information usefulness (UI).

H4a: Brand trust (CM) positively affects brand love (AM).

H4b: Brand trust (CM) positively influences co-creation intention (ICC).

H5a: Brand love (AM) positively affects eWOM adoption (AE).

H5b: Brand love (AM) positively influences co-creation intention (ICC).

H6: Co-creation intention (ICC) positively influences eWOM adoption (AE).

H7: Information usefulness (UI) positively influences eWOM adoption (AE).

H8: Emotional trust (CE) positively affects eWOM adoption (AE).

H9a: Cognitive trust (CC) positively influences emotional trust (CE).

H9b: Cognitive trust (CC) positively affects eWOM adoption (AE).

The structural analysis using PLS-SEM enabled the evaluation of the hypotheses formulated in the research model. The results indicate that H3, H4a, H4b, H5a, H5b, H6, and H9a received empirical support, while H1, H2, H7, H8, and H9b were rejected due to p-values ≥ 0.05 and t-values < 1.96 (see Table 3).

Table 3. Hypothesis Testing and Path Coefficients

Hypothesis	Relationship	β (O)	Standard Error	f2	t-Value	p-Value	Supported
H1	CR \rightarrow UI	0.173	0.1793	0.024	0.965	0.335	No
H2	CF \rightarrow UI	0.151	0.2658	0.015	0.568	0.570	No
H3	CI \rightarrow UI	0.446	0.2035	0.178	2.192	0.028	Yes
H4a	CM \rightarrow AM	0.793	0.0891	1.690	8.903	0.000	Yes
H4b	CM \rightarrow ICC	0.433	0.1211	0.211	3.577	0.000	Yes
H5a	AM \rightarrow AE	0.471	0.1601	0.607	2.941	0.003	Yes
H5b	AM \rightarrow ICC	0.432	0.1386	0.210	3.117	0.002	Yes
H6	ICC \rightarrow AE	0.332	0.1430	0.238	2.322	0.020	Yes
H7	UI \rightarrow AE	0.127	0.0888	0.077	1.430	0.153	No
H8	CE \rightarrow AE	0.109	0.1219	0.028	0.894	0.371	No
H9a	CC \rightarrow CE	0.768	0.0603	1.438	12.729	0.000	Yes
H9b	CC \rightarrow AE	0.046	0.0937	0.007	0.491	0.623	No

Note. Author's elaboration (2025) based on PLS-SEM model results; n = 5,000 subsamples; R² (AM = 0.628, ICC = 0.670, UI = 0.486, CE = 0.590, AE = 0.873).

The analysis of indirect effects in PLS-SEM involves calculating the product of the path coefficients that connect the independent variable to the dependent variable through the mediator. To assess statistical significance, the study relied on bootstrapping—a non-parametric procedure suitable for testing the significance of PLS-SEM outcomes such as path coefficients, outer weights, Cronbach's alpha, HTMT, and R² values. Bootstrapping also delivers confidence intervals and p-values for the indirect effect (Hair et al., 2019). This type of effect plays a particularly important role in the assessment of mediation (Nitzl et al., 2016). When the p-value falls below 0.05, the indirect effect reaches statistical significance, allowing the conclusion that the construct functions as a mediator.

In the present study, the analysis identified significant indirect effects for CM \rightarrow AM \rightarrow ICC and CM \rightarrow AM \rightarrow AE, indicating a mediating mechanism of brand love (AM) between brand trust (CM) and the outcomes co-creation intention (ICC) and eWOM adoption (AE). The remaining paths did not display statistically robust indirect effects, as their p-values did not meet the significance threshold; therefore, no additional mediating constructs were identified (see Table 4).

Table 4. Specific Indirect Effects – SmartPLS

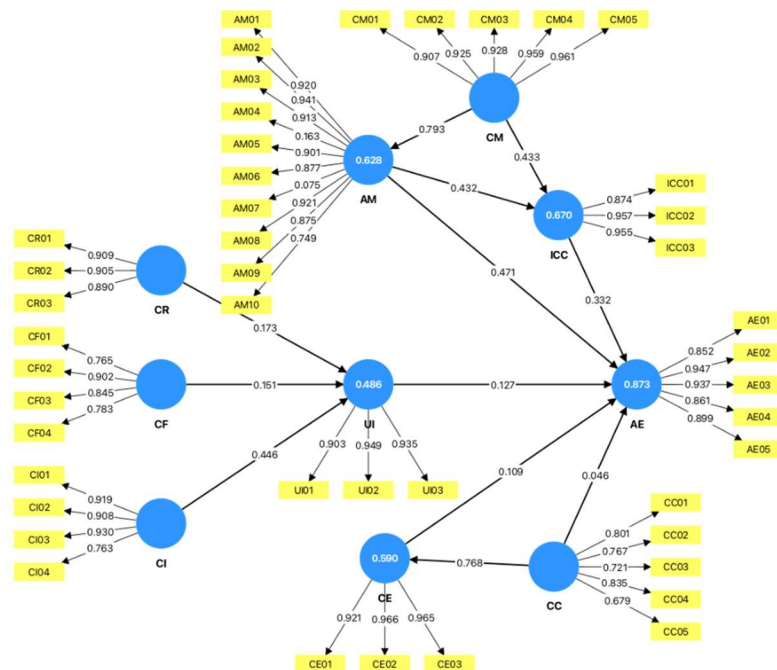
Path	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	t-Statistics (O/STDEV)	p-Values
CM -> AM -> ICC	0.342	0.343	0.121	2.821	0.005
CM -> AM -> AE	0.373	0.351	0.139	2.693	0.007
CM -> ICC -> AE	0.144	0.156	0.081	1.777	0.076
AM -> ICC -> AE	0.143	0.161	0.091	1.581	0.114
CM -> AM -> ICC -> AE	0.114	0.126	0.073	1.549	0.121
CI -> UI -> AE	0.057	0.066	0.058	0.987	0.324
CC -> CE -> AE	0.084	0.079	0.096	0.869	0.385
CR -> UI -> AE	0.022	0.026	0.031	0.701	0.483
CF -> UI -> AE	0.019	0.013	0.042	0.453	0.650

Note. Author's elaboration (2025) based on PLS-SEM model results.

Table 4 shows that brand trust (CM) exerts a positive and significant effect on co-creation intention (ICC) through brand love (AM) ($\beta = 0.342$; $t = 2.821$; $p = 0.005$). Similarly, brand trust (CM) positively and significantly influences eWOM adoption (AE) through brand love (AM) ($\beta = 0.373$; $t = 2.693$; $p = 0.007$). The remaining indirect paths did not reach statistical significance ($p < 0.05$), which indicates that they do not adequately explain eWOM adoption through those mediators.

Figure 2 displays the output graph for the structural model estimated in SmartPLS, obtained through the bootstrapping procedure with 5,000 subsamples. The figure presents R^2 values, path coefficients, and outer loadings, allowing a clear view of the magnitude and direction of the relationships specified in the research model.

Figure 2 SmartPLS Output Graph



Note. Author's elaboration (2025) (R^2 , Structural Model: Path Coefficients; Measurement Model: Outer Loadings).

Discussion

The results align with the characteristics of the analyzed population, which consists primarily of university students aged 18 to 34, a segment that exhibits high levels of social media adoption. Wallace et al. (2014, 2017) likewise examined consumer engagement using samples of Irish university students, given their habitual use of the internet. More recently, Wallace et al. (2022) explored brand–consumer relationships on social media and the interactions of Generations Y and Z. Research on social media platforms such as TikTok has continued to grow; for instance, Indrawati et al. (2023) analyzed eWOM impacts on purchase intention specifically within the beauty-product context. Erkan and Evans (2016) studied eWOM more broadly across products and services, without restricting their analysis to a particular category and considering multiple social platforms. Sociodemographic factors also offer opportunities for deeper understanding of eWOM adoption, along with receiver characteristics such as gender, consumer skepticism, and cognitive personalization (Cheung & Thadani, 2012).

The findings confirm that information quality positively influences information usefulness (H3). Systematic factors linked to online review quality, such as perceived informativeness and persuasive strength, significantly affect purchase intention (Zhang, Zhao, et al., 2014). Ngo et al. (2024) likewise reported that information quality, user needs, and attitudes strongly shape information adoption. In contrast, the present results show that the quantity of reviews (H1) and source credibility (H2) do not directly determine perceived information usefulness.

When individuals experience high involvement with a message topic, source credibility exerts minimal influence on attitude change because users concentrate on evaluating arguments rather than peripheral cues. Conversely, when involvement remains low, source credibility becomes an important predictor of general attitude change (Petty et al., 1983). Forman et al. (2008) found that online reviews provided by identifiable sources elicit stronger positive reception than anonymous ones, as consumers perceive them as more useful. When receivers face information overload arising from high review volume, they tend to process information heuristically, relying on source features.

Because information quality reflects central-route processing, it demands more cognitive effort than peripheral cues such as source credibility or review volume, which relate to low-involvement processing (Cheung & Thadani, 2012). Central or peripheral processing can shape final information adoption decisions; for source credibility, this process may emerge from influences that combine both routes (Bhattacharjee & Sanford, 2006). Moreover, Lee et al. (2008) noted that the volume of positive and negative reviews can influence consumer attitudes; negative reviews often carry greater perceived usefulness and weight than positive ones, underscoring the importance of considering review valence in information processing.

The results also indicate that brand trust strengthens brand love (H4a) and motivates co-creation intention (H4b). In turn, brand love affects both eWOM adoption (H5a) and co-creation (H5b). Co-creation intention also predicts eWOM adoption (H6), and cognitive trust positively shapes

emotional trust (H9a). Furthermore, information usefulness (H7), emotional trust (H8), and direct cognitive trust (H9b) showed significant explanatory power for eWOM adoption.

The analysis confirms the mediating role of brand love (AM). This finding suggests that consumer trust in a brand does not automatically lead to co-creation behaviors or eWOM adoption. Instead, these behaviors emerge more strongly when consumers develop an affective bond with the brand. In other words, trust alone does not directly translate into action; the transition toward co-creation and positive eWOM requires an emotional link that encourages users to participate and disseminate information online. Similarly, Wallace et al. (2022) emphasized the mediating role of brand love in the relationship between online brand interaction and consumer–brand identification, co-creation intention, and willingness to pay a premium price. As a mediating construct, brand love consolidates the affective dimension of consumer–brand relationships and clarifies how individuals actively engage in information sharing and online review dissemination. Carroll and Ahuvia (2006) demonstrated that brand love significantly enhances loyalty, word of mouth, and resistance to negative information. Loved brands resonate more deeply because they connect with consumers’ self-identity and provide meaning rooted in intrinsic motivations such as social progress or personal values (Batra et al., 2012).

The proposed model achieves partial validation, highlighting the relevance of emotional and relational factors in eWOM adoption. The evidence confirms that brand love functions as a key antecedent of positive outcomes among brand followers on social media (Wallace et al., 2022), whereas other proposed constructs lack sufficient empirical support.

Conclusions

Within digital platforms, users’ preference for visual content helps explain the growing prominence of YouTube and TikTok compared with other social networks. Although Facebook continues to function as an important source of reviews, its influence tends to concentrate on high-frequency, low-cost consumption decisions. Future research could therefore consider additional differentiating factors such as gender, age, cultural context, and message valence (positive vs. negative reviews). Larger samples would also allow a more accurate representation of the target population.

Moreover, studies should incorporate a variety of social media platforms selected according to the market they serve and their primary role as channels of interaction. Distinguishing between hedonic and utilitarian brand purchases likewise remains relevant, as does the inclusion of external variables that may shape decision-making—such as the participation of influencers or other stakeholders who increasingly function as key actors in eWOM adoption. In line with the dual-processing model of the ELM, future studies should examine receiver characteristics within central and peripheral routes, since these determine elaboration likelihood and moderate the influence of eWOM messages on purchase decisions.

The empirical findings confirm that eWOM adoption constitutes a common practice among young consumers, who consult online opinions from other users before making a purchase decision. The study demonstrates that brand love functions as a central mediating mechanism

between brand trust and both eWOM adoption and co-creation intention. These results highlight the need to differentiate between users who follow brands on social media and those who do not, in order to determine whether this distinction shapes emotional responses and, consequently, the model's outcomes regarding source credibility and review volume.

The analysis confirms that brand trust acts as a decisive factor that drives co-creation intention, indicating that credibility-based bonds foster consumers' active participation. Co-creation intention, in turn, positively influences eWOM adoption, strengthening the spread of experiences and recommendations in digital environments. Collectively, these results underscore the importance of trust and co-creation as mechanisms that amplify online information diffusion and consolidate consumer–brand relationships. In this sense, organizations should invest in producing high-quality content and nurturing trust-based, emotionally meaningful relationships with consumers. Such bonds promote the exchange of opinions, experiences, and recommendations in digital environments, positioning brand love as a catalyst for communicative behaviors with substantial social impact.

Consequently, marketers should orient their strategic efforts toward emphasizing intrinsic benefits—such as alignment with personal values, social causes, or meaningful experiences—rather than relying solely on extrinsic benefits. This approach strengthens consumer–brand relationships, deepens brand love, and enhances eWOM adoption across digital environments.

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