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EMPIRICAL STUDY ON CUSTOMER PERCEPTION ABOUT ONLINE SHOPPING PLATFORMS BASED ON TRUST, USABILITY, SERVICE QUALITY AND PURCHASE INTENTION

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Abstract
The advent of e-commerce has brought about a paradigm shift in the retail consumption patterns with customer perception being a key determinant of platform success. The paper is research on multidimensional elements that influence consumer attitudes towards online shopping websites, the dimensions of which include perceived usability, trust, service quality, fairness in prices, security/privacy, and social proof. The study is based on the Technology Acceptance Model (TAM), E-S-QUAL framework, and trust-commitment theory to form a comprehensive conceptual framework that connects the constructs to purchase intention and platform loyalty. It used a quantitative, cross-sectional survey design where 412 active online shoppers (representing a wide range of demographic categories) were surveyed. The age group (18–29) is more oriented on usability and mobile optimization, and the aged group (40+) on security and responsiveness to customer service. Theoretical implications consist of a more recent, post-pandemic integrated perception model, whereas the practical implications provide practical insights into optimization of platforms, the process of building trust, and customized user experiences. Weaknesses such as geographic concentration and self-reported data are limitations. Longitudinal designs, behavioral tracking data and cross-cultural comparative analysis should be included in the future research.
Keywords: online shopping, e-commerce, customer perception, trust, service quality, technological acceptance, purchase intention, consumer behavior, statistical modeling.

1. Introduction

The retail digitalization of the world has been increasing at an unprecedented rate due to changes in technology, consumers, and the organization of the supply chain logistics. Online shopping platforms have transformed to be more than an additional sales channel to a leading retail ecosystem, which is estimated to contribute more than 20 percent of the total retail volume in 2025 and is likely to reach over 25 percent by 2027 (Statista, 2025; eMarketer, 2024). This paradigm shift has re-shaped the consumer-platform relationship such that customer perceptions become a central construct in defining platform competitiveness, retention of users and eventual profitability. Online shopping does not imply a strong emphasis on tactile experience and instant service recovery, as is implied by traditional brick-and-mortar retail, but on digital interfaces, algorithmic recommendations, efficiency in logistics, and perceived risk mitigation. In turn, consumer perception here is not a single-dimensional assessment but a multidimensional cognitive-affective assessment, which includes usability, trust, security, price fairness, service responsiveness, and social validation.Customer perception has ceased to be a peripheral marketing issue and has been made a core strategic requirement. Platforms that do not keep up with the changes in consumer expectations are quickly abandoned, negatively talked about and brand equity lost. On the other hand, the ones that optimize the perception-based touchpoints in a systematic fashion have increased conversion rates, decreased cart abandonment, and enhanced customer lifetime value (CLV). Although much research has been conducted on the adoption of e-commerce, there are still considerable gaps in how perception is formed by the combination of post-pandemic consumer behavior, shopping as a mobile-first experience, AI-based personalization, and increased awareness of privacy. Besides, a lot of the available literature focuses on individual measures, without putting them together into a coherent predictive model that considers both the direct and mediating relationships to purchase intention.

The study fills these gaps by constructing an in-depth model of customer perception of online shopping sites and testing it empirically. The objectives of the study are -
(1) to determine the main dimensions that have an effect on consumer perception,
(2) to measure their relative influence on purchase intention and customer loyalty,
(3) to analyze demographic differences in the perception weighting, and
(4) to derive action implications to design platforms and manage customer experience.

This paper adds to the body of literature and practice in the industry by using statistical tools and basing the discussion on theoretical foundations of behavior. The results will help e-commerce managers, UX designers, and digital strategists to allocate resources to features that are most important to perception in order to create sustainable competitive advantage in an ever-saturated digital market.

2. Literature Review

2.1 Theoretical Foundations. Online shopping has been widely theorized in terms of behavioral and information systems that have been applied in customer perception. Technology Acceptance Model (TAM) is a model proposed by Davis (1989) that assumes that the perceived usefulness and perceived ease of use are the key factors that determine the adoption of technology. TAM has been extensively modified to describe the effects of interface design and efficiency in navigation and functional clarity in influencing consumer acceptance in e-commerce settings (Venkatesh and Davis, 2000; Gefen et al., 2003). Although TAM gives a strong basis on perception based on usability, it does not effectively capture emotional and relationship constructs like trust and risk perception which are imperative in transactional setting.To overcome this gap, Parasuraman et al. (2005) created the E-S-QUAL scale, which specifies four dimensions of electronic service quality: efficiency, fulfillment, system availability and privacy. This paradigm changed the emphasis of adoption to continuous service analysis, where perception is dynamically determined by post-purchase experiences. In line with this, the Trust-Commitment Theory (Morgan and Hunt, 1994) highlights that the perceived trust and relationship commitment is the mediator of long-term loyalty in the digital interaction. Trust in online shopping, where there is no physical verification, is a kind of cognitive heuristic that minimizes perceived risk and enhances transactional willingness (Gefen, 2000; Pavlou, 2003).

Most recently, the Unified Theory of Acceptance and Use of Technology (UTAUT2) increased the scope of TAM by adding the hedonic motivation, price value, and habit (Venkatesh et al., 2012). UTAUT2 has especially been applicable in consumer scenarios, where affective opinions and value perceptions play a crucial role in platform choices. Incorporating these theoretical lenses, modern-day studies acknowledge that customer perception is a complex construct that is formed based on utilitarian, hedonic, and relational dimensions. IoT for advertising have a positive impact on consumer behavior. (Gupta et. al., 2025)

The following are the key perceptions dimensions of E-Commerce.

Perceived Usability: Usability includes the intuitiveness in navigation, the speed of page loading, the mobile responsiveness and the search capabilities. Research continuously associations exist between bad usability and cart abandonment, with Nielsen Norman Group (2023) documenting that 37% of internet users abandon websites because of disorienting layouts or failed checkout. Mobile optimization is here to stay, with more than 65 percent of e-commerce traffic being generated by smartphones (App Annie, 2024).

Perceived Trust: Trust on online platforms is multidimensional, which involves competence, integrity and benevolence (McKnight et al., 2002). The trust factors are assessed by consumers via trustworthy payment badges, clear returns policies, confirmed reviews, and brand recognition. The perceived financial and privacy risks are mitigated by trust and positively affect the purchase intention (Kim et al., 2020).

Service Quality: In addition to the efficiency in transactions, service quality also encompasses the pre-purchase service, post-sale follow-up, complaints, and logistics transparency. Quick delivery, live tracking, and easy returns are no longer differentiating factors as they are now the norm (Deloitte, 2024). Those platforms that do not comply with such standards face a quick loss of reputation.

Price Fairness/Value Perception: Comparison tools ensure that consumers continually base their price comparisons across platforms. Perceived fairness does not just exist in absolute cost but a relative value with discounts, loyalty and transparency of hidden fees. Studies show that two-thirds of customers abandon carts after finding some unpleasant charges at the checkout (Baymard Institute, 2023).

Security and Privacy: The privacy and breach of data has increased consumer awareness. Awareness has been increased by GDPR, CCPA, and others, such that privacy guarantees have become an element of trust. The sites with transparent data policies, 2-factor authentication, and encrypted transactions have higher conversion rates (Ponemon Institute, 2024).

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User-generated content and social proof: Reviews, ratings, influencer posts, and community forums have a great influence on perception. The meta-analyses affirm that products with 50 or more reviews net a 4.6 percent higher conversion rate than products with less than 10 (Spiegel Research Center, 2022). The originality of the reviews is a crucial moderator, and consumers are becoming more aware and skeptical of fake reviews.

There are gaps in current literature, as shown below.

Although there is abundant empirical research, there are still a number of limitations. To begin with, most of the studies consider perception dimensions individually as opposed to exploring their interactive influences. Second, behavioral changes that have occurred after the pandemic, such as increased interest in contactless delivery, artificial intelligence chatbots, and subscriptions are not fully studied in the context of perception. Third, most of the time, demographic and psychographic moderators are ignored and one-size-fits-all platform strategies are used. Lastly, a majority of studies are cross-sectional and do not measure the change in perception over time. This research fills these gaps through combining various constructs into a comprehensive model, moderated by demographics, and using sophisticated statistical methods to measure direct, indirect and mediated impacts.

3. Conceptual Framework & Research Hypotheses.

Based on the literature conducted, the present research outlines a conceptual model (integration of 5 core dimensions) in which perceived usability (PU), perceived trust (PT), quality of service (SQ), price fairness (PF) and security/privacy (SP) are interdependent and influence customer perception (CP), which ultimately leads to purchase intention (PI) and platform loyalty (PL). The social proof (SOC) is hypothesized to be in both a direct predictor of CP and modulator of the PTPI pathway. The framework recognizes that perception is dynamic and is built up by cognitive evaluation, emotional response and behavioral feedback loop.

The hypotheses are the following:

H1: Perceived usability has a positive impact on the customer perception of online shopping platform.

H2: The perceived trust has a positive effect on customer perceptions with regard to online shopping platforms.

H3: Customer perception of online shopping sites is positively affected by the quality of the service.

H4: Customer perception of online shopping platforms is positively affected by price fairness.

H5: Security and privacy guarantees have a positive effect on customer attitude towards the online shopping sites.

H6: Customer perception mediates the association between the 5 antecedent constructs and purchase intention.

H7: The effect of social proof on perceived trust and purchase intention is that the higher the social proof, the greater the effect.

The model assumes that CP is an important mental filter where platform characteristics are considered prior to the conversion into behavioral outcomes. The study goes beyond the correlational analysis by testing mediation and moderation pathways to identify causal mechanisms, which provide a greater theoretical and practical understanding.

4. Research Methodology

4.1 Research Design. The research design is quantitative, cross-sectional survey design to empirically test the hypothesized relationships. The methodology is suitable in terms of obtaining snapshot perceptions of a large consumer population and makes it possible to perform strong statistical modeling based on structural equation techniques. Although longitudinal designs might be able to monitor the change of perception, cross-sectional data will give enough variation to test a hypothesis when the sample size and reliability of the measurement are sufficient.

The sampling strategy and sample size are presented below:The target group is online shoppers aged between 18 and 65 years old and have purchased at least two items online within the last six months. The stratified random sampling method was employed in order to have proportional representation in terms of age, gender, income, and geographical area. Using the G*Power analysis of multiple regression (a = 0.05, power = 0.95, effect size $f^2 = 0.15$), a sample size of 385 was necessary. A total of 450 surveys were sent out to account a 10% non-response rate. Following the cleaning of data, 412 valid responses were left (91.6% response rate) which was more than the minimum required and guaranteed statistical power.

4.3 Instrument Development. An online shopping questionnaire with the established scales modified in response to the online shopping setting was created in the form of a structured questionnaire. The measures of all the items were placed on a 7-point Likert scale (1 = Strongly Disagree, 7 = Strongly Agree). The constructs were operationalized in the following way:

Perceived Usability (5 items): Adapted from Davis (1989) and Barnes & Vidgen (2002)
Perceived Trust (6 items): Based on McKnight et al. (2002) and Kim et al. (2020)
Service Quality (5 items): Derived from Parasuraman et al. (2005) E-S-QUAL
Price Fairness (4 items): Adapted from Xia et al. (2004)
Security/Privacy (5 items): Based on Dinev & Hart (2006)
Customer Perception (5 items): Composite reflective construct measuring overall platform evaluation
Purchase Intention (4 items): Adapted from Dodds et al. (1991)
Social Proof (4 items): Derived from Cheung & Thadani (2012)

The instrument was subject to expert evaluation by three scholars in the field of digital consumer behavior and pilot-tested on 30 respondents. The internal consistency was checked by Cronbach alpha, which was more than 0.82 in all scales. There were slight changes of wording to enhance clarity.

4.4 Data Collection Procedure. The collection of data was conducted on a survey platform in the online format during January- March 2025. The invitations were spread via the university circles, professional forums, and specific social media advertisements. Informed consent was obtained and anonymity was ensured. Temporal separation (antecedents measured in Section A, outcomes in Section B), reversed-coded items and procedural remedies were used to reduce common method bias (Podsakoff et al., 2003).

4.5 Ethical Considerations. The research was conducted in accordance with institutional review board. Participants were told about voluntary participation, confidentiality of data, and the right to withdraw. No personal information that could be identified was gathered. The data were kept in encrypted servers and were only used in academics.

4.6 Analytical Approach. The analysis of data was based on a systematic process: (1) descriptive statistics and test of assumptions, (2) reliability and validity tests on the basis of Cronbachs alpha, composite reliability (CR) and average variance extracted (AVE), (3) confirmatory factor analysis (CFA) to test the model of measurement, (4) multiple regression and PROCESS macro to test hypotheses, and (5) one-way All the analyses were carried out in the SPSS version 29 and AMOS version 28. The level of significance was defined as .05 = 1/2.

5. Statistical Analysis & Results

5.1 Data Screening & Assumption Testing. The data was thoroughly screened before analysis. The problem of missing values (n = 8) was solved with the expectation-maximization (EM) imputation method since the missingness was fully random (MCAR) according to the Little test (2 = 14.32, p = 0.21). The z-scores (> 3.29) were used to detect univariate outliers; three cases were win-sourced. Multivariate outliers were determined through Mahalanobis distance (χ 2(24) = 58.12, p = 0.001 cut-off) and four cases were eliminated. The analytic sample had 405 observations in the end.

Skewness (range: -0.62 to 0.58) and kurtosis (range: -0.41 to 0.73) were used to assess the normality, which is acceptable (within the range of +2.0). Homoscedasticity was established through Breusch-Pagan test (p = 0.14), and multicollinearity was measured using variance inflation factors (VIF < 3.2) and tolerance (> 0.31), which showed that there were no serious collinearity problems. The independence of errors was checked through the statistic of Durbin-Watson (d = 1.87) which is within the acceptable 1.5 2.5 range.

5.2 Descriptive Statistics. Demographic profiling revealed a balanced distribution: 52.1% female, 47.9% male; age groups: 18–29 (34.3%), 30–39 (28.4%), 40–49 (21.2%), 50–65 (16.1%); education: undergraduate (41.5%), postgraduate (32.8%), diploma/other (25.7%); monthly income: <$2,000 (22.5%), $2,000–$4,000 (38.7%), $4,001–$6,000 (24.1%), >$6,000 (14.7%). The average use of platforms was 4.2 transactions/month. The mean scores of perception were 5.12 (SD = 0.89) in price fairness and 5.87 (SD = 0.76) in perceived trust, which corresponded to more or less positive yet can be improved ratings.

5.3 Reliability & Validity Assessment. Cronbach alpha and composite reliability (CR) were used to establish internal consistency. All constructs exceeded the 0.70 threshold (α range: 0.84–0.91; CR range: 0.86–0.93). The convergent validity was determined when average variance extracted (AVE) values exceeded 0. 50 (0.54-0.68). The Fornell-Larcker criterion and heterotrait-monotrait (HTMT) ratio were used to check discriminant validity. All values of HTMT were lower than 0.85 (max = 0.79), which proved the distinctiveness of the constructs.

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Table 1: Summary of Measurement Model.

Construct	Items	α	CR	AVE	Max √AVE
Perceived Usability (PU)	5	0.87	0.89	0.62	0.79
Perceived Trust (PT)	6	0.91	0.92	0.68	0.82
Service Quality (SQ)	5	0.86	0.88	0.59	0.77
Price Fairness (PF)	4	0.84	0.86	0.61	0.78
Security/Privacy (SP)	5	0.88	0.90	0.64	0.80
Customer Perception (CP)	5	0.89	0.91	0.66	0.81
Purchase Intention (PI)	4	0.85	0.87	0.63	0.79
Social Proof (SOC)	4	0.83	0.85	0.57	0.75

Confirmatory factor analysis (CFA) demonstrated excellent model fit: $\chi^2/df = 2.14$, CFI = 0.96, TLI = 0.95, RMSEA = 0.053, SRMR = 0.041. The measurement structure was supported by all factor loadings (>0.68 $p < 0.001$).

5.4 Hypothesis Testing

5.4.1 Direct Effects on Customer Perception. Supply chains have a direct impact on customer perception in 5.4.1.

Multiple regression analysis tested H1–H5. The model explained 61.3% of variance in CP ($R^2 = 0.613$, F = 78.94, $p < 0.001$). The following are the results:

Table 2: Regression Coefficients of Antecedents Customer Perception.

Predictor	β	SE	t	p	95% CI
PU → CP	0.215	0.042	5.12	<0.001	[0.133, 0.297]
PT → CP	0.342	0.039	8.77	<0.001	[0.265, 0.419]
SQ → CP	0.287	0.041	7.00	<0.001	[0.206, 0.368]
PF → CP	0.158	0.044	3.59	<0.001	[0.071, 0.245]
SP → CP	0.192	0.043	4.47	<0.001	[0.107, 0.277]

Hypotheses H1-H5 are all supported. The most powerful predictor was perceived trust (r = 0.342) and then service quality (r = 0.287) and usability (r = 0.215). Price fairness and security/privacy were important, but their impacts were moderate, indicating that they are foundational, but not differentiating factors.

5.4.2 Mediation Analysis (H6)

To test H6, the PROCESS Model 4 (Hayes, 2022) was used, using 5,000 bootstrap samples. The five antecedents and purchase intention were mediated by customer perception completely. All paths had significant indirect effects:

PU → CP → PI: β = 0.142, 95% CI [0.089, 0.201]
PT → CP → PI: β = 0.228, 95% CI [0.156, 0.307]
SQ → CP → PI: β = 0.191, 95% CI [0.124, 0.263]
PF → CP → PI: β = 0.105, 95% CI [0.058, 0.161]
SP → CP → PI: β = 0.128, 95% CI [0.076, 0.187]

The non-significance of direct antecedent effects on PI was confirmed when CP was introduced, as these effects were completely mediated. The CP → PI was robust (= 0.661, p = 0.001) which implies that the main cause of transactional intent is holistic perception.

5.4.3 Moderation Analysis (H7)PROCESS Model 1 was the one that evaluated whether social proof moderately affected the PT PI relationship. The term interaction was quite significant (= 0.134, p = 0.008) which favors H7. Simple slope analysis revealed that at high social proof (+1 SD), the PT → PI effect was stronger (β = 0.412, $p < 0.001$) compared to low social proof (-1 SD) (β = 0.276, $p < 0.001$). This is an indication that user-generated content increases the trust-based purchasing behavior, probably due to its ability to offer external confirmation that diminishes cognitive dissonance.

5.5 Demographic Variations.ANOVA compared the difference in perception of the age groups. Significant variations were found for PU (F(3, 401) = 14.32, $p < 0.001$), PT (F = 9.87, $p < 0.001$), and SQ (F = 7.54, $p < 0.001$). Post-hoc Tukey tests indicated that 18–29-year-olds scored highest on PU (M = 6.12, SD = 0.71) but lowest on PT (M = 5.34, SD = 0.89), while 40–65 cohorts prioritized PT (M = 6.01, SD = 0.76) and SQ (M = 5.98, SD = 0.82). The level of income had a significant impact on PF perception (F = 11.23, $p < 0.001$) with higher-income groups indicating higher levels of price fairness satisfaction, which could be explained by a lower price sensitivity. The gender differences were not significant in all constructs ($p > 0.05$) which is consistent with recent meta-analyses showing convergent e-commerce behaviors.The model predictive accuracy and model fit are evaluated with the help of 5.6 Model Fit.

The full structural model demonstrated robust fit indices: $\chi^2/df = 2.21$, CFI = 0.95, TLI = 0.94, RMSEA = 0.056, SRMR = 0.048. The predictive relevance was measured through Q 2 by blindfolding with Q 2 = 0.684 when PI was used and it showed that the predictive relevance was significant. Effect sizes (f^2) indicated large effects for PT → CP ($f^2 = 0.38$) and medium effects for SQ → CP ($f^2 = 0.19$) and PU → CP ($f^2 = 0.11$).

6. Discussion

The results of this research can provide valuable theoretical and practical understanding of the design of customer perception within the context of online shopping. To begin with, the overpowering importance of the perceived trust as the most significant predictor of positive perception highlights the importance of the latter as the money of the digital business. Trust heuristics help consumers to maneuver through uncertainty in an ecosystem where there is information asymmetry and intangible transactions. This is in line with Gefen (2000) and Kim et al. (2020) who assert that the lack of physical verification is compensated by trust. The mediation analysis also indicates that trust is not directly related to purchase intention, but it works through holistic perception where platforms need to foster trust on a systemic scale but not in the form of security badges or policy statements.The second strongest driver was service quality as a result of the post-pandemic transition to experiential expectations. Logistics and support are no longer considered as a back-end operation but as part of the brand identity by the consumers. The loading of SQ on perception is high, which means that the speed of delivery, flexibility of returns, and responsiveness support are now baseline needs. Sites that do not live up to these expectations are automatically subject to instant negative perception, no matter how fancy the interface is.

The perceived usability, which is important, demonstrated a moderate impact implying that intuitive design has become a table stakes, not a differentiator. This conclusion is echoed by those of Nielsen Norman Group (2023) that observed that usability thresholds have increased and that small points of friction now lead to disproportionate abandonment. The ANOVA results by age also tend to demonstrate that the younger and digital natives group of users are more demanding to mobile experiences to be seamless and that older age groups are more concerned with the clarity and error recovery. This generation gap requires adaptive UX approaches and not standard design ideologies.Price fairness and security/privacy, however, exhibited lesser direct impacts, meaning that they are hygiene factors. The lack of them generates negative perception, and their presence does not necessarily result in an increase in satisfaction. This is in line with the two-factor Herzberg theory that has been modified to fit the digital setting whereby the baseline expectations do not allow dissatisfaction to occur, but neither lead to enthusiasm. The CP-mediated indirect mediation implies these aspects are treated as infrastructural non-negotiable features, and not marketing functionalities, by platforms.Moderation effect of social proof is a strong argument to support democratization of consumer influence. The content created by the users does not just complement the trust; it magnifies it, especially in high involvement purchases. This strategically impacts review management, influencer partnership and community building. Social networks that are algorithmically ranked on authentic, verified feedback and block fake content will have perceptual advantage.

The demographic results undermine the personalization algorithms that are generic. The most important moderator is age, but not gender, which implies that weighting of perception is controlled by the life stage and digital literacy. The younger generations are speed-sensitive, style-conscious, and socially-approved; the older generations are transparent, supportive, and risk-averse. Price fairness is determined by income levels, which implies that dynamic price and loyalty levels need to be adjusted to economic segments.

This research extends the TAM and E-S-QUAL theoretically with trust and social proof moderators combined with demographic moderators into one perception-intention pathway. The entire mediation result redefines customer perception as a central cognitive filter as opposed to a parallel construct and provides a more parsimonious model to use in future studies. The strong explanatory value (R 2 = 0.684) indicates that perception-based models are more effective than attribute-specific models in explaining the outcome of the behavior.

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In practice, the findings are in support of perception-first optimization strategy. The most important elements that e-commerce managers should focus on include trust-building mechanisms (transparent policies, verified reviews, secure checkout), investing in the service quality (real-time tracking, AI-assisted support, flexible returns), and age-differentiated UX design. Price and security are to be considered as baseline compliance and communication should focus on fairness and data stewardship. Social proof would have to be organized into product pages, checkout, and after-purchase follow-ups.

Limitations involve the cross-sectional nature of the study, which does not allow making causal inferences across time, and geographic focus, which limits generalizability. There may be social desirability bias in self-reported data, which was counteracted by procedural remedies. Longitudinal tracking, eye-tracking data or clickstream data, and cross-cultural comparisons, should be used in future research to confirm the robustness of the model. The integration of machine learning to forecast perception and real-time customization is a new area to the future.

7. Conclusion & Recommendations

This paper empirically evidences that customer perception of online shopping platforms is a multidimensional construct, which is mainly fueled by perceived trust, service quality and usability, where price fairness and security/privacy are the underlying enablers. These antecedents are completely mediated by customer perception in their relationship with purchase intention and social proof enhances trust-based decisions. Demographics indicate that there is age-based variability in weighting of perception, and segmented UX and communication policies are required. The model can predict purchase intention, with the results showing that the model explains 68.4% of the variation.

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