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KEYWORDS	ABSTRACT
AI-driven e-commerce, customer satisfaction, customer loyalty, personalized price promotions, trust, perceived usefulness, service quality, PLS-SEM, Pakistan	The swift development of artificial intelligence (AI)-based e-commerce websites has radically reshaped the way consumer's act and business relations in the Pakistani online market. Although this has changed, there remains a notable gap in the academic literature on the particular psychological, technological precursors of customer satisfaction and customer loyalty in the Pakistani environment especially in a large urban area like Karachi. This paper explores how Trust, Perceived Usefulness, Service Quality, Perceived Enjoyment, and Perceived Personalization affect Customer Satisfaction, which in turn affects Customer Loyalty, in the context of active users of AI-based e-commerce platforms in Karachi. Moreover, the research evaluates the direct impact of the Personalized Price Promotions (PPP) on Customer Loyalty and also tests the PPP to mediate Customer Satisfaction Customer Loyalty. A cross-sectional, quantitative research design was used. A structured questionnaire based on rigorously tested international scales was used to gather data on 100 respondents. The SmartPLS 4.0 was used to run the Partial Least Squares Structural Equation Modeling (PLS-SEM) to evaluate the measurement model and the structural relationships. Results reveal that Trust ($\beta = 0.241, p = .006$), Perceived Usefulness ($\beta = 0.305, p = .009$), Service Quality ($\beta = 0.328, p = .006$), and Perceived Enjoyment ($\beta = 0.198, p = .039$) each exert significant positive effects on Customer Satisfaction, which in turn significantly predicts Customer Loyalty ($\beta = 0.378, p < .001$). Individualized Price Promotions turned out to be the best direct predictor of Customer Loyalty ($\beta = 0.495, p < .001$). It has significant explanatory power as the model explains 84.6% of the variance in Customer Satisfaction and 74.0% in Customer Loyalty. Surprisingly, PPP showed no significant predictive power of Customer Satisfaction ($\beta = -0.042, p = .734$), and PPP was no significant in moderating the relationship between Satisfaction and Loyalty ($\beta = -0.013, p = .603$). The implications of these findings to e-commerce managers and platform developers in Pakistan are significant as trust-building mechanisms, functional utility, service reliability and emotional involvement were considered crucial in the development of consumer satisfaction and retention. The research contributes to the growing body of literature on AI-based e-commerce in the setting of developing countries and offers a basis to further longitudinal and cross-cultural research.
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Introduction

The spread of artificial intelligence (AI) products around the world has irrevocably changed the nature of business, and especially in the online retail industry. E-commerce sites have developed beyond their mere online stores into dynamic, AI-based systems that can learn consumer behavior and personalize their recommendations, better pricing, and real-time customer service interactions (Hassan et al., 2025). The above developments are not limited to the developed world; emerging markets like Pakistan are experiencing unprecedented growth in digital trade, driven by the increasing smartphone adoption, the rising 4G/5G network, and the increasing number of digitally savvy consumers (Bhardwaj et al., 2025).

The e-commerce industry in Pakistan has been under an astonishing growth in the recent years. The annual report by the State Bank of Pakistan stated that the number of digital transactions increased over 40% in between 2021 and 2024, and the use of AI-based solutions like chat bots, personalized recommendation systems, and dynamic pricing algorithms turned into the part of e-commerce platforms like Daraz, Foodpanda, and Naheed. Karachi, the biggest commercial city and the most populated in Pakistan, is the centre of this digital revolution, with the biggest portion of online retail transactions in the nation being in Karachi (Pakistan Telecommunication Authority, 2024). Regardless of such a fast increase, there is still a lack of scholarly sources that analyze consumer behavior in the context of Pakistani AI-driven e-commerce settings.

Theoretically, consumer satisfaction and loyalty have long been considered as the key results of effective service delivery and relationship marketing (Khan et al., 2022). The classical models of consumer evaluation of digital services include Technology Acceptance Model (TAM; Davis, 1989), Expectation-Confirmation Theory (ECT; Oliver, 1980), and E-SERVQUAL (Parasuraman et al., 2005). Nonetheless, these models were created prior to AI and need to be expanded to support the more complex dynamics brought about by AI personalization, predictive analytics, and automated service delivery (Kamal and Himel, 2023).

Empirical studies have recently started to investigate these dynamics. In a survey of Egyptian e-commerce customers, Hassan et al. (2025) proved that trust has a strong positive impact on either satisfaction or loyalty, and the level of personalization of AI chatbots mediates the relationships between the two. Equally, Hallikainen et al. (2022) in an online grocery setting, in Finland, demonstrated that individualized price-reductions are more effective in dampening the negative effects of cognitive effort on customer loyalty than are product-recommendations. These results highlight the intricacy of AI-mediated consumer experiences and situational specificity of their outcomes. Nevertheless, both studies do not cover the particular set of antecedents which act in a developing-country setting with its own set of cultural norms, limitations of a technological infrastructure, and consumer demands.

The current study fills this gap by discussing the motivation of customer satisfaction and loyalty in view of users of AI-driven e-commerce platforms in Karachi, Pakistan. Based on TAM, ECT, Relationship Marketing Theory and Social Cognitive Theory, the research formulates and

evaluates a broad model that includes Trust, Perceived Usefulness, Service Quality, Perceived Enjoyment and Perceived personalization as antecedents of Customer Satisfaction, subsequently predicting Customer Loyalty. The contribution of Personalized Price Promotions (PPP) to the Satisfaction-Loyalty relationship is also discussed. The analytical method used is PLS-SEM because it is appropriate to develop a theory, works with small-to-medium sample sizes, and allows complex reflective models (Hair et al., 2019).

Problem Statement

Although the use of AI in e-commerce in Pakistan is rapidly increasing, there is an essential knowledge gap in terms of psychological and technological factors that determine customer satisfaction and loyalty in the context of e-commerce. Current literature is mainly based on the Western or East Asian setting (Hassan et al., 2025; Hallikainen et al., 2022; Zhang et al., 2011), with the Pakistani consumer experience remaining unexplored. This does not assume that the results of high-income economies that have established digital infrastructure and high levels of consumer trust in online transactions will also apply to a developing economy like Pakistan with low levels of digital literacy, inefficient consumer protection systems, and culturally specific attitudes towards privacy and technology.

Moreover, although such individual constructs as trust (Aslam et al., 2020), perceived usefulness (Davis, 1989), service quality (Parasuraman et al., 2005), and personalization (Hallikainen et al., 2022) have been examined separately, their combined impact on the integrated model, mediated by customer satisfaction and moderated by personalized price promotions. This is a major theoretical gap that impedes the academic knowledge and managerial decision making.

Practically speaking, e-commerce managers in Pakistan are under increasing pressure to figure out what technological and psychological leverages are the most effective to retain consumers. Devoid of empirically-based understanding of the local context, strategic investments in AI capabilities, e.g. personalization engines and dynamic pricing, might end up being misaligned with real consumer requirements and expectations. This issue is directly mentioned in the current research as it presents solid empirical evidence conducted among the e-commerce consumers in Karachi.

Research Objectives

The primary objectives of this study are as follows:

1. To examine the impact of key antecedents on Customer Satisfaction in AI-based e-commerce.
2. To analyze the relationship between Customer Satisfaction and Customer Loyalty.
3. To investigate the direct effect of Personalized Price Promotions on Customer Loyalty.

4. To examine the moderating role of Personalized Price Promotions between Customer Satisfaction and Customer Loyalty

Research Questions

In line with the stated objectives, this study seeks to answer the following research questions:

1. How do Trust, Perceived Usefulness, Service Quality, Perceived Enjoyment, and Perceived Personalization influence Customer Satisfaction in AI-based e-commerce platforms in Karachi?
2. Does Customer Satisfaction significantly affect Customer Loyalty in AI-driven e-commerce?
3. Do Personalized Price Promotions have a direct impact on Customer Loyalty?
4. Does Personalized Price Promotions moderate the relationship between Customer Satisfaction and Customer Loyalty?

Research Gap

The evaluation of the available literature shows that there are a number of significant gaps in research which are filled by the given study. First, most empirical studies on AI-driven e-commerce consumer behavior have focused on high-income economies (Hassan et al., 2025; Hallikainen et al., 2022; Zhang et al., 2011), and there is very little focus on the context of developing countries where the AI infrastructure is still emerging, and consumer trust in online purchases is yet to be developed. Second, although the individual constructs of trust, service quality and personalization have been researched, not many studies have investigated all five antecedents together in a coherent model through customer satisfaction and even moderated by personalized price promotions. Third, the contribution of perceived enjoyment, a hedonic construct, and the utilitarian constructs to predicting satisfaction has been under researched in the Pakistani digital retail setting.

Significance of the Study

Even though the amount of research on how artificial intelligence (AI) affects e-commerce is increasing, there are still a number of areas that require further investigation. First off, the majority of the material that is currently accessible comes from developed nations and depicts consumer behavior in highly educated, trusted, and technologically advanced civilizations (Chen et al., 2022; Zhou et al., 2022). As a result, these empirical research' findings cannot be applied to developing nations like Pakistan, where there are still significant cultural, economic, and technological hurdles (Akhtar et al., 2023; Sadiq et al., 2023). Second, most of the trials that have been carried out do not take into account how comprehensive the study's central idea—customer satisfaction—is. The majority of researchers have concentrated on examining how customer happiness is impacted by trust, service quality, and the perceived utility of AI (Pillarisetty &

Mishra, 2022; Tulcanaza-Prieto et al., 2023). Furthermore, little study has been done on how fun and customized services affect customer satisfaction in underdeveloped nations (Ifekanandu et al., 2023; Lopes et al., 2024). Thirdly, despite the fact that price promotions are essential to any marketing strategy, little is known about their dual mediation as a moderating variable influencing the relationship between satisfaction and loyalty and an independent variable predicting customer loyalty (Celestin et al., 2024; Mandagie & Kristaung, 2025; Raji et al., 2024). By creating a structural model that takes into account several antecedents of consumer happiness and moderating elements of satisfaction–loyalty association—specifically, personalized pricing promotions—this work seeks to close these research gaps.

Literature Review

AI-Driven E-Commerce: An Overview

AI has infiltrated all aspects of e-commerce, including product discovery and recommendation, customer service, fraud detection, and dynamic pricing (Guha et al., 2021). Recommendation systems (commonly referred to as recommendation agents) are AI-based tools that process large volumes of consumer behavior and purchase history data, alongside other contextual indicators, to provide personalized product recommendations, which are likely to match personal preferences and purchase intentions (Xiao and Benbasat, 2007; Necula and Pavlovaia, 2023). These systems have been attributed to enhance the efficiency of online product discovery radically, lessening the mental effort, and boosting the conversion rates (Zhang et al., 2011).

Another notable form of AI in online shopping is chatbots and virtual assistants, which offer 24/7 customer services, respond to inquiries, take in complaints, and lead buyers through their shopping process (Chen et al., 2023). It has been shown that AI chatbots can increase customer satisfaction when they are socially present, provide the right information, and empathetically respond to consumer concerns (Hassan et al., 2025; Cheng and Jiang, 2022). Predictive analytics and dynamic pricing algorithms are another aspect of AI use since they allow platforms to optimize their pricing decisions in-the-moment based on demand indicators, competitor prices, and each individual consumer willingness to pay (Seele et al., 2021; Hallikainen et al., 2022).

Big players like Daraz, which belong to Alibaba, have implemented advanced AI solutions to recommend products, gauge seller performance, and streamline buyer experience (Pakistan Telecommunication Authority, 2024). Nonetheless, the depth and efficiency of these AI systems in influencing customer satisfaction and loyalty within Pakistani setting is less explored, which inspires the current research.

Trust and Customer Satisfaction

The concept of trust plays a key role in e-commerce consumer behavior study. Trust is defined as the perception of the consumer that the platform will fulfill its promises, safeguard their personal information, and operate fairly (Stewart and Gosain, 2006; Komiak and Benbasat, 2006), trust eliminates the perceived risk involved in online transactions and will lead to acceptance of the

platform. Several empirical investigations validate the importance of trust as a strong positive predictor of customer satisfaction on the Internet (Aslam et al., 2020; Hassan et al., 2025). Trust in the AI-driven environment goes beyond institutional reliability to include trust in AI systems themselves what scholars refer to as AI trust or algorithm trust (de Fine Licht and de Fine Licht, 2020). Positive assessments of shopping experience are more probable among consumers who believe that AI systems are precise, clear, and helpful (Ameen et al., 2021). On the other hand, AI decision-making can lead to a loss of trust and lack of satisfaction even when the performance of the platform is actually good, due to a lack of transparency (so-called black box) (de Fine Licht & de Fine Licht, 2020). The current research operationalizes trust based on four items that measure perceived reliability, integrity, openness, and product delivery fidelity based on Hassan et al. (2025) and Komiak and Benbasat (2006).

Based on the foregoing, the study hypothesizes:

H1: Trust has a significant positive effect on Customer Satisfaction in AI-driven e-commerce platforms in Karachi, Pakistan.

Perceived Usefulness and Customer Satisfaction

One of the key constructs of TAM, Perceived Usefulness (Davis, 1989) indicates the faith of the consumer that the utilization of a platform will make shopping more efficient, help make better buying decisions, and provide tangible functional advantages. Regarding the e-commerce environment, applications that are highly beneficial in terms of using AI to simplify product discovery, streamline the checkout process, and provide relevant recommendations are seen as more helpful, which might make them more satisfying (Zhang et al., 2011; Xiao and Benbasat, 2018). As Kamal and Himel (2023) show, an AI-enhanced personalization, when perceived to be functional instead of as a mere ornament, leads to a significant increase in consumer satisfaction in the digital retail setting. Studies conducted in the Pakistani setting indicate that perspectives helpfulness may be of particular importance with the rather limited time resources at the disposal of consumers and the great cognitive load of using complicated e-commerce websites of a digital market that are yet to become an established trend (Sharma and Sharma, 2019). When the platforms are successful in decreasing the effort needed in the search of desired items and the process of transactions, they provide the perceived utilitarian value that will be converted into satisfaction.

H2: Perceived Usefulness has a significant positive effect on Customer Satisfaction.

Service Quality and Customer Satisfaction

An established antecedent of customer satisfaction in both offline and online retail environment is service quality, which is operationalized using the E-SERVQUAL dimensions of reliability, responsiveness, assurance, and customer service (Parasuraman et al., 2005; Pekovic and Rolland, 2020). The service quality in AI-based e-commerce includes the reliability of platform operation (uptime, accuracy of payment processing), the responsiveness of AI-driven customer service

agents, the accuracy and timeliness of customer service agents in fulfilling orders, and the professionalism of human customer service agents in situations when complex queries have to be escalated by the AI systems (Chen et al., 2023). As shown by Malhotra and Kharub (2025), AI-based logistics and customer service functions are known to considerably boost perceived service quality and, as a result, satisfaction in e-commerce platforms. Likewise, Hassan et al. (2025) conclude that the dimensions of service quality mediated by AI-based chatbot personalization have a positive impact on satisfaction. With the Pakistani situation where the order fulfillment delays and product authenticity issues continue to be a thorn in the flesh of the e-commerce sites, service quality is bound to have a particularly strong influence on satisfaction.

H3: Service Quality has a significant positive effect on Customer Satisfaction.

Perceived Enjoyment and Customer Satisfaction

Perceived Enjoyment- the extent to which the experience of using an e-commerce site is seen as either enjoyable and intrinsically motivating, is the hedonic component of consumer consideration (Davis et al., 1992). Hedonic motivations especially apply to AI-based platforms, which include gamification features, visually appealing interfaces, interactive product visualization, and amusing AI chatbot conversations (Tyrvaenen et al., 2020). The scientific community has repeatedly shown that hedonic value is a substantial addition to satisfaction when it comes to utilitarian factors, especially in a usage scenario that is marked by the extensive browsing and experience-based consumption (Liu-Thompkins et al., 2022). The Pakistani e-commerce environment has seen websites like Daraz integrate entertainment-based functionalities like flash sales, games and interactive promotional activities during major shopping events (e.g., 11.11 sale). All these are meant to add to the perceived fun and, with increased satisfaction, create loyalty. The current research includes perceived enjoyment as a customer satisfaction antecedent similar to the flow theory (Csikszentmihalyi, 1990) and hedonic motivation theory (Davis et al., 1992).

H4: Perceived Enjoyment has a significant positive effect on Customer Satisfaction.

Perceived Personalization and Customer Satisfaction

One of the most widely researched sources of satisfaction and loyalty in e-commerce is personalization, or customization of products, content and purchase experiences, based on behavioral data (Chellappa & Sin, 2005). Recommendation agents that are powered by AI interpret purchase history, browsing data, and demographics to provide personalized product recommendations that suit the consumer requirements (Necula and Pavlovoaia, 2023; Zhang et al., 2011). In the event that consumers feel that such recommendations are truly their preference- a state of perceived personalization- they are likely to experience less cognitive work and more satisfaction (Komiak and Benbasat, 2006; Xiao and Benbasat, 2018). Nevertheless, personalization and satisfaction do not always have a positive association. Hallikainen et al. (2022) conclude that the effect of personalized product recommendations on the cognitive effort-loyalty relationship in online groceryshopping is not significant, indicating that it is context

specific. Moreover, in the case of AI-mediated personalization, a feeling of reactance and dissatisfaction can be triggered when consumers feel that they are being intruded upon, their preferences are treated as data points, or the personalization is the result of an opaque algorithmic process (Ameen et al., 2022). This vagueness prompts the introduction of the perceived personalization as a research construct and is justified to be empirically explored in the Karachi context.

H5: Perceived Personalization has a significant positive effect on Customer Satisfaction.

Customer Satisfaction and Customer Loyalty

Customer satisfaction is generally considered to be one of the strongest and theoretically-based forecasts of customer loyalty in both store and online retail settings (Oliver, 1999; Liu-Thompkins et al., 2022). Happy customers will be more prone to behavioural (repeat purchase, buy more), and attitudinal (positive word-of-mouth, preference of the platform to competitors) loyalty (Watson et al., 2015; Dick and Basu, 1994). The satisfaction-loyalty relationship in the e-commerce arena has been validated in various cultural and geographic settings (Khan et al., 2022; Faraoni et al., 2019).

Within the context of AI promotion of interactions, satisfaction with AI-mediated interactions, such as chatbot service, personalized recommendations, and automated order processing, contributes to loyalty via the expectancy-confirmation mechanism: the higher the expectations of the consumers are met or surpassed by AI-mediated interaction, the more satisfaction is generated, thus solidifying the commitment to the platform (Hassan et al., 2025; Bhattachar The current research assumes that customer satisfaction is the most important mediator in the model wherein the antecedent perceptions are correlated to the loyalty outcomes.

H6: Customer Satisfaction has a significant positive effect on Customer Loyalty.

Personalized Price Promotions: Direct Effects and Moderation

A potent way in which AI-based platforms can increase customer loyalty is personalized price promotions (PPP), which is described as a discount, voucher, or other promotional offers personalized algorithmically based on individual consumer buying history and preferences (Hallikainen et al., 2022; Seele et al., 2021). In contrast to generic promotions, customized price incentives convey actual economic value that is accurately adjusted to individual consumer tastes, increasing the perceived value and decreasing switching incentives (Martin et al., 2009). Hallikainen et al. (2022) show how personalized price promotion, but not personalized product recommendation, is effective in reducing the negative effect of cognitive effort on customer loyalty when buying online groceries.

The moderating hypothesis will assume that high levels of PPP will increase the positive relationship between customer satisfaction and loyalty by providing an extrinsic incentive layer to support intrinsic satisfaction-based loyalty intentions. Nonetheless, studies also indicate that in

situations where personalized pricing is perceived as discriminatory or unfair, it can negatively impact on trust and suppress the satisfaction-loyalty channel (Haws and Bearden, 2006; Hinz et al., 2011). The framework and degree to which PPP moderates the situation in e-commerce in Pakistan is therefore an empirical question of some practical importance.

H7: Personalized Price Promotions have a significant positive direct effect on Customer Loyalty.

H8: Personalized Price Promotions moderate the Customer Satisfaction–Customer Loyalty relationship, such that higher PPP strengthens this relationship.

Research Methodology

Population, Sampling, and Data Collection

The target population is adult people (18 years old and above) living in Karachi, Pakistan, who have used at least one e-commerce platform powered by AI (Daraz, Foodpanda, Naheed, or similar) at least once within the six months before the survey. The study location was chosen to be Karachi, which is the biggest commercial centre in Pakistan and it has the highest proportion of e-commerce transactions in Pakistan.

A purposive sampling methodology was used to make sure that the respondents had a pertinent experience with AI-based e-commerce systems. The method is in line with the previous studies in the area (Hassan et al., 2025) and fits the situation when the study needs to examine a population that has particular traits, in this case, active e-commerce users. The data were gathered via online structured questionnaire via Google Forms during a period of four weeks in the early part of 2025. The survey link was shared via university contacts, social media (WhatsApp, Facebook, LinkedIn) and professional contacts within the business community of Karachi. Response bias was minimized by ensuring that the study purpose was clarified to the respondents, and that the respondents remained completely anonymous.

One hundred and twenty questionnaires were received. A total of 12 respondents were screened out due to incompleteness and straight-lines, resulting in a final usable sample of 100 respondents. This is a reasonable size, as ten times the maximum number of arrows to any construct in the model is the minimum needed to estimate PLS-SEM (Hair et al., 2019), and it is within the range of other studies with similar designs (Hassan et al., 2025).

Questionnaire Design and Scale Description

The questionnaire was divided into two parts. Section A included demographic data (gender, age, level of education, occupation, frequency of shopping, and platform of choice). Section B included 32 Likert-scale items addressing the eight constructs of theory on a 5-point scale of 1 (Strongly Disagree) to 5 (Strongly Agree).

All scales used in measurement were carefully-validated scales published in peer-reviewed journals:

Trust: Four items modified based on Hassan et al. (2025) and Komiak and Benbasat (2006) to measure the perceived reliability, data protection, transparency, and delivery fidelity.

Perceived Usefulness: Four questions based on the original TAM scale developed by Davis (1989), which included ease of shopping, efficiency, support of decision making and overall utility.

Service Quality: Four questions based on the Parasuraman et al. (2005) E-SERVQUAL items (query responsiveness, platform reliability, quality of customer service, and delivery efficiency) were adapted.

Perceived Enjoyment: Items based on Davis et al. (1992), and flow theory (Csikszentmihalyi, 1990), and which measure enjoyment, entertainment value, happiness and overall pleasantness.

Perceived Personalization: 4 items based on Hallikainen et al. (2022) and Xiao and Benbasat (2018), which consider preference matching, provide tailoring, content relevance, and engagement.

Customer Satisfaction: Fang et al. (2014) and Hassan et al. (2025) include four items that evaluate satisfaction overall, expectation fulfillment, pleasantness of experience, and quality of decision.

Customer Loyalty: Four questions modified after Harris and Goode (2004) and Hassan et al. (2025), which reflect the repurchase intention, willingness to recommend, platform preference, and emotional attachment.

Individualized Price Promotions: Four items based on Hallikainen et al. (2022), which gauge receipt of interest-matched price cuts, customization, the impact of promotion on purchase intentions, and relevance.

Pilot Testing and Refinement

The questionnaire was reviewed in two phases before the actual data collection phase. The draft instrument was first examined by three subject matter experts, who were two academics focusing on e-commerce and consumer behavior, and one e-commerce industry practitioner, located in Karachi. Their comments were used to adjust the wording of items to be more understandable and culturally suitable. In particular, the Service Quality scale included two items that have been reformulated to better fit the context of the Pakistani platform (e.g., the references to websites have been replaced by references to platforms/apps).

The second stage involved carrying out a pilot study on 20 active e-commerce users in Karachi that were not in the actual sample. All constructs had Cronbach alpha coefficients that surpassed 0.80 in the pilot testing, which is a satisfactory internal consistency. Subtle modifications were made on the basis of the feedback on the ambiguity of the items, which resulted in the final 32-item tool used in the primary study.

Analytical Strategy: PLS-SEM

As the key analytical method, the partial least squares Structural Equation Modeling (PLS-SEM), which was performed with the help of SmartPLS 4.0 (Ringle et al., 2024) was chosen due to a number of reasons. First, PLS-SEM is especially appropriate in studies aiming at the development and extension of theories, in which the research purpose is not to test a theoretically predetermined model but to explain and predict the endogenous constructs (Hair et al., 2019). Second, PLS-SEM is suitable when the sample size ($n \geq 100$) is small-to-medium and does not assume the multivariate normality, which makes it suited to the current sample of 100 respondents (Ringle et al., 2024). Third, PLS-SEM works well with more complex models that have more than one construct and a direct or moderating relationship (Hair et al., 2019).

The analysis was performed according to the two steps suggested by Anderson and Gerbing (1988) and implemented in recent PLS-SEM studies (Hassan et al., 2025; Hallikainen et al., 2022). Stage 1 involved measuring the measurement model to test construct reliability and validity using composite reliability, Cronbach alpha, average variance extracted (AVE), and discriminant validity (Fornell-Larcker criterion and HTMT ratio). During Stage 2, the structural model was tested using path coefficients, t-statistics, p-values, effect sizes (f^2), R^2 values, Q^2 (predictive relevance) and SRMR (model fit). To produce path coefficient confidence intervals and test indirect (mediation) effects, bootstrapping was used (with 5,000 subsamples).

The product indicator method was used as a moderation analysis (Hair et al., 2019), making the interaction term ($PPP \times CS$) by multiplying the standardized scores of PPP and CS. All constructs were theorized as reflective, which was consistent with their being specified theoretically (every item can be an interchangeable manifestation of their respective latent variables).

Ethical Considerations

This paper has followed strict ethical principles in the course of the research. They were all given a clear explanation of the purpose of the study, that their participation was voluntary and that they have the right to withdraw any time without the consequence. The informed consent was taken online at the outset of the online survey. All the answers were anonymous- no information that could be used to identify a person was gathered. Printed data were kept in a secured institutional server which was a password-protected server, which could only be accessed by the research team. The institutional authority in Shah Abdul Latif University, Khairpur reviewed and approved the research protocol.

Results

Descriptive Statistics and Demographic Profile

One hundred usable responses were finally acquired to be analyzed. Table 1 gives the demographic picture of the respondents. The sample was also mostly male (56%) with females taking 44%. The largest age cohort was 18–25 years (42%), followed by 26–35 years (31%),

36–45 years (18%), and 46 and above (9%). The education background was varied: 35% had undergraduate degrees, 48% graduate degrees, and 17% postgraduate degrees. Regarding occupation, 28% belonged to students, 45% to employed professionals, 19% business owners and 8% others. Almost fifty percent of the respondents (48%) were regular online shoppers, 38% were occasional and 14% were rarely shoppers. The most preferred platform (51%), Foodpanda (22%), Naheed (14%), and other platforms (13%). All these attributes portray the urban, digitally literate, and comparatively educated consumer profile that characterises the active e-commerce consumer base in Karachi.

Table 1 Demographic Profile of Respondents (N = 100)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	56	56.0
	Female	44	44.0
Age	18–25	42	42.0
	26–35	31	31.0
	36–45	18	18.0
	46+	9	9.0
Education Level	Undergraduate	35	35.0
	Graduate	48	48.0
	Postgraduate	17	17.0
Occupation	Student	28	28.0
	Employed	45	45.0
	Business Owner	19	19.0
	Other	8	8.0
Shopping Frequency	Rarely	14	14.0
	Occasionally	38	38.0
	Frequently	48	48.0
Preferred Platform	Daraz	51	51.0
	Foodpanda	22	22.0
	Naheed	14	14.0
	Others	13	13.0

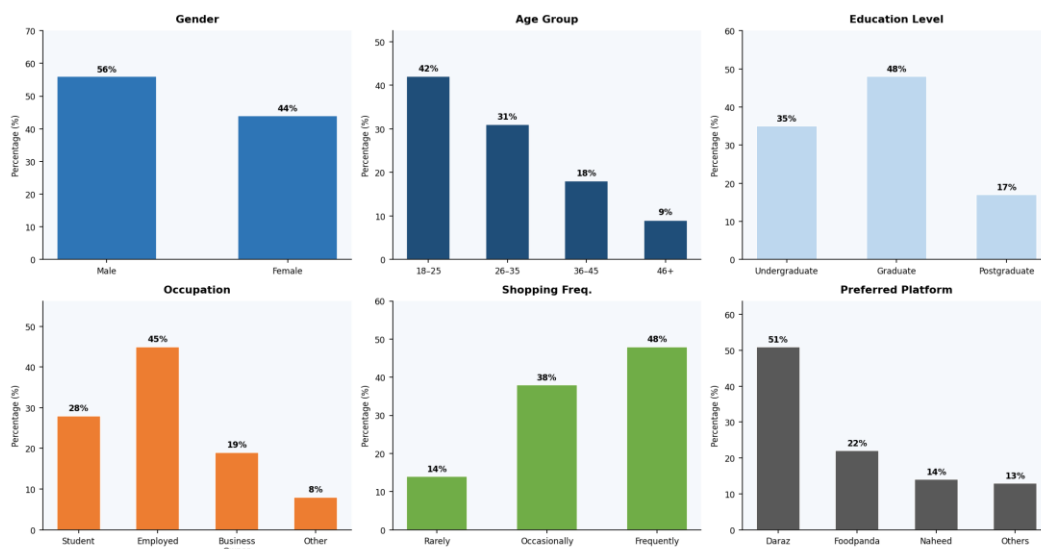
Note. Values represent frequency counts and corresponding percentages of the total sample (N = 100)

Measurement Model Assessment

Construct Reliability and Convergent Validity

In accordance with the conventional practice of PLS-SEM (Hair et al., 2019), internal consistency reliability and convergent validity of the measurement model were evaluated. Cronbach α (0.70) values of the eight constructs (see Table 2) were above the suggested alpha of 0.70, with a value of 0.902 (Perceived Enjoyment) at the lowest end to 0.968 (Personalized Price Promotions), which is

a very good indicator of internal consistency. The composite reliability (ρ_c) values (0.932 to 0.976) are considered to be better than those of Cronbach alpha when dealing with a reflective construct (Hair et al., 2019), so they are all significantly higher than the 0.70 mark. The values of the Average Variance Extracted (AVE) were between 0.773 (Perceived Enjoyment) and 0.912 (Personalized Price Promotions), which are greater than the recommended 0.50, which confirms convergent validity of all constructs (Fornell and Larcker, 1981).



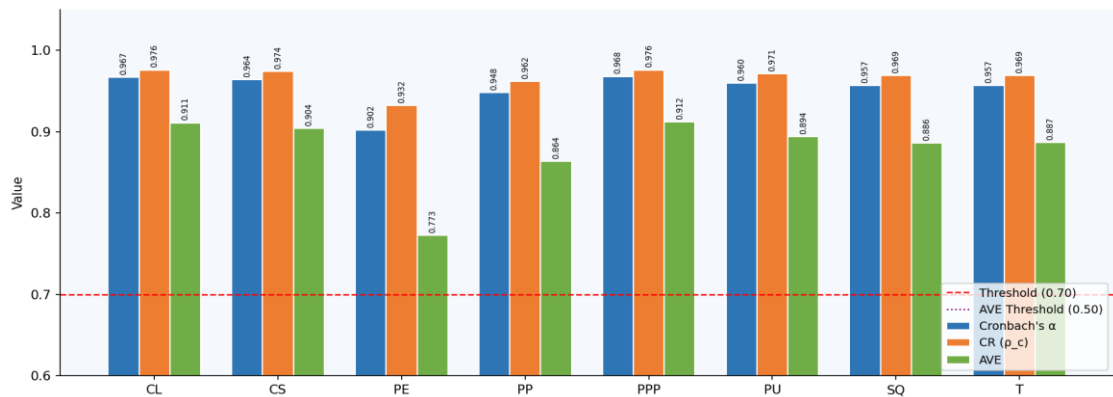
Note. Six sub-charts display frequency distributions (%) for gender, age, education, occupation, shopping frequency, and preferred platform. Source: Primary data

Figure 1 Demographic Profile of Respondents (N=100)

Table 2 Construct Reliability and Validity

Construct	Cronbach's α	ρ_a	CR(ρ_c)	AVE	Items
Customer Loyalty (CL)	0.967	0.968	0.976	0.911	4
Customer Satisfaction (CS)	0.964	0.965	0.974	0.904	4
Perceived Enjoyment (PE)	0.902	0.904	0.932	0.773	4
Perceived Personalization (PP)	0.948	0.950	0.962	0.864	4
Pers. Price Promotions (PPP)	0.968	0.968	0.976	0.912	4
Perceived Usefulness (PU)	0.960	0.962	0.971	0.894	4
Service Quality (SQ)	0.957	0.957	0.969	0.886	4
Trust (T)	0.957	0.958	0.969	0.887	4

Note. CA = Cronbach's Alpha; ρ_a = Rho_A (alternative composite reliability); CR = Composite Reliability (ρ_c); AVE = Average Variance Extracted. All values meet the recommended thresholds (CA > 0.70; CR > 0.70; AVE > 0.50).



Note. Grouped bar chart comparing Cronbach's α , Composite Reliability (CR), and Average Variance Extracted (AVE) for all eight constructs. Red dashed line = minimum threshold of 0.70 (CA, CR); purple dotted line = AVE threshold of 0.50

Figure 2 Construct Reliability and Validity (Cronbach's Alpha,CR,AVE)

Outer Loadings

Table 3 shows the outer loadings of all the indicator items. The loading of all the 32 items was above the recommended threshold of 0.70 (Hair et al., 2019), with scores between 0.869 (PE4) and 0.973 (CL3). These large loadings confirm the fact that all the indicators are reliable assessments of their latent constructs. None of the items were dropped, and all the loadings were of quality. The unidimensionality of each construct is also affirmed by the pattern of loadings since items were mostly loaded on their target construct.

Table 3 Table 3Outer Loadings of Indicator Items

Construct	Item	Loading	Outer VIF	Decision
Customer Loyalty	CL1	0.965	—	Retained
	CL2	0.941	—	Retained
	CL3	0.973	—	Retained
	CL4	0.938	—	Retained
Customer Satisfaction	CS1	0.924	—	Retained
	CS2	0.964	—	Retained
	CS3	0.952	—	Retained
	CS4	0.962	—	Retained
Perceived Enjoyment	PE1	0.879	—	Retained
	PE2	0.889	—	Retained
	PE3	0.880	—	Retained
	PE4	0.869	—	Retained
Perceived Personalization	PP1	0.922	—	Retained
	PP2	0.932	—	Retained
	PP3	0.940	—	Retained

Pers. Price Promotions	PP4	0.925	—	Retained
	PPP1	0.958	—	Retained
	PPP2	0.959	—	Retained
	PPP3	0.944	—	Retained
Perceived Usefulness	PPP4	0.958	—	Retained
	PU1	0.964	—	Retained
	PU2	0.929	—	Retained
	PU3	0.951	—	Retained
Service Quality	PU4	0.938	—	Retained
	SQ1	0.935	—	Retained
	SQ2	0.948	—	Retained
	SQ3	0.943	—	Retained
Trust	SQ4	0.939	—	Retained
	T1	0.947	—	Retained
	T2	0.931	—	Retained
	T3	0.959	—	Retained
	T4	0.930	—	Retained

Note. CL = Customer Loyalty; CS = Customer Satisfaction; PE = Perceived Enjoyment; PP = Perceived Personalization; PPP = Personalized Price Promotions; PU = Perceived Usefulness; SQ = Service Quality; T = Trust. All loadings exceed the 0.70 threshold.

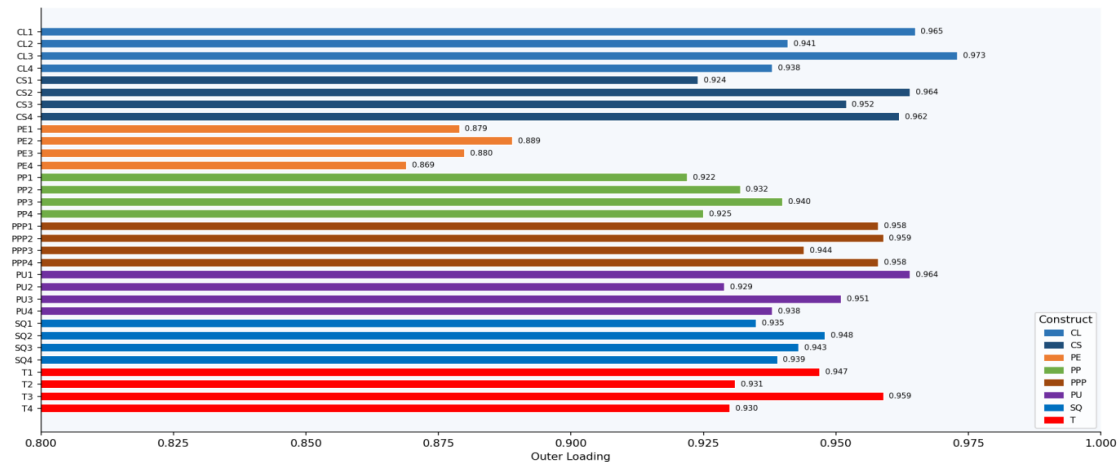


Figure 3 Outer Loading of All Indicator Items

Note. Horizontal bar chart displaying standardized outer loadings for all 32 indicator items grouped by construct. Red dashed line = minimum acceptable loading of 0.70

Discriminant Validity

Two criteria were used to determine discriminant validity: the Fornell-Larcker criterion (Fornell and Larcker, 1981) and the Heterotrait-Monotrait (HTMT) ratio (Henseler et al., 2015). Table 4 shows the two indicators. The Fornell-Larcker criterion is indicated when the square root of the AVE (diagonal values) of each construct is greater than the correlations of the construct with all the other constructs. As shown in Table 4, the square root of AVE (diagonal: CL = 0.955, CS = 0.951, PE = 0.879, PP = 0.930, PPP = 0.955, PU = 0.945, SQ = 0.942, T = 0.942) exceeds all inter-construct correlations, confirming discriminant validity. The HTMT ratios (values in parentheses in Table 4) vary between 0.661 (SQ-PPP) and 0.882 (PU-CS), which is below the conservative 0.90 index proposed by Henseler et al. (2015), which also confirms the presence of discriminant validity. These findings establish that each construct is an empirical phenomenon that is not overly overlapping with other constructs in the model.

Table 4: Table 4Discriminant Validity: Fornell-Larcker Criterion and HTMT Ratios

Construct	CL	CS	PE	PP	PPP	PU	SQ	T
CL	0.955							
CS	0.843 (0.814)	0.951						
PE	0.750 (0.801)	0.796 (0.852)	0.879					
PP	0.789 (0.823)	0.760 (0.793)	0.751 (0.809)	0.930				
PPP	0.831 (0.858)	0.831 (0.860)	0.748 (0.799)	0.715 (0.744)	0.955			
PU	0.817 (0.847)	0.850 (0.882)	0.773 (0.829)	0.760 (0.796)	0.739 (0.765)	0.945		
SQ	0.687 (0.714)	0.807 (0.839)	0.639 (0.686)	0.790 (0.831)	0.636 (0.661)	0.735 (0.766)	0.942	
T	0.760 (0.788)	0.814 (0.846)	0.763 (0.817)	0.672 (0.704)	0.773 (0.802)	0.756 (0.787)	0.669 (0.698)	0.942

Note. Diagonal elements represent the square root of AVE. Off-diagonal elements represent inter-construct correlations (Fornell-Larcker). Values in parentheses represent HTMT ratios. All HTMT values fall below the 0.90 threshold (Henseler et al., 2015).

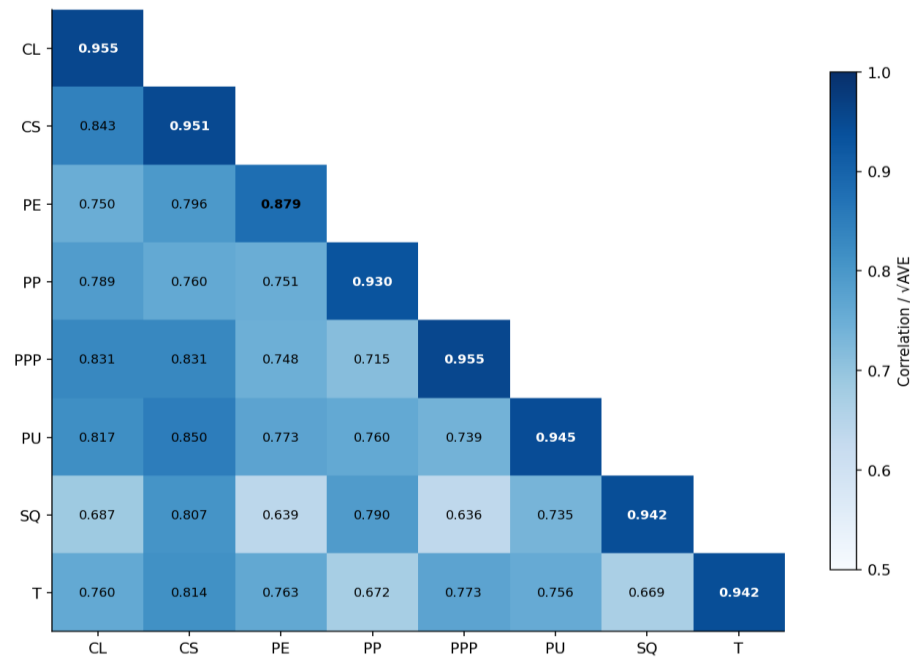


Figure 4: Discriminant Validity – Fornell-Larcker Criterion

Note. Heatmap of the lower-triangular correlation matrix. Diagonal elements (bold) represent the square root of AVE; off-diagonal elements are inter-construct correlations. Darker shading indicates stronger correlation.

Structural Model Assessment

Path Coefficients and Hypothesis Testing

PLS-SEM (with 5,000 bootstrap subsamples) was used to estimate the structural model to obtain t-statistics and p-values of path coefficients, as suggested by Hair et al. (2019). Table 5 shows path coefficients (β), sample means, standard deviation, t-statistics, p-values and hypothesis decisions of all the eight hypothesized relationships.

Table 5 Structural Model Path Coefficients

Hypothesis / Path	β	M	STDEV	t-stat	p-value	Decision
Direct Effects						
H1: Trust $\rightarrow$ Customer Satisfaction	0.241	0.249	0.087	2.767	0.006	Supported
H2: Perceived Usefulness $\rightarrow$ Customer Satisfaction	0.305	0.274	0.117	2.613	0.009	Supported
H3: Service Quality $\rightarrow$ Customer Satisfaction	0.328	0.333	0.119	2.747	0.006	Supported
H4: Perceived Enjoyment $\rightarrow$ Customer Satisfaction	0.198	0.165	0.096	2.063	0.039	Supported

Satisfaction							
H5: Perceived Personalization	→ Customer Satisfaction	-0.042	0.007	0.122	0.340	0.734	Not Supported
H6: Customer Satisfaction	→ Customer Loyalty	0.378	0.381	0.097	3.876	<.001	Supported
H7: Pers. Price Promotions	→ Customer Loyalty	0.495	0.490	0.115	4.319	<.001	Supported
Moderating Effect							
H8: PPP × CS	→ Customer Loyalty	-0.013	-0.012	0.026	0.520	0.603	Not Supported

Note. β = standardized path coefficient; M = bootstrap sample mean; $STDEV$ = bootstrap standard deviation; t -stat = t -statistic; p -value based on two-tailed bootstrapping with 5,000 subsamples. * $p < .05$; ** $p < .01$; *** $p < .001$. PPP = Personalized Price Promotions; CS = Customer Satisfaction; CL = Customer Loyalty.

Figure 5. Structural Model Path Coefficients

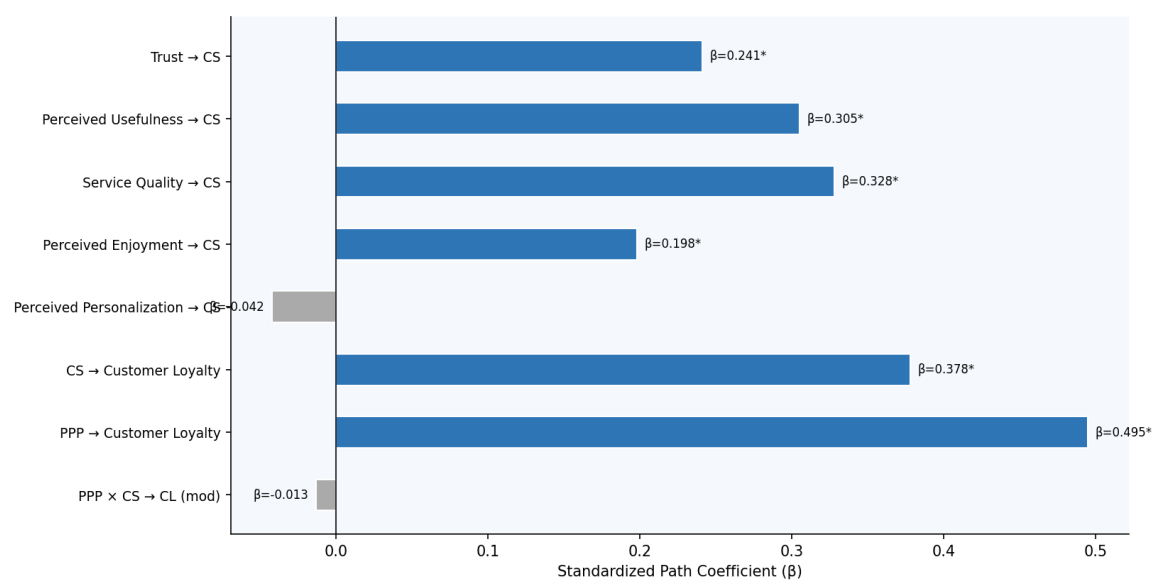


Figure 5 Structural Model Path Coefficients

Note. Horizontal bar chart of standardized path coefficients (β). Blue bars indicate statistically significant paths ($p < .05$); grey bars indicate non-significant paths. Asterisk (*) denotes significance

Looking on the direct effects, Customer Satisfaction is significantly predicted by Trust ($H1: \beta = 0.241$ and $t = 2.767$ and $p = .006$), which confirms the Hypothesis 1. Customer Satisfaction is being strongly positively impacted by Perceived Usefulness ($H2: \beta = 0.305$; $t = 2.613$; $p = .009$) as it supports Hypothesis 2. The strongest antecedent of Customer Satisfaction among the utilitarian

constructs is Service Quality (H3: $\beta = 0.328$, $t = 2.747$, $p = 0.006$) which supports Hypothesis 3. Customer Satisfaction is also significantly predicted by Perceived Enjoyment (H4: $\beta = 0.198$, $t = 2.063$, $p = .039$) which supports Hypothesis 4. However, surprisingly, Perceived Personalization (H5: $\beta = 0.042$, $t = -0.340$, $p = .734$) does not have a significant influence on Customer Satisfaction, which disproves Hypothesis 5.

In terms of the satisfaction loyalty pathway, Customer Satisfaction (H6: $\beta = 0.378$, $t = 3.876$, $p < .001$) is a significant predictor of Customer Loyalty, thus confirming Hypothesis 6. Hypothesis 7 was supported as the strongest direct predictor of Customer Loyalty in the model was Personalized Price Promotions (H7: $\beta = 0.495$, $t = 4.319$, $p < .001$). The PPP x CS interaction term (H8: $\beta = -0.013$, $t = 0.520$, $p = .603$) was not statistically significant, and thus PPP does not significantly moderate Customer Satisfaction Customer Loyalty relationship, not supporting Hypothesis 8.

Path Diagram

The path diagram of PLS-SEM with standardized path coefficients are shown in Figure 2. The graphical representation makes it obvious which relationships among constructs are of relatively high magnitude, and bold arrows show which of them are statistically significant.

Mediation Analysis

The mediating role of Customer Satisfaction in the relationships between the five antecedent constructs and Customer Loyalty was evaluated based on indirect effects estimated using bootstrapping (5,000 subsamples), as suggested by Hair et al. (2019) and Preacher and Hayes (2008). Table 6 shows the indirect effects with bias-corrected confidence intervals.

Table 6 Mediation Analysis Results: Indirect Effects via Customer Satisfaction

Indirect Path	B	STDEV	t-stat	p-value	95% CILL	95% CIUL
Trust → CS → Customer Loyalty	0.091	0.044	2.057	0.040	0.033	0.215
Perceived Usefulness → CS → Customer Loyalty	0.115	0.055	2.104	0.035	0.014	0.224
Service Quality → CS → Customer Loyalty	0.124	0.053	2.352	0.019	0.031	0.236
Perceived Enjoyment → CS → Customer Loyalty	0.075	0.042	1.767	0.077	-0.006	0.154
Perceived Personalization → CS → Customer Loyalty	-0.016	0.047	0.331	0.740	-0.085	0.095

Note. β = indirect path coefficient; STDEV = bootstrap standard deviation; t-stat = t-statistic; CI LL/UL = 95% confidence interval lower/upper limits (bias-corrected). Significant indirect effects (CI does not include zero) are in bold.

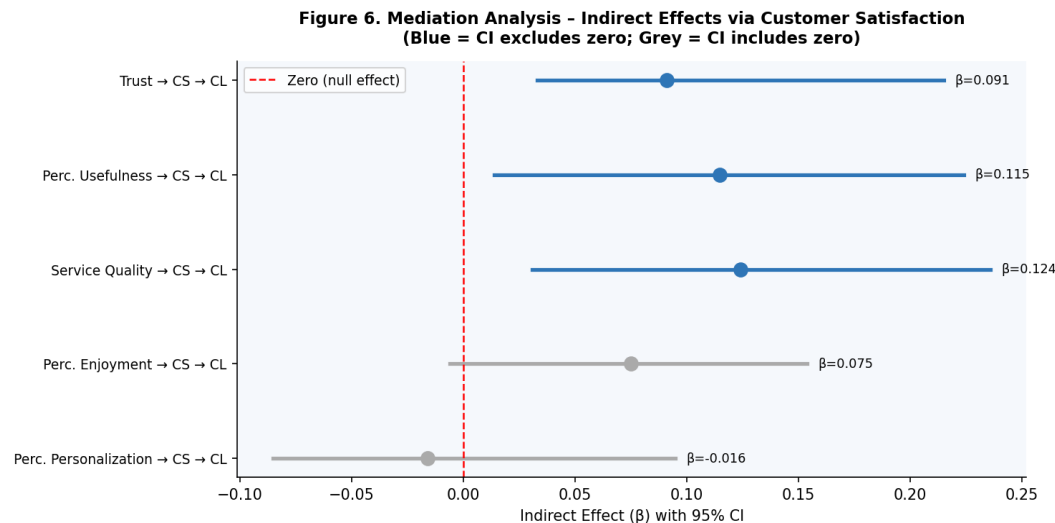


Figure 6: Mediation Analysis – Indirect Effects via Customer Satisfaction

Note. Forest plot of indirect path coefficients with 95% bias-corrected bootstrap confidence intervals (5,000 subsamples). Blue = confidence interval excludes zero (significant mediation); grey = CI includes zero (non-significant). Red dashed line = zero (null effect).

The mediation analysis reveals that Customer Satisfaction fully mediates the relationships of Trust ($\beta_{\text{indirect}} = 0.091$, $p = .040$, 95% CI [0.033, 0.215]), Perceived Usefulness ($\beta_{\text{indirect}} = 0.115$, $p = .035$, 95% CI [0.014, 0.224]), and Service Quality ($\beta_{\text{indirect}} = 0.124$, $p = .019$, 95% CI [0.031, 0.236]) with Customer Loyalty, as their confidence intervals exclude zero. The indirect relationship between Perceived Enjoyment and Customer Satisfaction and Customer Loyalty was almost significant ($\beta_{\text{indirect}} = 0.075$, $p = 0.77$, 95% CI = -0.006, 0.154) indicating a tendency that should be considered in larger-sample studies in the future. There was no significant indirect influence on Customer Loyalty via Customer Satisfaction with Perceived Personalization ($\beta_{\text{indirect}} = 0.016$, $p = .740$) in line with the non-significant direct influence of PP on CS.

Model Fit and Predictive Accuracy

Table 7 shows the model fit measures and predictive power measures. The model accounts for 84.6% of the variance in Customer Satisfaction ($R^2 = 0.846$, $R^2_{\text{adjusted}} = 0.837$) and 74.0% of the variance in Customer Loyalty ($R^2 = 0.740$, $R^2_{\text{adjusted}} = 0.732$). The effect size benchmarks of Cohen (1988) show that an R^2 above 0.26 is a significant value of explanatory power; therefore, the current findings show that the model has a high explanatory power. A Q^2 statistic which is a measure of predictive relevance, calculated by blindfolding by Stone-Geisser, gave 0.369 Customer Satisfaction and 0.196 Customer Loyalty, which are both significantly above zero, indicating that the model is predictively relevant (Hair et al., 2019).

Effects sizes (f^2) indicate that the Personalized Price Promotions have a large impact on Customer Loyalty ($f^2= 0.289$) and Customer Satisfaction has a medium-to-large impact ($f^2= 0.123$). The SRMR of 0.084 in the model that is lower than the recommended value of 0.10 (Henseler et al., 2016) suggests the satisfactory model fit. All these measures testify to the fact that the suggested model is both theoretically well-specified and empirically strong.

Table 7: Model Fit and Predictive Accuracy Metrics

Criterion	Value	Threshold
R^2 – Customer Satisfaction	0.846	≥ 0.26 (substantial)
R^2 Adjusted – Customer Satisfaction	0.837	≥ 0.26
R^2 – Customer Loyalty	0.740	≥ 0.26 (substantial)
R^2 Adjusted – Customer Loyalty	0.732	≥ 0.26
Q^2 (CS)	0.369	> 0 (predictive relevance)
Q^2 (CL)	0.196	> 0
f^2 (PPP $\rightarrow$ CL)	0.289	> 0.35 (large)
f^2 (CS $\rightarrow$ CL)	0.123	0.15–0.35 (medium)
SRMR	0.084	< 0.10

Note. R^2 = coefficient of determination; Q^2 = Stone-Geisser predictive relevance (blindfolding); f^2 = Cohen's effect size; SRMR = Standardized Root Mean Square Residual. Effect size benchmarks: $f^2 \geq 0.02$ (small), ≥ 0.15 (medium), ≥ 0.35 (large; Cohen, 1988).

Table 8 Summary of Hypothesis Testing Results

H#	Hypothesis	Result	Support
H1	Trust positively influences Customer Satisfaction	$\beta = 0.241, p = .006$	Supported
H2	Perceived Usefulness positively influences Customer Satisfaction	$\beta = 0.305, p = .009$	Supported
H3	Service Quality positively influences Customer Satisfaction	$\beta = 0.328, p = .006$	Supported
H4	Perceived Enjoyment positively influences Customer Satisfaction	$\beta = 0.198, p = .039$	Supported
H5	Perceived Personalization positively influences Customer Satisfaction	$\beta = -0.042, p = .734$	Not Supported
H6	Customer Satisfaction positively influences Customer Loyalty	$\beta = 0.378, p < .001$	Supported
H7	Personalized Price Promotions positively influence Customer Loyalty	$\beta = 0.495, p < .001$	Supported
H8	PPP moderates the CS–CL relationship	$\beta = -0.013, p = .603$	Not Supported

Note. H = Hypothesis number; β = standardized path coefficient. * $p < .05$; ** $p < .01$; *** $p < .001$.

Discussion

Trust and Customer Satisfaction (H1: Supported)

The fact that Trust is a significant predictor and positively correlated with Customer Satisfaction ($\beta = 0.241$, $p = .006$) is not a new discovery given the body of existing literature on trust in e-commerce consumer behavior (Aslam et al., 2020; Hassan et al., 2025; Soleimani, 2022). Trust, as a key psychological facilitator, in the context of Pakistani culture, where online shoppers are more worried about authenticity of the products, security of payments, and data privacy, serves as a mediating variable between the awareness of a platform and real satisfaction. Consumers who feel that a platform is trustworthy in making its offers, protects their personal data, and behaves in a transparent manner have a qualitatively different shopping experience with a lower level of anxiety and more confidence, which is expressed as satisfaction. This observation is in line with the Relationship Marketing Theory (Morgan and Hunt, 1994) which places trust as the prerequisite to the sustaining, rewarding customer-firm relationships. It is also closer to the explanation of the Social Presence Theory presented by Hassan et al. (2025): AI systems with trustful, reliable, and transparent behavior evoke a feeling of social presence that boosts user satisfaction. Trust, in terms of TAM, may be conceptualized as a dimension of Perceived Ease of Use: platforms that consumers trust, will lessen the cognitive effort to navigate, which then reduces friction and leads to increased satisfaction. The fact that Trust has a slightly smaller effect on satisfaction than that of Service Quality and Perceived Usefulness is an indication that although trust is a necessary condition of satisfaction, it is more of a threshold variable: in the absence of trust, satisfaction will be severely suppressed but in the presence of trust, functional performance is also necessary to produce high levels of satisfaction.

Perceived Usefulness and Customer Satisfaction (H2: Supported)

H2 ($\beta = 0.305$, $p = .009$) is confirmed, which highlights the persistence of the Perceived Usefulness construct of the TAM in determining consumer satisfaction in AI-driven e-commerce. In Karachi, e-commerce users who view the platform as having a significant positive impact on shopping efficiency (through correct AI suggestions, simplified checkout, and available product information) are much more satisfied. This result reiterates and generalizes the initial propositions of Davis (1989) to the AI-mediated commerce setting and is compatible with recent studies that reveal that perceived functional utility is a strong predictor of satisfaction in digital service settings (Kamal and Himel, 2023; Sharma and Sharma, 2019). A relatively high impact of Perceived Usefulness ($\beta = 0.305$) as compared to Trust ($\beta = 0.241$) indicates that Pakistani e-commerce customers consider the functional utility of platforms to a large extent when making satisfaction judgments. This could indicate the pragmatic nature of the Karachi consumer market, with a highly efficient and effective accomplishment of shopping activities being one of the main factors in platform assessment, considering the hectic urban living. The lesson to platform developers is obvious: an investment in AI functionality that has a real impact on increasing the efficiency of shopping (e.g., predictive search, one-click purchases, AI-generated product feeds) will pay off in consumer satisfaction.

Service Quality and Customer Satisfaction (H3: Supported)

Among the utilitarian constructs, Service Quality was the most statistically significant antecedent of Customer Satisfaction ($\beta = 0.328$, $p = .006$), which is unaffected by the e-SERVQUAL theory (Parasuraman et al., 2005) and other recent e-commerce studies (Malhotra and Kharub, 2025; Pekovic and Rolland With logistical issues (such as failure of last-mile delivery, product returns, and insufficient responsiveness of customer service) being persistent problems of the Pakistani e-commerce environment that its participants must overcome, the quality of service becomes a rather relevant determinant of satisfaction. Customers with a high level of platform reliability, AI and human customer service responsiveness, and order fulfillment are highly satisfied. This result has a significant contextual meaning: in markets with a mixed consistency in the delivery of service quality standards, the difference between service quality is great, and it is a particularly strong predictor of satisfaction. The satisfaction effect is increased when platforms are able to provide high-quality consistent service in a market context where failures are frequent. This reading is consistent with the Expectation-Confirmation Theory paradigm (Bhattacharjee, 2001): in a situation where the expectation of service quality by consumers has been adjusted to a rather low point, either confirming or disconfirming these expectations has a strong influence on the formation of satisfaction.

Perceived Enjoyment and Customer Satisfaction (H4: Supported)

The meaningful positive relationship between Perceived Enjoyment and Customer Satisfaction ($\beta = 0.198$, $p = .039$) validates the applicability of hedonic motivations in AI-driven e-commerce satisfaction and propounds TAMs hedonic dimension (Davis et al., 1992) to the Pakistani context. This result indicates that the experiential, entertainment-based elements of e-commerce: interactive, gamified, visually appealing interface, and entertaining interaction with AI chatbots have a significantly positive impact on consumer satisfaction, despite the fact that the utilitarian motives and the dominance of utilitarianism as the most significant factor in the developing-country market may be assumed. The relative low intensity of the pleasure effect when compared to service quality and perceived usefulness, however, indicates that one might expect a hierarchical effect: consumers will base their satisfaction assessment primarily on functional and reliability aspects of their platform experience (service quality, perceived usefulness), after which the contribution of hedonic enjoyment is incrementally valuable. This is aligned with the hierarchy of needs as applied by Maslow to consumer situations: the basic functional needs must be satisfied satisfactorily before the experiential and hedonic factors have a significant impact of increasing satisfaction. The business implication here is that platform managers must initially invest in the reliability of the service, and the usefulness of the functionality, and then devote substantial resources to the entertainment-related functionality.

Perceived Personalization and Customer Satisfaction (H5: Not Supported)

Surprisingly, Perceived Personalization was not a significant predictor of Customer Satisfaction ($\beta = -.042$, $p = .734$). One of the most theoretically interesting findings of the study is this null

finding and deserves discussion. Although the literature tends to assume that there is a positive relationship between personalization and satisfaction (Komiak and Benbasat, 2006; Xiao and Benbasat, 2018), there are a number of contextual and methodological reasons that may explain the inability to prove H5. To start with, consumer distrust in data collection methods might dampen the benefits of personalization in the Pakistani environment. A study by Ameen et al. (2022) indicates that consumers with a focus on privacy will experience a personalization-privacy paradox: even though AI-driven personalization can bring satisfaction, this advantage will be overridden by the feeling of being intruded upon or surveilled by the AI. In a country with limited regulations on data protection and limited awareness of the rights to consumer data, such as in Pakistan, issues related to the misuse of data can cause an ambivalence to personalization options that would otherwise be embraced in other areas. Second, the perceived personalization might not be achieved as a result of the actual quality of the personalization offered by platforms that are usually frequented in Karachi. Unless AI recommendation systems are skilled at capturing the preferences of people, which can happen due to the poor quality of the available data or the immaturity of the algorithm to understand the local market, the consumers might fail to feel any meaningful personalization despite the fact that such personalization is nominally available. Third, the negative but insignificant coefficient indicates a potential suppressive process: the more consumers perceive the level of personalization, the more they may be aware of the use of algorithms to control the shopping experience, which decreased the authenticity and spontaneity of the shopping experience and, consequently, suppressed the satisfaction to a minor extent. This conclusion aligns with the fact that in online grocery settings, personalized product recommendations have no significant effect on the cognitive effort-loyalty relationship (Hallikainen et al., 2022), and the fact that in online grocery settings, AI personalization may lead to negative effects in terms of satisfaction (Hassan et al., 2025).

Customer Satisfaction and Loyalty (H6: Supported)

One of the strongest and best-established relationships in the consumer behavior literature is verified by the significant positive impact of Customer Satisfaction on Customer Loyalty ($\beta = 0.378$, $p < .001$) (Oliver, 1999; Liu-Thompkins et al., 2022). Karachi-based consumers who expressed satisfaction with e-commerce will be much more likely to demonstrate the attitudinal loyalty (platform preference, willingness to recommend, emotional attachment) and the behavioral loyalty (repurchase intention, continued use). This result is similar to and generalizes the result of Hassan et al. (2025), who found that satisfaction partially mediates the trust-loyalty relationship in AI-driven e-commerce, and to the evidence presented by Khan et al. (2022), that satisfaction mediates the relationship between customer relationship management and loyalty in e-commerce. The mediation analysis also indicates that Customer Satisfaction is a complete mediating factor between the impact of Trust, Perceived Usefulness, and Service Quality on Customer Loyalty, and thus the antecedents impact the customer loyalty through their ability to create satisfaction as opposed to their direct effects on customer loyalty. The result has significant theoretical consequences to the consumer behavior model ordering: in AI-driven e-commerce, satisfaction is not only a result in itself but is the key psychological mediator that allows transforming functional and relational platform attributes into loyalty behaviors in the long run.

Personalized Price Promotions and Loyalty (H7: Supported)

Personalized Price Promotions was the only strong direct predictor of Customer Loyalty in the model ($\beta = 0.495$, $p < .001$) and had great effect size ($f^2 = 0.289$). This result is similar to the observation by Hallikainen et al. (2022) who found that personalized price promotion is more effective than product recommendations in mitigating negative effect of cognitive effort on customer loyalty in online retailing. The theoretical relevance of the discovery that algorithmically personalized pricing incentives have a strong positive impact on loyalty is not only theoretically relevant but also of practical importance in the Pakistani context, where price sensitivity is high, and consumers highly value discounts and promotional offers as a determinant of the platform choice (Pakistan Telecommunication Authority, 2024). The given outcome can be justified with the help of the theory of perceived value: customized price discounts will provide a real-life economic benefit that will decrease the cost-benefit analysis in favor of switching to other platforms. Consumers get both an economic incentive (lower prices) and a psychological one (the platform knows their preferences), and thus feel a two-fold motivation to stay loyal when they are offered customized discounts that are tuned to their purchase history and preferences. Moreover, in the behavioral economics view, personalized promotions take advantage of loss aversion: a consumer who sees a personalized offer as an exclusive and limited time offer might become fearful of switching platforms and lose the benefits of being targeted at.

Moderating Role of PPP (H8: Not Supported)

The moderate role of Personalized Price Promotions in the Customer Satisfaction-Loyalty relationship ($\beta = 0.013$, $p = 0.603$) is one of the findings which should be interpreted carefully. Although, PPP has a potent direct impact on loyalty, it does not seem to significantly increase or decrease the satisfaction-loyalty pathway. This implies that PPP and Customer Satisfaction are independent drivers of loyalty and not multiplicative. In other words, the generation of the effects of PPP loyalty does not depend on the degree of customer satisfaction and vice versa.

There are a number of possible explanations. To begin with, the limited sample size ($n = 100$) could have low statistical power to identify a moderate moderation effect. Second, the insignificant negative sign of the interaction coefficient indicates that at very high levels of PPP, the increment in loyalty brought by satisfaction might be slightly smaller—perhaps since it is at such high levels that PPP develops more extrinsically-driven form of loyalty, which is less tied to internal satisfaction conditions. This reading is consistent with the self-determination theory (Ryan and Deci, 2000), which theorizes that excessive extrinsic rewards will crowd out intrinsic motivation: when personalized discounting is the main factor influencing loyalty, satisfaction will cease to be a more decisive factor. Further studies on bigger samples are needed to retest this hypothesis and establish the hypothesis as a true null hypothesis or a lack of statistical power.

Theoretical Contributions

The research has a number of significant theoretical contributions to the research on AI-driven e-commerce consumer behavior. First, it applies the integrated application of TAM, ECT,

Relationship Marketing Theory, and E-SERVQUAL to the context of a developing country, Karachi, Pakistan, and shows that these theoretical frameworks can be used to explain a market with its own technological infrastructure, culture, and regulatory framework. The effective replication of the trust-satisfaction, perceived usefulness-satisfaction, service quality-satisfaction and enjoyment-satisfaction connections in cross cultural contexts makes the cross cultural validity of these theoretical propositions stronger. Second, the study expands the knowledge of personalization and satisfaction relationship through empirical evidence of context-dependency of this relationship. The non-significant and directionally negative impact of Perceived Personalization on Customer Satisfaction in the Pakistani setting, in contrast to the positive ones reported in the Western setting, presents the significance of taking data privacy issues, quality of algorithms, and cultural attitudes to AI into consideration during the operationalization of the impact of personalization. The discovery is part of the growing body of research on the personalization-privacy paradox (Ameen et al., 2022) and context-specificity of AI personalization impacts. Third, the paper adds to the increasing amount of research on Personalized Price Promotions as a customer retention tool in the context of AI-based e-commerce. The study contributes to the work of Hallikainen et al. (2022), as it uses the latter to apply a price-sensitive model of the developing-country setting and shows the independence of the loyalty impacts of PPP on the satisfaction-mediated-loyalty relationship ($f^2 = 0.289$). This result indicates that PPP might be executed via a different psychological process experienced value improvement and switching cost generation, instead of via the moderation of the affective state of satisfaction. Finally, the study's methodological contribution—the application of PLS-SEM with SmartPLS 4.0 to simultaneously evaluate a complex model with multiple antecedents, a mediator, and a moderator in a Pakistani e-commerce context—provides a methodological template for future quantitative research in this domain.

Practical Implications

Implications for E-Commerce Platform Managers

The results can be used by the managers of e-commerce platforms that are currently in operation in Karachi and, more generally, the emerging digital marketplace in Pakistan. Service Quality is the most significant predictor of satisfaction ($\beta = 0.328$), which is why the emphasis on the reliability of the platform, the effectiveness of order fulfillment, and both AI-mediated and human responsive customer service should be given priority. Minimizing the number of service failures, enhancing the accuracy and responsiveness of AI chatbots, and optimizing logistics processes should be the top priority of platform managers that can be invested in with the highest returns to consumer satisfaction improvement. The high positive direct impact of Personalized Price Promotions on Customer Loyalty ($\beta = 0.495$, $f^2 = 0.289$) is a good reason to invest in algorithmic in personalized pricing mechanisms. Pakistan-based e-commerce services need to build advanced data analytics to create personalized discounts, loyalty programs, and incentives based on individual purchasing history and behavioral patterns. Social platforms, such as Daraz, that are currently using some types of targeted promotions, need to make the personalization algorithms more sophisticated and accurate, to get the most out of the retention effects. The Trust

finding ($\beta = 0.241$) indicates the necessity of the explicit trust-building strategies, especially in the context of nascent digital consumer protection in Pakistan. Platform operators must establish transparent information policies, seek clear and informed permission to collect data, give transparent explanations of how AI-based recommendation systems operate (like the Google Why This Ad? feature), and invest in effective data security infrastructure. By making these investments, consumers are made aware that the platform is trustworthy and operates with integrity, which has a direct impact on satisfaction. The insignificance of the Perceived Personalization effect on Satisfaction warns of excess investment in the superficial personalization factors. Before encouraging personalization as a platform differentiator, managers are advised to make sure that personalization systems provide truly relevant and true recommendations. Incorrect or obtrusive personalization does not only fail to contribute to satisfaction but can even deactivate it catalyzing privacy concerns.

Implications for Policymakers and Platform Regulators

The results have implications on the regulatory environment of e-commerce in Pakistan. The importance of trust in determining consumer satisfaction implies a strong necessity in having effective consumer protection systems, such as enforceable data privacy laws, explicit guidelines on AI transparency in business use, and easily accessible redressal mechanisms of grievances. To increase consumer trust on a systemic level, policymakers need to speed up the adoption of the Personal Data Protection Bill and establish specific principles of the AI-based commercial use.

Additionally, the sensitivity to the price as seen in the high direct impact of PPP on loyalty underscores how the digital pricing practices, such as dynamic and personalized pricing, could increase or decrease consumer welfare. Regulators need to come up with a framework that would see personalized pricing done in a transparent manner, not unfairly discriminating against the various consumers, and not taking advantage of vulnerable populations. Digital literacy could also be boosted by public awareness efforts regarding the digital rights that consumers have and the role of AI in e-commerce, allowing them to interact with AIs more confidently.

Limitations and Future Research Directions

The current study has a number of limitations which can be used to interpret the findings and to inform future studies. First, the cross-sectional design does not allow making causal inferences and dynamic changes in consumer attitudes and behaviors over time. Research in the future needs to use longitudinal designs to monitor the development of satisfaction and loyalty as customers gain experience with AI-driven platforms and platforms develop greater AI capabilities. Second, the sample of 100 respondents, although sufficiently large to estimate PLS-SEM, is too small to statistically detect minor moderation effects and limits the extrapolation of the results to the larger Pakistani population. The future research must use larger and nationally representative samples that cover a wide geographical area and include smaller cities and rural areas where e-commerce penetration is increasing at high rates but consumer behavior can be quite different than in Karachi. Third, the authors have limited the study to one geographic area (Karachi) and a

convenience sample of digitally active and educated consumers, which could limit the applicability of the results to the heterogeneous consumer market in Pakistan. Further studies must use stratified sampling of various cities, education levels and income brackets to determine the heterogeneity of the satisfaction-loyalty model among consumer groups. Fourth, self-reported, perceptual measures, or measures that are prone to common method bias, were used to measure all constructs. Future research ought to be a triangulation of the perceptual data with objective behavioral data, including platform transaction data, app usage data, and the real purchase frequency, to offer a comprehensive, objective evaluation of the satisfaction-loyalty relationship. Fifth, the non-significant result of Perceived Personalization should be investigated further. The next generation of research ought to break down personalization into its individual dimensions- product recommendation accuracy, content personalization and communication personalization and analyze how these dimensions influence the level of satisfaction differently in the Pakistani setting. The mechanisms behind the null finding could also be informative through qualitative research that examines consumer attitudes towards AI personalization in Pakistan. Lastly, future studies ought to expand the model by including other constructs that may be beneficial to the Pakistani AI-based e-commerce environment such as perceived security risk, quality of mobile platform, social influence, and platform governance quality. Comparative studies of cross-cultural relationships in Pakistan and other developing countries (e.g., India, Bangladesh, Nigeria) may help to show to what degree the relationships in the model are universal, rather than culturally specific.

Conclusion

This research aimed to explore the customer satisfaction and loyalty factors on users of AI-based e-commerce sites in Karachi, Pakistan, a setting which, although of great economic and strategic significance, has not been fully addressed in the international literature on e-commerce. The study used a quantitative, cross-sectional research design and PLS-SEM data analysis model using SmartPLS 4.0 to test a composite model based on TAM, Expectation-Confirmation Theory, Relationship Marketing Theory, and E-SERVQUAL. The findings are strong empirical evidence of the propositions of the model. Four of the five antecedent constructs, including Trust, Perceived Usefulness, Service Quality, and Perceived Enjoyment, have significant and positive predictive capabilities of Customer Satisfaction with Service Quality as the strongest being ($\beta = 0.328$) followed by Perceived Usefulness ($\beta = 0.305$), Trust ($\beta = 0.241$), and Perceived Enjoyment ($\beta = 0.198$). The Perceived Personalization fails to play a significant role in predicting Customer Satisfaction in the Pakistani context, which is explained by the combination of privacy issues, the restriction of the quality of the algorithms, and the cultural peculiarities of the Pakistani online market.

Customer Loyalty, in its turn, is greatly predicted by Customer Satisfaction ($\beta = 0.378$), which serves as a full mediation of the influence of Trust, Perceived Usefulness, and Service Quality on the loyalty. Individualized Price Promotion turns out to be the strongest direct determinant of Customer Loyalty ($\beta = 0.495$, $f^2 = 0.289$), which is why individualized and data-driven pricing incentives are crucially important in promoting customer retention in the e-commerce market of

price-sensitive Pakistan. The mediation effect of PPP in satisfaction-loyalty relationship is not significant ($\beta = -0.013$), indicating that the two processes, namely, satisfaction-driven loyalty and promotion-driven loyalty are mostly independent. The model is found to have significant explanatory power, capturing 84.6% of the variance in Customer Satisfaction and 74.0% of the variance in Customer Loyalty and all reliability, validity and model fit measures are found to have met or surpassed recommended thresholds. These findings can attest to the theoretical consistency and empirical soundness of the model. The research makes theoretical contributions to study the process of personalization by applying the existing consumer behavior models to the context of AI-commerce in a developing country, identifying the context-specificity of the personalization effects, and progressing the knowledge of the loyalty-generating mechanism of PPP. In practice, the results advise e-commerce managers in Pakistan to focus on improving the quality of services, transparency of trust-building strategies, enhancement of functional utility using AI, and personalized pricing as the most efficient motivators to consumer satisfaction and retention. The findings highlight the significance of strong consumer protection systems, clear AI governance policies, and digital literacy policies to facilitate the sustainable growth of the e-commerce system in Pakistan to policymakers. As AI keeps realigning the lines of commercial interaction on a global level and in Pakistan, empirically based insights into the particular psychological and technological factors of consumer satisfaction and loyalty in this regard are invaluable to the advancement of scholarship and the application of practical judgment. This work makes a valuable contribution to this knowledge and forms a basis of future longitudinal, cross-cultural, and methodologically diverse studies of AI-oriented commerce in the developing world.

References

- Ameen, N., Hosany, S., & Paul, J. (2022). The personalisation-privacy paradox: Consumer interaction with smart technologies and shopping mall loyalty. *Computers in Human Behavior*, 126, Article 106976. <https://doi.org/10.1016/j.chb.2021.106976>
- Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, 114, Article 106548. <https://doi.org/10.1016/j.chb.2020.106548>
- Anderson, J. C., & Gerbing, D. W. (1988). Structural equation modeling in practice: A review and recommended two-step approach. *Psychological Bulletin*, 103(3), 411–423. <https://doi.org/10.1037/0033-2909.103.3.411>
- Aslam, W., Hussain, A., Farhat, K., & Arif, I. (2020). Underlying factors influencing consumers' trust and loyalty in e-commerce. *Business Perspectives and Research*, 8(2), 186–204. <https://doi.org/10.1177/2278533720929667>
- Bhardwaj, S., Sharma, N., Goel, M., Sharma, K., & Verma, V. (2025). Enhancing customer targeting in e-commerce and digital marketing through AI-driven personalization strategies. In *Advances in Digital Marketing Era of Artificial Intelligence* (pp. 41–60). IGI Global.
- Bhattacharjee, A. (2001). Understanding information systems continuance: An expectation-confirmation model. *MIS Quarterly*, 25(3), 351–370. <https://doi.org/10.2307/3250921>

- Bryman, A. (2016). Social research methods (5th ed.). Oxford University Press.
- Chellappa, R. K., & Sin, R. G. (2005). Personalization versus privacy: An empirical examination of the online consumer's dilemma. *Information Technology and Management*, 6(2-3), 181-202. <https://doi.org/10.1007/s10799-005-5879-y>
- Chen, J. S., Le, T. T. Y., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management*, 49(11), 1512-1531. <https://doi.org/10.1108/IJRDM-08-2020-0312>
- Chen, Q., Lu, Y., Gong, Y., & Xiong, J. (2023). Can AI chatbots help retain customers? Impact of AI service quality on customer loyalty. *Internet Research*, 33(6), 2186-2212. <https://doi.org/10.1108/INTR-09-2021-0686>
- Cheng, Y., & Jiang, H. (2022). Customer-brand relationship in the era of artificial intelligence: Understanding the role of chatbot marketing efforts. *Journal of Product & Brand Management*, 31(2), 252-264. <https://doi.org/10.1108/JPBM-11-2019-2624>
- Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.
- Csikszentmihalyi, M. (1990). Flow: The psychology of optimal experience. Harper & Row.
- Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340. <https://doi.org/10.2307/249008>
- Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, 22(14), 1111-1132. <https://doi.org/10.1111/j.1559-1816.1992.tb00945.x>
- de Fine Licht, K., & de Fine Licht, J. (2020). Artificial intelligence, transparency, and public decision-making: Why explanations are key when trying to produce perceived legitimacy. *AI & Society*, 35(4), 917-926. <https://doi.org/10.1007/s00146-020-00960-w>
- Dick, A. S., & Basu, K. (1994). Customer loyalty: Toward an integrated conceptual framework. *Journal of the Academy of Marketing Science*, 22(2), 99-113. <https://doi.org/10.1177/0092070394222001>
- Fang, Y., Qureshi, I., Sun, H., McCole, P., Ramsey, E., & Lim, K. H. (2014). Trust, satisfaction, and online repurchase intention. *MIS Quarterly*, 38(2), 407-A9. <https://doi.org/10.25300/MISQ/2014/38.2.04>
- Faraoni, M., Rialti, R., Zollo, L., & Pellicelli, A. C. (2019). Exploring e-loyalty antecedents in B2C e-commerce: Empirical results from Italian grocery retailers. *British Food Journal*, 121(2), 574-589. <https://doi.org/10.1108/BFJ-05-2018-0306>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39-50. <https://doi.org/10.1177/002224378101800104>
- Guha, A., Grewal, D., Kopalle, P. K., Haenlein, M., Schneider, M. J., Jung, H., Moustafa, R., Hegde, D. R., & Hawkins, G. (2021). How artificial intelligence will affect the future of retailing. *Journal of Retailing*, 97(1), 28-41. <https://doi.org/10.1016/j.jretai.2021.01.005>

- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hallikainen, H., Luongo, M., Dhir, A., & Laukkanen, T. (2022). Consequences of personalized product recommendations and price promotions in online grocery shopping. *Journal of Retailing and Consumer Services*, 69, Article 103088. <https://doi.org/10.1016/j.jretconser.2022.103088>
- Harris, L. C., & Goode, M. M. (2004). The four levels of loyalty and the pivotal role of trust: A study of online service dynamics. *Journal of Retailing*, 80(2), 139–158. <https://doi.org/10.1016/j.jretai.2004.04.002>
- Hassan, N., Abdelraouf, M., & El-Shihy, D. (2025). The moderating role of personalized recommendations in the trust–satisfaction–loyalty relationship: An empirical study of AI-driven e-commerce. *Future Business Journal*, 11, Article 66. <https://doi.org/10.1186/s43093-025-00476-z>
- Haws, K. L., & Bearden, W. O. (2006). Dynamic pricing and consumer fairness perceptions. *Journal of Consumer Research*, 33(3), 304–311. <https://doi.org/10.1086/508440>
- Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, 43(1), 115–135. <https://doi.org/10.1007/s11747-014-0403-8>
- Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management & Data Systems*, 116(1), 2–20. <https://doi.org/10.1108/IMDS-09-2015-0382>
- Hinz, O., Hann, I.-H., & Spann, M. (2011). Price discrimination in e-commerce? An examination of dynamic pricing in name-your-own price markets. *MIS Quarterly*, 35(1), 81–98. <https://doi.org/10.2307/23043490>
- Igbaria, M., Parasuraman, S., & Baroudi, J. J. (1996). A motivational model of microcomputer usage. *Journal of Management Information Systems*, 13(1), 127–143. <https://doi.org/10.1080/07421222.1996.11518115>
- Jiang, C., Rashid, R. M., & Wang, J. (2019). Investigating the role of social presence dimensions and information support on consumers' trust and shopping intentions. *Journal of Retailing and Consumer Services*, 51, 263–270. <https://doi.org/10.1016/j.jretconser.2019.06.014>
- Kamal, M., & Himel, A. S. (2023). Redefining modern marketing: An analysis of AI and NLP's influence on consumer engagement, strategy, and beyond. *Eigenpub Review of Science and Technology*, 7(1), 203–223.
- Khan, R. U., Salamzadeh, Y., Iqbal, Q., & Yang, S. (2022). The impact of customer relationship management and company reputation on customer loyalty: The mediating role of customer satisfaction. *Journal of Relationship Marketing*, 21(1), 1–26. <https://doi.org/10.1080/15332667.2021.1886353>
- Khrais, L. T. (2020). Role of artificial intelligence in shaping consumer demand in e-commerce. *Future Internet*, 12(12), Article 226. <https://doi.org/10.3390/fi12120226>

- Komiak, S. Y., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly*, 30(4), 941–960. <https://doi.org/10.2307/25148760>
- Li, M. W., Teng, H. Y., & Chen, C. Y. (2020). Unlocking the customer engagement–brand loyalty relationship in tourism social media: The roles of brand attachment and customer trust. *Journal of Hospitality and Tourism Management*, 44, 184–192. <https://doi.org/10.1016/j.jhtm.2020.06.012>
- Liu-Thompkins, Y., Khoshghadam, L., Shoushtari, A. A., & Zal, S. (2022). What drives retailer loyalty? A meta-analysis of the role of cognitive, affective, and social factors across five decades. *Journal of Retailing*, 98(1), 92–110. <https://doi.org/10.1016/j.jretai.2021.04.002>
- Malhotra, G., & Kharub, M. (2025). Elevating logistics performance: Harnessing the power of artificial intelligence in e-commerce. *International Journal of Logistics Management*, 36(1), 290–321. <https://doi.org/10.1108/IJLM-03-2023-0109>
- Martin, W. C., Ponder, N., & Lueg, J. E. (2009). Price fairness perceptions and customer loyalty in a retail context. *Journal of Business Research*, 62(6), 588–593. <https://doi.org/10.1016/j.jbusres.2008.05.017>
- Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing*, 58(3), 20–38. <https://doi.org/10.1177/002224299405800302>
- Necula, S. C., & Păvăloaia, V. D. (2023). AI-driven recommendations: A systematic review of the state of the art in e-commerce. *Applied Sciences*, 13(9), Article 5531. <https://doi.org/10.3390/app13095531>
- Oliver, R. L. (1980). A cognitive model of the antecedents and consequences of satisfaction decisions. *Journal of Marketing Research*, 17(4), 460–469. <https://doi.org/10.1177/002224378001700405>
- Oliver, R. L. (1999). Whence consumer loyalty? *Journal of Marketing*, 63(Special Issue), 33–44. <https://doi.org/10.1177/00222429990634s105>
- Pakistan Telecommunication Authority. (2024). Annual report 2023–2024. <https://www.pta.gov.pk>
- Parasuraman, A., Zeithaml, V. A., & Malhotra, A. (2005). E-S-QUAL: A multiple-item scale for assessing electronic service quality. *Journal of Service Research*, 7(3), 213–233. <https://doi.org/10.1177/1094670504271156>
- Pekovic, S., & Rolland, S. (2020). Recipes for achieving customer loyalty: A qualitative comparative analysis of the dimensions of customer experience. *Journal of Retailing and Consumer Services*, 56, Article 102171. <https://doi.org/10.1016/j.jretconser.2020.102171>
- Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, 40(3), 879–891. <https://doi.org/10.3758/BRM.40.3.879>
- Ringle, C. M., Wende, S., & Becker, J.-M. (2024). SmartPLS 4. SmartPLS GmbH. <https://www.smartpls.com>
- Ryan, R. M., & Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. *Contemporary Educational Psychology*, 25(1), 54–67. <https://doi.org/10.1006/ceps.1999.1020>

- Seele, P., Dierksmeier, C., Hofstetter, R., & Schultz, M. D. (2021). Mapping the ethicality of algorithmic pricing: A review of dynamic and personalized pricing. *Journal of Business Ethics*, 170(4), 697–719. <https://doi.org/10.1007/s10551-019-04371-w>
- Sharma, S. K., & Sharma, M. (2019). Examining the role of trust and quality dimensions in the actual usage of mobile banking services: An empirical investigation. *International Journal of Information Management*, 44, 65–75. <https://doi.org/10.1016/j.ijinfomgt.2018.09.013>
- Soleimani, M. (2022). Buyers' trust and mistrust in e-commerce platforms: A synthesizing literature review. *Information Systems and e-Business Management*, 20(1), 57–78. <https://doi.org/10.1007/s10257-021-00545-0>
- Stewart, K. J., & Gosain, S. (2006). The impact of ideology on effectiveness in open source software development teams. *MIS Quarterly*, 30(2), 291–314. <https://doi.org/10.2307/25148732>
- Tyrväinen, O., Karjaluoto, H., & Saarijärvi, H. (2020). Personalization and hedonic motivation in creating customer experiences and loyalty in omnichannel retail. *Journal of Retailing and Consumer Services*, 57, Article 102233. <https://doi.org/10.1016/j.jretconser.2020.102233>
- Vashishth, T. K., Sharma, K. K., Kumar, B., Chaudhary, S., & Panwar, R. (2025). Enhancing customer experience through AI-enabled content personalization in e-commerce marketing. In *Advances in Digital Marketing Era of Artificial Intelligence* (pp. 7–32). IGI Global.
- Vidhya, V., Donthu, S., Veeran, L., Lakshmi, Y. S., & Yadav, B. (2023). The intersection of AI and consumer behavior: Predictive models in modern marketing. *Remittances Review*, 8(4), 2410–2424. <https://doi.org/10.33182/rr.v8i4.168>
- Watson, G. F., Beck, J. T., Henderson, C. M., & Palmatier, R. W. (2015). Building, measuring, and profiting from customer loyalty. *Journal of the Academy of Marketing Science*, 43(6), 790–825. <https://doi.org/10.1007/s11747-015-0439-4>
- Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS Quarterly*, 31(1), 137–209. <https://doi.org/10.2307/25148784>
- Xiao, B., & Benbasat, I. (2018). An empirical examination of the influence of biased personalized product recommendations on consumers' decision making outcomes. *Decision Support Systems*, 110, 46–57. <https://doi.org/10.1016/j.dss.2018.03.005>
- Zeithaml, V. A., Parasuraman, A., & Malhotra, A. (2002). Service quality delivery through web sites: A critical review of extant knowledge. *Journal of the Academy of Marketing Science*, 30(4), 362–375. <https://doi.org/10.1177/009207002236911>
- Zhang, T., Agarwal, R., & Lucas, H. C., Jr. (2011). The value of IT-enabled retailer learning: Personalized product recommendations and customer store loyalty in electronic markets. *MIS Quarterly*, 35(4), 859–881. <https://doi.org/10.2307/41409969>