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| RESEARCH ARTICLE

Decoding Customer Satisfaction and Loyalty in the Era of Smartphone Shopping Applications in India– Moderating Effect of Experience

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| ABSTRACT
The widespread adoption of smartphones has revolutionized individual activities, enabling users to engage in diverse tasks at any time and from any location. By recognizing this shift, marketers are increasingly tailoring their strategies through a mobile-first approach to enhance the user experience. This trend is particularly prominent in emerging markets like India, where mobile shopping applications are experiencing rapid growth. In the face of intensified market competition and evolving customer expectations, understanding the determinants of customer satisfaction and loyalty is paramount for marketers in mobile shopping applications. This study delves into the post-adoption behavior of customers, presenting a research model integrating the Technology Acceptance Model (TAM) and the Expectation-Confirmation Model (ECM). Drawing data from 535 current users of mobile shopping applications, the empirical validation of the research framework reveals that perceived trust, perceived usefulness, confirmation, and attitude emerge as pivotal factors influencing satisfaction. Additionally, loyalty is shaped by satisfaction, perceived usefulness, attitude, and perceived trust. The study further elucidates the indirect effects of mobile shoppers' beliefs on satisfaction and loyalty. Implications and avenues for future research are discussed, shedding light on the intricate dynamics of customer interaction in the mobile shopping landscape.

| KEYWORDS

Mobile shopping application, loyalty, satisfaction, price saving orientation, multi-group analysis

| ARTICLE INFORMATION

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1. Introduction

The advent of mobile technologies has profoundly reshaped modern life, offering users unprecedented convenience and efficiency. This technological revolution, marked by the transition from feature phones to smartphones, has significantly enhanced daily activities, saving time, effort, and costs. With their advanced computing capabilities and connectivity, smartphones have become indispensable digital companions, influencing global lifestyles (Gao et al., 2015). They serve multifaceted purposes, including information access, social networking, entertainment, and e-commerce. The global adoption of smartphones continues to rise, with 4.74 billion users in 2023, projected to reach 5.13 billion by 2028 (Statista, 2023a).

In India, smartphone adoption exceeded one billion users in 2023 and is projected to grow to 1.28 billion by 2028 (Statista, 2023b). This growth is driven by technological advancements, affordability, improved internet access, and government initiatives promoting digital literacy and a digitized economy. These factors have contributed to India's transformation into one of the fastest-growing smartphone markets, with mobile Internet user penetration rising from 18.5% in 2016 to 34% in 2021 (Statista, 2019). The average Indian user spends over three hours daily on mobile Internet, exceeding the global average (Hootsuite and We are Social, 2019), underscoring the integral role of smartphones in shaping lifestyles and consumer behaviors (Zhou, 2011).

The global rise of e-commerce further complements this trend. In 2021, retail e-commerce sales reached $5.2 trillion, projected to grow to $8.1 trillion by 2026 (eMarketer, 2022a). In India, online shopping sales are expected to exceed $145 billion by 2025, driven by an estimated 220 million online shoppers (IBEF, 2023). Key players such as Flipkart, Amazon, and Reliance dominate this market, leveraging creative marketing strategies to attract consumers. The adoption of smartphones has amplified mobile commerce (m-commerce), allowing consumers to shop anytime, anywhere, fostering seamless transactions and reshaping consumer expectations (Susanto et al., 2023).

This shift towards mobile-first experiences has prioritized smartphone-based user interfaces, influencing how businesses design and promote their platforms. Mobile shopping applications have transitioned from simple browsing tools to comprehensive platforms facilitating end-to-end purchases (Thakur, 2018). Globally, mobile commerce contributes 65.7% of total retail e-commerce sales, a figure projected to grow further (eMarketer, 2018). In India, mobile commerce's share of retail e-commerce is anticipated to surpass 80% by 2024, highlighting its growing importance in consumer transactions.

The adoption of mobile shopping is rooted in the Technology Acceptance Model (TAM), which emphasizes perceived ease of use and perceived usefulness as key determinants of technology acceptance (Davis et al., 1989). While TAM effectively explains initial adoption, it may not fully capture cultural and contextual influences, such as trust, social factors, and perceived risk, particularly in diverse markets like India (Susanto et al., 2023). Integrating TAM with the Expectation Confirmation Model (ECM) allows for a deeper exploration of post-adoption behaviors, addressing how user satisfaction, trust, and expectations influence loyalty.

Traditionally, mobile shopping involved product research and price comparisons, with purchases occurring through desktops or physical stores (Holmes et al., 2014). Today, consumers rely on mobile apps for an integrated shopping experience, accessing services ranging from research to payment and delivery. With millions of apps available, shopping apps rank among the most used in India, reflecting changing consumer behaviors (Statista, 2023c). Despite this progress, challenges remain, particularly in addressing customer concerns about product quality, delivery service, and trust in online platforms (Bain & Company et al., 2018).

This study addresses the critical gap in understanding post-adoption behaviors, satisfaction, and loyalty in mobile shopping applications. While existing research has primarily focused on initial adoption, long-term engagement remains underexplored, especially in fast-evolving markets like India (Lu et al., 2017; Fleischmann et al., 2016). This gap is significant as the long-term viability of mobile shopping platforms hinges on sustained user engagement (Shankar et al., 2016). The study investigates key questions such as: What drives satisfaction and loyalty among mobile shopping app users? What factors shape these behaviors? How does user experience alter these dynamics? By integrating TAM and ECM and incorporating contextual factors such as hedonic motivation, price-saving orientation, perceived trust, and perceived risk, this research contributes to a comprehensive understanding of post-adoption behavior in the Indian mobile shopping context. It provides valuable insights into consumer behavior, offering practical recommendations for businesses to enhance user experiences and foster loyalty in a competitive digital marketplace.

The remaining sections are structured as follows: a review of relevant literature, an explanation of the theoretical foundation and hypotheses, a description of the methods employed, presentation of results, and discussion of findings. The paper concludes by highlighting theoretical and practical implications, addressing limitations, and proposing future research directions.

2. Literature Review

2.1 Purchase Intention of Mobile Shopping

Numerous studies over the past decade have explored customers' purchase intentions in the context of mobile shopping, contributing significantly to the evolving landscape of consumer behavior (Wu & Wang, 2006; Lu & Su, 2009; Yang & Kim, 2012; Zhong, 2013; Agrebi & Jallais, 2015; Keong, 2016; Lee et al., 2017; Ghazali et al., 2018; Natarajan et al., 2018; Chung, 2019; Shaw & Sergueena, 2019; Sarkar et al., 2020). These studies draw on various information systems adoption theories, most notably the Technology Acceptance Model (TAM) (Aldás-Manzano et al., 2009; Chen & Lan, 2014; Agrebi & Jallais, 2015; Chen et al., 2018; Chi, 2018; Akroush et al., 2020), Diffusion of Innovation (DOI) (Chung, 2019), Theory of Planned Behavior (TPB) (Yang, 2012; Zhong, 2013), Stimulus-Organism-Response (S-O-R) (Li et al., 2012; Liu et al., 2019; Zheng et al., 2019; Chopdar & Balakrishnan, 2020), Behavioral Reasoning Theory (Gupta & Arora, 2017), UTAUT (Yang, 2010), and UTAUT2 (Tak & Panwar, 2017; Chopdar & Sivakumar, 2019; Shaw & Sergueeva, 2019).

Extensive exploration of factors influencing mobile shopping adoption includes perceived usefulness, perceived ease of use, subjective norms, perceived behavioral control, attitude, performance expectancy, effort expectancy, social influence, facilitating conditions, relative advantage, privacy, price value, habit, anxiety, compatibility, innovativeness, information quality, service quality, perceived value, and perceived risk. Additionally, factors such as deal proneness (Tak & Panwar, 2017), perceived enjoyment (Zhong, 2013), and trust (Chen, 2018) have been scrutinized for their impact on consumers' behavioral intentions to use mobile shopping platforms. This extensive body of research offers a nuanced understanding of the complex factors that influence consumer decisions in mobile shopping.

2.2 Post-Adoption Behavior of Mobile Shopping

Numerous studies have examined the factors influencing post-adoption behavior in mobile shopping, with outcomes ranging from satisfaction and loyalty to word-of-mouth and engagement. Extensive investigations have confirmed the impact of a wide array of factors on mobile shopping post-adoption behavior. Notable factors include impulsiveness, involvement, trust, aesthetics, navigability, service experience, self-efficacy, self-connect, social facilitation, intrinsic enjoyment, time filler, monetary evaluation, shopping convenience, application usability, technical quality, information quality, security quality, perceived usefulness (for information and shopping), search convenience, evaluation convenience, post-purchase convenience, performance value, value for money, social value, emotional value, and flow (Lin & Wang, 2006; San-Martin & Lopez-Catalan, 2013; Thakur, 2016; Mahapatra, 2017; Shang & Wu, 2017; Sohn, 2017; Sarkar & Khare, 2019). This body of research highlights the intricate interplay of diverse factors that shape the dynamics of post-adoption behavior in mobile shopping.

Yang et al. (2012), in their study of Chinese consumers, empirically validated a model grounded in coping theory, showing that satisfaction with the task process (experience) strongly and positively influenced consumers' intentions to continue using the mobile shopping channel. Thakur (2018) further investigated this concept in the Indian context, identifying significant impacts of self-efficacy and satisfaction on the continuance intention of mobile shopping customers, though these factors did not influence word-of-mouth behavior.

Lee and Kim (2019) noted that consumers' intentions to reuse mobile applications for apparel shopping were largely influenced by two factors: the consumer's need for mobile app atmospherics and entertainment gratification. Similarly, Sarkar et al. (2020) argued that decision-making styles significantly influenced Indian consumers' perceptions and usage of mobile shopping applications. A cross-cultural study by Alalwan et al. (2020) highlighted the importance of mobile interactivity features—active control, personalization, ubiquitous connectivity, synchronicity, and responsiveness—on customer engagement. Importantly, increased customer loyalty was observed among individuals who showed high levels of engagement with mobile shopping activities. Maduku and Thusi (2022) found that usefulness, utilitarian value, and satisfaction significantly influence mobile shopping continuance intention among South African shoppers. Similarly, Jain et al. (2021) reported that mobile service quality (M-S-QUAL) and perceived usefulness positively affect shopping satisfaction and continuance intention. Additionally, perceived value dimensions, including ubiquity, app incentives, and epistemic value, have been found to positively influence continuance intention (Dobre et al., 2023). Jiang et al. (2024) suggest that the mediating role of perceived usefulness between perceived consistency, complementarity, ease of use, and consumer satisfaction is supported only in experience-oriented apps, not in transaction-oriented apps. This highlights the complexity of user preferences across different types of mobile shopping applications.

These studies collectively provide valuable insights into the nuanced dynamics influencing consumer engagement, loyalty, and continued usage of mobile shopping applications.

2.3 Technology Acceptance Model (TAM)

Davis (1989) introduced the Technology Acceptance Model (TAM), a widely adopted framework for understanding users' acceptance of specific technologies. Grounded in the Theory of Reasoned Action (TRA), TAM emphasizes how users perceive the ability of a technology to enhance task efficiency. The model identifies perceived usefulness, which reflects an individual's belief that using technology improves career success, and perceived ease of use, which denotes the perceived effort required to interact with the technology, as key determinants of technology adoption (Davis, 1993). TAM posits that users' attitudes, based on the Fishbein and Aizen (1975) model, influence their willingness to adopt a technology. The model asserts that both perceived usefulness and perceived ease of use directly affect behavioral intention, which in turn influences actual system usage. As users perceive greater benefits and ease of use, they are more likely to adopt and experiment with the technology, leading to higher acceptance (Davis, 1989). This foundational understanding provides a comprehensive lens for evaluating technology adoption dynamics, particularly in the rapidly evolving context of mobile shopping applications.

The Technology Acceptance Model (TAM) has been widely applied and extended in the context of mobile commerce, providing valuable insights into consumer behavior and adoption patterns. Several studies have utilized TAM to investigate factors influencing mobile commerce adoption. For instance, research has shown that perceived usefulness and perceived ease of use significantly impact attitudes and intentions towards using mobile commerce applications (Chi, 2018; Natarajan et al., 2017). Additionally, factors such as perceived enjoyment, perceived risk, and personal innovativeness have been incorporated into extended TAM models to better understand mobile shopping behavior (Akram et al., 2020; Natarajan et al., 2017).

Interestingly, some studies have found contradictions or variations in the importance of TAM constructs. For example, Shang and Wu (2017) revealed that perceived usefulness does not motivate all user groups equally, with differences observed between food and non-food mobile shoppers. Furthermore, Sleiman et al. (2021) highlighted the critical role of trust in mobile payments, with government monitoring emerging as the most significant factor in building trust, followed by reputation and security.

In conclusion, TAM has proven to be a versatile framework for understanding mobile commerce adoption, with various extensions and modifications tailored to specific contexts. Researchers have incorporated additional constructs such as brand equity (Chi, 2018), social connectedness (Cho & Son, 2019), and self-image congruence (Wu et al., 2020) to enhance the model's explanatory power. These studies collectively demonstrate the importance of considering both utilitarian and hedonic factors in predicting mobile commerce adoption and continuance intention.

2.4 Expectance-Confirmation Model (ECM)

Bhattacherjee (2001) proposed the Expectation-Confirmation Model (ECM) to examine post-adoption behavior in information systems (IS), aiming to understand users' decisions to continue using a system, akin to consumers' repurchase decisions. Key constructs integral to ECM include:

- Perceived Usefulness: As defined by Davis (1989), this refers to an individual's belief that using a technology enhances career success. Perceived usefulness is crucial at the pre-acceptance stage and continues to impact users' satisfaction and their intention to continue using the system post-acceptance.

• Confirmation: This concept refers to the comparison between users' actual experiences and their initial expectations of the IS. A positive confirmation (i.e., when expectations are met or exceeded) is associated with greater satisfaction, reinforcing the importance of aligning user experiences with their expectations.
• Satisfaction: Defined as "the summary psychological state resulting when the emotion surrounding disconfirmed expectations is coupled with the consumers' prior feelings about the consumption experience" (Oliver, 1980), satisfaction reflects the overall psychological state derived from the interplay between users' emotional reactions to disconfirmed expectations and their previous experiences.
• Continuance Intention: Introduced by Bhattacherjee (2001), this term refers to a user's intention to continue using a technology over the long term. Continuance intention is a critical indicator of users' enduring commitment to a technology.

The ECM provides valuable insights into post-adoption dynamics, extending beyond initial acceptance to explore factors influencing users' ongoing engagement with IS. By focusing on the relationships between confirmation, satisfaction, and continuance intention, the model deepens our understanding of how users' expectations and experiences shape their long-term commitment to technology.

The Expectation-Confirmation Model (ECM) has been widely applied in mobile commerce (m-commerce) research to assess users' continuance intention. A meta-analysis of 61 publications from the last decade found support for all relationships in the extended ECM in the m-commerce context (Chauhan et al., 2021). The model has been used to examine various aspects of m-commerce, including mobile shopping, mobile banking, and social commerce.

In the context of mobile shopping, an integrated model based on ECM and the Technology Acceptance Model (TAM) was used to investigate consumers' continuance intention for food and non-food items. The study found that satisfaction and perceived ease of use significantly impacted different user groups, while perceived usefulness only affected continuance intention for non-food m-shoppers (Shang & Wu, 2017). Similarly, ECM was applied to examine the effect of perceived playfulness on the continuous use intention of e-commerce platforms, revealing that confirmation positively affects perceived usefulness and playfulness, which in turn influence customer satisfaction and continuance intention (Wei et al., 2020).

Interestingly, some studies have found contradictions or variations in the ECM relationships. For instance, in the context of social commerce, while confirmation of expectations positively affected information usefulness and satisfaction, the influence of information usefulness on information adoption and continuance intention was stronger for American consumers compared to Chinese consumers (Chiu et al., 2022). Additionally, in the case of AI-enabled mobile banking apps, both perceived intelligence and anthropomorphism were found to increase user satisfaction via confirmation and perceived usefulness, ultimately fostering users' willingness to continue using mobile banking (Lee et al., 2023). In conclusion, the ECM has proven to be a versatile and robust model for understanding user behavior in various m-commerce contexts. However, its application may vary depending on factors such as cultural differences, user types, and specific m-commerce applications.

3. Research Model and Hypotheses

As previously discussed, the Technology Acceptance Model (TAM) has been widely used to explore users' pre-adoption behaviors across various technologies, while the Expectation-Confirmation Model (ECM) is typically employed to evaluate post-adoption behaviors. This study synthesizes both perspectives by integrating elements of TAM and ECM, along with additional factors relevant to the context of mobile shopping. The conceptual framework (refer to Figure 1) includes nine key factors: hedonic motivation, price-saving orientation, perceived risk, confirmation, perceived usefulness, perceived trust, attitude, satisfaction, and loyalty.

This research model departs from the traditional TAM by omitting perceived ease of use. This decision aligns with Wu's (2013) assertion that perceived ease of use and confirmation of expectations share similarities, especially in post-adoption technology use. Both are cognitive constructs that arise from a consumer's post-consumption expectations after initial online system use (Wu, 2013). Furthermore, Bhattacherjee (2001) found that the impact of perceived ease of use on satisfaction was statistically insignificant.

In addition, the model includes attitude, a construct derived from both the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB). According to Abdul-Muhmin (2010), online shoppers' attitudes influence both pre- and post-purchase behavior, with post-purchase attitudes positively affecting online repurchase intentions. The inclusion of hedonic motivation, which aligns with perceived enjoyment, underscores the role of an enjoyable shopping experience in fostering customer engagement and loyalty (Bilgihan et al., 2016).

The model also incorporates three essential factors—perceived risk, price-saving orientation, and perceived trust—to assess their influence on the post-purchase behavior of mobile shopping customers. This comprehensive approach reflects a deeper understanding of the complex influences shaping customer behavior in the mobile shopping landscape.

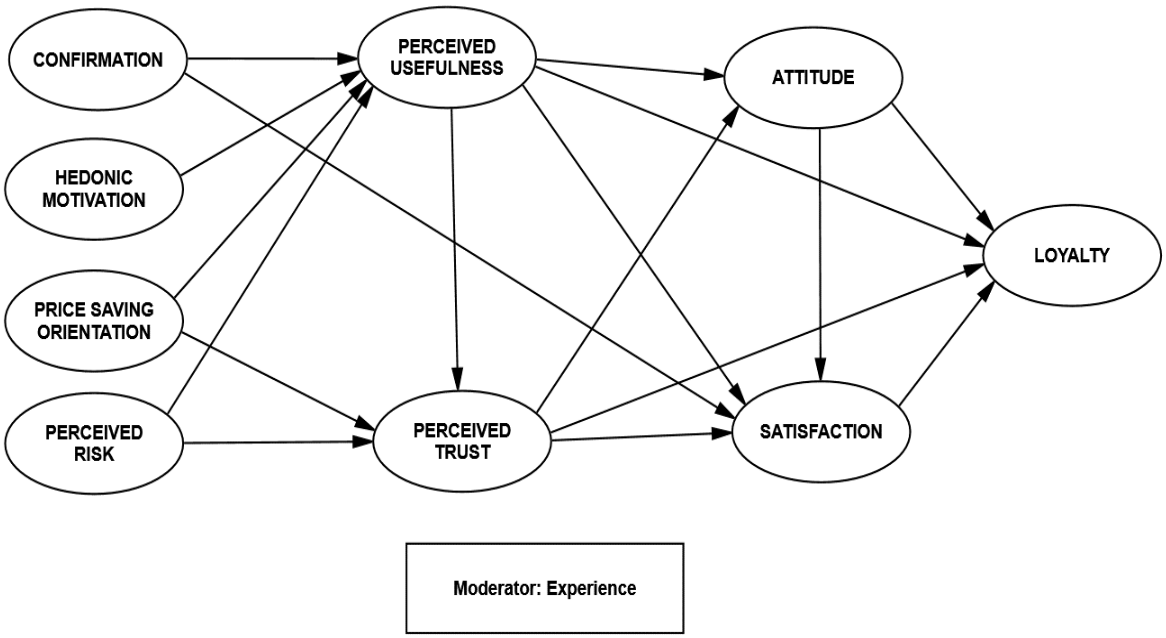

Figure 1. Research model

3.1 Confirmation

Confirmation, as defined by Bhattacherjee (2001), refers to the gap between pre-purchase expectations and the perceived performance of products or services after an initial consumption period. The Expectation-Confirmation Model (ECM) highlights the significant influence of confirmation on satisfaction. During the early stages of adopting mobile shopping apps, consumers may have uncertainties regarding the benefits, which shape their expectations. These perceptions of the app's actual performance are then compared against their pre-adoption expectations, prompting adjustments to those expectations based on the user's experiences.

When users perceive that mobile shopping apps surpass their initial expectations, confirmation occurs, reinforcing post-purchase expectations, and vice versa. Consequently, the satisfaction level of users with mobile shopping apps significantly hinges on the level of confirmation. Previous studies affirm the positive impact of confirmation on both perceived usefulness and satisfaction within the realm of mobile shopping services (Kang et al., 2010; Chong, 2013; Shang and Wu 2017; Sarkar and Khare, 2019; Bölen, and Özen, 2020; Maduku and Thusi, 2023). A study by Al-Hattami (2021) found that confirmation significantly impacts both perceived usefulness and satisfaction, key predictors of continuance intention of online shopping consumers in India. He further stated that when users' expectations are confirmed, they are more likely to find the platform useful and be satisfied with their experience, increasing their likelihood of continued usage. These findings underscore the pivotal role of confirmation in shaping user perceptions and satisfaction in the dynamic landscape of mobile shopping applications. Hence, it is proposed that

H1a: Confirmation positively influences perceived usefulness of mobile shopping applications.

H1b: Confirmation positively influences satisfaction with mobile shopping applications.

3.2 Hedonic motivation

Hedonic motivation, often referred to as perceived enjoyment, is defined as "the activity of using a specific system is perceived to be enjoyable in its own right, aside from any performance consequences resulting from system use" (Venkatesh, 2000). Recognizing its critical role, Yang (2010) argues that hedonic motivation is a key driver of mobile shopping service utilization. This assertion is empirically supported by various studies within the mobile shopping context (Lu & Su, 2009; Chong, 2013; Schramm-Klein & Wagner, 2014; Keong, 2016; Madan & Yadav, 2018; Natarajan et al., 2018; Chopdar & Sivakumar, 2019; Akroush et al., 2020).

This study anticipates that consumers' perception of mobile shopping applications as enjoyable and entertaining will positively influence their perception of the channel's usefulness. The growing body of evidence underscores the integral role of hedonic motivation in shaping users' experiences and fostering positive perceptions within the mobile shopping landscape. Therefore, it is proposed that:

H2: Hedonic motivation has a positive impact on perceived usefulness of mobile shopping applications.

3.3 Price saving orientation

The Internet and mobile shopping platforms offer shoppers numerous advantages, with a key focus on the importance of price comparison, which can lead to significant cost savings (Alba et al., 1997; Reibstein, 2002). A compelling incentive for consumers to choose mobile shopping applications is the potential to acquire products or services at lower costs compared to traditional shopping channels. The concept of price-saving orientation, as defined by Escobar-Rodríguez and Carvajal-Trujillo (2014), refers to the monetary savings achieved by purchasing products at discounted prices through mobile applications. This notion is supported by Gupta and Arora (2017), who found that price-saving orientation positively influences the adoption of mobile shopping. Based on these insights, it is hypothesized that price-saving orientation positively impacts both perceived usefulness and perceived trust in the mobile shopping context.

H3a: Price saving orientation positively affects perceived usefulness of mobile shopping applications.

H3b: Price saving orientation positively affects perceived trust in mobile shopping applications.

3.4 Perceived risk

Perceived risk is widely recognized as a significant barrier to the adoption and use of technology. Despite the robust security features embedded in mobile devices and the additional security measures within apps, consumers often experience anxieties, concerns, and uncertainties when using mobile shopping platforms. As a result, perceived risk acts as a deterrent to purchase behavior, stemming from the anticipated potential losses associated with mobile shopping. Customers who are more risk-averse are likely to stick with a mobile shopping provider that has established trust, reducing their inclination to switch providers due to perceived uncertainties.

Privacy and security are identified as crucial determinants of customer loyalty in the context of mobile wallet services, and these factors ensure that users feel safe and secure when conducting transactions, which is vital for retaining customers in the post-COVID-19 era (Al-Hattami et al., 2023) The adverse impact of perceived risk on the adoption and usage of the mobile shopping channel has been substantiated in prior studies (Groß, 2016; Marriott & Williams, 2018; Natarjan et al., 2018; Phong et al., 2018; Shaw & Sergueeva, 2019; Sarkar et al., 2020). Susanto et al. (2023) emphasized that mobile commerce users' risk perceptions need to be addressed in order to enhance their level of satisfaction. Therefore, it is hypothesized that customers' perceptions of risk associated with mobile shopping are inversely related to both perceived usefulness and perceived trust.

H4a: Perceived risk negatively affects perceived usefulness of mobile shopping applications.

H4b: Perceived risk negatively affects perceived trust in mobile shopping applications.

3.5 Perceived usefulness

Within the framework of the Technology Acceptance Model (TAM), perceived usefulness is a critical predictor of the behavioral intention to engage with technology, a consensus supported by extensive prior research. In the context of mobile shopping applications, perceived usefulness refers to users' perceptions of the benefits these apps offer in terms of time, location, and payment conveniences compared to other shopping channels. Bhattacherjee (2001) highlighted the significant role of perceived usefulness in influencing users' post-acceptance satisfaction and their intention to continue using the technology. Sohn (2017) examined the impact of technical quality, information quality, aesthetic quality, and security quality on users' perceptions of the usefulness of mobile shopping for both information gathering and purchasing.

Empirical research by Kaushik et al. (2020) in India validated the positive effect of perceived usefulness on trust in mobile shopping apps. Yang (2012) identified a significant influence of perceived usefulness on users' attitudes toward using mobile shopping, a finding corroborated by earlier studies (Aldás-Manzano et al., 2009; Groß, 2015; Chi, 2018; Ghazali et al., 2018; Cheong & Mohammed-Baksh, 2019; Akroush et al., 2020; McLean et al., 2020). Additionally, the positive impact of perceived usefulness on attitude has been consistently affirmed in the literature. The ripple effect of perceived usefulness extends to post-purchase behaviors, with research demonstrating its significant impact on both satisfaction and loyalty within the mobile shopping domain (Kang et al., 2010; Chong, 2013; Schramm-Klein & Wagner, 2014; Shang & Wu, 2017; Chopdar & Sivakumar, 2019; Sarkar & Khare, 2019; Bölen & Özen, 2020; Kalinić et al., 2020; Jain et al., 2021; Maduku & Thusi, 2023). Al-Hattami (2021) emphasized the pivotal role of perceived usefulness in driving continued online shopping, particularly during the COVID-19 pandemic. He further suggested that when consumers perceive online shopping as beneficial, they are more likely to experience satisfaction and continue using these services.

Given these insights, it is anticipated that perceived usefulness will have a substantial impact on post-purchase behaviors—specifically satisfaction and continuance intention—in mobile shopping. Therefore, the following hypotheses are proposed:

H5a: Perceived usefulness positively impacts perceived trust in mobile shopping applications.

H5b: Perceived usefulness significantly influences attitude toward mobile shopping applications.

H5c: Perceived usefulness positively influences satisfaction with mobile shopping applications.

H5d: Perceived usefulness positively influences loyalty toward mobile shopping applications.

3.6 Perceived trust

In the realm of Information Systems (IS) theories, considerable attention has been dedicated to understanding the critical role of customer trust in technology-based service providers. Various definitions and conceptual frameworks in previous technology adoption and usage studies highlight the multifaceted nature of trust. One widely cited definition describes trust as "the willingness of a party to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to the trust or, irrespective of the ability to monitor or control that other party" (Mayer et al., 1995). Trust serves as a fundamental mechanism for technology users to mitigate perceived risk in financial transactions and to navigate the complexities of less controllable social environments.

When users perceive technology-based services, including mobile services, as less risky and more reliable, it tends to enhance satisfaction and fosters a willingness to continue using these services. Trust perceptions regarding technology are positively correlated with the likelihood of technology adoption (Marriott & Williams, 2018; Phong et al., 2018; Akroush et al., 2020). Specifically, Kaushik et al. (2020) demonstrated a significant direct effect of perceived trust on users' attitudes toward mobile retail apps.

Customers' trust perceptions regarding a firm's ability and integrity to deliver high-quality services have a profound influence on their satisfaction levels and intentions to continue shopping through mobile apps. Trust has been identified as a crucial factor in enhancing customer loyalty to mobile wallet services, acting as both a key determinant and a moderator in the relationship between service quality and customer loyalty (Al-Hattami et al., 2023). The interconnections between trust, satisfaction, and loyalty have been consistently significant in mobile shopping contexts (Lin & Wang, 2006; Kang et al., 2010; Chong, 2013; San-Martin & Lopez-Catalan, 2013; Kalinić et al., 2020; Chen, 2018; Bölen & Özen, 2020; Susanto et al., 2023).

Building on these discussions, it is hypothesized that perceived trust positively influences attitude, satisfaction, and loyalty toward mobile shopping applications.

H6a: Perceived trust positively influences attitude toward mobile shopping applications.

H6b: Perceived trust positively influences satisfaction with mobile shopping applications.

H6c: Perceived trust positively influences loyalty toward mobile shopping applications.

3.7 Attitude

In the context of this study, attitude is conceptualized as "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (Eagly & Chaiken, 1993). Specifically, in the realm of mobile shopping, consumers' attitudes represent positive beliefs and anticipated outcomes derived from their shopping experiences facilitated through smartphones. The literature consistently affirms the pivotal role of attitude in influencing both the adoption and usage of mobile shopping applications (Aldás-Manzano et al., 2009; Yang, 2012; Holmes et al., 2014; Groß, 2015; Musa et al., 2016; Gupta & Arora, 2017; Ghazali et al., 2018; Cheong & Mohammed-Baksh, 2019; Chen et al., 2018; Akroush et al., 2020).

Based on these findings, it is postulated that consumers' attitudes are positively associated with satisfaction and loyalty toward mobile shopping applications. This suggests that a favorable attitude, shaped by positive evaluations of the mobile shopping experience, contributes to higher levels of satisfaction and a sustained commitment to using mobile shopping applications.

H7a: Attitude positively affects satisfaction with mobile shopping applications.

H7b: Attitude positively influences loyalty toward mobile shopping applications.

3.8 Satisfaction

Customer satisfaction is widely recognized as a critical factor influencing the success of a firm's marketing efforts, impacting repeat sales, positive word-of-mouth, and customer loyalty. According to Anderson et al. (1994), highly satisfied customers tend to demonstrate greater loyalty to a firm, which fosters increased repurchase behavior. Moreover, enhanced customer satisfaction is associated with reduced costs in acquiring new customers (Fornell, 1992). Satisfied customers are also more likely to engage in positive word-of-mouth, improving the firm’s overall reputation and reducing marketing expenses (Bitner, 1990; Oliver, 1980; Reichheld & Sasser, 1990).

In the context of technology adoption literature, user satisfaction is influenced by various perceptions and beliefs regarding the technology. Furthermore, customer satisfaction is posited to mediate the relationship between these beliefs and loyalty toward mobile shopping applications. As noted by Liu et al. (2011), satisfaction is a cumulative outcome resulting from multiple interactions with a mobile technology, building over time. Consistent with Expectation-Confirmation Theory, user satisfaction is a strong predictor of the intention to continue using a technology (Bhattacherjee, 2001). Previous empirical studies have supported the association between satisfaction and loyalty toward mobile shopping applications (Lin & Wang, 2006; Kang et al., 2010; Chong, 2013; Schramm-Klein & Wagner, 2014; Shang & Wu, 2017; Groß, 2018; Thakur, 2018; Yang et al., 2012; Sarkar & Khare, 2019; Kalinić et al., 2020; Chen, 2018; Jain et al., 2021; Susanto et al., 2023; Maduku & Thusi, 2023). These findings reinforce the idea that a satisfied user is more likely to exhibit loyalty toward mobile shopping applications. Thus, the following hypothesis is proposed:

H8: Satisfaction positively influences loyalty toward mobile shopping applications.

3.9 The moderating influence of experience in using mobile shopping applications

Customer experience plays a pivotal role in shaping behaviors and intentions in the context of mobile commerce (m-commerce). Positive past experiences significantly influence future behaviors, consistent with Fishbein and Ajzen’s (1975) assertion that individuals’ actions are influenced by their prior experiences. Individuals with greater technological expertise exhibit reduced risk aversion, enhancing perceived usefulness and motivating continued usage (O'Cass & Fenech, 2003; Smith & Brynjolfson, 2001). Furthermore, experience in online purchasing is positively correlated with buying behavior, driven by expectations of benefits and fewer challenges (Hsu et al., 2007; Dholakia & Uusitalo, 2002).

In the context of e-commerce and mobile services, prior experience influences adoption and usage intentions (Kwak et al., 2002; Ristola, 2010; Niemelä-Nyrhinen, 2009). Studies by Liebana-Cabanillas et al. (2014) emphasize the moderating role of experience in the acceptance of mobile payments. Notably, users’ experience evolves over time, shaping their perceptions and motivations related to technology adoption (Venkatesh et al., 2003, 2012; Lu & Lee, 2012). Early users often focus on hedonic benefits, while more experienced users tend to prioritize utilitarian outcomes (Sundar, 2008). In m-commerce, increased experience is positively associated with a more favorable assessment of technologies, leading to enhanced user loyalty (Rohm & Swaminathan, 2004; Yang et al., 2007). Furthermore, Deng et al. (2010) affirm that the positive effect of customer satisfaction on loyalty becomes more pronounced with continued use. Rodgers et al. (2005) also highlight the moderating role of shopper experience in the relationship between satisfaction and online loyalty.

In the financial sector, consumers with prior internet experience exhibit more favorable attitudes toward electronic banking, fostering perceived benefits and mitigating perceived difficulties (Lee et al., 2005; Bhattacherjee, 2001). Additionally, satisfaction with previous experiences and perceived usefulness significantly influence customers' intentions to continue engaging in online financial transactions (Bhattacherjee, 2001). The literature further extends to online retailing, underscoring the importance of customer experience in shaping attitudes and behaviors (Ameen et al., 2021; Pappas et al., 2014; Tsao et al., 2016). In particular, the moderating role of online shopping experience, measured by past internet purchases, influences trust, purchase intention, and customer loyalty (Corbit et al., 2003; Faraoni et al., 2018; Moriuchi & Takahashi, 2016; Zhang et al., 2003).

Prior experience with mobile commerce applications (MCAs) shapes customers' perceptions and expectations. Interestingly, the impact of prior experience may vary across different customer segments. For instance, millennials tend to view digital commerce as a typical way of shopping and making payments, especially during the COVID-19 pandemic (Akram et al., 2021). This suggests that younger generations, with potentially more prior experience in mobile technology, may have different expectations and behaviors compared to older generations. Furthermore, the product purchase context can moderate the relationship between perceived usefulness and purchase intention (Singh & Srivastav, 2018), indicating that prior experience with specific product categories may influence customer behavior in m-commerce.

This highlights that customer experience is a multifaceted determinant across various domains, shaping perceptions and behaviors in the evolving digital commerce landscape.

H9: The extent of users' experience with mobile shopping applications moderates the relationships outlined in H1 to H8, resulting in significant variations between the two groups (low experience and high experience) in terms of mobile shopping behavior and loyalty

4. Research Methodology

4.1 Survey Instrument

To evaluate the research model, empirical data was collected using a structured survey instrument consisting of three sections. The first section measured all latent constructs included in the study. Each of the nine constructs was assessed using three or four items, adapted from relevant literature. Specifically:

- Perceived usefulness was measured using items adapted from Davis (1989) and Wu (2013).
- Confirmation employed scale items based on Bhattacherjee (2001).
- Hedonic motivation was adapted from Venkatesh et al. (2012) and Lin and Lu (2015).
- Perceived risk and price-saving orientation utilized measurements developed by Lu et al. (2011) and Escobar-Rodríguez and Carvajal-Trujillo (2013), respectively.
- Perceived trust was assessed using items from Lee (2005) and Gao et al. (2015).
- Attitude was measured with items based on Davis et al. (1989).
- Satisfaction and loyalty were measured using items adapted from Bhattacherjee (2001), Park and Kim (2013), Zeithaml et al. (1996), and Lin and Wang (2006).

All items were rated on five-point Likert scales ranging from strongly disagree (1) to strongly agree (5), as recommended by Revilla et al. (2014), who suggest that five-point scales yield more reliable, valid, and higher-quality results compared to higher-order scales. The second section of the questionnaire captured demographic variables such as gender, age, education, and income. The final section explored respondents' technology-related characteristics, including smartphone usage, mobile shopping preferences, and application usage. Participants were asked to provide their perceptions and beliefs regarding their most preferred mobile shopping application.

To enhance clarity and minimize potential measurement issues (Sekaran, 2006), the questionnaire underwent pre-testing by six researchers and practitioners specializing in marketing and information technology. Modifications were made based on their feedback to align the instrument with the context of mobile shopping applications, thereby confirming the face validity of the scales used (Zikmund et al., 2013). Although the measurement scales were adapted from established literature, a pilot study conducted with 60 postgraduate management students further validated the reliability and validity of the scales. The measurement items utilized in the survey are provided in the Appendix.

4.2 Sampling and Data Collection

The study employed non-probability convenience sampling, a widely used approach in online and mobile shopping research (Aldás-Manzano et al., 2009; Shang & Wu, 2017; Ghazali et al., 2018; Tarhini et al., 2019). Data was collected over a 12-week period using a structured online survey administered via SurveyMonkey, a widely accepted platform for web-based surveys in mobile shopping research (Yang & Kim, 2012; Chen et al., 2018; Kalinić et al., 2020; Sarkar & Khare, 2019).

The target population consisted of active smartphone users in India, a group estimated to reach 500 million by the end of 2019 (ICEA, 2020).

Respondents with prior experience in mobile application shopping were recruited through email, social networks, and instant messaging applications. Measures to prevent duplicate responses included collecting unique identifiers such as email addresses and IP addresses. After eliminating responses with excessive missing values, 535 valid responses were obtained from the 800 invitations sent, yielding a response rate of approximately 66.9%. The relevance of the survey topic and targeting respondents with prior mobile shopping experience likely contributed to this high response rate. At the beginning of the survey, a written consent statement was displayed, informing participants that their participation was entirely voluntary and that they could withdraw at any time without any repercussions. By proceeding with the survey, participants provided implied consent to participate. This study followed all ethical guidelines, ensuring confidentiality and voluntary participation.

To ensure an adequate sample size for Structural Equation Modeling (SEM), statistical power considerations and established guidelines were followed. A minimum sample size exceeding 200 is recommended for increased statistical power (Hoe, 2008), with Kline (2016) also advocating for at least 200 participants for SEM analyses. Additionally, Hair et al. (2019) suggest a desirable ratio of 15 to 20 observations per variable for population studies. Following this guideline, the study adopted a ratio of 20 observations per variable, estimating a minimum sample size of 180 for robust multivariate data analysis. The 535 valid responses received comfortably exceeded this threshold, achieving a robust 20:1 ratio and ensuring generalizability and reliability in the analysis.

Characteristics	**Category**	**Frequency**	**(%)**
Gender	Male	341	63.7
	Female	194	36.3
Age	18-24	117	21.9
	25-34	234	43.7
	35-44	143	26.7
	45-55	28	5.2
	Above 55	13	2.4
Education	Graduation	215	40.2
	Post-graduation	189	35.3
	Professional and others	131	24.5
Occupation	Student	67	12.5
	Employee	356	66.5
	Self-employed	76	14.2
	Unemployed	22	4.1
	Others	14	2.6
Average Family Monthly Income (INR)	Less than 40000	126	23.6
	40001 to 80000	181	33.8
	80001 to 120000	142	26.5
	Above 120000	86	16.1
Type of Operating System in Smartphone	Android	401	75.0
	IOS	114	21.3
	Others	20	3.7
Smartphone Usage Experience (years)	<3	66	12.3
	3-6	169	31.6
	6-9	266	49.7
	>9	34	6.4
Average hours of smartphone usage/day	<3	165	30.8
	3-6	211	39.4

	>6	159	29.7
Smartphone activities other than shopping (multiple responses)	Social Networking	517	96.6
	Entertainment	506	94.6
	Map	469	87.7
	Banking	492	92.0
	Bill Payments	488	91.2
	Games	186	34.8
	Stock Trading	148	27.7
	Ticket booking	488	91.2
	Learning	277	51.8
	News	415	77.6
Favourite mobile shopping applications	Amazon	252	47.5
	Flipkart	161	30.1
	Myntra	53	9.9
	Others (PayTM, Meesho, Nykaa etc.)	69	12.9
Preferred products purchased through mobile shopping applications (multiple responses)	Electronic Gadgets	326	60.9
	Clothing & Accessories	314	58.7
	Home Décor & Furnishings	209	39.1
	Jewelry	148	27.7
	Baby Products	91	17.0
	Personal Care Products	212	39.6
	Food and Health Supplements	253	47.3
	Books	161	30.1
	Toys and Video Games	79	14.8
	Online Subscriptions	183	34.2
	Others	97	18.1
Shopping experience on mobile applications (years)	Low experience: Less than 3 years	340	63.5
	High experience: More than 3 years	195	36.5
Mobile Shopping frequency in a year	At least once in a year	134	25.0
	Few times in a year	194	36.3
	At least once in a month	119	22.2
	At least once in a week	51	9.5
	Few times in a week	37	6.9
Most preferred means of payment on mobile shopping applications (multiple responses)	Cash on delivery	352	66.0
	Digital wallet	383	71.6
	Internet banking	414	77.4
	Debit card	462	86.4
	Credit card	271	50.7
Important reasons for shopping on mobile	Convenience	392	73.3
	Time Savings	386	72.1
	Flash sales of new products	307	57.4

applications (multiple responses)	Free Shipping	283	52.9
	Wider product choice	314	58.7
	Discounts and Offers	423	79.1
	Easy comparison	265	49.5
	E-commerce Firm Reputation	231	43.2
Major concerns about shopping through mobile applications (multiple responses)	Higher shipping costs	289	54.0
	Longer delivery time	335	62.6
	Out-of-stock	290	54.2
	Return/Replacement Issues	193	36.1
	Poor product quality	267	49.9
	Security and privacy Issues	91	17.0
	Poor shopping experience	197	36.8
	Poor After Sales Service by Seller	213	39.8

Table 1. Profile of the respondents (N = 535)

Descriptive profiles of respondents were generated using IBM SPSS, revealing key insights into the characteristics of active users of mobile shopping applications in India. As depicted in Table 1, the sample predominantly comprised men (63.7 percent) compared to women (36.3 percent). Within the age distribution, 43.7 percent fell in the 25 to 34 years category, while 26.7 percent belonged to the 35 to 44 years age group. Regarding education, the majority of respondents were graduates (40.2 percent), with an additional 35.3 percent holding post-graduate degrees. Employment status indicated that 66.5 percent of respondents were employed, either in the public or private sector.

Income distribution showed that 33.8 percent of respondents fell into the INR 40001 to 80000 monthly income category, followed by 26.5 percent in the INR 80001 to 120000 range. Smartphone preferences leaned towards the Android operating system, with 75 percent of respondents utilizing Android-based devices. Approximately half of the respondents reported using smartphones for 6 to 9 years, and around 40 percent used their smartphones for 3 to 6 hours daily. Apart from shopping, the survey explored various smartphone activities. Notably, the majority engaged in bill payments (96.6 percent), banking (92.0 percent), ticket booking (91.2 percent), entertainment (89.9 percent), and social networking (88.4 percent). Electronic gadgets (60.9 percent), clothing & accessories (58.7 percent), food & health supplements (47.3 percent), and home décor & furnishings (39.1 percent) emerged as the most purchased product categories.

Regarding shopping behavior, 66.5 percent of respondents had been using mobile shopping applications for less than 3 years, while 36.5 percent reported a usage duration of more than 3 years. Frequency of mobile application shopping varied, with approximately 36 percent shopping a few times a year and 25 percent at least once a year. Payment methods on mobile shopping applications were diverse, with significant usage of debit cards (86.4 percent), Internet banking (77.4 percent), digital wallets (71.6 percent), and cash on delivery (66.0 percent). The primary motivations for shopping through mobile applications included attractive discounts and offers (79.1 percent), convenience (73.3 percent), and time savings (72.1 percent). Concerns among respondents included a delay in delivery time (62.6 percent), out-of-stock issues (54.2 percent), and higher shipping costs (54.0 percent). These insights provide a comprehensive profile of distinct customer segments actively using mobile shopping applications in India.

5. Results

5.1 Descriptive Statistics

The descriptive statistics for all constructs, as outlined in Table 2, were computed using the Statistical Package for Social Sciences (SPSS) software. A notable finding was that the majority of respondents expressed a high level of loyalty to their preferred mobile shopping applications. They perceived mobile shopping apps as significantly more user-friendly compared to traditional shopping channels. Respondents held positive beliefs regarding the entertainment value and fun associated with mobile shopping apps. While the respondents generally considered these apps trustworthy, they were also drawn by discounts and offers. On average, respondents perceived mobile shopping apps as useful, although their satisfaction level was moderately expressed. Notably, a considerable portion of respondents did not strongly believe that shopping via mobile apps posed significant risks to their security and privacy over mobile internet.

To ensure the robustness of the data, the univariate normality was assessed by examining the skewness and kurtosis values of all variables. As recommended by George and Mallery (2019), skewness and kurtosis values within the range of -2 to +2 indicate normal distribution. The results in Table 2 demonstrated that all variables met these criteria, supporting univariate normality. Additionally, multivariate normality was assessed using Mardia's method (Mardia, 1970). The Mardia's coefficient was 247.902, which is below the threshold of 1155 (calculated as p(p+2), where p=33). Thus, the data in this study can be considered to exhibit multivariate normality.

Reliability of the constructs was evaluated using Cronbach's alpha, with values above 0.70 indicating reliability (Nunnally & Burnstein, 1994). The results in Table 2 showed that Cronbach's alpha coefficients for all constructs ranged from 0.84 to 0.97, well above the acceptable threshold. This indicates that the items used to measure the constructs are reliable, contributing to the overall robustness of the study.

Variable	No. of items	Mean	S.D.	Skewness	Kurtosis	Cronbach's Alpha
Perceived Usefulness	4	2.979	0.926	-0.039	-0.085	0.948
Confirmation	4	3.626	0.792	-0.517	0.880	0.976
Hedonic Motivation	3	3.095	0.898	0.010	-0.105	0.965
Perceived Risk	3	2.867	0.726	0.236	0.858	0.904
Price Saving Orientation	3	3.062	0.729	-0.260	1.430	0.959
Perceived Trust	4	3.071	0.768	-0.270	0.960	0.950
Attitude	4	3.212	0.728	-0.183	1.015	0.907
Satisfaction	4	2.912	0.666	-0.099	0.783	0.918
Loyalty	4	3.459	0.689	-0.476	1.036	0.845

Table 2. Descriptive Statistics (n = 535)

The examination of multicollinearity in the data involved assessing the variance inflation factor (VIF) and Tolerance. As recommended by Hair et al. (2019), all predictor variables exhibited VIF values below 10, and Tolerance values exceeding 0.10. This outcome provides assurance that the dataset is free from multicollinearity issues. The VIF and Tolerance results indicate that the predictor variables in the study are not highly correlated, supporting the independence of these variables in the regression analysis.

5.2 Exploratory Factor Analysis

The exploratory factor analysis (EFA) was conducted to assess the unidimensionality of all constructs, utilizing principal components factor analysis with Varimax rotation. In the initial EFA run, 33 items were scrutinized, leading to the extraction of nine factors. Items PT4, ATT4, and PU4 were subsequently excluded due to inadequate factor loadings below 0.50 (Hoang et al., 2006). Following this refinement, the remaining 30 items underwent a second EFA (refer to Table 3). The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy and Bartlett's tests of sphericity were employed to evaluate the data's suitability for factor analysis. For all post-adoption beliefs related to mobile shopping, the KMO measure (0.918) and Bartlett's tests ($\chi 2$, $p \leq 0.000$) affirmed the appropriateness of factor analysis. Employing eigenvalues greater than 1, a nine-factor model was derived with factor loadings surpassing 0.50 for each item, elucidating 88.02% of the total variance.

	PU	CONF	HM	PR	PO	PT	ATT	SAT	LOY
Perceived usefulness (PU)									
PU1	.795								
PU2	.806								
PU3	.844								
Confirmation									
CONF1		0.868							
CONF2		0.882							
CONF3		0.891							
CONF4		0.895							
Hedonic motivation (HM)									
HM1			0.914						
HM2			0.910						

HM3			0.894						
Perceived risk (PR)									
PR1				-0.860					
PR2				-0.794					
PR3				-0.832					
Price saving orientation (PO)									
PO1					0.829				
PO2					0.831				
PO3					0.865				
Perceived trust (PT)									
PT1						0.855			
PT2						0.864			
PT3						0.855			
Attitude (ATT)									
ATT1							0.866		
ATT2							0.820		
ATT3							0.813		
Satisfaction (SAT)									
SAT1								0.813	
SAT2								0.772	
SAT3								0.788	
SAT4								0.741	
Loyalty (LOY)									
LOY1									0.705
LOY2									0.766
LOY3									0.807
LOY4									0.711
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 7 iterations									

Table 3. Exploratory factor analysis

5.3 Common Method Bias

The potential impact of common method bias on survey research validity was considered in this study using Harman's one-factor test (Harman, 1967), conducted through exploratory factor analysis. The underlying assumption is that the emergence of a single factor explaining a substantial proportion of covariance (above 50%) among measures suggests the presence of common method bias in the dataset (Podsakoff et al., 2003). All items were subjected to an exploratory factor analysis, employing unrotated principal component factor analysis. The first factor, capturing 45.46% of the covariance among measures, indicated that common method bias is unlikely to significantly affect the findings in this study.

5.4 Confirmatory Factor Analysis

Construct	Items	Standard Loadings	t-value (loadings)	Composite Reliability	Average Variance Extracted	Maximum Shared Variance
	PU1	0.929	28.556	0.947	0.857	0.358

Perceived usefulness (PU)	PU2	0.963	30.366			
	PU3	0.883	25.881			
Confirmation (CONF)	CONF1	0.956	29.893	0.978	0.919	0.358
	CONF2	0.952	29.648			
	CONF3	0.948	29.482			
	CONF4	0.978	31.206			
Hedonic Motivation (HM)	HM1	0.952	29.816	0.967	0.908	0.276
	HM2	0.954	30.027			
	HM3	0.952	29.579			
Perceived risk (PR)	PR1	0.983	30.563	0.915	0.784	0.320
	PR2	0.786	21.446			
	PR3	0.875	25.148			
Price Saving Orientation (PO)	PO1	0.917	27.648	0.960	0.889	0.393
	PO2	0.941	28.908			
	PO3	0.969	30.499			
Perceived Trust (PT)	PT1	0.904	26.923	0.951	0.867	0.352
	PT2	0.906	26.991			
	PT3	0.981	31.114			
Attitude (ATT)	ATT1	0.898	25.940	0.908	0.768	0.316
	ATT2	0.903	26.139			
	ATT3	0.981	22.813			
Satisfaction (SAT)	SAT1	0.867	24.824	0.923	0.799	0.494
	SAT2	0.936	28.188			
	SAT3	0.878	25.316			
Loyalty (LOY)	LOY1	0.794	21.046	0.848	0.650	0.494
	LOY2	0.846	23.071			
	LOY3	0.776	20.368			

Table 4. Confirmatory Factor Analysis

The measurement model in this study underwent evaluation through confirmatory factor analysis in AMOS software, utilizing a widely accepted maximum likelihood method. AMOS was chosen for its robust capabilities in handling complex models, performing confirmatory factor analysis, and providing comprehensive model fit indices. Its user-friendly interface and widespread acceptance in social science research made it the most suitable tool for this study. The initial CFA led to the removal of two items (SAT4 and LOY4) based on the recommendation by Anderson and Gerbing (1988) to enhance model fit. Composite Reliability (CR), Average Variance Extracted (AVE), and Maximum Shared Variance (MSV) were employed to assess the composite reliability, convergent, and discriminant validity of the measurement model. The Master Validity Tool plugin (Gaskin et al., 2019) facilitated the computation of these values. The measurement model (see figure 2) demonstrated reliability, with CR values exceeding 0.70 for all constructs (Fornell & Larcker, 1981). Table 4 presents results confirming convergent validity, with all items in CFA being statistically significant ($p < 0.01$), and factor loadings of all construct items surpassing 0.70. AVE values for all constructs exceeded 0.50 (Hair et al., 2019), and CR ≥ AVE for each latent variable, further supporting convergent validity.

	PU	**CONF**	**HM**	**PR**	**PO**	**PT**	**ATT**	**SAT**	**LOY**
PU	0.926								
CONF	0.532	0.959							

HM	0.525	0.362	0.953						
PR	-0.450	-0.442	-0.394	0.885					
PO	0.518	0.432	0.355	-0.414	0.943				
PT	0.425	0.421	0.345	-0.392	0.455	0.931			
ATT	0.439	0.418	0.371	-0.444	0.417	0.497	0.876		
SAT	0.595	0.509	0.359	-0.476	0.627	0.593	0.477	0.896	
LOY	0.598	0.598	0.392	-0.566	0.605	0.563	0.562	0.703	0.806

Table 5. Discriminant Validity
(Note: Leading diagonal shows the square root of AVE of each construct)

Discriminant validity of the measurement model was assessed by comparing Average Variance Extracted (AVE) and Maximum Shared Variance (MSV) values (refer to Table 5). The Master Validity Tool plugin by Gaskin et al. (2019) facilitated this analysis. AVE values for all constructs exceeded their corresponding MSV values, thereby confirming the discriminant validity of the model. In accordance with Fornell and Larcker (1981), Table 5 demonstrates that the square roots of AVE are greater than the inter-construct correlations, satisfying the discriminant validity criterion for the model.

	PU	**CONF**	**HM**	**PR**	**PO**	**PT**	**ATT**	**SAT**
PU								
CONF	0.519							
HM	0.532	0.367						
PR	0.455	0.468	0.408					
PO	0.522	0.443	0.366	0.464				
PT	0.428	0.407	0.349	0.405	0.465			
ATT	0.430	0.421	0.381	0.482	0.427	0.504		
SAT	0.579	0.413	0.361	0.493	0.632	0.592	0.481	
LOY	0.586	0.608	0.392	0.583	0.609	0.541	0.566	0.701

Table 6. HTMT Analysis

Discriminant validity was additionally assessed using the Heterotrait-Monotrait Ratio (HTMT) procedure through the Master Validity Tool (Gaskin et al., 2019). Following the recommendation by Henseler et al. (2015), all values were found to be below the threshold of 0.90 (refer to Table 6), further confirming the discriminant validity of the measurement model in this study. Based on these results, it can be concluded that the measurement model exhibits good reliability, convergent validity, and discriminant validity. The recommended and actual values of the model fit indices for the measurement model are presented in Table 7. Notably, the actual values of all model-fit indices surpass the recommended values, indicating a strong fit between the model and the data.

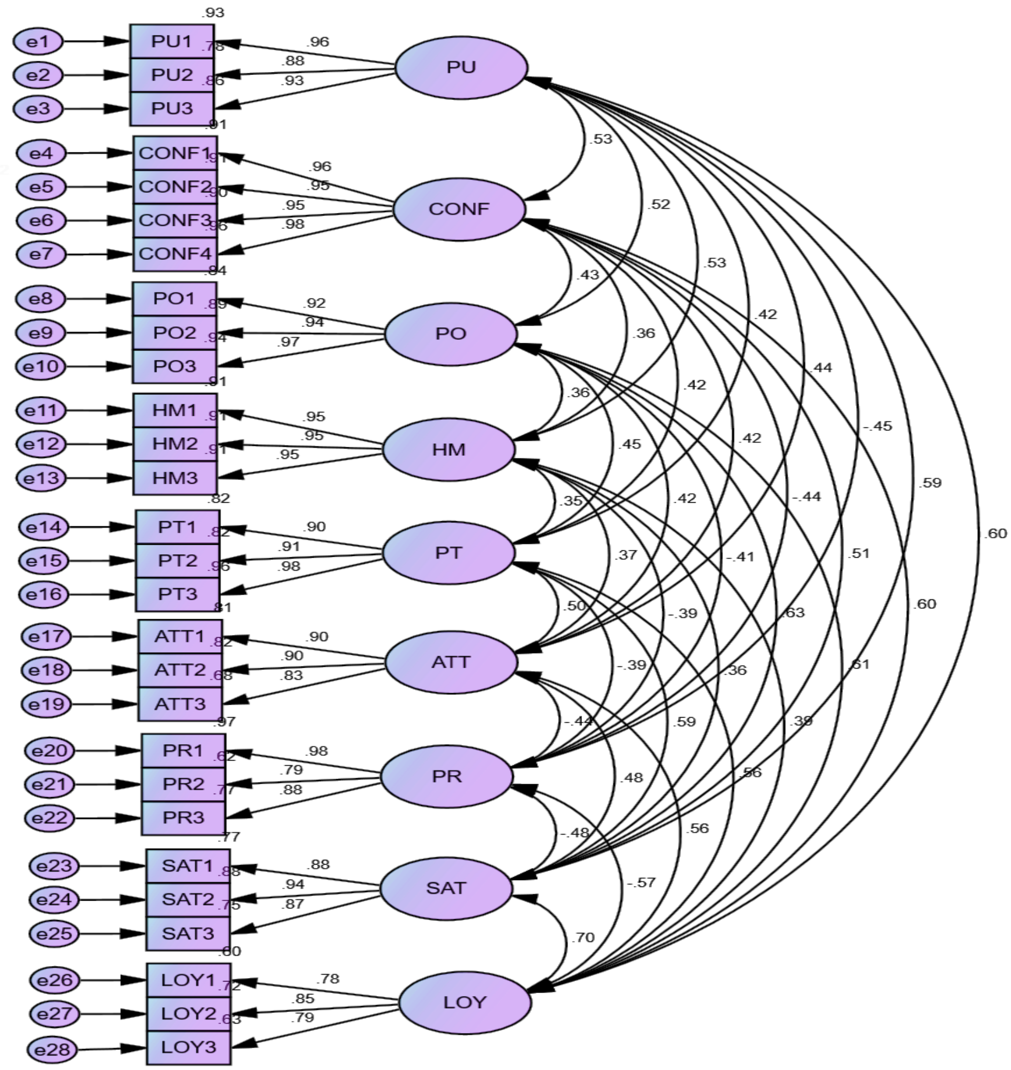

Figure 2: Measurement model

Items	Criterion guidelines	Values
Chi-square		622.738
Degree of freedom		311
Absolute fit measures		
GFI	>.80 (Jöreskog and Sörbom, 1989)	0.924
RMSEA	<.08 (MacCallum et al., 1996)	0.043
SRMR	<.08 (Jöreskog and Sörbom 1989)	0.029
Normed chi-square/df	<3 (Hayduk 1987)	2.002
Incremental fit measures		
NFI	>.90 (Bentler 1992)	0.964
CFI	>.90 (Gerbing and Anderson, 1992)	0.982
Parsimony fit measure		
AGFI	>.80 (MacCallum and Hong 1997)	0.901

Table 7. Goodness of fit – Measurement model

5.5 Invariance Test

Further, a multi-group moderation test is planned for the structural model, incorporating a categorical moderator variable known as experience. To ensure the robustness of subsequent findings, it is imperative to execute configural, metric, and scalar invariance tests on the measurement model. These tests are deemed essential to affirm the equivalence of constructs, allowing any discerned differences to be attributed to the moderating effect (Byrne, 2010; Hair et al., 2019).

Configural invariance, indicating that the specified model fits the data uniformly across all groups, was assessed. Two distinct groups, namely Low Experience and High Experience, were formulated within the measurement model, and the model was executed unconstrained. As depicted in Table 8, all model fit values surpassed the predefined criteria, signifying congruence in data fit for both groups and consistency in the factor structure.

Items	**Criterion guidelines**	**Values**
Chi-square		999.900
Degree of freedom		622
Absolute fit measures		
GFI	>.80 (Jöreskog and Sörbom, 1989)	0.886
RMSEA	<.08 (MacCallum et al., 1996)	0.034
SRMR	<.08 (Jöreskog and Sörbom 1989)	0.031
Normed chi-square/df	<3 (Hayduk 1987)	1.608
Incremental fit measures		
NFI	>.90 (Bentler 1992)	0.944
CFI	>.90 (Gerbing and Anderson, 1992)	0.978
Parsimony fit measure		
AGFI	>.80 (MacCallum and Hong 1997)	0.851

Table 8: Goodness of fit – Configural invariance test

Subsequently, the metric invariance test, considered a more stringent evaluation, was conducted. Initially, the measurement model with two unconstrained groups was executed, followed by constraining the model to equality across groups. The ensuing chi-square difference test, detailed in Table 9, yielded a non-significant p-value (0.197 > 0.05), indicating that the model-level differences between groups were not substantial. The third and pivotal step involved examining scalar invariance, gauging the equality of intercepts across groups (Campbell et al. 2008). This test ensures that both groups utilize the response scale uniformly (Steenkamp & Baumgartner, 1998). For the scalar invariance test, intercepts were constrained across groups, and the subsequent chi-square difference test, detailed in Table 8, indicated a p-value of 0.231 (> 0.5), affirming the attainment of full scalar invariance for the measurement model.

	$\chi 2$	**df**	**P-value**
Unconstrained base modela	999.900	622	
Fully constrained model (factor loadings constrained)b	1021.588	639	
Fully constrained model (intercepts constrained)c	1049.349	665	
Number of groups	2		
Difference (a-b)	21.688	17	0.197ns
Difference (a-c)	49.449	43	0.231ns
ns represents not significant			

Table 9: Metric and Scalar invariance test

5.5 Structural Model and Hypotheses Testing

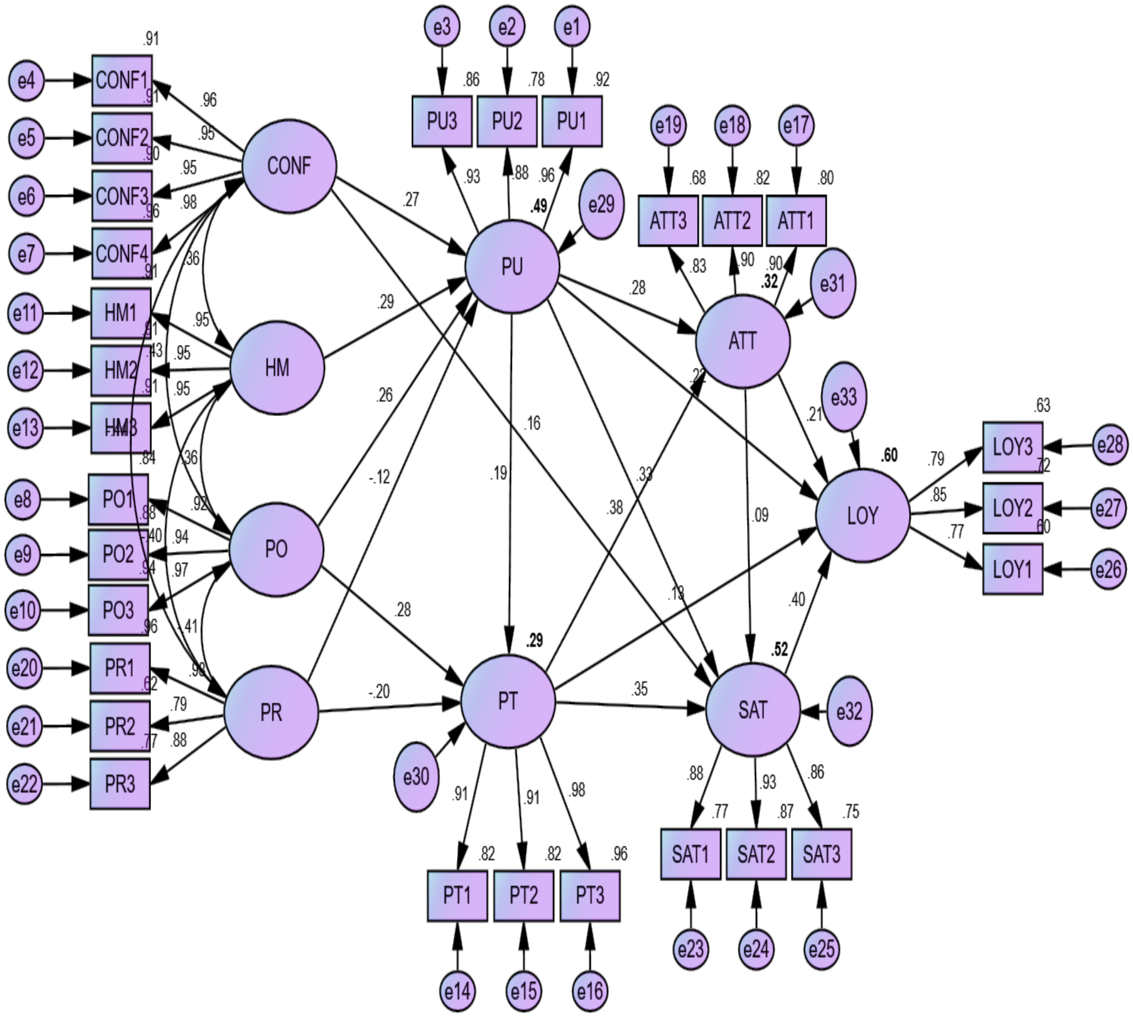

Figure 3: Result of structural model

The outcome of the hypothesized structural model is depicted in Figure 3. The goodness-of-fit indices, as presented in Table 10, signify a robust model fit. In alignment with the existing literature on mobile shopping post-adoption behavior, all the hypothesized relationships (H1 to H8) are observed to be statistically significant (refer to Table 11).

Items	**Criterion guidelines**	**Values**
Chi-square		806.624
Degree of freedom		324
Absolute fit measures		
GFI	>.80 (Jöreskog and Sörbom, 1989)	0.904
RMSEA	<.08 (MacCallum et al., 1996)	0.053
SRMR	<.08 (Jöreskog and Sörbom 1992)	0.073
Normed chi-square/df	<3 (Hayduk 1987)	2.490
Incremental fit measures		
NFI	>.90 (Bentler 1992)	0.954
CFI	>.90 (Gerbing and Anderson, 1992)	0.972
Parsimony fit measure		
AGFI	>.80 (MacCallum and Hong 1997)	0.880

Table 10. Goodness of fit – Structural model

The examination of the structural model unveiled that 60.2% of the variance in loyalty could be attributed to four proposed antecedents, namely satisfaction, attitude, perceived trust, and perceived usefulness. Moreover, confirmation, along with perceived usefulness, perceived trust, and attitude, elucidated 52.2% of the variance in satisfaction. The model elucidates 31.6% of the variance in attitude, with both perceived trust and perceived usefulness exhibiting noteworthy relationships with attitude. The four proposed antecedents, namely confirmation, hedonic motivation, price saving orientation, and perceived risk, collectively explicated 48.7% of the variance in perceived usefulness, affirming the positive and significant influence of confirmation, hedonic motivation, and price saving orientation, as well as the negative relationship of perceived risk with perceived usefulness. Lastly, it was noted that perceived usefulness, price saving orientation, and perceived risk significantly accounted for 28.9% of the variance in perceived trust.

Hypotheses	Structural Path	Standard Regression Weight	t-Value	p-Value	Result
H1a	Confirmation → Perceived usefulness	0.270	6.933	0.000	Supported
H1b	Confirmation → Satisfaction	0.162	4.091	0.000	Supported
H2a	Hedonic motivation → Perceived usefulness	0.290	7.584	0.000	Supported
H3a	Price saving orientation → Perceived usefulness	0.257	6.580	0.000	Supported
H3b	Price saving orientation → Perceived trust	0.280	5.932	0.000	Supported
H4a	Perceived risk → Perceived usefulness	-0.116	-2.938	0.003	Supported
H4b	Perceived risk → Perceived trust	-0.196	-4.397	0.000	Supported
H5a	Perceived usefulness → Perceived trust	0.191	3.970	0.000	Supported
H5b	Perceived usefulness → Attitude	0.284	6.431	0.000	Supported
H5c	Perceived usefulness → Satisfaction	0.330	7.335	0.000	Supported
H5d	Perceived usefulness → Loyalty	0.222	4.825	0.000	Supported
H6a	Perceived trust → Attitude	0.379	8.497	0.000	Supported
H6b	Perceived trust → Satisfaction	0.346	8.275	0.000	Supported
H6c	Perceived trust → Loyalty	0.129	2.839	0.028	Supported
H7a	Attitude → Satisfaction	0.093	2.199	0.028	Supported
H7b	Attitude → Loyalty	0.210	4.772	0.000	Supported
H8a	Satisfaction → Loyalty	0.395	7.370	0.000	Supported

Table 11. Results of hypothesis testing

The comprehensive overview of the direct, indirect, and total effects of all latent variables is presented in Table 12. The direct and total effect of perceived usefulness on loyalty stood at 0.492, emerging as the most influential predictor of loyalty compared to both the direct and indirect effects of other variables in the structural model. The total effect of perceived trust (0.359) on loyalty towards mobile shopping applications surpassed that of attitude (0.247) on loyalty. The total (indirect) effects of price saving orientation, hedonic motivation, and confirmation were positively and significantly associated with loyalty, while perceived risk exhibited an indirect negative influence. Perceived usefulness emerged as the most pivotal predictor of customers' satisfaction with mobile shopping applications, yielding the highest direct and total effect of 0.429 on satisfaction. The total effect of perceived trust on satisfaction was 0.381, surpassing that of attitude on satisfaction. Likewise, the indirect effects of price saving orientation, hedonic motivation, confirmation, and perceived risk on satisfaction were found to be significant.

	Perceived Usefulness	Perceived Trust	Attitude	Satisfaction	Loyalty
Direct Effects					
Confirmation	0.270			0.162	
Hedonic Motivation	0.290				
Price Saving Orientation	0.257	0.280			
Perceived Risk	-0.116	-0.191			
Perceived Usefulness		0.192	0.284	0.330	0.222
Perceived Trust			0.379	0.346	0.129

Attitude				0.093	0.210
Satisfaction					0.395
Indirect Effects					
Confirmation		0.052	0.096	0.116	0.197
Hedonic Motivation		0.055	0.103	0.125	0.143
Price Saving Orientation		0.049	0.198	0.217	0.227
Perceived Risk		-0.022	-0.116	-0.124	-0.127
Perceived Usefulness			0.073	0.099	0.270
Perceived Trust				0.035	0.230
Attitude					0.037
Satisfaction					
Total Effects					
Confirmation	0.270	0.052	0.096	0.278	0.197
Hedonic Motivation	0.290	0.055	0.103	0.125	0.143
Price Saving Orientation	0.257	0.329	0.198	0.217	0.227
Perceived Risk	-0.116	-0.218	-0.116	-0.124	-0.127
Perceived Usefulness		0.192	0.357	0.429	0.492
Perceived Trust			0.379	0.381	0.359
Attitude				0.093	0.247
Satisfaction					0.395

Table 12. The direct, indirect, and total effects

Perceived trust emerged as the most influential predictor of customers' attitude towards mobile shopping applications, surpassing even perceived usefulness in its predictive power. The total effects of price saving orientation, perceived risk, hedonic motivation, and confirmation on attitude were all found to be significant. Notably, the total effect of price saving orientation on perceived trust was 0.329, surpassing both the direct and total effects of perceived usefulness on perceived trust. Additionally, perceived risk exhibited a significant (negative) impact on perceived trust, with perceived usefulness acting as a mediator. Both hedonic motivation and perceived ease of use demonstrated significant indirect effects on perceived trust.

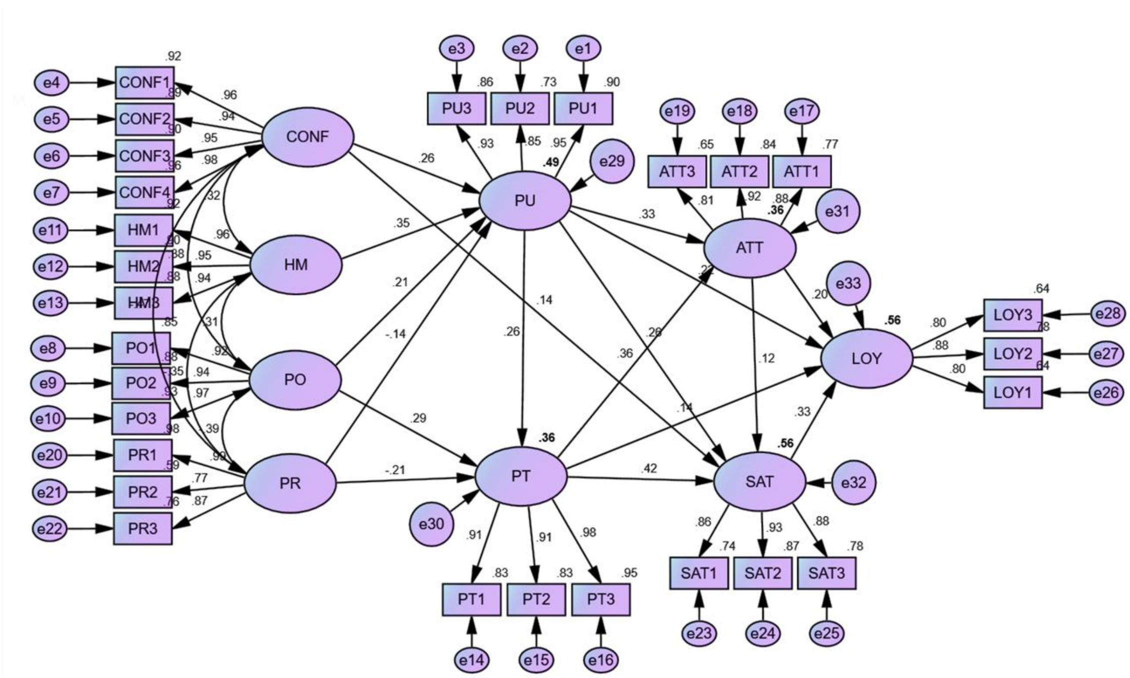

Figure 4: Structural Model for Respondents with Low Experience

5.6 Multi-group analysis

The examination of moderation effects through Multi-Group Analysis (MGA) followed the two-step procedure recommended by Byrne (2010). Firstly, the Chi-square ($\chi2$) difference between constrained and unconstrained models was assessed. A statistically significant $\Delta\chi2$ value of 33.670, with 17 degrees of freedom and a p-value of 0.009 (see Table 13), indicated that experience moderates the entire structural model. Further analysis delved into the moderation impact of experience on individual paths within the structural model (see Figures 4 &5).

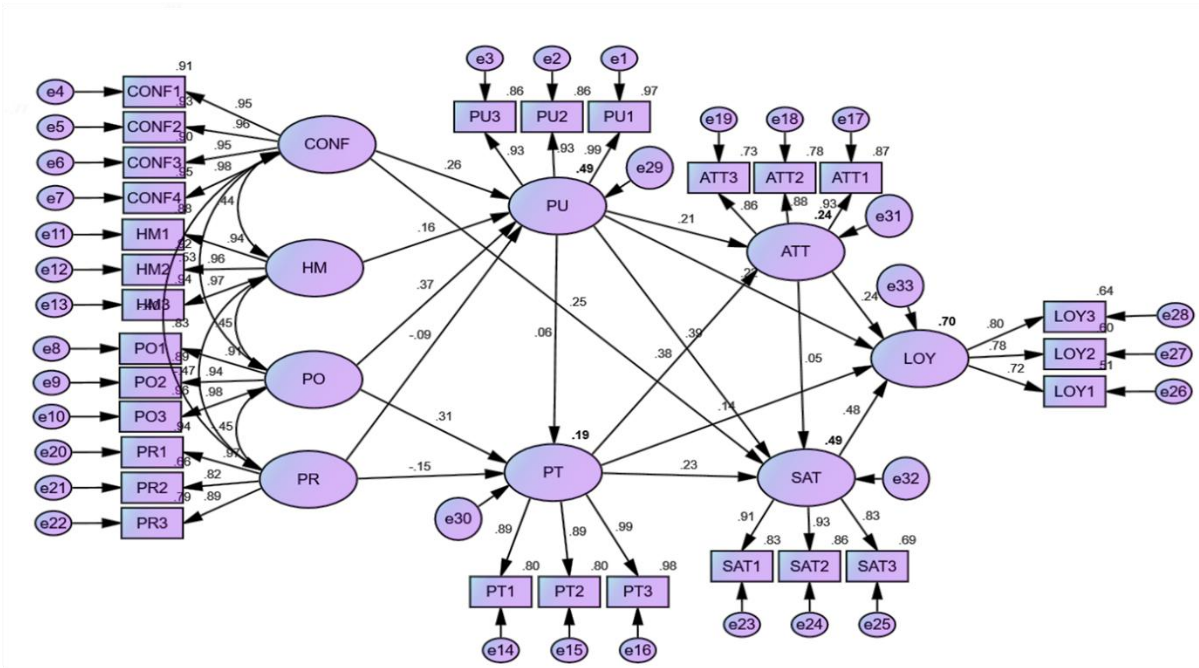

Figure 5: Structural Model for Respondents with High Experience

The results (see Table 14) revealed significant distinctions between low-experience and high-experience groups in the relationships between Hedonic Motivation, Price Saving Orientation, and Perceived Usefulness; Perceived usefulness and Perceived Trust; and Perceived Trust and Satisfaction.

Models	Chi-square	DF	Chi-square/DF	P-value
Unconstrained	1201.787	648		0.000
Constrained	1235.457	665		0.000
Chi-square significance ($\Delta\chi2$)	33.670	17		0.009

Table 13: Chi-square significance

Specifically, for low-experience mobile shopping app customers, HM had a more pronounced effect on PU ($\beta = 0.350$; $p < 0.001$) compared to the high-experience group ($\beta = 0.157$; $p < 0.010$). Conversely, PO exhibited a stronger impact on PU for high-experience customers ($\beta = 0.373$; $p < 0.001$) than for their low-experience counterparts ($\beta = 0.210$; $p < 0.001$). Notably, the effect of PU on PT was significantly positive among low-experience shoppers ($\beta = 0.264$; $p < 0.001$) but insignificant among high-experience shoppers. Lastly, PT had a more robust effect on satisfaction for low-experience individuals ($\beta = 0.420$; $p < 0.001$) than for those with high experience ($\beta = 0.230$; $p < 0.001$).

Hypotheses	Structured path	Low Experience Beta	High Experience Beta	Difference in Betas	P-Value for Difference
H9-1a	Confirmation → Perceived usefulness	0.256***	0.264***	-0.007	0.781
H9 – 1b	Confirmation → Satisfaction	0.137**	0.245***	-0.108	0.222

H9 – 2a	Hedonic motivation → Perceived usefulness	0.350***	0.157*	0.193	**0.041***
H9 – 3a	Price saving orientation → Perceived usefulness	0.210***	0.373***	-0.163	**0.028***
H9 – 3b	Price saving orientation → Perceived trust	0.287***	0.311***	-0.025	1.000
H9 – 4a	Perceived risk → Perceived usefulness	-0.144**	-0.087	-0.057	0.576
H9 – 4b	Perceived risk → Perceived trust	-0.206***	-0.151†	-0.054	0.467
H9 – 5a	Perceived usefulness → Perceived trust	0.264***	0.057	0.207	**0.022***
H9 – 5b	Perceived usefulness → Attitude	0.334***	0.211**	0.122	0.261
H9 – 5c	Perceived usefulness → Satisfaction	0.261***	0.388***	-0.127	0.218
H9 – 5d	Perceived usefulness → Loyalty	0.222***	0.217**	0.005	1.000
H9 – 6a	Perceived trust → Attitude	0.361***	0.375***	-0.015	0.278
H9 – 6b	Perceived trust → Satisfaction	0.420***	0.230***	0.191	**0.085†**
H9 – 6c	Perceived trust → Loyalty	0.144*	0.139*	0.005	0.803
H9 – 7a	Attitude → Satisfaction	0.125*	0.047	0.077	0.307
H9 – 7b	Attitude → Loyalty	0.203***	0.237***	-0.034	0.780
H9 – 8a	Satisfaction → Loyalty	0.335***	0.481***	-0.147	0.100
	Significance Indicators: † p < 0.100; * p < 0.050; ** p < 0.010; *** p < 0.001				

Table 14: Results of Multi-group analysis

6. Discussion

This study explored the determinants influencing customer satisfaction and loyalty in the context of mobile shopping in India, integrating constructs from the Technology Acceptance Model (TAM) and Expectation Confirmation Model (ECM) with additional contextual factors. All hypothesized relationships (H1 to H8), as well as the moderating effects of user experience (H9), were confirmed, providing robust evidence for the theoretical framework. The confirmation process emerged as a pivotal driver of satisfaction and perceived usefulness, underscoring the alignment between customer expectations and actual experiences in mobile shopping. This aligns with previous research indicating that managing expectations significantly impacts satisfaction and perceived value (Kang et al., 2010; Nguyen & Ha, 2021).

Hedonic motivation was found to positively influence perceived usefulness and indirectly enhance satisfaction, trust, and attitude, demonstrating the importance of enjoyable and engaging user experiences (Zhou, 2011; Chi, 2018). Similarly, price-saving orientation significantly impacted perceived usefulness and trust, highlighting the role of economic benefits such as discounts and deals in shaping user perceptions (Gupta & Arora, 2017). Perceived risk negatively affected both perceived usefulness and trust, reaffirming its role as a critical barrier in the adoption and continued use of mobile shopping applications. Addressing security and privacy concerns is vital for fostering trust and enhancing perceived value (Madan & Yadav, 2018; Qalati et al., 2021).

A symbiotic relationship between perceived usefulness and trust was confirmed, with perceived usefulness enhancing trust and trust, in turn, influencing satisfaction, attitude, and loyalty. Trust emerged as the strongest predictor of attitude, surpassing perceived usefulness, emphasizing its central role in fostering positive beliefs about mobile shopping (Nguyen & Ha, 2021). Satisfaction, along with trust, usefulness, and attitude, was identified as a key determinant of loyalty, with satisfaction exerting the most substantial influence. This highlights the importance of consistently delivering reliable and high-quality services to foster long-term loyalty (Kim et al., 2023).

The Multi-Group Analysis (MGA) revealed significant moderating effects of user experience. For low-experience users, perceived risk had a stronger negative influence on perceived usefulness, while perceived usefulness exerted a greater impact on attitude. For high-experience users, perceived usefulness had a more pronounced effect on satisfaction, which, in turn, had a stronger influence on loyalty. These findings underscore the importance of tailoring strategies to address the distinct needs of novice and experienced mobile shopping users, ensuring engagement and satisfaction across all experience levels.

7. Theoretical and Practical Implications

This study provides significant theoretical contributions to the understanding of customer satisfaction and loyalty in mobile shopping contexts by integrating contextual factors into established frameworks such as the Technology Acceptance Model (TAM) and Expectation-Confirmation Model (ECM). By expanding the applicability of these models, the research sheds light on the complex interplay of cognitive, affective, and behavioral factors shaping post-adoption behavior in mobile shopping.

First, the study reinforces the pivotal role of the confirmation process in shaping user perceptions and satisfaction, aligning with Expectation-Confirmation Theory (Bhattacherjee, 2001). Consistent with previous findings (Kang et al., 2010; Sarkar & Khare, 2018; Nguyen & Ha, 2021), the results demonstrate that confirmation significantly influences perceived usefulness and satisfaction. This emphasizes the critical importance of managing customer expectations to ensure alignment with the actual benefits derived from mobile shopping. Furthermore, as noted by Zhang et al. (2018), confirmation not only fosters satisfaction but also enhances the perceived utility of mobile shopping platforms, affirming its central role in post-adoption behavior.

Second, the inclusion of hedonic motivation underscores the relevance of affective factors in shaping user perceptions and behaviors. Hedonic motivation emerged as a key driver of perceived usefulness, consistent with findings from Zhou (2011), Chi (2018), and Tarhini et al. (2019). This highlights the importance of designing mobile shopping platforms that balance functional efficiency with entertainment and engagement. Notably, Nguyen et al. (2023) and Hu et al. (2021) observed that hedonic motivation indirectly impacts satisfaction through perceived usefulness and trust, reinforcing the significance of pleasurable experiences in influencing long-term engagement.

Third, the incorporation of price-saving orientation extends TAM and ECM by addressing economic considerations in technology adoption. Indian consumers' emphasis on cost-saving features and attractive deals aligns with prior findings (Gupta & Arora, 2017; Sullivan & Kim, 2017; Ly et al., 2022), which demonstrate the strong influence of financial incentives on trust and perceived usefulness. By highlighting the role of rational economic behavior, this study enriches our understanding of mobile shopping adoption in price-sensitive markets.

Fourth, the research underscores the adverse effects of perceived risk on trust and perceived usefulness, consistent with existing literature (Hu & Liu, 2013; Madan & Yadav, 2018; Qalati et al., 2021). By demonstrating that perceived risk acts as a significant deterrent to positive attitudes and behaviors, the findings align with studies by Sarkar and Khare (2017) and Baidoun and Salem (2023), which emphasize the importance of mitigating security and privacy concerns to foster trust. Furthermore, the mediating role of trust in reducing the impact of perceived risk, as noted by Qalati et al. (2021), highlights its critical function in shaping user perceptions and intentions.

The study also reveals a symbiotic relationship between perceived usefulness and trust, offering theoretical depth to their interdependence. As noted by Nguyen and Ha (2021) and Lavuri et al. (2023), perceived usefulness enhances trust by demonstrating the reliability and value of mobile shopping platforms. Interestingly, the bidirectional nature of this relationship, as proposed by Zamil et al. (2020), suggests that trust further reinforces perceptions of utility, creating a positive feedback loop. These findings underscore the nuanced interplay between functionality and reliability in driving technology acceptance and sustained usage.

Another critical contribution lies in identifying perceived trust as the strongest predictor of attitude, surpassing perceived usefulness. This finding is consistent with Baidoun and Salem (2024), who emphasize that trust is central to fostering positive consumer beliefs. Studies by Zamil et al. (2020) and Lavuri et al. (2023) similarly highlight the pivotal role of trust in influencing attitudes and intentions. However, the results also align with studies like Um (2018), which recognize the complementary contributions of usefulness, enjoyment, and risk perceptions in shaping attitudes. This nuanced perspective enriches the theoretical understanding of attitude formation in mobile shopping.

The study's focus on user experience as a moderating factor offers a novel extension to TAM and ECM. The Multi-Group Analysis (MGA) revealed significant differences between low- and high-experience users, consistent with findings from Deng et al. (2010) and Rohm and Swaminathan (2004). For novice users, perceived risk was a more prominent determinant of perceived usefulness, underscoring the need to address initial concerns. Conversely, for experienced users, perceived usefulness had a stronger influence on satisfaction, highlighting its growing importance with familiarity. These insights align with studies by Kwak et al. (2002) and Venkatesh et al. (2003), which emphasize the evolving role of experience in shaping technology perceptions and motivations.

Finally, the study extends the theoretical discourse on loyalty by identifying satisfaction, trust, usefulness, and attitude as its key determinants. Satisfaction emerged as the most influential factor, consistent with findings by Bhattacherjee (2001) and Nguyen and Ha (2021). The study also confirms the role of trust as a critical enabler of loyalty, as highlighted by Kim et al. (2023) and Husain (2017). By integrating usefulness and attitude into the framework, this research provides a more holistic understanding of the drivers of loyalty, aligning with Lavuri et al. (2023), who emphasize the multifaceted nature of loyalty formation in mobile shopping.

In summary, this study advances theoretical models of mobile shopping behavior by integrating contextual factors, emphasizing the interplay of cognitive and affective determinants, and highlighting the moderating role of user experience. These contributions not only enhance the explanatory power of TAM and ECM but also offer a comprehensive framework for understanding post-adoption behavior in dynamic digital markets.

The findings of this study offer valuable insights for practitioners in the mobile shopping industry, providing strategies to enhance user experience, satisfaction, and loyalty. One of the most critical areas of focus is mitigating perceived risks, as these negatively impact perceived usefulness and trust. Mobile shopping platforms should address user concerns regarding security and privacy by implementing robust protective measures, ensuring secure transactions, and clearly communicating transparent privacy policies. These steps can significantly reduce users' perceived risks and improve their overall confidence in the platform.

Another key takeaway is the importance of integrating hedonic elements into mobile shopping applications. Features that make the shopping experience enjoyable and engaging can enhance perceived usefulness and satisfaction. Designing platforms that balance functionality with entertainment can create a more compelling user experience, encouraging continued engagement and loyalty. Similarly, the emphasis on economic benefits highlights the need for mobile shopping platforms to prioritize cost-saving features, including attractive promotions, discounts, and deals, to appeal to price-sensitive consumers and retain their loyalty.

For instance, well-known platforms like Amazon and Flipkart have effectively boosted customer loyalty by creating personalized shopping experiences based on user preferences and behavior. Special sales events such as Flipkart's Big Billion Day and Amazon's Prime Day demonstrate how price-saving orientation can attract and retain a broad customer base. These platforms also address customer concerns about perceived risks by offering user-friendly interfaces, secure payment systems, and transparent policies, which build trust among their users. Additionally, features like reward points and interactive elements, often gamified, add an engaging layer to the shopping experience, enhancing hedonic motivation and encouraging customers to continue using the platforms.

Managing and aligning customer expectations is another critical area of practical focus. By ensuring that customer expectations align with the actual benefits of the platform, businesses can enhance user satisfaction. Clear communication, accurate product information, and consistent service delivery are vital strategies for building trust and sustaining positive user perceptions. Furthermore, trust plays a central role in shaping user attitudes, making it imperative for platforms to foster trust through transparent business practices, reliable customer support, secure payment options, and dependable product delivery processes.

Enhancing the perceived usefulness of mobile shopping platforms should also be a priority. Regular updates, improved functionality, and features tailored to evolving customer needs can significantly increase the perceived utility of these applications. Strategic marketing communication that highlights both the reliability and utility of mobile shopping platforms can further enhance user attitudes. By effectively conveying the platform's trustworthiness and functional benefits, businesses can strengthen their brand image and customer retention.

Building satisfaction through trust is another actionable strategy for practitioners. Consistent service quality, reliable delivery, and responsive customer support can foster user trust and significantly improve satisfaction. In turn, this satisfaction can be leveraged to promote loyalty. Personalized offerings, efficient customer service, and well-designed loyalty programs can help businesses cultivate long-term customer relationships and drive repeat purchases.

Tailoring strategies based on user experience levels allows businesses to address diverse customer needs. For less-experienced users, platforms should focus on reducing perceived risks and clearly communicating the practical benefits of mobile shopping.

Marketing campaigns and educational initiatives can highlight the utility of the platform, making it more accessible and appealing to novice users. For experienced users, optimizing perceived usefulness becomes critical. Continuous innovation and improved functionality can help maintain satisfaction and loyalty among this group, ensuring sustained engagement.

The nuanced relationship between perceived usefulness and satisfaction across experience levels further emphasizes the importance of customized strategies. For novice users, emphasizing practical benefits contributes to satisfaction, while experienced users value continuous improvement and innovation. These insights provide actionable guidance for platforms aiming to optimize user experiences and foster loyalty across varied customer segments.

8. Conclusion

This study provides a comprehensive examination of the factors influencing customer satisfaction and loyalty in the context of mobile shopping in India. By integrating the Technology Acceptance Model (TAM) and Expectation-Confirmation Model (ECM) with contextual factors such as perceived trust, price-saving orientation, hedonic motivation, and perceived risk, the research advances theoretical understanding and offers actionable insights for practitioners.

The findings highlight the critical role of confirmation in aligning customer expectations with actual benefits, with a notable impact on perceived usefulness and satisfaction. The study also underscores the importance of hedonic motivation, price-saving orientation, and trust in shaping users' attitudes and behaviors. These insights reinforce the need for mobile shopping platforms to balance functionality with enjoyable user experiences, while also addressing economic considerations and risk concerns.

From a practical perspective, the study emphasizes strategies to foster trust, enhance user satisfaction, and increase loyalty through consistent service quality, transparent communication, and innovative features that cater to users' evolving needs. The moderating effect of user experience further informs the importance of tailoring strategies to different user segments, providing valuable guidance for future marketing and platform development.

In summary, this research contributes to the understanding of post-adoption behavior in mobile shopping, offering a more nuanced view of customer engagement and retention. The insights gained here can help shape more effective strategies for both researchers and practitioners in the mobile shopping industry.

8.1 Limitations and Future Research

Despite these contributions, this study has some limitations. The cross-sectional nature of the data restricts the ability to capture dynamic changes in user perceptions over time, suggesting that future research could adopt a longitudinal design. Additionally, while the study focused on the Indian market, it may not fully represent mobile shopping behaviors in other cultural or regional contexts. Future studies could expand the scope to explore cultural differences in mobile shopping behavior. The reliance on self-reported data is another limitation, which may introduce common method bias. Future research could address this by using objective measures or integrating alternative data collection methods. Finally, the study predominantly examines individual-level factors, and future research could explore how organizational or platform-level variables impact the mobile shopping experience.

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Appendix. Measurement scale and items

Perceived usefulness (adapted from Davis, 1989, Wu 2013)

PU1: I believe that mobile shopping application is useful for searching and purchasing products and services.
PU2: I feel that searching and shopping with mobile application is very convenient.
PU3: I feel that searching and shopping via mobile application is faster and effective.
PU4*: In general, I feel that the mobile shopping application is very useful for searching and shopping products and services.

Confirmation (adapted from Bhattacherjee, 2001)

CONF1: My experience with using mobile shopping application was better than I expected
CONF2: The service level or function provided by mobile shopping applications was better than I expected
CONF3: My expectation for using the mobile shopping applications was satisfied as a whole
CONF4: Overall, most of my expectations from using mobile shopping applications were confirmed

Hedonic motivation (adapted from Venkatesh et al. 2012; Lin and Lu 2015)

HM1: I think it is fun and interesting to use mobile shopping application.
HM2: I think the process of shopping via mobile shopping application would be enjoyable and exciting.
HM3: Overall, I feel using the mobile shopping application is very delighting and entertaining.

Perceived risk (adapted from Lu et al. 2011)

PR1: I believe the risk of purchasing products through mobile shopping application is very high.
PR2: I do not feel secure sending sensitive information over mobile shopping application.
PR3: Overall, I feel shopping via mobile shopping application is highly riskier compared with other methods of shopping.

Price saving orientation (adapted from Escobar-Rodríguez and Carvajal-Trujillo, 2013)

PO1: I can save money by examining the prices of different mobile shopping applications.
PO2: I like to search for cheap product deals in different mobile shopping applications.
PO3: Mobile shopping applications offer better value for money.

Perceived trust (adapted from Lee, 2005; Gao et al. 2015)

PT1: I believe that the mobile shopping applications are reliable and trustworthy.
PT2: I think that the mobile shopping applications keep their promises and commitment.
PT3: I believe that mobile shopping applications keep their customer's interest in mind.
PT4*: In general, I trust mobile shopping applications for buying products and services.

Attitude (adapted from Davis et al. 1989)

ATT1: I believe that mobile shopping application is involving and valuable.
ATT2: I feel that using mobile shopping application is a wise idea.
ATT3: I think that using mobile shopping application is a good idea.
ATT4*: I like the idea of shopping through mobile shopping applications.

Satisfaction (adapted from Bhattacherjee, 2001; Park and Kim, 2013)

SAT1: I believe that mobile shopping application meets my expectations.
SAT2: I am satisfied with my decision to use mobile shopping application.
SAT3: My experience with mobile shopping application was very satisfactory.
SAT4**: Overall, I am satisfied with the level of services offered by mobile shopping application.

Loyalty (adapted from Zeithaml and Berry, 1996; Lin and Wang, 2006)

LOY1: I intend to continue using mobile shopping applications in the future.
LOY2: I intend to shop more frequently in mobile shopping applications in the future.
LOY3; I say positive things about the mobile shopping application to other people.
LOY4**: I recommend mobile shopping applications to my family and friends.

** Dropped after the exploratory factor analysis*
*** Dropped after the confirmatory factor analysis*