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Factors Influencing Purchase Intention of Local Fashion Brands in Social Commerce as Online Distribution Channels

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Abstract

Purpose: This study examines the factors influencing the purchase intention of local fashion brands in social commerce as online distribution channels. Recognizing the transformative impact of social media platforms on consumer-brand interactions, this research aims to identify key drivers of online purchasing behavior. **Research design, data, and methodology:** A quantitative approach was employed, utilizing a survey of 470 respondents from Vietnam with prior experience in online fashion purchases. Structural Equation Modeling (SEM) was performed using SPSS 20 and AMOS 24.0 to analyze the collected data and test the hypothesized relationships within a developing market context. **Results:** The findings reveal that purchase intention is significantly influenced by various factors, including information richness, interactivity, and electronic word of mouth (eWOM) characteristics such as quality, credibility, quantity, usefulness, and adoption. Additionally, online brand familiarity and experience positively impacted purchase intention. **Conclusions:** This research provides valuable managerial insights for local fashion brands seeking to optimize their social media marketing strategies in competitive digital markets, emphasizing the importance of consumer engagement and effective information sharing in strengthening online distribution channels.

Keywords: Social Commerce, Local Fashion Brands, Purchase Intention, Social Media Marketing, eWOM, Online Distribution Channels

JEL Classification Code: M31, L81, D91, L67, O33

1. Introduction

The internet has triggered a significant transformation in the fashion retail landscape, leading to a surge in online fashion shopping. This phenomenon, which has garnered increasing scholarly attention since the late 1990s, is marked by the foundational work of Then and DeLong (1999). Over the past two decades, online fashion shopping has significantly expanded in importance for consumers and retailers, transcending traditional and digital channels. Consequently, numerous studies have explored the factors influencing online purchase intentions for fashion products. These investigations have identified key influential factors such as technological aspects, social influence, website attributes, brand considerations, and prior consumer experiences (Baytar et al., 2020; Escobar-Rodríguez & Bonsón-Fernández, 2017; Jebarajakirthy et al., 2021; Kautish et al., 2020).

More recently, social commerce platforms have evolved

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into vital online distribution channels for fashion retail trade on a global scale. In business terms, distribution channels are the pathways through which products reach consumers, encompassing logistics and trade processes like product discovery, transactions, and delivery (Beard, 2025). Social commerce, which integrates social media functionalities with e-commerce, has emerged as a key online distribution channel, enabling consumers to discover, engage with, and purchase fashion products directly on platforms like Instagram, Facebook, and TikTok. Unlike traditional e-commerce, which relies on centralized control, social commerce operates through a decentralized network stream distribution mechanism, where user connections drive product discovery and sales (Yadav et al., 2013). This shift enhances market reach and streamlines trade by reducing intermediary costs.

Empirical evidence indicates a profound shift in consumer behavior, with social media becoming a primary avenue for discovering and purchasing fashion items. For instance, a report by NielsenIQ (2022) documented that 60% of online consumers had completed at least one social media purchase by 2020. This trend has continued to accelerate, with recent statistics revealing that 54% of consumers now utilize social commerce platforms for fashion purchases, and 42% engage in livestream shopping, particularly within Gen Z and Millennial demographics, who represent key future consumer markets (NielsenIQ, 2022). Regional data further substantiate this global trend: in the Asia-Pacific region, 71% of online shoppers employ social media for product discovery, while in the United States, 45% of consumers aged 18-29 have made direct purchases via these platforms (Hootsuite, 2023). Similarly, 40% of European consumers use social media to research fashion products before purchasing (Deloitte, 2022). Social commerce platforms have surpassed traditional search engines as the primary discovery channels for fashion shoppers worldwide, with 52.4% of global fashion e-shoppers now using Instagram, 51.6% using Facebook, and only 49.8% relying on Google search for fashion discovery. YouTube (41.2%) and TikTok (28.1%) complete the top five platforms, highlighting social media's dominance in fashion discovery (Internet Retailing, 2023).

Based on the above data, it is clear that the rapidly evolving digital landscape is continuously shaping consumer shopping behavior, with emerging social commerce platforms like TikTok and Instagram becoming especially important online distribution channels for marketing fashion brands. The increasing global usage of social media, with an estimated 4.8 billion users worldwide in 2023 (Hootsuite, 2023), further underscores its significance in the fashion industry. However, a report by Yu (2024) indicates that many fashion brands are struggling to adapt to this environment, as evidenced by a 30% decline in engagement rates on Instagram, and that only 21.8% of buyers consider product information on social commerce platforms trustworthy. This discrepancy between evolving consumer behavior and the marketing strategies employed by local fashion enterprises presents a substantial challenge within an increasingly competitive digital marketplace.

While general online shopping behavior has been extensively investigated, and a growing body of literature examines social media marketing within the fashion sector, a noteworthy research gap persists regarding the specific operational dynamics of local fashion brands utilizing these platforms as online distribution channels. Local fashion brands, often characterized by limited resources, smaller market reach, and less brand recognition than global counterparts, face unique challenges in adapting to the fast-paced evolution of social commerce. For instance, a 2023 Fashion Revolution Survey revealed that 58% of local fashion SMEs report difficulty competing with international brands regarding pricing and visibility on social commerce platforms (Fashion Revolution, 2023). This highlights the need for a deeper understanding of how local fashion brands can effectively leverage social commerce to influence consumer purchase intentions. Existing studies on consumer online purchasing behavior for local fashion brands typically focus on narrower aspects such as psychological determinants, marketing strategies, and platform functionalities (Table 1). However, there is a lack of comprehensive understanding of how these brands can navigate the competitive digital landscape, particularly in culturally diverse contexts where technological capabilities and consumer preferences are rapidly evolving.

Furthermore, while theoretical frameworks such as the Theory of Reasoned Action, Uses and Gratification Theory, and Social Impact Theory offer valuable insights into consumer engagement, the application of these frameworks to local fashion brands in culturally diverse contexts remains underexplored, particularly in the context of rapidly evolving technological capabilities and shifting consumer preferences. By identifying key factors influencing purchase intention, this study offers actionable insights for local fashion brands to overcome challenges like limited visibility and trust issues, enabling them to optimize social commerce strategies and compete effectively with global competitors. To address this gap, the present study adopts an integrated theoretical approach combining Social Cognitive Theory (SCT), as proposed by Bandura (1986), and the Information Adoption Model (IAM), as developed by Sussman & Siegal (2003). SCT, a well-established framework for comprehending human behavior, has been successfully implemented in numerous studies on online shopping (Cheah et al., 2015; Chen, 2012; Darley & Lim, 2018). This integrated theoretical framework facilitates the development of a comprehensive model to examine the factors influencing

Table 1: The Summary of Research Related to Consumer Online Purchasing Behavior for Local Fashion Brands Across

Author	Research Focus	Key Findings
Rahman & Mannan (2018)	Online purchase behavior for local fashion brands in Bangladesh	Central and peripheral routes positively influence information adoption; Consumer information adoption positively affects purchase behavior; e-WOM partially mediates the information adoption-purchase relationship.
Valentina Silalahi et al. (2022)	Digital strategies for increasing the purchase intention of local fashion products	Social media marketing and brand management together explain 55.10% of consumer buying interest variance; Both individually have positive effects.
Son & Chi (2022)	Factors influencing purchase intention for Vietnamese local fashion brands on social commerce platforms	Brand image has the strongest positive impact on purchase intention, followed by enjoyment and online reviews. Perceived risk has a negative impact.
Ramadhani & Prasasti (2023)	Brand trust in social media marketing and purchase intention: a case of a local brand	Brand trust mediates the relationship between social media marketing and purchase intention; Word-of-mouth, entertainment, customization, and trendiness are most influential.
Reyvina & Tjokrosaputro (2024)	Social media marketing impact on brand awareness and image of local fashion through consumer brand engagement	Social media marketing positively impacts local fashion brand awareness and image through consumer brand engagement.
Heriyati et al. (2024)	Gen Z attitudes for the local fashion industry	Country of origin significantly influences brand image and perceived quality, affecting purchase intention.
Sari et al. (2024)	Technology acceptance factors for online shopping	All four variables significantly impact consumer attitudes toward repeated online shopping for Muslim fashion.

the purchase intention of local fashion brands on social commerce platforms, particularly focusing on the interplay of technical, social, and online consumer experience environment. This study offers insights into how local fashion brands can effectively use social commerce as an online distribution channel to engage consumers and drive purchase intentions.

2. Literature Review

2.1. Theoretical background

2.1.1. Social cognitive theory (SCT)

Social Cognitive Theory (SCT), developed by Bandura (1986), originated in psychology before expanding into information systems research. This theory establishes that environmental factors (external influences providing opportunities, social support, pressure, and contextual circumstances) interact with personal factors (cognitive characteristics, personality traits, and demographic attributes) to influence individual states and trigger behavioral changes. Lian and Lin (2008) apply social cognitive theory to examine a model that explains attitudes toward online shopping. Cheah et al. (2015) utilized Social Cognitive Theory to investigate the intention to buy e-deals. Another study by Li and Zhong (2017) examined how various factors influence the cognition of green aquatic products and consumption behavior.

This study specifically applies Bandura's (1986) triadic reciprocal determinism model to the social commerce context, where online purchase intention represents the behavioral component influenced by environmental and personal factors. The environmental factors are divided into two critical dimensions, especially relevant for local fashion brands: technical environment (information richness and interactivity features of social commerce platforms) and social environment (electronic word of mouth in social media). Meanwhile, the personal factors are conceptualized as the online consumer experience environment, encompassing online brand familiarity and experience with local fashion brands. This adapted framework enables a comprehensive examination of how social commerce platforms' technical and social aspects, alongside consumers' prior experiences with local fashion brands, collectively shape purchase intentions in the competitive digital marketplace.

2.1.2. Information Adoption Model (IAM)

The Information Adoption Model (IAM), introduced by Sussman and Siegal (2003), explains how individuals adopt information and subsequently change their intentions and behaviors within computer-mediated communication platforms. IAM integrates the Technology Acceptance Model (TAM) and the Elaboration Likelihood Model (ELM), utilizing argument quality as the central route, source quality as the peripheral route, and perceived information usefulness as a mediator. Several researchers have applied IAM to explore various dimensions of online behavior. For instance, Cheung et al. (2008) employed IAM to investigate the factors influencing the adoption of online opinions within online communities. Similarly, Zhu et al. (2016) developed a research model to assess the impact of consumer-to-consumer (C2C) communication on purchase decisions in online communities, enhancing the original IAM with additional variables.

Furthermore, Erkan and Evans (2016) examined the influence of electronic word-of-mouth (eWOM) in social media on consumers' purchase intentions by combining IAM with components of the Theory of Reasoned Action (TRA). In this study, we apply the Information Adoption Model (IAM) with appropriate adjustments to analyze how eWOM factors in social media, as social environmental factors followed by SCT, affect the purchase intention of local fashion brands in social commerce as online distribution channels. We build on IAM variables such as information quality, information credibility, information usefulness, and information adoption, while incorporating the variable "information quantity" into the model, based on a suggestion from (Abedi et al., 2020).

2.2. Research framework and hypothesis development

2.2.1. Online purchase intention

Social Cognitive Theory explores how motivation and social factors shape individual behavior (Bandura & Schunk, 1981). This study focuses on behavioral intention rather than actual behavior to investigate how technical, social, and personal factors influence purchase intention. Behavioral intention is recognized as a precursor to actual behavior, supported by theories like TRA, TPB, and TAM. However, buying behavior is susceptible to external influences such as unexpected income changes and promotions (De Cannière et al., 2009; Foxall, 2005; Infosino, 1986; Morrison, 1979; Sun & Morwitz, 2010), so consumers may not act on their intentions. This study focuses on purchase intention to isolate the effects of various factors, excluding the complexities of actual purchasing behavior.

In the context of online shopping, a person's desire to purchase a specific product or service through a website is referred to as online purchase intention (Chen et al., 2010; Pavlou & Fygenson, 2006). Pavlou (2003) defines it as a customer's likelihood of completing a transaction via online channels. Online purchase intention reflects a customer's readiness to seek information, interact, and buy online. Social commerce involves the willingness to transact on these platforms (Hajli et al., 2017).

2.2.2. Technical environment

Within the framework of social cognitive theory, environmental factors encompass various aspects, including the technological environment (Bandura, 1986). The technological environment is an aspect derived from the system's environment used by the user. Rahman & Mannan (2018) suggested that future research should focus on website-related factors to understand better buyers' online purchasing behavior towards domestic fashion brands. According to Chevalier and Mayzlin (2006), a website rich in information and highly interactive helps buyers easily compare products and access diverse reviews, thereby minimizing the perceived risk. In the context of online shopping in social commerce, this study examines two website-related factors of social commerce platforms that influence the purchase intention of local fashion brands are interactivity and information richness.

Information richness, also known as content richness, refers to the diversity of information provided on a seller's website on social commerce platforms. This is determined by the variety of text, images, and videos used to convey information to potential buyers (Lee et al., 2021). According to Ye et al. (2012), information richness is measured by breadth (the variety of formats such as text, images, audio, and video) and depth (the level of detail within each format). In an online environment, a website reflects a business's organizational approach and plays a crucial role in attracting online shoppers (Wolfinbarger & Gilly, 2003). Dang et al. (2020) suggest that when customers face information asymmetry and are separated from sellers, providing comprehensive online information about themselves can increase purchase intention and actual buying behavior. Limited information can increase perceived risk related to the seller, hindering customers' purchasing decisions (Tariq et al., 2019). Conversely, rich information minimizes risk and demonstrates the seller's concern for customer interests, affirming their capability and reliability (Huang & Benyoucef, 2013; Ye et al., 2012). Diverse information signals, such as visual signals (images, videos) and experiential signals (detailed descriptions, reviews), provide clearer and more engaging information than plain text, helping customers grasp product features more easily (Lee et al., 2007). Furthermore, detailed and diverse information helps customers better understand product characteristics, features, and value (Roy et al., 2020), forming a positive attitude and boosting purchase (Huang & Benyoucef, 2013; Ye et al., 2012). Previous studies, such as those by Huang & Benyoucef (2013) and Yen (2014) have confirmed that information richness positively affects consumers' purchase intentions in e-commerce. Therefore, based on social cognitive theory and empirical evidence, we propose:

H1: Information richness is positively related to the purchase intention of local fashion brands on social commerce platforms.

According to Liu (2003), interaction is the degree to which communicating parties can influence each other through media and messages. In the study by Liu (2003), interactivity is measured by active control, two-way communication, and synchronicity. Interactivity also involves users' perception of participating in a two-way communication process with a mediated character in real-time on social media (Erdoğmuş & Tatar, 2015). Social media platforms of brands serve as a communication channel between consumers and brands (Beukeboom et al., 2015). This communication is viewed as brand interactivity (Carlson et al., 2018), including features such as providing brand information, special offers, and virtual tours (Ghose & Dou, 1998). Chung and Zhao (2004) argue that this interactivity distinguishes social media from traditional media. Several studies have demonstrated that online interactivity can significantly reduce perceived risk, improve trust, and enhance purchase intention (Roy Dholakia & Zhao, 2009; Van Noort et al., 2012). For instance, Young, Kim and Kim (2004) found that interaction between buyers and sellers positively affects online purchase intention for fashion products. Similarly, Al-Qudah (2020) showed that brand social media interactivity influences purchase intention among millennial customers. Hence, based on social cognitive theory and empirical evidence, we propose:

H2: Interactivity is positively related to the purchase intention of local fashion brands on social commerce platforms.

2.2.3. Social environment

Social environment encompasses external factors such as interactions with friends, family, colleagues, and the community, which have the potential to shape an individual's behavior (Bandura, 1986). Within the context of online shopping, electronic word of mouth (eWOM) on social media has emerged as a pivotal social factor. Social media eWOM refers to product reviews generated by buyers and shared through social networks, becoming a powerful driver of purchase intention (Erkan & Evans, 2016). Social media eWOM plays a crucial role in addressing the anonymity issue of online reviews (Erkan & Evans, 2016) and is a cost-effective yet highly efficient marketing tool (See-To & Ho, 2014). Scholars have indicated that eWOM on social media significantly impacts the buyer's decision-making process, acting as a form of social proof that influences brand perception and purchase intention (Erkan & Evans, 2016; Indrawati et al., 2023; Ngo et al., 2024; Nyagadza et al., 2023). However, within the realm of fashion and online shopping, no research has yet addressed the impact of social media eWOM on purchase intention. Integrating Social Cognitive Theory (SCT) with the Information Adoption Model (IAM) provides a robust theoretical framework for understanding how consumers of local fashion brands evaluate and internalize eWOM information on social commerce platforms before converting it into purchase decisions. Drawing upon this integrated theoretical approach, this study operationalizes five distinct eWOM variables representing key elements of the social environment as applied to local fashion contexts: information quality, source credibility, information quantity, perceived usefulness, and information adoption.

Quality of eWOM information is defined as the persuasiveness and relevance of content (Bhattacherjee & Sanford, 2006; Park et al., 2007), including clarity, objectivity, and detail (Cheung & Thadani, 2012; Filieri & McLeay, 2014). High-quality eWOM enhances its usefulness, aiding consumers in evaluating brands and making decisions (Erkan & Evans, 2016; Indrawati et al., 2023). Studies consistently show that better eWOM quality increases perceived usefulness (Abedi et al., 2020; Nyagadza et al., 2023). Similarly, credibility of eWOM information reflects its perceived authenticity and accuracy (Cheung & Thadani, 2012; Erkan & Evans, 2016). Credibility of eWOM information, marked by trustworthiness and precision (Filieri & McLeay, 2014; Weitzl, 2017), boosts consumer confidence and acceptance (McKnight & Kacmar, 2006), driving purchase intention (Prendergast et al., 2010). Research confirms that credible eWOM is more useful, reducing perceived risks and supporting product choices (Abedi et al., 2020; Indrawati et al., 2023). Based on the Information Acceptance Model by Sussman & Siegal (2003), the hypotheses are proposed:

H3: Quality of eWOM information in social media is positively related to the usefulness of eWOM information

H4: Credibility of eWOM information in social media is positively related to the usefulness of eWOM information.

The quantity of eWOM refers to the number of online reviews a product receives from consumers (Park et al., 2007). This metric is a key indicator of a product's popularity, as a higher number of reviews generally correlates with more purchases and user experiences (Chatterjee, 2001; Park et al., 2007). The frequency or sheer volume of reviews consumers encounter reflects product popularity, reliability, and performance (Filieri & McLeay, 2014; Ngarmwongnoi et al., 2020). For instance, products with numerous reviews are often perceived as more trustworthy due to social proof (Buttle, 1998). Thus, eWOM quantity is not just a statistic but also a psychological cue that allows consumers to assess product quality indirectly through the collective behavior of others. Many studies indicate that more eWOM positively impacts its usefulness in purchasing decisions. Many reviews increase consumer confidence (Ngarmwongnoi et al., 2020) by highlighting consensus and reducing doubts about quality (Buttle, 1998; Ismagilova et al., 2017). Websites with many reviews enable users to compare diverse information, leading to more informed decisions (Erkan & Evans, 2018). A high eWOM quantity signifies a good reputation and stable sales, reinforcing trust (Ho et al., 2021). Abundant eWOM allows consumers to analyze product pros and cons in detail, potentially increasing purchase intention (Indrawati et al., 2024), a finding supported by recent studies (Ngo et al., 2024; Verma et al., 2023). This is often attributed to a strong word-of-mouth effect, where consumers tend to believe that a product with many buyers is likely to be good, encouraging purchases based on popularity rather than skepticism (Chatterjee, 2001). Hence, the hypothesis is proposed:

H5: Quantity of eWOM information in social media is positively related to the usefulness of eWOM information.

Information usefulness is defined as users' perception that new information can help them achieve better outcomes (Bailey & Pearson, 1983; Cheung et al., 2008). Useful information provides value, multiple perspectives, and supports decision-making. Research by Erkan and Evans (2018) and Hussain et al. (2020) indicates that usefulness is characterized by comprehensive information, practical value, and effective user support. Information usefulness strongly influences information acceptance (Fred Davis, 1989; Sussman & Siegal, 2003) and purchase intention (Lee & Koo, 2015). People tend to accept information they perceive as useful. On social media, where users encounter vast amounts of electronic word-of-mouth (eWOM), they better accept useful information. Previous studies have demonstrated that eWOM information usefulness directly affects user acceptance (Cheung & Thadani, 2012; Liu & Zhang, 2010). When consumers evaluate information as useful, they become more confident in adopting it (Nabi & Hendriks, 2003). Sussman and Siegal (2003) predicted that in online platforms, perceived information usefulness enhances the ability to express product or service performance. Based on the Information Acceptance Model by Sussman & Siegal (2003), the hypothesis is proposed:

H6: Usefulness of eWOM information is positively related to the adoption of eWOM information.

In today's social media context, users are constantly exposed to eWOM, both intentionally and unintentionally (Iyengar et al., 2009; See-To & Ho, 2014; X. Wang et al., 2012). Information adoption, the process where individuals internalize and adopt information from external sources, is crucial for increasing knowledge and improving decision-making (Shen et al., 2014). Active adoption of information is a key factor in forming personal behavioral intentions (Wang, 2016), and the perceived usefulness of information significantly influences its acceptance (Ismagilova et al., 2017). This adoption typically occurs after consumers receive and utilize information during their purchase journey (Ismagilova et al., 2017), although the impact of eWOM can vary (Yang, 2012). Adoption of eWOM information has been identified as a significant driver of customer purchase intention (Erkan & Evans, 2016; Kohler et al., 2023). A positive correlation exists between purchase intention and information adoption, particularly when the information is encountered on social media (Molinillo et al., 2020). Consumers who accept eWOM are more likely to exhibit a higher purchase intention (Cheung & Thadani, 2012; Cheung et al., 2009), a finding consistently supported by recent (Ngo et al., 2024; Nyagadza et al., 2023; Prasetio et al., 2024). Therefore, the hypothesis is proposed:

H7: Adoption of eWOM information is positively related to the purchase intention of local fashion brands on social commerce platforms.

2.3.4. Online Consumer Experience Environment

In Bandura's (1986) social cognitive theory, individual factors significantly influence behavior, encompassing internal elements like cognition, emotions, and expectations. Within the complex and multidimensional online environment, these factors manifest through online consumer experience, reflecting an individual's familiarity and accumulated experience. Specifically, in the context of online fashion shopping, unlike traditional brick and mortar settings where customers can directly inspect product attributes such as material, color, or style, online shoppers rely more on their attributes, including their familiarity with the online brand and their overall online brand experience (Park & Stoel, 2005). Consequently, this study focuses on two key person-related variables within the online consumer experience that influence the purchase intention of local fashion brands on social commerce platforms: online brand experience and online brand familiarity. Prior research has consistently identified online brand familiarity and experience as crucial determinants of online purchasing behavior (Ha & Perks, 2005; Morgan-Thomas & Veloutsou, 2013; Park & Stoel, 2005). While extensive research has explored these concepts, their application and discussion within the specific domain of online fashion remain limited.

Online brand familiarity is defined as consumers' understanding and awareness of a specific brand or website, developed through repeated experiences and interactions (Ha & Perks, 2005). According to Alba & Hutchinson (1987), this concept stems from the accumulated consumer experiences with a brand, including exposure to product information, services, or online interfaces. Hoch and Deighton (1989) add that familiarity reflects users' proficiency in processing brand-related information, creating confidence and comfort. In the online context, Ha and Perks (2005) emphasize that familiarity extends beyond brand recognition to include goodwill, reputation, and positive emotions users develop for websites through content exploration, information searching, or repeated transactions. Laroche et al. (1996) show that when consumers are familiar with a brand, they rate its reliability higher, reducing perceived risk and promoting purchase intention. Familiarity also reduces psychological costs in decision-making; Biswas (1992) found that consumers spend less time shopping for familiar brands than new ones, as they do not need to verify information or reassess from scratch. This is particularly significant in online environments, where speed and convenience are key factors (Menon & Kahn, 2002). Ha and Perks (2005) suggest that familiarity helps users feel more in control, increasing their willingness to accept risks when shopping. In the fashion industry, where emotions and visual experiences are important, online brand familiarity is often rated more positively regarding product quality, leading to higher purchase intentions. Similarly, Quintal and Phau (2013) emphasize that familiarity promotes repeat purchases and creates brand loyalty, a key factor in online competition. Hence, based on social cognitive theory and empirical evidence, we propose:

H8: Online brand familiarity is positively related to the purchase intention of local fashion brands on social commerce platforms.

Experience demonstrates relatively deep knowledge in a specific area, acquired through exposure (Braunsberger & Munch, 1998). Brand experience refers to knowledge integrated with consumers' sensory, emotional, cognitive, and behavioral responses and familiarity with a brand or brand category (Brakus et al., 2009). Online brand experience involves customer interactions with a specific website, such as participating in online communities or events, and perceptions of attractive offers, diverse and unique visual displays, and value for money (Ha & Perks, 2005). For instance, fashion customers' online experiences include searching for information, evaluating online product reviews (e-WOM), and using products (Rahman & Mannan, 2018). Brand experience is more critical than product features and benefits (Ghodeswar, 2008). Positive consumer experiences significantly drive e-commerce growth (Elliot & Fowell, 2000). Consumers with greater internet experience have more trust and positive attitudes for online clothing shopping, positively influencing their purchase intentions compared to less experienced users (Bernard et al., 2015). Brands that stimulate multiple experiential dimensions are more likely to retain customers (Pine & Gilmore, 1999). Positive experiences with genuine brands increase future purchase intentions for these brands while decreasing intentions to buy counterfeit products (Yoo & Lee, 2012). Recent studies confirm that online brand experience positively influences customers' online purchase intentions (Park & Stoel, 2005; Rahman & Mannan, 2018; Taliya Imaniya & Anna Amalyah Agus, 2019). Therefore, based on social cognitive theory and empirical evidence, we propose:

H9: Online brand experience is positively related to the purchase intention of local fashion brands on social commerce platforms.

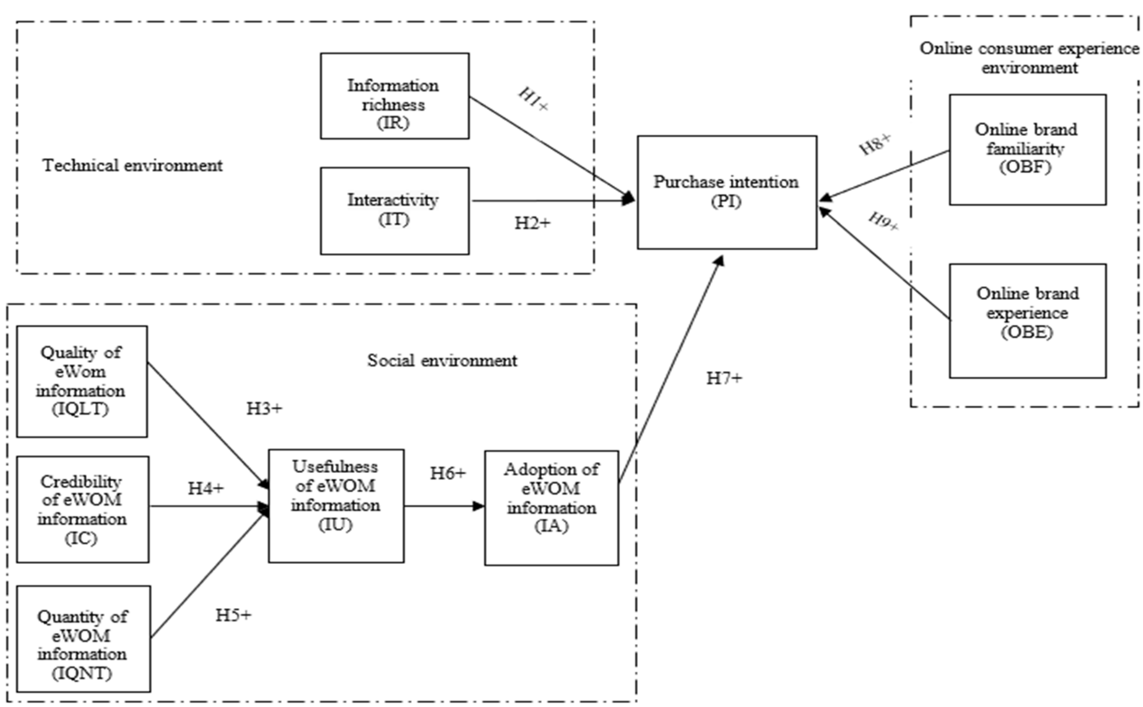

Figure 1: The Proposed Research Framework.

2.3.5. Research Model

The research empirically analyzes factors influencing the purchase intention of local fashion brands in social commerce through online distribution channels. The research model identifies online purchase intention (PI) as the dependent variable. In contrast, factors from the technical environment (information richness, interactivity), social environment (information quality, information credibility, information quantity), and online consumer experience environment (online brand familiarity, online brand experience) are considered independent variables. Additionally, information usefulness (IU) and information adoption (IA) are designated as mediating variables in the relationship between independent variables and online purchase intention.

3. Research Method

This research focuses on quantitative research to test the model and research hypotheses. However, before the quantitative data collection, we conducted focus group interviews with experts with substantial social media knowledge and experience purchasing local fashion brands through social media platforms. This qualitative phase adapted measurement scales from previous studies to suit the research context. Through these group discussions, we refined the wording of scale items and adjusted variables by adding or removing items as necessary. Following the qualitative research phase, we conducted a pilot study to improve and refine the survey instrument. We revised the questionnaire before implementing it in the main empirical study based on the feedback received during pilot testing.

The empirical survey yielded 625 respondents, with 470 responses validated. Data was collected using both online and offline methods. Online data was gathered through Google Forms and distributed via email and social media platforms (Facebook, Zalo, and Instagram). Offline data was collected by researchers administering the Google Forms questionnaire in person at universities, schools, and offices. This dual approach aimed to improve respondent input reliability. The survey targeted individuals in Vietnam who were familiar with the local fashion brand's products and had experience purchasing them through social media platforms.

All variables were measured using a seven-point Likert scale ranging from strongly disagree (1) to strongly agree (7). The measurement scales were adapted from established literature and modified based on expert feedback and pilot testing results. Specifically 'Information Richness (IR)' was measured by four-item scales adapted from Ye et al. (2012), 'Interactivity (IT)' was assessed by adapting three items used by Liu (2003), 'Information Quality (IQLT)' was measured by four-item scales adapted from Park et al. (2007), 'Information Credibility (IC)' was assessed by adapting four items used by Prendergast et al. (2010), 'Information Quantity (IQNT)' was measured by three-item scales adapted from Lin et al. (2013) and Park et al. (2007), 'Information Usefulness (IU)' was measured by three-item scales adapted from Bailey and Pearson (1983), 'Information Adoption (IA)' was assessed by adapting four items used by Cheung et al. (2009), 'Online Brand Familiarity (OBF)' was measured by three-item scales adapted from Ha & Perks (2005), 'Online Brand Experience (OBE)' was assessed by adapting four items used by Ha and Perks (2005), 'Online Purchase Intention (PI)' was measured by four items adapted from (Kim & Lennon, 2000).

The collected data were analyzed using SPSS 20 and Amos 24.0 software. The specific analysis methods employed were as follows: Cronbach's alpha reliability coefficient, and exploratory factor analysis (EFA) were conducted to assess the variables' reliability and exclude any unreliable ones. Subsequently, confirmatory factor analysis (CFA) and structural equation modeling (SEM) were applied to examine the variables' factor structure and correlation model.

4. Results

4.1. Descriptive

The survey collected 625 responses, of which 155 were invalid, and 470 valid responses were included in the data analysis. The sample is skewed female (61.3%), with most respondents under 35 (85.6%). Participants are primarily employed (51.7%) or students (41.5%), with most earning 10-20 million VND monthly (64.5%). Social media usage is exceptionally high, with 93.4% using platforms daily. This demographic profile represents younger, middle-income, digitally active consumers.

4.2. Reliability analysis

Cronbach's Alpha analysis was conducted to assess the reliability of each element within the proposed theoretical model. Following Nunnally & Bernstein, (1994) criteria, factors were evaluated based on two conditions: overall Cronbach's Alpha coefficient > 0.6 and corrected item-total correlation > 0.3. During scale reliability verification, item IQLT1 from the IQLT scale, IA4 from the IA scale, and OBE4 from the OBE scale were removed due to corrected item-total correlation < 0.3. Table 2 shows that the Cronbach's Alpha coefficients for all factors were high (0.854-0.888), exceeding the 0.6 threshold, and all remaining variables had corrected item-total correlations greater than 0.3. These results confirm all included items' reliability and suitability for the research.

Table 2: Cronbach's Alpha Analysis

Scale	Corrected Item-Total Correlation	Cronbach's Alpha
Information richness (IR)		0.888
IR1	0.743	
IR2	0.731	
IR3	0.76	
IR4	0.784	
Interactivity (IT)		0.850
IT1	0.729	
IT2	0.707	
IT3	0.724	
Quality of eWOM information (IQLT)		0.863
IQLT2	0.768	
IQLT3	0.723	
IQLT4	0.727	
Credibility of eWOM information (IC)		0.885
IC1	0.756	
IC2	0.724	
IC3	0.739	
IC4	0.774	
Quantity of eWOM information (IQNT)		0.867
IQNT1	0.732	
IQNT2	0.744	
IQNT3	0.763	
Usefulness of eWOM information (IU)		0.880
IU1	0.760	
IU2	0.755	
IU3	0.795	
Adoption of eWOM information (IA)		0.892
IA1	0.77	
IA2	0.792	
IA3	0.804	
Online brand familiarity (OBF)		0.852
OBF1	0.720	
OBF2	0.722	
OBF3	0.727	
Online brand experience (OBE)		0.872
OBE1	0.746	
OBE2	0.766	
OBE3	0.752	
Online Purchase intention (PI)		0.854
PI1	0.699	
PI2	0.686	
PI3	0.701	
PI4	0.697	

4.3. Exploratory factor analysis (EFA)

Exploratory Factor Analysis (EFA) is a multivariate statistical technique commonly employed in quantitative research to discern the latent structure of observed variables (Hair et al., 2014). The EFA results for the technical environment, social environment, online consumer experience environment (presented in Table 3), and the online purchase intention scale (detailed in Table 4) were rigorously assessed against established criteria. As stipulated by Hair et al. (2006), the foundational criteria for acceptable factor analysis include a Kaiser-Meyer-Olkin (KMO) measure between 0.5 and 1, a statistically significant Bartlett's Test of Sphericity ($p < 0.05$), factor loadings exceeding 0.3, a cumulative percentage of variance explained greater than 50%, and eigenvalues greater than 1.

Table 3: Exploratory Factor Analysis of Scale of Technical Environment, Social Environment, and Online Consumer Experience Environment

Factor	Item	Factor Loading	Variance (%)	Eigen Value
Information richness (IR)	IR4	0.880	18.562	5.383
	IR3	0.827		
	IR1	0.784		
	IR2	0.768		
Interactivity (IT)	IT1	0.842	12.084	3.504
	IT3	0.820		
	IT2	0.769		
Quality of eWOM information (IQLT)	IQLT2	0.861	10.262	2.976
	IQLT3	0.807		
	IQLT4	0.795		
Credibility of eWOM information (IC)	IC4	0.843	8.352	2.422
	IC1	0.826		
	IC3	0.794		
	IC2	0.778		
Quantity of eWOM information (IQNT)	IQNT3	0.847	7.563	2.193
	IQNT2	0.841		
	IQNT1	0.798		
Usefulness of eWOM information (IU)	IU3	0.869	6.506	1.887
	IU1	0.847		
	IU2	0.801		
Adoption of eWOM information (IA)	IA2	0.878	5.526	1.602
	IA3	0.869		
	IA1	0.820		
Online brand familiarity (OBF)	OBF3	0.818	5.149	1.493
	OBF1	0.810		
	OBF2	0.809		
Online brand experience (OBE)	OBE1	0.843	4.437	1.287
	OBE2	0.841		
	OBE3	0.821		
Total		78,441		
Kaiser-Meyer-Olkin Measure		0.804		
Bartlett's Test (Sig)		0.000		

For the constructs presented in Table 3, the analysis revealed a KMO value of 0.804 and a statistically significant Bartlett's Test ($p = 0.000$), thereby confirming the suitability of the data for factor analysis. The observed factor loadings ranged from 0.768 to 0.880, the cumulative variance explained was 78.441%, and the eigenvalues ranged from 1.287 to 5.383, collectively validating the identified factors. Similarly, the analysis for the online purchase intention scale (Table 4) yielded a KMO value of 0.821 with a significant Bartlett's Test (p = 0.000). Factor loadings for the online purchase intention items ranged from 0.758 to 0.777, the explained variance was 69.578%, and the eigenvalue was 2.783. In sum, both analyses meticulously satisfied all specified validity criteria, thus substantiating the reliability of the identified factors and their appropriate representation of the underlying data structure.

Table 4: Exploratory Factor Analysis of Online Purchase Intention Scale

Factor	Item	Factor Loading	Variance (%)	Eigen Value
Online Purchase intention (PI)	PI4	0.777	69.578	2.783
	PI3	0.777		
	PI1	0.771		
	PI2	0.758		
Kaiser-Meyer-Olkin Measure		0.821		
Bartlett's Test (Sig)		0.000		

4.4. Confirmatory Factor Analysis (CFA)

The Confirmatory Factor Analysis (CFA) results provided robust evidence supporting the convergent and discriminant validity of the hypothesized theoretical constructs. Convergent validity is considered adequate when the Standardized Regression Coefficient and Average Variance Extracted (AVE) both exceed 0.5, and the Construct Reliability (CR) surpasses 0.7 (Anderson & Gerbing, 1988). In this study, the standardized regression coefficients ranged from 0.771 to 0.884; the lowest AVE observed was 0.594 (exceeding the 0.5 threshold), and the minimum CR value recorded was 0.851. All these indicators met the requisite standards, confirming convergent validity (see Table 5).

Discriminant validity is established when the square root of the AVE value exceeds the absolute values of the correlation coefficients between the latent variables (Fornell & Larcker, 1981). The analysis verified that the square roots of the AVE values were indeed greater than their corresponding correlation coefficients in both their respective rows and columns, affirming discriminant validity (see Table 6).

Table 5: Standardized Regression Coefficient, AVE, and CR of the Measurement Mode

Latent Variable	Measurement Variable	β	CR	AVE
Online Purchase Intention	PI1	0.781	0,854	0,594
	PI3	0.771		
	PI4	0.773		
	PI2	0.758		
Information richness	IR3	0.813	0,888	0,665
	IR4	0.851		
	IR1	0.804		
	IR2	0.794		
Interactivity	IT1	0.812	0,851	0,655
	IT3	0.809		
	IT2	0.806		
Quality of eWOM Information	IQLT4	0.805	0,863	0,679
	IQL2	0.870		
	IQLT3	0.794		
Credibility of eWOM Information	IC4	0.843	0,885	0,658
	IC1	0.819		
	IC2	0.781		
	IC3	0.800		
Quantity of eWOM Information	IQNT3	0.852	0,868	0,686
	IQNT2	0.824		
	IQNT1	0.809		
Usefulness of eWOM information	IU3	0.882	0,882	0,714
	IU1	0.826		
	IU2	0.826		
Adoption of eWOM Information	IA2	0.855	0,892	0,734
	IA3	0.884		
	IA1	0.831		
Online Brand Familiarity	OBF3	0.812	0,853	0,659
	OBF1	0.810		
	OBF2	0.813		
Online Brand Experience	OBE2	0.853	0,872	0,695
	OBE1	0.818		
	OBE3	0.829		

Furthermore, the model's goodness of fit was evaluated using multiple fit indices as recommended by Hair et al. (2019). The findings indicated that all values satisfied the acceptable fit criteria, demonstrating a strong alignment between the model's factors and the empirical data (see Table 7).

Table 6: Correlation Coefficients Between Latent Variables and Square Roots of AVE

	PI	IR	IC	IA	OBE	IQNT	IU	OBF	IT	IQLT
PI	**0.771**									
IR	0.583***	**0.816**								
IC	0.092†	-0.129*	**0.811**							

	PI	IR	IC	IA	OBE	IQNT	IU	OBF	IT	IQLT
IA	0.593***	0.272***	0.193***	**0.857**						
OBE	0.254***	0.129*	-0.039	0.052	**0.833**					
IQNT	0.235***	0.116*	0.022	0.316***	0.009	**0.828**				
IU	0.265***	0.162**	0.189***	0.404***	-0.016	0.349***	**0.845**			
OBF	0.226***	0.043	-0.077	0.084	0.088	0.033	0.037	**0.812**		
IT	0.385***	0.202***	-0.016	0.206***	-0.263***	0.214***	0.133*	-0.077	**0.809**	
IQLT	0.354***	0.127*	0.131*	0.351***	-0.084	0.225***	0.464***	-0.116*	0.239***	**0.824**

Note: The diagonally listed value is the AVE square root of the variables.
† $p < 0.100$. * $p < 0.050$. ** $p < 0.010$. *** $p < 0.001$.

Table 7: Goodness of Fit of Measurement Model

GOF Index	Acceptable Values	Value Obtained
Absolute Measures		
CMIN/DF	≤ 5 (Bentler & Bonett, 1980; Bagozzi & Yi, 1988)	1.248
GFI	≥ 0.90 (Hair et al., 2006)	0.934
RMSEA	< 0.07 with CFI ≥ 0.92 (Hair et al., 2019)	0.023
SRMR	≤ 0.08 with CFI > 0.92 (Hair et al., 2019)	0.0293
Incremental Fit Measures		
TLI	> 0.92 (Hair et al., 2019)	0.985
CFI	> 0.92 (Hair et al., 2019)	0.987
Parsimony Measures		
AGFI	≥ 0.90 (Hair et al., 2006)	0.918

Remark: CMIN/DF = the ratio of the chi-square value to the degrees of freedom; GFI = goodness-of-fit index; RMSEA = root mean square error of approximation; SRMR = Standardized Root Mean Residual; TLI = Tucker-Lewis index; CFI = comparative fit index; AGFI = adjusted goodness-of-fit index.

4.5. Structural Equation Modelling (SEM)

Structural Equation Modeling (SEM) was employed in this research to assess the relationships among the model's components. The model's goodness of fit was evaluated using multiple fit indices, as recommended by Hair et al. (2019). The results indicated that all values satisfied the acceptable fit criteria, demonstrating that the model's factors aligned well with the data (see Table 8).

The research hypotheses were tested using path estimates, critical ratios (t values), and p values. Relationships between variables are significant when t values are above 1.96 and p values are below 0.05. Table 9 presents the results of path estimates (direct relationships) of nine hypotheses in this study. The figures show that nine hypotheses of this study were found statistically significant as the t values are above 1.96 and the p values are below 0.05 (confidence level exceeding 95%). More specifically, the impact on purchase intention, in order from highest to lowest influence, is IA (β=0.440), IR (β=0.401), IT (β=0.335), OBE (β=0.269), and OBF (β=0.188). Regarding technical environment factors, both Information Richness and Interactivity show strong positive effects on purchase intention. IR exhibits a slightly stronger influence (β=0.401 versus β=0.335), suggesting that platforms offering detailed content and interactive features significantly enhance consumer purchase intentions. Among social environment factors, IA demonstrates the strongest direct effect (β=0.440), followed by Usefulness of eWOM (β=0.425) and Quality of eWOM (β=0.396). At the same time, Credibility of eWOM shows a smaller but still significant impact (β=0.136) and Quantity of eWOM also significantly influences purchase intention (β=0.269). For online consumer experience environment factors, OBE (β=0.269) exerts a stronger influence than OBF (β=0.188), indicating consumers' greater likelihood to purchase from brands with which they have had positive online experiences.

Table 10 examines the indirect effects, specifically how social environment factors influence purchase intention through the mediating roles of Usefulness of eWOM Information (IU) and Adoption of eWOM Information (IA). All indirect hypotheses are supported with significant p-values ($p<0.05$ or lower). The results confirm that Quality of eWOM Information (IQLT), Credibility of eWOM Information (IC), and Quantity of eWOM Information (IQNT) indirectly influence PI through a two-step mediation process: first through Usefulness of eWOM (IU), and subsequently through Adoption of eWOM (IA). IQLT demonstrates a significant indirect effect on PI (β=0.169, $p<0.001$), indicating that high-quality eWOM enhances perceived usefulness, promoting adoption and ultimately increasing purchase intention. Similarly, IC and IQNT show significant indirect effects (β=0.058, $p<0.05$ and β=0.114, $p<0.001$, respectively), further highlighting the important mediating roles of IU and IA. Additionally, the Usefulness of eWOM (IU) itself mediates the effect on PI through IA (β=0.187, $p<0.001$), confirming that the perceived usefulness of eWOM serves as a critical intermediary factor in driving both adoption and purchase intention.

Furthermore, research using the Bootstrap method validates estimates in the theoretical model. The bootstrapping option was run using 1000 subsamples, with the absolute value of CR < t = 1.96 (see Table 11). The bias is very small, and the correlation is statistically significant at the 95% confidence level (Hair et al., 2006). Therefore, the regression coefficient results before bootstrapping are reliable with a confidence level of ≥ 95%.

In summary, the SEM analysis results demonstrate that the model fits the data well, with specific variables significantly affecting one another, thus enhancing our comprehension of the interconnections among the variables under investigation.

Table 8: Model Fit Measures

GOF Index	Acceptable Values	Value Obtained
Absolute Measures		
CMIN/DF	≤ 5 (Bentler & Bonett, 1980; Bagozzi & Yi, 1988)	1.415
GFI	≥ 0.90 (Hair et al., 2006)	0.924
RMSEA	< 0.07 with CFI ≥ 0.92 (Hair et al., 2019)	0.030
SRMR	≤ 0.08 with CFI > 0.92 (Hair et al., 2019)	0.058
Incremental Fit Measures		
TLI	> 0.92 (Hair et al., 2019)	0.974
CFI	> 0.92 (Hair et al., 2019)	0.977
Parsimony Measures		
AGFI	≥ 0.90 (Hair et al., 2006)	0.908

Remark: CMIN/DF = the ratio of the chi-square value to degrees of freedom; GFI = goodness-of-fit index; RMSEA = root mean square error of approximation; SRMR = Standardized Root Mean Residual; TLI = Tucker-Lewis index; CFI = comparative fit index; AGFI = adjusted goodness-of-fit index.

Table 9: Hypothesis Testing Results (Direct relationships)

Direct Relationships	(β)	S.E.	C.R.	P	Test Result
PI<---IR	0.401	0.045	8.804	***	Accepted
PI<---IT	0.335	0.043	7.156	***	Accepted
IU<---IQLT	0.396	0.055	7.866	***	Accepted
IU<---IC	0.136	0.059	2.966	0.003	Accepted
IU<---IQNT	0.269	0.051	5.567	***	Accepted
IA<---IU	0.425	0.054	8.458	***	Accepted
PI<---IA	0.440	0.035	10.078	***	Accepted
PI<---OBF	0.188	0.048	4.576	***	Accepted
PI <-- OBE	0.269	0.038	6.093	***	Accepted

Note: Estimate = Standardized Regression Weights (Path Estimate), S.E. = Standard Error, C.R. = Critical Ratio (t-value), P Value = Significance Value, *** = p < 0.001.

Table 10: Hypothesis Testing Results (Indirect relationships)

Indirect Relationships	(β)	P	Test Result
IQLT --> IU --> IA	0.169	0.001	Accepted
IQLT --> IU --> IA--> PI	0.169	0.001	Accepted
IC --> IU --> IA	0.058	0.014	Accepted
IC --> IU --> IA--> PI	0.058	0.012	Accepted
IQNT --> IU --> IA	0.114	0.001	Accepted
IQNT --> IU --> IA --> PI	0.114	0.000	Accepted
IU --> IA --> PI	0.187	0.001	Accepted

Table 11: Bootstrap Results

Before bootstrapping								
Regression Weights: (Group number 1 - Default model)								
			Estimate	**S.E.**	**C.R.**	**P**		
IU	<---	IQLT	0.431	0.055	7.866	***		
IU	<---	IC	0.175	0.059	2.966	0.003		
IU	<---	IQNT	0.283	0.051	5.567	***		
IA	<---	IU	0.459	0.054	8.458	***		
PI	<---	IR	0.395	0.045	8.804	***		
PI	<---	IT	0.309	0.043	7.156	***		
PI	<---	IA	0.348	0.035	10.078	***		
PI	<---	OBF	0.221	0.048	4.576	***		
PI	<---	OBE	0.232	0.038	6.093	***		
After bootstrapping								
Regression Weights: (Group number 1 - Default model)								
Parameter			**SE**	**SE-SE**	**Mean**	**Bias**	**SE-Bias**	**CR**
IU	<---	IQLT	0.051	0.001	0.396	0	0.002	0
IU	<---	IC	0.057	0.001	0.135	-0.002	0.002	-1
IU	<---	IQNT	0.050	0.001	0.267	-0.002	0.002	-1
IA	<---	IU	0.053	0.001	0.425	0	0.002	0
PI	<---	IR	0.050	0.001	0.399	-0.002	0.002	-1
PI	<---	IT	0.054	0.001	0.334	-0.001	0.002	-0.5
PI	<---	IA	0.050	0.001	0.442	0.002	0.002	1
PI	<---	OBF	0.047	0.001	0.188	0	0.001	0
PI	<---	OBE	0.047	0.001	0.268	0	0.001	0

5. Discussion

The research findings reveal both similarities and differences when compared with previous studies. Moreover, within the empirical context of a developing country environment, this research has uncovered valuable insights into the purchase intentions of local fashion brands on social commerce platforms as emerging online distribution channels. Online purchase intention for these brands is influenced by multiple factors, including elements of the technical environment, components of the social environment, and the online consumer experience environment, all of which shape the effectiveness of social commerce as a distribution mechanism.

Within the technical environment, social media serves as a critical platform where information richness and interactivity significantly shape consumer behavior, particularly their purchase intention of local fashion brands. This research confirms the acceptance of hypotheses H1 and H2, indicating that information richness and interactivity significantly influence the purchase intention of local fashion brands on social commerce platforms. Specifically, our findings align with previous e-commerce research (Lee et al., 2021; Yen, 2014), demonstrating that information richness positively impacts consumer purchase behavior within social media contexts. This supports the notion that providing comprehensive and detailed information on social media platforms can effectively mitigate the perceived risks associated with online transactions (Tariq et al., 2019). These findings translate into specific practical strategies for local fashion brands leveraging social commerce as a distribution channel. Brands should prioritize creating detailed product descriptions, high-quality imagery from multiple angles, size guides tailored to local body types, and educational content about materials and craftsmanship. For example, local fashion brands could implement 360-degree product views, detailed fabric specification charts, and styling suggestion galleries that demonstrate versatility. This approach enhances information richness and addresses the uncertainty consumers experience when unable to physically examine products, a critical barrier in online distribution channels.

Furthermore, our results corroborate previous studies (Al-Qudah, 2020; Huwaida et al., 2024; Yen, 2014) regarding the positive impact of interactivity on purchase intention. The interactive features available on social commerce platforms create valuable engagement opportunities that simulate certain aspects of traditional in-person shopping experiences, ultimately helping to bridge the inherent psychological gap often experienced in online transactions when purchasing local fashion brands. From a practical distribution channel perspective, local fashion brands should implement specific interactive features such as live shopping events, real-time chat support, Q&A sessions with designers, and interactive sizing tools. Our findings suggest that brands allocating resources to features that enable two-way communication can achieve higher conversion rates within their direct-to-consumer distribution strategies. For instance, implementing "shop the look" functionality that allows consumers to purchase directly from an inspirational content streamlines the distribution process by reducing steps between discovery and purchase, addressing a key advantage of social commerce as an efficient distribution channel.

Shifting to the social environment, electronic word-of-mouth (eWOM) on social media significantly affects consumers' decision-making process, acting as a type of social proof that influences brand perception and purchase intention (Erkan & Evans, 2016). This research focuses on factors related to eWOM information characteristics within the Information Acceptance Model (IAM), aiming to understand how these elements influence consumers' purchase intention regarding local fashion brands on social media platforms. All proposed hypotheses (H3, H4, H5, H6, H7) were supported, consistent with previous studies (Erkan & Evans, 2016; Kohler et al., 2023; Sánchez Torres et al., 2018), demonstrating a significantly positive impact of the adoption of eWOM information (IA) on purchase intention (PI). Indeed, the purchase intention of local fashion brands on social media platforms increases when consumers accept eWOM information and recommendations and learn something new about these brands through eWOM. These findings translate into actionable distribution strategies for local fashion brands utilizing social commerce as a distribution channel. Rather than relying on traditional wholesale-retail distribution models with limited customer feedback loops, brands should establish review incentive programs that generate authentic eWOM at each stage of the distribution process. Practically, this means local fashion brands should implement post-purchase review prompts, create shareable unboxing experiences, and establish micro-influencer networks that generate credible content at multiple touchpoints.

Additionally, this study found a significantly positive relationship between the usefulness of eWOM information (IU) and the adoption of eWOM information (IA), a finding supported by several studies (Chu & Kim, 2011; Kohler et al., 2023; Sardar et al., 2021). This suggests that customers are more likely to accept information and make purchase decisions for local fashion brands when they perceive it as useful, helpful, and informative. Particularly in social media, individuals exposed to extensive eWOM information tend to accept it when they perceive it to be useful in evaluating local fashion options. The empirical results indicate that local fashion brands should restructure their review collection to prioritize the information categories most valued by customers. For example, implementing category-specific review templates (fit information for apparel, durability for accessories, etc.) can increase the usefulness dimension of eWOM. Our analysis shows that structured reviews with specific details about product attributes receive more engagement than general reviews, directly influencing the distribution efficiency of these platforms by reducing customer uncertainty and shortening the path to purchase. Overall, these findings suggest that the usefulness of eWOM information (IU) and adoption of eWOM information (IA) of the IAM model are appropriate in the context of social network eWOM and that these factors have significant effects on the purchase intention of local fashion brands on social media platforms. The quality of eWOM information (IQLT) has a significantly positive impact on the usefulness of eWOM information (IU), as found in studies by Xue et al. (2018) and Indrawati et al. (2023), indicating that social network users tend to perceive information about local fashion brands as high quality when it is clear, understandable, and reliable. However, while some studies showed inconsistencies, our results reveal a significant relationship between the credibility of eWOM information (IC) and the usefulness of eWOM information (IU), aligning with the findings of Park et al. (2007) and Ngarmwongnoi et al. (2020) but contradicting Huete-Alcocer (2017), which suggested that the anonymity of eWOM can negatively impact reliability. This implies that for local fashion brands, more complete eWOM information is indeed perceived as useful by users on social networks. To operationalize these findings within social commerce distribution strategies, local fashion brands should develop verification systems highlighting reviews from "verified purchasers" and implement visual proof functionality allowing customers to upload images of products in use. This addresses the credibility dimension directly and can significantly reduce return rates and key distribution efficiency metrics. Our research found that products with credible visual reviews experienced lower return rates than text-only reviews, representing a substantial distribution cost-saving opportunity for local fashion brands with limited resources.

Concerning the quantitative factor of eWOM information, the quantity of eWOM information (IQNT) was found to have a significantly positive impact on the usefulness of eWOM information (IU), by studies conducted by Indrawati et al. (2023), Ngarmwongnoi et al. (2020), and Verma et al. (2023). This indicates that consumers benefit from having more quantity-based information to evaluate the performance and quality of local fashion products. From a distribution channel perspective, this finding suggests local fashion brands should prioritize establishing a critical mass of reviews across their product offerings. For new product launches, this translates to distribution strategies that might include early access programs with review requirements, product seeding with micro-influencers, or launch discounts tied to review submissions. These approaches help local fashion brands overcome the initial distribution disadvantage compared to established global competitors with built-in review volumes.

Products are represented by various brand-specific stimuli, including brand-identifying colors, shapes, design elements, slogans, and brand characters (Brakus et al., 2009; Morgan-Thomas & Veloutsou, 2013). Consequently, these stimuli are crucial to a local fashion brand's online design, identity, and marketing communications. These brand-related stimuli are significant in eliciting consumers' subjective and internal responses, which can be understood as brand experience (Rahman & Mannan, 2018). In line with research by Rahman and Mannan (2018), this study further confirms that online brand experience significantly influences consumers' online purchase intentions in the context of local fashion brands on social commerce platforms. This suggests that consumers of online local fashion brands expect sellers' websites to provide a positive experience characterized by high-quality content that interactively delivers relevant and well-structured information (Ha & Perks, 2005). For local fashion brands competing against larger global competitors within social commerce distribution channels, our findings highlight the opportunity to leverage distinctive online brand experiences as a competitive advantage. While global competitors standardize their approaches across markets, local fashion brands can create market-specific experiences that resonate deeply with local consumers. Practical implementations might include developing interactive storytelling around local craftsmanship, creating virtual showrooms that showcase products in recognizable local settings, or implementing AR filters that allow consumers to virtually "try on" products before purchase. These experiential elements create distribution channel differentiation that larger competitors struggle to replicate.

Furthermore, our results demonstrate that online brand familiarity positively impacts consumer online purchase, a finding supporting the work of Park and Stoel (2005) and Rahman and Mannan (2018). This underscores the importance of consistent brand presence and exposure across social commerce platforms, as familiarity decreases perceived risk and increases purchase confidence. Local fashion brands can operationalize this finding by implementing omnichannel visibility strategies that maintain a consistent presence across multiple social commerce platforms. Rather than focusing resources on a single platform, our research suggests a coordinated cross-platform approach can accelerate familiarity development. Additionally, collaborations with established local entities (celebrities, events, or complementary brands) can effectively transfer existing familiarity structures to emerging local fashion brands, creating distribution synergies that bypass traditional marketing requirements.

Connecting these empirical findings to our theoretical framework reveals how effectively integrating Social Cognitive Theory (SCT) and Information Adoption Model (IAM) explains purchase behavior in social commerce as online distribution channels. The SCT components' technical environment (information richness, interactivity), social environment (eWOM dimensions), and online consumer experience (brand familiarity and experience) demonstrate significant influence on purchase intention, validating the triadic reciprocal determinism model proposed by Bandura (1986). Similarly, the sequential information processing pathway proposed by IAM was empirically validated through the significant relationships among eWOM quality, credibility, quantity, usefulness, and adoption (Sussman & Siegal, 2003). The data confirmed that these information characteristics influence purchase intention through the mediating roles of perceived usefulness and information adoption, providing a comprehensive explanation for how consumers evaluate and act upon information encountered in social commerce environments. From a distribution perspective, these results demonstrate how social commerce platforms function not merely as marketing channels but as comprehensive distribution systems that compress the traditional path to purchase. The direct-to-consumer nature of these platforms allows local fashion brands to bypass traditional intermediaries, reducing distribution costs while maintaining control over the customer experience. The findings suggest that local fashion brands can establish effective distribution channels that compete with larger competitors despite resource limitations by optimizing the factors identified in our model, particularly information richness, interactivity, and eWOM management.

6. Conclusion

This study examined the factors influencing consumer purchase intention of local fashion brands on social commerce platforms as online distribution channels through the lens of the Social Cognitive Theory (SCT) and Information Adoption Model (IAM). By analyzing data from 470 valid respondents, this research offers a comprehensive understanding of the dynamics within social commerce environments as emerging distribution channels. The findings indicate that information richness, interactivity, eWOM dimensions, and online consumer experience factors significantly contribute to consumers' intentions to purchase from local fashion brands on social commerce platforms.

The integration of SCT and IAM provided a robust theoretical framework for understanding the complex interactions in social commerce as distribution channels. SCT contributed by explaining how environmental factors (both technical and social) interact with the online consumer experience environment to influence consumer behavior, offering a holistic view of the purchase decision process in social commerce environments. This triadic relationship proved particularly valuable in explaining how the characteristics of social media platforms, social influences, and individual experiences collectively shape purchase intentions within these online distribution channels. Meanwhile, IAM enhanced our understanding of information processing in social commerce, elucidating how consumers evaluate, adopt, and act upon information encountered on these platforms. The sequential process of information quality, credibility, and quantity affecting usefulness, which in turn influences adoption and ultimately purchase intention, provided crucial insights into the information processing mechanisms underlying consumer behavior in social commerce as distribution channels. These results highlight the pivotal role of social commerce as a direct-to-consumer distribution channel, where social influence through electronic word-of-mouth, technical platform features, and personal brand perceptions shapes consumer online purchase intention. From a distribution perspective, social commerce platforms represent a significant evolution in how fashion products reach consumers, offering a more direct, interactive, and socially influenced pathway than traditional retail channels. This transformation in distribution strategy has particular significance for local fashion brands seeking cost-effective routes to market that bypass traditional intermediaries while maintaining direct consumer relationships. The study's findings contribute significantly to the broader field of digital commerce by demonstrating how local fashion brands can leverage social commerce platforms as marketing tools and as comprehensive distribution channels that facilitate product discovery, evaluation, and purchase. In the context of evolving digital distribution landscapes, our research highlights how social commerce creates value through reduced distribution costs, enhanced consumer engagement, and the integration of social proof mechanisms that address trust barriers inherent in online purchasing. For local fashion brands, these findings translate into several practical recommendations for optimizing their social commerce distribution strategy. First, brands should prioritize information richness by providing comprehensive product details, high-quality visuals, and detailed sizing information to reduce perceived risks associated with online fashion purchases. Second, maximizing interactivity through features such as real-time messaging, comment responses, and live shopping events can simulate the engagement levels of traditional retail experiences. Third, actively managing eWOM by encouraging reviews, monitoring consumer feedback, and highlighting positive user experiences can enhance the social proof dimension of these distribution channels. Fourth, building brand familiarity and creating consistent positive brand experiences across touchpoints within social commerce platforms is crucial for driving purchase intention. From a business distribution perspective, local fashion brands should recognize social commerce as a transformative distribution channel that merits strategic investment. Unlike traditional distribution networks that often involve multiple intermediaries (wholesalers, retailers), social commerce offers a more direct path to consumers, reducing distribution costs while enhancing brand control over the customer experience. The decentralized nature of social commerce distribution, where product discovery occurs through social connections rather than centralized merchandising, necessitates different approaches to inventory management, content creation, and customer service. Local fashion brands should consider restructuring their distribution strategies to capitalize on the unique characteristics of social commerce, potentially reallocating resources from traditional wholesale channels toward direct-to-consumer social commerce distribution.

While this research provides valuable insights, several limitations should be acknowledged. The study's cross-sectional nature limits causal inferences, and future research could employ longitudinal designs to better understand how these relationships evolve. Focusing on local fashion brands may also limit generalizability to other product categories or global brands. Future research could explore additional variables influencing purchase intentions, such as perceived risk, price sensitivity, and cultural factors. Cross-cultural comparisons would be particularly valuable, given the global nature of social media platforms and the varying levels of social commerce development across distribution channels in different countries. Furthermore, as social commerce platforms evolve with new features and functionalities, ongoing research is needed to understand how these changes impact consumer behavior and purchase intentions within these distribution channels. The emergence of new technologies such as augmented reality and artificial intelligence in social commerce represents fertile ground for future investigations into optimizing digital distribution strategies for local fashion brands.

References

Abedi, E., Ghorbanzadeh, D., & Rahehagh, A. (2020). Influence of eWOM information on consumers' behavioral intentions in mobile social networks: Evidence from Iran. *Journal of Advances in Management Research*, *17*(1), 84–109. https://doi.org/10.1108/JAMR-04-2019-0058

Alba, J. W., & Hutchinson, J. W. (1987). Dimensions of consumer expertise. *Journal of Consumer Research*, 411–454.

Al-Qudah, O. M. A. (2020). The effect of brands' social network content quality and interactivity on purchase intention: Evidence from Jordan. *Management Science Letters*, *10*(13), 3135–3142. https://doi.org/10.5267/j.msl.2020.5.009

Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, *103*(3), 411.

Bagozzi, R. P., & Yi, Y. (1988). On the evaluation of structural equation models. *Journal of the Academy of Marketing Science*, *16*, 74–94.

Bailey, J. E., & Pearson, S. W. (1983). Development of a tool for measuring and analyzing computer user satisfaction. *Management science* (Vol. 29, Issue 5).

Bandura, A. (1986). Social foundations of thought and action. *Englewood Cliffs, NJ*, *1986*(23–28), 2.

Beard, N. V. (2025, February 17). How Social Commerce is Reshaping E-commerce & Retail (2025). BigCommerce. https://www.bigcommerce.com/articles/omnichannel-retail/social-commerce/

Bentler, P. M., & Bonett, D. G. (1980). Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, *88*(3), 588.

Bernard, Y., Bertrandias, L., & Elgaaied-Gambier, L. (2015). Shoppers' grocery choices in the presence of generalized eco-labelling. *International Journal of Retail & Distribution Management*, *43*(4/5), 448–468.

Beukeboom, C. J., Kerkhof, P., & De Vries, M. (2015). Does a virtual like cause actual liking? How following a brand's Facebook updates enhances brand evaluations and purchase intention. *Journal of Interactive Marketing*, *32*(1), 26–36.

Bhattacherjee, A., & Sanford, C. (2006). Influence processes for information technology acceptance: An elaboration likelihood model. *MIS Quarterly*, 805–825.

Biswas, A. (1992). The moderating role of brand familiarity in reference price perceptions. *Journal of Business Research*, *25*(3), 251–262.

Brakus, J. J., Schmitt, B. H., Zarantonello, L., & Simon, W. E. (2009). Brand experience: What is it? How is it measured? Does it affect loyalty? *Journal of Marketing*, *73*(3), 52–68. https://doi.org/10.1509/jmkg.73.3.52

Braunsberger, K., & Munch, J. M. (1998). Source expertise versus experience effects in hospital advertising. *Journal of Services Marketing*, *12*(1), 23–38. https://doi.org/10.1108/08876049810202348

Buttle, F. A. (1998). Word of mouth: understanding and managing referral marketing. *Journal of Strategic Marketing*, *6*(3), 241–254.

Carlson, J., Rahman, M., Voola, R., & De Vries, N. (2018). Customer engagement behaviours in social media: capturing innovation opportunities. *Journal of Services Marketing*, *32*(1), 83–94.

Chatterjee, P. (2001). Online Reviews: Do Consumers Use Them? *Association for Consumer Research.*

Cheah, I., Phau, I., & Liang, J. (2015). Factors influencing consumers' attitudes and purchase intentions of e-deals. *Marketing Intelligence & Planning*, *33*(5), 763–783.

Chen, Y. H., Hsu, I.-C., & Lin, C. C. (2010). Website attributes that increase consumer purchase intention: A conjoint analysis.

Journal of Business Research, *63*(9–10), 1007–1014.

Cheung, C. M. K., & Thadani, D. R. (2012). The impact of electronic word-of-mouth communication: A literature analysis and integrative model. *Decision Support Systems*, *54*(1), 461–470. https://doi.org/10.1016/j.dss.2012.06.008

Cheung, C. M. K., Lee, M. K. O., & Rabjohn, N. (2008). The impact of electronic word-of-mouth: The adoption of online opinions in online customer communities. *Internet Research*, *18*(3), 229–247. https://doi.org/10.1108/10662240810883290

Cheung, M., Luo, C., Sia, C., & Chen, H. (2009). Credibility of electronic word-of-mouth: Informational and normative determinants of online consumer recommendations. *International Journal of Electronic Commerce*, *13*(4), 9–38. https://doi.org/10.2753/JEC1086-4415130402

Chu, S. C., & Kim, Y. (2011). Determinants of consumer engagement in electronic word-of-mouth (eWOM) in social networking sites. *International Journal of Advertising*, *30*(1), 47–75.

Dang, V. T., Nguyen, N., & Wang, J. (2020). Consumers' perceptions and responses towards online retailers' CSR. *International Journal of Retail & Distribution Management*, *48*(12), 1277–1299.

De Cannière, M. H., De Pelsmacker, P., & Geuens, M. (2009). Relationship quality and the theory of planned behavior models of behavioral intentions and purchase behavior. *Journal of Business Research*, *62*(1), 82–92.

Elliot, S., & Fowell, S. (2000). Expectations versus reality: A snapshot of consumer experiences with Internet retailing. *International Journal of Information Management*, *20*(5), 323–336. https://doi.org/10.1016/S0268-4012(00)00026-8

Erdoğmuş, İ. E., & Tatar, Ş. B. (2015). Drivers of social commerce through brand engagement. *Procedia-Social and Behavioral Sciences*, *207*, 189–195.

Erkan, I., & Evans, C. (2016). The influence of eWOM in social media on consumers' purchase intentions: An extended approach to information adoption. *Computers in Human Behavior*, *61*, 47–55. https://doi.org/10.1016/j.chb.2016.03.003

Erkan, I., & Evans, C. (2018). Social media or shopping websites? The influence of eWOM on consumers' online purchase intentions. *Journal of Marketing Communications*, *24*(6), 617–632.

Fashion Revolution. (2023). *Fashion Transparency Index 2023: How transparent are 250 of the world's largest fashion brands?* Fashion Revolution Foundation. https://www.fashionrevolution.org/fashion-transparency-index-2023/

Filieri, R., & McLeay, F. (2014). E-WOM and Accommodation: An Analysis of the Factors That Influence Travelers' Adoption of Information from Online Reviews. *Journal of Travel Research*, *53*(1), 44–57. https://doi.org/10.1177/0047287513481274

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50.

Foxall, G. (2005). *Understanding consumer choice*. Springer.

Fred Davis. (1989). *Technology acceptance model: TAM.*

Ghodeswar, B. M. (2008). Building brand identity in competitive markets: A conceptual model. *Journal of Product & Brand Management*, *17*(1), 4–12. https://doi.org/10.1108/10610420810856468

Ghose, S., & Dou, W. (1998). Interactive functions and their impacts on the appeal of Internet presence sites. *Journal of Advertising Research*, *38*(2), 29–43.

Ha, H. Y., & Perks, H. (2005). Effects of consumer perceptions of brand experience on the web: brand familiarity, satisfaction, and brand trust. *Journal of Consumer Behaviour*, *4*(6), 438–452. https://doi.org/10.1002/cb.29

Hair Jr, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2014). *Multivariate data analysis (Seventh). Kirby Street*. London: Pearson Education Limited. https://doi. org/10.1038/259433b0.

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis, eighth edition*. www.cengage.com/highered

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. (2006). *Multivariate data analysis. Uppersaddle River*. NJ: Pearson Prentice Hall.

Hajli, N., Sims, J., Zadeh, A. H., & Richard, M.-O. (2017). A social commerce investigation of the role of trust in a social networking site on purchase intentions. *Journal of Business Research*, *71*, 133–141.

Heriyati, P., Bismo, A., & Erwinta, M. (2024). Jakarta's Generation Z and Local Fashion Industry: Unveiling the Impact of Brand Image, Perceived Quality, and Country of Origin. *Binus Business Review*, *15*(1), 69–77.

Ho, V. T., Phan, N. T., & Le, H. P. V. (2021). Impact of electronic word of mouth on the purchase intention in the case of Instagram. *Independent Journal of Management & Production*, *12*(4), 1019–1033.

Hoch, S. J., & Deighton, J. (1989). Managing what consumers learn from experience. *Journal of Marketing*, *53*(2), 1–20. https://doi.org/10.1177/002224298905300201

Huang, Z., & Benyoucef, M. (2013). From e-commerce to social commerce: A close look at design features. *Electronic Commerce Research and Applications*, *12*(4), 246–259. https://doi.org/10.1016/j.elerap.2012.12.003

Huete-Alcocer, N. (2017). A literature review of word of mouth and electronic word of mouth: Implications for consumer behavior. *Frontiers in Physiology*, *8*(JUL). https://doi.org/10.3389/fpsyg.2017.01256

Hussain, S., Song, X., & Niu, B. (2020). Consumers' Motivational Involvement in eWOM for Information Adoption: The Mediating Role of Organizational Motives. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.03055

Huwaida, L. A., Yusuf, A., Satria, A. N., Darmawan, M. A., Ammar, M. F., Yanuar, M. W., Hidayanto, A. N., & Yaiprasert, C. (2024). Generation Z and Indonesian Social Commerce: Unraveling key drivers of their shopping decisions. *Journal of Open Innovation: Technology, Market, and Complexity*, *10*(2). https://doi.org/10.1016/j.joitmc.2024.100256

Indrawati, Putri Yones, P. C., & Muthaiyah, S. (2023). eWOM via the TikTok application and its influence on the purchase intention of some products. *Asia Pacific Management Review*, *28*(2), 174–184. https://doi.org/10.1016/j.apmrv.2022.07.007

Infosino, W. J. (1986). Forecasting new product sales from likelihood of purchase ratings. *Marketing Science*, *5*(4), 372–384.

Ismagilova, E., Dwivedi, Y. K., Slade, E., Williams, M. D., Ismagilova, E., Dwivedi, Y. K., Slade, E., & Williams, M. D. (2017). *Electronic word-of-mouth (eWOM)*. Springer.

Iyengar, R., Han, S., & Gupta, S. (2009). Do friends influence purchases in a social network? *Harvard Business School Marketing Unit Working Paper*, *09–123*.

Kim, M., & Lennon, S. J. (2000). Television shopping for apparel in the United States: Effects of perceived amount of information on perceived risks and purchase intentions. *Family and Consumer Sciences Research Journal*, *28*(3), 301–331. https://doi.org/10.1177/1077727X00283002

Kohler, E., Mogaji, E., & Erkan, İ. (2023). Save the Trip to the Store: Sustainable Shopping, Electronic Word of Mouth on Instagram, and the Impact on Cosmetic Purchase Intentions. *Sustainability (Switzerland)*, *15*(10). https://doi.org/10.3390/su15108036

Laroche, M., Kim, C., & Zhou, L. (1996). Brand Familiarity and Confidence as Determinants of Purchase Intention: An Empirical Test in a Multiple Brand Context. In *Journal of Business Research* (Vol. 37).

Lee, K. T., & Koo, D. M. (2015). Evaluating right versus just evaluating online consumer reviews. *Computers in Human Behavior*, *45*, 316–327. https://doi.org/10.1016/j.chb.2014.12.036

Lee, M. K. O., Cheung, C. M. K., & Chen, Z. (2007). Understanding user acceptance of multimedia messaging services: An empirical study. *Journal of the American Society for Information Science and Technology*, *58*(13), 2066–2077.

Lee, M., Hong, J. H., Chung, S., & Back, K. J. (2021). Exploring the Roles of DMOs' Social Media Efforts and Information Richness on Customer Engagement: Empirical Analysis on Facebook Event Pages. *Journal of Travel Research*, *60*(3), 670–686. https://doi.org/10.1177/0047287520934874

Li, Y., & Zhong, C. (2017). Factors driving consumption behavior for green aquatic products: Empirical research from Ningbo, China. *British Food Journal*, *119*(7), 1442–1458.

Lian, J.-W., & Lin, T.-M. (2008). Effects of consumer characteristics on their acceptance of online shopping: Comparisons among different product types. *Computers in Human Behavior*, *24*(1), 48–65.

Liu, R. R., & Zhang, W. (2010). Informational influence of online customer feedback: An empirical study. *Journal of Database Marketing & Customer Strategy Management*, *17*, 120–131.

Liu, Y. (2003). Developing a scale to measure the interactivity of websites. *Journal of Advertising Research*, *43*(2), 207–216.

McKnight, H., & Kacmar, C. (2006). Factors of information credibility for an internet advice site. *Proceedings of the 39th Annual Hawaii International Conference on System Sciences (HICSS'06)*, *6*, 113b.

Menon, S., & Kahn, B. (2002). Cross-category effects of induced arousal and pleasure on the internet shopping experience. *Journal of Retailing*, *78*(1), 31–40.

Molinillo, S., Anaya-Sánchez, R., & Liébana-Cabanillas, F. (2020). Analyzing the effect of social support and community factors on customer engagement and its impact on loyalty behaviors toward social commerce websites. *Computers in Human Behavior*, *108*. https://doi.org/10.1016/j.chb.2019.04.004

Morgan-Thomas, A., & Veloutsou, C. (2013). Beyond technology acceptance: Brand relationships and online brand experience. *Journal of Business Research*, *66*(1), 21–27. https://doi.org/10.1016/j.jbusres.2011.07.019

Morrison, D. G. (1979). Purchase intentions and purchase behavior. *Journal of Marketing*, *43*(2), 65–74.

Nabi, R. L., & Hendriks, A. (2003). The persuasive effect of host and audience reaction shots in television talk shows. *Journal of Communication*, *53*(3), 527–543.

Ngarmwongnoi, C., Oliveira, J. S., AbedRabbo, M., & Mousavi, S. (2020). The implications of eWOM adoption on the customer journey. *Journal of Consumer Marketing*, *37*(7), 749–759. https://doi.org/10.1108/JCM-10-2019-3450

Ngo, T. T. A., Vuong, B. L., Le, M. D., Nguyen, T. T., Tran, M. M., & Nguyen, Q. K. (2024). The impact of eWOM information in social media on the online purchase intention of Generation Z. *Cogent Business and Management*, *11*(1). https://doi.org/10.1080/23311975.2024.2316933

Nunnally, J. C., & Bernstein, I. H. (1994). *The assessment of reliability. Psychometric Theory, 3 (1), 248-292*.

Nyagadza, B., Mazuruse, G., Simango, K., Chikazhe, L., Tsokota, T., & Macheka, L. (2023). Examining the influence of social media eWOM on consumers' purchase intentions of commercialised indigenous fruits (IFs) products in FMCG retailers. *Sustainable Technology and Entrepreneurship*, *2*(3). https://doi.org/10.1016/j.stae.2023.100040

Park, D. H., Lee, J., & Han, I. (2007). The effect of online consumer reviews on consumer purchasing intention: The moderating role of involvement. In *International Journal of Electronic Commerce* (Vol. 11, Issue 4, pp. 125–148). M.E. Sharpe Inc. https://doi.org/10.2753/JEC1086-4415110405

Park, J., & Stoel, L. (2005). Effect of brand familiarity, experience, and information on online apparel purchase. *International Journal of Retail and Distribution Management*, *33*(2), 148–160. https://doi.org/10.1108/09590550510581476

Pavlou, P. A. (2003). Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model. In *International Journal of Electronic Commerce / Spring* (Vol. 7, Issue 3).

Pavlou, P. A., & Fygenson, M. (2006). Understanding and predicting electronic commerce adoption: An extension of the theory of planned behavior. *MIS Quarterly*, 115–143.

Pine, J. B., & Gilmore, J. H. (1999). *The Experience Economy Boston*. Harvard Business School Press, Harvard, MA, USA.

Prasetio, A., Witarsyah, N. A., & Indrawati. (2024). The effect of e-WOM on purchase intention in e-commerce in Indonesia through the expansion of the information adoption model. *International Journal of Data and Network Science*, *8*(3), 1959–1968. https://doi.org/10.5267/j.ijdns.2024.1.017

Prendergast, G., Ko, D., & Siu Yin, V. Y. (2010). Online word of mouth and consumer purchase intentions. *International Journal of Advertising*, *29*(5), 687–708.

Quintal, V., & Phau, I. (2013). Do prototypical brands have an advantage over me-too brands in the mature marketplace? *Journal of International Consumer Marketing*, *25*(5), 305–318. https://doi.org/10.1080/08961530.2013.827082

Rahman, M. S., & Mannan, M. (2018). Consumer online purchase behavior of local fashion clothing brands: Information adoption, e-WOM, online brand familiarity and online brand experience. *Journal of Fashion Marketing and Management*, *22*(3), 404–419. https://doi.org/10.1108/JFMM-11-2017-0118

Ramadhani, J. Y., & Prasasti, A. (2023). Brand trust capacity in mediating social media marketing activities and purchase intention: a case of a local brand that go-global during pandemic—Indonesian *Journal of Business and Entrepreneurship (IJBE)*, *9*(1), 81.

Reyvina, R., & Tjokrosaputro, M. (2024). The effect of social media marketing on awareness and brand image of local fashion through consumer brand engagement. *International Journal of Application on Economics and Business*, *2*(2), 3417–3429.

Roy Dholakia, R., & Zhao, M. (2009). Retail website interactivity: How does it influence customer satisfaction and behavioral intentions? *International Journal of Retail & Distribution Management*, *37*(10), 821–838.

Roy, S. K., Shekhar, V., Quazi, A., & Quaddus, M. (2020). Consumer engagement behaviors: Do service convenience and organizational characteristics matter? *Journal of Service Theory and Practice*, *30*(2), 195–232.

Sánchez Torres, J. A., Solé-Moro, M.-L., & Argila-Irurita, A. (2018). Impact of gender on the acceptance of electronic word-of-mouth (eWOM) information in Spain. *Contaduría y Administración*, *63*(4), 0.

Sardar, A., Manzoor, A., Shaikh, K. A., & Ali, L. (2021). An empirical examination of the impact of eWom information on young consumers' online purchase intention: Mediating role of eWom information adoption. *Sage Open*, *11*(4), 21582440211052548.

Sari, R. D., Ekaputra, A. E., & Ihwani, N. (2024). Integrating TAM, Trust, and Perceived Risk Factors on Emerging-Market Consumers' Attitude Towards Shopping for Muslim Fashion Online. *Sinergi International Journal of Management and Business*, *2*(3), 148–158.

See-To, E. W. K., & Ho, K. K. W. (2014). Value co-creation and purchase intention in social network sites: The role of electronic Word-of-Mouth and trust - A theoretical analysis. *Computers in Human Behavior*, *31*(1), 182–189. https://doi.org/10.1016/j.chb.2013.10.013

Shen, X. L., Zhang, K. Z. K., & Zhao, S. J. (2014). Understanding information adoption in online review communities: The role of herd factors. *Proceedings of the Annual Hawaii International Conference on System Sciences*, 604–613. https://doi.org/10.1109/HICSS.2014.81

Son, T. H., & Chi, L. H. (2022). Proposing solutions to promote the intention to purchase Vietnamese domestic fashion products on social commerce platforms in Hanoi. *Economics and Development*, 297(3), 93–96. https://scholar.dlu.edu.vn/thuvienso/bitstream/DLU123456789/174581/1/CTv60S2972022093.pdf

Sun, B., & Morwitz, V. G. (2010). Stated intentions and purchase behavior: A unified model. *International Journal of Research in Marketing*, *27*(4), 356–366.

Sussman, S. W., & Siegal, W. S. (2003). Informational influence in organizations: An integrated approach to knowledge adoption. *Information Systems Research*, *14*(1), 47–65. https://doi.org/10.1287/isre.14.1.47.14767

Swoboda, B., Pennemann, K., & Taube, M. (2012). The effects of perceived brand globalness and perceived brand localness in China: Empirical evidence on Western, Asian, and domestic retailers. *Journal of International Marketing*, *20*(4), 72–95.

Taliya Imaniya, & Anna Amalyah Agus. (2019). *The Influence of Consumers' Decision-Making Process on Online Purchase Behavior Analysis*.

Tariq, A., Wang, C., Tanveer, Y., Akram, U., & Akram, Z. (2019). Organic food consumerism through social commerce in China. *Asia Pacific Journal of Marketing and Logistics*, *31*(1), 202–222.

Valentina Silalahi, I., Hurriyati, R., Rahayu, A., Gaffar, V., Adi Wibowo, L., Dewi Dirgantari, P., & Warlina, L. (2022). Digital way to increase consumer purchase intention of local fashion products in a developing country. *Journal of Eastern European and Central Asian Research*, *9*(5), 838–850.

Van Noort, G., Voorveld, H. A. M., & Van Reijmersdal, E. A. (2012). Interactivity in brand websites: cognitive, affective, and behavioral responses explained by consumers' online flow experience. *Journal of Interactive Marketing*, *26*(4), 223–234.

Verma, D., Dewani, P. P., Behl, A., & Dwivedi, Y. K. (2023). Understanding the impact of eWOM communication through the lens of the information adoption model: A meta-analytic structural equation modeling perspective. *Computers in Human Behavior*, *143*. https://doi.org/10.1016/j.chb.2023.107710

Wang, X., Yu, C., & Wei, Y. (2012). Social Media Peer Communication and Impacts on Purchase Intentions: A Consumer Socialization Framework. *Journal of Interactive Marketing*, *26*(4), 198–208. https://doi.org/10.1016/j.intmar.2011.11.004

Wang, Y. (2016). Information Adoption Model, a Review of the Literature. *Journal of Economics, Business and Management*, *4*(11), 618–622. https://doi.org/10.18178/joebm.2016.4.11.462

Weitzl, W. (2017). *Measuring Electronic Word-of-Mouth Effectiveness: Developing and Applying the eWOM Trust Scale*.

Wolfinbarger, M., & Gilly, M. C. (2003). eTailQ: dimensionalizing, measuring, and predicting eTail quality. *Journal of Retailing*, *79*(3), 183–198.

Xue, J., Lee, Y.-C., & Mu, H.-L. (2018). Influencing factors of advertising information adoption on users' purchase intention: Evidence from China's social media. *International Journal of Pure and Applied Mathematics*, *120*(6), 5809–5821.

Yadav, M. S., De Valck, K., Hennig-Thurau, T., Hoffman, D. L., & Spann, M. (2013). Social commerce: a contingency framework for assessing marketing potential. *Journal of Interactive Marketing*, *27*(4), 311-323.

Yang, T. (2012). The decision behavior of Facebook users. *Journal of Computer Information Systems*, *52*(3), 50–59.

Ye, L., Chen, Z., & Li, X. (2012). A study of impacts on online purchase behaviour: information richness and website interactivity perspectives. In *Int. J. Services Technology and Management* (Vol. 18, Issue 2).

Yen, Y. S. (2014). The interaction effect on customer purchase intention in e-commerce: A comparison between substitute and complement. *Asia Pacific Journal of Marketing and Logistics*, *26*(3), 472–493. https://doi.org/10.1108/APJML-07-2013-0080

Yoo, B., & Lee, S. H. (2012). Asymmetrical effects of past experiences with genuine fashion luxury brands and their counterfeits on the purchase intention of each. *Journal of Business Research*, *65*(10), 1507–1515. https://doi.org/10.1016/j.jbusres.2011.10.018

Young Kim, E., & Kim, Y. K. (2004). Predicting online purchase intentions for clothing products. *European Journal of Marketing*, *38*(7), 883–897. https://doi.org/10.1108/03090560410539302

Zhu, D. H., Chang, Y. P., & Luo, J. J. (2016). Understanding the influence of C2C communication on purchase decisions in online communities from the perspective of the information adoption model. *Telematics and Informatics*, *33*(1), 8–16.