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The Influence of E-Commerce Features on Consumer Purchase Decision: A Study of Logistics Integration, Artificial Intelligence Integration, Gamification, and Social Commerce Elements

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Abstract

The rapid growth of e-commerce in Indonesia has led to significant changes in consumer behavior, with features such as artificial intelligence (AI), social commerce, gamification, and logistics integration playing key roles in shaping purchasing decisions. Despite their extensive use, empirical evidence on the comparative impact of these features on consumer behavior remains limited. This study aims to evaluate the influence of these four features on consumer purchase decisions, platform traffic, and sales within the Indonesian e-commerce context. Using a quantitative approach, a survey was conducted with 260 respondents from the Jabodetabek region, focusing on their perceptions and usage patterns of e-commerce features. The research employed multiple linear regression analysis to examine the relationships between these features and consumer behavior. The findings indicate that social commerce has the strongest influence on purchase decisions, while gamification significantly impacts platform traffic and sales. Artificial intelligence and logistics integration also contribute positively, but to a lesser extent. The study provides actionable insights for e-commerce platforms to prioritize features that most effectively drive consumer engagement and loyalty. Practically, it suggests that platforms should focus on enhancing social commerce and logistics integration features for immediate improvements, while gamification and artificial intelligence can be further optimized for long-term growth. This research contributes to both theory and practice by extending the Stimulus–Organism–Response (S-O-R) framework and providing e-commerce professionals with strategies for feature optimization and user segmentation.

INTRODUCTION

E-commerce is rapidly transforming consumer behavior in developing markets by altering the way consumers interact with digital platforms. This shift has been further accelerated in Indonesia through the widespread adoption of technology and the country's relatively high level of digital participation. According to Trade.gov (2024), Indonesia is currently responsible for over half of the e-commerce revenue in ASEAN, with market value expected to exceed USD 125 billion by 2027. As the market matures, however, growth has become less dependent on promotional marketing and more focused on sustainable feature innovation that delivers real value to users.

In earlier years, many e-commerce players competed for market share through price subsidies and steep discounts. While these approaches were effective in boosting user acquisition, they eroded profitability and failed to build long-term customer loyalty. Similarly, the post-pandemic "tech winter" has forced firms to re-evaluate their spending priorities, shifting attention toward product differentiation through platform features. Logistics integration, artificial intelligence (AI), gamification, and social commerce features have emerged as four key levers driving the online shopping experience (Alkudah et al. 2024; Bardelli et al. 2024; Malhotra et al. 2025).

Previous studies on artificial intelligence have demonstrated its potential in enabling personalization, dynamic pricing, and automated assistance, thereby enhancing customer satisfaction and purchase intentions. Gamification has been shown to increase user engagement and repeat purchasing by appealing to users' intrinsic motivation. Likewise, social commerce elements contribute to social proof, fostering trust and encouraging impulse buying through reviews, influencer marketing, and livestream commerce. On the other hand, the reliability of logistics remains a critical factor in generating customer satisfaction and retention. However, despite their widespread use, empirical evidence on the effects of these features on consumer purchasing behavior remains limited, and there is a lack of comparative insight evaluating these features head-to-head (He et al. 2025; Liu et al. 2025). This study aims to bridge this research gap by building on prior studies and developing a unified framework to investigate how the integration of these four features influences consumer purchasing decisions in the context of Indonesian e-commerce.

This study presents three interrelated research questions: (1) Which e-commerce platform features most significantly influence consumer purchase decisions among Indonesian online shoppers aged 25–35? (2) Are there significant differences in feature preferences and behavioral impact across different user segments (e.g., income levels, gender, purchase frequency)? and (3) How can the implementation of these features be optimized to drive growth in platform traffic and sales? These questions support the study's objective of identifying the most impactful e-commerce features while also providing deeper insights into consumer segmentation and preferences. The third research question builds on Research Questions 1 and 2 to generate actionable insights applicable to the e-commerce industry.

Overall, this study aims to contribute to both theory and practice. Theoretically, it extends the Stimulus–Organism–Response (S–O–R) framework and the Buyer Decision Process framework by applying them within a multi-feature model of digital consumer behavior. Practically, it provides e-commerce professionals with guidance on user segmentation, feature prioritization, and feature development strategies.

METHODS

This study targeted Indonesian consumers between the age groups 25-35 who shop online as one of the most active and tech-savvy customers of e-commerce in Indonesia. Respondents were recruited from the Jabodetabek region (Jakarta, Bogor, Depok, Tangerang, and Bekasi), given its high internet penetration and dense concentration of e-commerce users. A purposive sampling technique was used to confirm existing experience of e-commerce transactions.

A total of 260 valid responses were obtained via an online questionnaire distributed via social commerce and professional networks. This sample size is sufficient for regression analysis and is representative of the profile of Indonesia's urban online shoppers. The questionnaires contained descriptive questions as well as 5-point Liker scale questions to measure consumer sentiment.

The survey questionnaire consists of the following sections:

1. Demographic Information: Age, sex, income, education, and frequency of online shopping.
2. Feature Engagement: The usage and consumer awareness rate of the features. perception of the features as to their popularity.
3. Consumer Purchase Decision: Consumers' confidence, frequency of purchases, and impulsiveness.
4. Platform Traffic: Visit frequency and the amount of time spent browsing and the extent of users' return to the platform.
5. Sales: The impact of the features on customers overall spending, to include purchase volume and transaction size.

RESULT AND DISCUSSION

Respondent Demographics and Descriptive Statistics

A total of 260 valid responses were collected from Indonesian online shoppers aged 25–35. Respondents were primarily from the Jabodetabek region. The largest age group was 25 years old (18%), while both the mean and median age were 28. Respondents were predominantly female (70%) and highly educated, with 88.5% holding a Bachelor's degree and 8.5% a Master's degree, suggesting a technologically literate user base. Most respondents reported spending between Rp 500,000–3,000,000 per month on e-commerce, with the majority shopping two to three times monthly or weekly**,** indicating habitual but planned shopping behaviour.

Table 1. Respondent Demographics

Variable	Category	Percentage (%)
Age	25 years	18.0
Age	28 years	12.5
Gender	Female	70.0
Gender	Male	30.0
Education	Bachelor's degree	88.5
Education	Master's degree	8.5
Spending	Rp 500.000 to Rp 1.000.000	36.9
Spending	Rp 1.000.000 to Rp 3.000.000	30.0
Purchase Frequency	2-3 times a month	41.5
Purchase Frequency	Once a week	34.2

Sourch: Data from an online questionnaire filled out by 260 e-commerce respondents from the Jabodetabek area

Feature usage patterns revealed distinct preferences. AI features were moderately adopted (28.8% used them 2–3 times a month and 22.4% once a week), though many used them less frequently, indicating that AI has not yet become a habitual driver of purchase behaviour. It was also demonstrated that social commerce features are consistently used (30.6% weekly and 27.1% 2–3 times monthly), thus reinforcing the position of social commerce attributes as social proof and trust-building instruments. Gamification had the lowest adoption – 65.3% use it less than once a month, not significantly influencing purchasing behaviour. The most common use category that was to the best extent applied in these survey results was logistics features: 39.4% used them 2–3 times/month, and 30%

weekly, which is an indicator of their centrality for risk management, and transformation of intent into sale.

Table 2. Feature Usage Frequency

Feature	Usage Frequency	Percentage (%)
Artificial Intelligence	2–3 times/month	28.8
Artificial Intelligence	Less than once a month	23.5
Social Commerce	Once/week	30.6
Social Commerce	2–3 times/month	27.1
Gamification	< Once/month	65.3
Gamification	2–3 times/month	12.4
Logistics	2–3 times/month	39.4
Logistics	Once/week	30.0

Sourch: Data on the frequency of usage of e-commerce features (AI, social commerce, gamification, logistics) from 260 respondents

Multiple Linear Regression

In this study, three dependent variables, such as consumer purchase decision, platform traffic, and sales, were used against four independent variables (artificial intelligence, social commerce, gamification, and logistics), while for each of the outcome, separate multiple regression analyses were conducted. This strategy allowed for multiple predictors to be tested at the same time, (and overlap adjusted for), yielding a fuller picture of the relative effects of those predictor(s) (Hair et al., 2019; Pallant, 2020). This strategy is consistent with previous e-commerce studies investigating the impact of platform characteristics on consumer behaviour (Jiang et al., 2015; Svatosova, 2020).

In this work both beta coefficient and semi partial correlation are considered. Semi-partial correlations (sr^2) are distinct from β coefficients that assess and adjust the relative strength of all variables in the model, since they only capture the unique variance produced by the feature while removing the resulting inflation due to the intercorrelation between multiple predictors. This distinction is relevant because all four of the e-commerce features are conceptually linked which could have something in common in impacting buyer behaviour. The sr^2 value thus provides a better understanding of the actual incremental effects of each feature, showing that social commerce exerts the strongest independent impact, while logistics, gamification and AI have a positive effect upon performance via related but slightly different effects. Diagnostic testing confirmed that the assumptions of regression were met and thus the validity of such interpretations was affirmed.

Consumer purchase decision in multiple regression analysis explained 37.8% of variance (Adjusted $R^2 = 0.378$). At the 5% p level, all predictors were significant. Social commerce showed the strongest effect ($\beta = 0.335$, $sr^2 = 0.056$), followed by gamification ($\beta = 0.175$, $sr^2 = 0.029$). AI ($\beta = 0.293$, $sr^2 = 0.020$) and logistics ($\beta = 0.186$, $sr^2 = 0.019$) also showed significant, but smaller, impact.

Table 3. Multiple Regression of Consumer Purchase Decision

Predictor	B	SE B	β	t	p	sr^2
Intercept	-0.423	0.382		-1.11	0.27	—
AI	0.198	0.055	0.193	3.63	<.001	0.020
Social Commerce	0.389	0.063	.0.335	6.17	<.001	0.056
Gamification	0.175	0.040	0.226	4.41	<.001	0.029
Logistics	0.291	0.081	.0.186	3.61	<.001	0.019

Sourch: Results of multiple linear regression from data of 260 respondents on consumer purchase decisions

For platform traffic, gamification proved to be the most significant predictor (β = 0.326, sr^2 = 0.060), indicating its ability to induce repeat visits through interactive rewards. Social commerce was the second strongest predictor (β = 0.304, sr^2 = 0.047), indicating the importance of interaction and peer content in the generation of browsing activity. Logistics (β = 0.174, sr^2 = 0.017) and AI (β = 0.128, sr^2 = 0.009) further contributed, indicating that operational reliability and personalization are contributors to the perpetuity of user engagement, albeit to a lesser extent.

Table 4. Multiple Regression of Platform Traffic

Predictor	B	SE B	β	t	p	sr²
Intercept	-1.040	0.401		-2.59	0.01	—
AI	0.155	0.061	0.128	2.54	0.01	0.009
Social Commerce	0.421	0.066	0.304	6.38	<.001	0.047
Gamification	0.300	0.052	0.326	5.77	<.001	0.060
Logistics	0.325	0.085	0.174	3.82	<.001	0.017

Sourch: Results of multiple linear regression from data of 260 respondents on platform traffic

In contrast to purchase decisions, gamification emerged as the primary driver of Sales volume (β = 0.319, sr^2 = 0.91), proving that reward mechanics effectively incentivize higher spending levels. Social commerce followed as a strong secondary driver (β = 0.250, sr^2 = 0.050), supporting impulse purchases through validation. Meanwhile, Logistics (β = 0.143, sr^2 = 0.018) and AI (β = 0.124, sr^2 = 0.022) provided smaller contributions, functioning as operational enablers rather than primary engines of expenditure growth.

Table 5. Multiple Regression of Sales

Predictor	B	SE B	β	t	p	sr²
Intercept	-1.039	0.395		-2.63	0.01	—
AI	0.254	0.059	0.124	4.31	<.001	0.022
Social Commerce	0.356	0.064	0.250	5.56	<.001	0.050
Gamification	0.302	0.049	0.319	6.16	<.001	0.091
Logistics	0.275	0.083	0.143	3.31	0.001	0.018

Sourch: Results of multiple linear regression from data of 260 respondents on sales volume.

Overall, regression analysis indicated social commerce emerged as the most dominant driver of all three outcomes, while logistics play a strong role in purchase decisions and platform traffic. Gamification is especially successful in encouraging traffic and sales but less so for purchase decisions, and AI contributes in a supporting capacity across all outcomes. The combination of the β values and the sr^2 values clarifies the relative strength and the unique variance explained by each, allowing us to see how each one of those features influenced consumer behaviour.

K-Means Clustering and ANOVA Analysis

For the purposes of this study, K-means clustering was used to profile respondents and segregated them by gender, frequency of shopping, and spending level according to the questionnaire values. Three different consumer sub-groups were formed. Cluster consisted largely of moderate female consumers purchasing 2–3 times monthly and spending less than Rp 1,000,000 and comprises value-conscious individuals sensitive to cost-saving features. Cluster 2 contains heavy female shoppers who buy frequently and spend between Rp 1,000,000–3,000,000 monthly; they are the core consumers of e-commerce, engaged heavily with social features and promotional services. Cluster 3 consists of 100% males who are on a heavy, high-spending user base who are more functional and have a higher concern towards logistics rather than social influence-driven.

Table 6. ANOVA Results by Feature

Feature	df	F	p	η^2
AI	2, 257	4.56	.012	.034
Social Commerce	2, 257	6.72	<.001	.050
Gamification	2, 257	3.89	.021	.029
Logistics	2, 257	5.43	.005	.041

Sourch: Results of ANOVA analysis from data of 260 respondents comparing the influence of e-commerce features

ANOVA was performed for each feature after. Overall, the results yielded no significant differences in perceptions of AI ($p = 0.772$) and gamification ($p = 0.970$) across clusters; AI seems to be a baseline expectation and gamification has universal but limited appeal. Social commerce features, on the other hand, differed greatly ($p = 0.037$), with Cluster 2 (heavy female shoppers) giving the most perceived value whereas male shoppers in Cluster 3 showed less influence. Logistics also varied considerably ($p = 0.040$), such that high-spending Clusters 2 and 3 users prioritized delivery speed, reliability, and return policies as top priorities. The pooled clustering and ANOVA result show that while all of the features have a positive contribution, social commerce and logistics are the two most important drivers of consumer behaviour; however, their differences between consumer groups have also been shown. These findings underline the importance of segmentation and differentiated strategies: social commerce to target female-heavy segments; and logistics to high-value male and female shoppers for loyalty.

Effect Size of Consumer Features

This study defines the four e-commerce features as baseline expectation, baseline enabler, supporting feature, and primary driver. A primary driver refers to the feature with the strongest unique contribution, the one that directly shapes purchase intent and should be prioritized for platform strategy. A supporting feature has a moderate effect size and works best when integrated with other features, boosting engagement and reinforcing the role of primary drivers. Baseline expectations are features that may not show strong unique effects but are essential for credibility; consumers already expect them, and failure to deliver would reduce trust. On the other hand, baseline enablers play a critical back-end role in ensuring the platform operates smoothly, but by themselves they do not create strong differentiation. Based on these definitions, each of these features can be optimized differently.

Table 7. Effect Sizes of E-commerce Features on Consumer Purchase Decision

Feature	Cont.	Strategic Role	How to Optimize Feature
AI	1.95%	Baseline Expectation	Enhance search and recommendation systems; improve chatbot usability.
Social Commerce	5.64%	Primary Driver	Boost UGC visibility; refine trend curation; partner with micro-influencers; reward sellers/brands with algorithm boosts or rebates.
Gamification	2.88%	Supporting Feature	Focus on purchase-linked rewards; reduce time-based mechanics; link with social/UGC features.

Logistics	1.93%	Baseline Enabler	Maintain reliable tracking; sustain affordable/free shipping; integrate with checkout and social commerce.

Sourch: Data from multiple regression analysis to measure the impact of features on purchase decisions

The goal of AI is to serve as a baseline expectation within the SOR model and can enhance the shopping experience by lowering the friction of shopping by enhancing relevance rather than by increasing the emotional engagement itself. According to the survey, consumers prefer AI-based search (4.04) and recommendations (3.59) more than chatbots (3.04), where it has become a hygiene factor that improves the user experience with personalized recommendations and automated support by AI (Pappas et al., 2017; Areiqat et al., 2021; Simões, 2024). The integration of AI in search and recommendation systems and ensuring that chatbots are trained and contextualized will improve adoption in order to optimize impact by improving the search experience and make customer purchases easier and faster.

Table 8. Questionnaire Results for AI Questions

Question	Score
AI-based product recommendations help me discover products I like.	3.59
AI chatbots or virtual assistants make my shopping experience easier.	3.04
AI-driven search functions (e.g., image search) improve my ability to find products.	4.04

Sourch: Data from a survey on consumer perceptions of AI features

Social commerce is shown to be the strongest driver of consumer purchase decision, with the highest sr^2 effect. Stimuli such as livestreams, reviews, and influencer content create trust, audience engagement, and purchase intention—all of which translate into subsequent consumer behaviour within the SOR framework. Consumers on the other hand are more dependent on UGC (4.44) while virality is considered a low priority (3.03), indicating that authenticity is more important than virality (Huang & Benyoucef, 2013; Attar et al., 2022; Xiang, 2022). Platforms should encourage UGC visibility to maximize its impact in this area, be sure to promote credible reviews and micro-influencer content, optimize trend curation methods and incentives for sellers to create authentic content.

Table 9. Questionnaire Results for Social Commerce Questions

Question	Score
I enjoy interacting with sellers or brand content on the platform.	3.46
I engage with user-generated content (reviews, comments) to help decide purchases.	4.44
I follow trends or viral products I see on the platform.	3.03

Sourch: Data from a survey on consumer perceptions of social commerce features

Gamification, which has moderate sr^2 effect, is an extensible but not a primary driver. It increases engagement if linked to other features, and works best when providing tangible rewards such as coupons (2.42) versus simply increasing length of time users spend on the app (2.18). In the SOR framework, gamification also acts as a stimulus, producing pleasure and perceived gain that increase purchase intent, consistent with previous studies (Hamari, Koivisto, & Sarsa, 2014). Platforms should concentrate on improving current-style tools by connecting gamification to purchase incentives like vouchers, points, and group challenges so that it can drive the purchase (rather than serve as a standalone form of entertainment).

Table 10. Questionnaire Results for Gamification Questions

Question	Score
Gamification makes me spend more time on the app.	2.18
I am more likely to make a purchase when I receive rewards or coupons from games.	2.42
I feel more satisfied shopping when gamification features are available.	2.15

Sourch: Data from a survey on consumer perceptions of gamification features

Logistics serves as a baseline enabler in the SOR framework, also as a stimulus and a reinforcer. Although the sr^2 effect is modest, the survey results indicate that reliable tracking (4.67), affordable shipping (4.43), and free shipping (4.62) are of great importance. This is in line with previous studies which claimed that good logistics reduce risk, increase satisfaction, and stimulate repeat purchases (Ahmad et al., 2014; Tian et al., 2025; and Zia et al., 2024), especially in Indonesia's cost-sensitive market where free shipping plays a significant role (Yanchuk et al., 2020). On a strategy level, logistics should be consistent and integrated with the front-end features, providing the backbone for overall success of the platform.

Table 11. Questionnaire Results for Logistics Questions

Question	Score
Free shipping options influence my purchasing decisions.	4.62
Reliable delivery tracking makes me trust the platform more.	4.67
Affordable shipping rates encourage me to purchase more frequently.	4.43

Sourch: Data from a survey on consumer perceptions of logistics features.

Discussion

The present study analyzed the influence of the primary aspects of e-commerce platforms—logistics, AI, gamification, and social commerce—on consumer purchasing behavior in Indonesia. The results validate that all four factors have a significant influence on buyer behavior in relative value but have a unique effect. Results of standardized coefficients (β) indicated that while social commerce attributes had the highest effect on the purchase decision, gamification emerged as the primary driver for traffic and sales. The semi-partial correlation squared (sr2) outputs provide more detailed information about individual feature independent value.

In purchase decision, the model explained 37.8% of the variance (Adjusted R^2 = 0.378) and all predictors were significant at the 5% level. Social commerce had the biggest impact (β=0.335; sr2=5.6%), followed by gamification (β = 0.226; sr^2 = 2.9%), while AI (β = 0.193; sr^2 = 2.0%) and logistics (β=0.186; sr2=1.9%) had smaller but significant impacts. From the sr^2, it can be seen the social commerce features account for the most unique variance, which indicates their indivisible strength to affect consumer confidence and intent after adjusting through overlapping effects. This means that trust, reviews, and influencer content still play a vital role in purchase motivation in Indonesia's e-commerce landscape.

Conversely, gamification is proving to play an outsized role in generating platform traffic and sales, contributing 6.0% and 5.8% of their unique variance, respectively. That is, social commerce is best used to trigger purchase decisions, while gamified tactics are more effective at keeping people engaging with one another and promoting reuse. AI and logistics, which are both necessary for user satisfaction and operational reliability, are helpful in the long run but not as powerful for short-term sales impact.

Several strategic implications stem from the findings that e-commerce platforms may pursue to drive superior customer behavior along the customer journey when it comes to strategy-building. The sr2 effect size analyses show that it stands to reason that different platforms should vary approaches based on the result (purchase intent, traffic, or sales performance). Social commerce elements are the largest areas of investment in the purchase determination, the biggest influence on consumer intention. Gamification has a moderate impact on decisions (sr^2 = 2.9%), with AI (sr^2 = 2.0%) and logistics (sr^2 = 1.9%) providing supportive impacts. However, gamification has the strongest influence on platform traffic (sr^2 = 6.0%) and sales (sr^2 =.8%), whereas social commerce (sr^2 = 4.7%) and logistics (sr^2 = 1.7%) follow as secondary drivers.

Table 12. Strategic Implementation

Time Period	Initiative
Short term (0-6 months)	Focus on social commerce and logistics features. Promote user-generated content, live shopping, influencer partnerships, and review mechanisms and ensure the reliability of delivery and free-shipping consistency (sr^2 = 5.64%).
Medium term (6-12 months)	Focus on gamification to increase platform traffic (sr^2 = 6.01%) and sales (sr^2 = 5.80%). Emphasize purchase rewards, loyalty points, group-based competitions, and combine incentives with logistics plans (like free shipping vouchers).
Long term (12+ months)	Use investment with AI to establish AI integration strategy as a strategic differentiator (sr^2 = 2%). Further develop predictive personalization, dynamic pricing and AI-powered suggestions.

Sourch: Data from a survey on consumer perceptions of logistics features.

As shown in Table 12, the strategic roadmap converts numerical results into three execution-oriented stages. In the short term (0–6 months), e-commerce should aim to enhance social commerce and logistics functionality. At this stage, businesses will prioritise actions that increase trust and confidence of consumers in their experience, including increasing the visibility of user-generated content, adding live shopping and engagement with influencers, as well as better product review systems. Equally, logistics reliability – including rapid delivery and consistent free-shipping programs (sr^2 = 5.64%) – is also required to enhance perceptions of service quality and satisfaction following transactions. Altogether, the actions are consistent with the evaluation and response stages of the SOR model, whose positive social and operational indicators influence positive intentions to purchase.

In the medium term (6–12 months), emphasis is placed on gamification, which is strong in terms of increase of platform traffic (sr^2 = 6.01%) and sales (sr^2 = 5.80%). Platforms must ensure that there are loyalty programs, reward-based activities, and group challenges that encourage people to come back to the site and make a purchase. By tying these mechanics to logistical incentives such as free shipping vouchers, this method would not only keep consumers using the app, but also connect entertainment with physical rewards for purchases that may in turn bind emotional and behavioural attachments, further motivating consumers.

Over the long run (12+ months), sustained growth is likely through increased adoption of AI as a strategic differentiator (sr^2 = 2%) in the long run. Platforms should combine predictive personalization, dynamic pricing systems, intelligent chatbots, and recommendation systems into integrated and adaptive shopping experiences. AI-driven insights can improve customer retention and thereby provide assists when marketing campaigns to changing consumer needs by creating seamless personalized journeys to individualize marketing activities. This phased-in implementation approach shows a trend-driven path where trust is achieved via social validation and operational excellence in the short term, engaging experiences that transcend user habits and gamifications in the mid-term, then a sustainable competitive advantage in the long term driven by smart, AI-supported individualization. This series is not only indicative of statistical hierarchy of independent effects but the relationship between strategic decisions and consumer psychology and market maturity in the evolving e-commerce scenario of Indonesia.

Segment-level strategies are also required: younger and heavy e-commerce users respond better to social commerce and gamification while older (and price-sensitive) shopper base seeks reliable logistics and helpful AI. Targeting these disparate needs across segments helps feature investments add maximum value across segments.

CONCLUSION

The study finds that social commerce and logistics features exert the strongest influence on consumer purchase decisions in Indonesian e-commerce, with social commerce shaping trust, credibility, and emotional engagement through reviews, influencers, and user-generated content, while logistics reliability drives post-purchase satisfaction, repeat purchases, and platform loyalty. In contrast, artificial intelligence (AI) and gamification serve as complementary enablers that enhance personalization, engagement, and long-term user interaction. These results suggest that platform managers should adopt a phased investment strategy—prioritizing social commerce and logistics for immediate gains in trust and conversion, leveraging gamification for medium-term engagement growth, and deepening AI integration for sustained personalization and predictive capabilities. Theoretically, the study extends the Buyer Decision Process and Stimulus–Organism–Response (S–O–R) frameworks to digital commerce in emerging markets, highlighting how distinct platform features act as stimuli that drive cognitive, affective, and behavioral responses. Overall, it underscores that successful e-commerce platforms must go beyond price competitiveness by building integrated social, experiential, and intelligent ecosystems to foster trust, engagement, and long-term growth. Future research should explore longitudinal and cross-market comparisons to examine how the relative impact of these features evolves over time and across different levels of market maturity.

REFERENCES

Ahmad, S. Z., Abu Bakar, A. R., Faziharudean, T. M., & Mohamad Zaki, K. A. (2014). An empirical study of factors affecting e-commerce adoption among small- and medium-sized enterprises in a developing country: Evidence from Malaysia. *Information Technology for Development, 21*(4), 555–572.

Alkudah, N. M., & Almomani, T. O. (2024). The integration of artificial intelligence techniques in e-commerce: Enhancing online shopping experience and personalization. *Global Journal of Economics & Business, 14*(6).

Areiqat, A. Y., Hamdan, A., Alheet, A. F., & Alareeni, B. (2021). Impact of artificial intelligence on e-commerce development. In *The importance of new technologies and entrepreneurship in business development: In the context of economic diversity in developing countries* (Vol. 195, pp. 571–578).

Attar, R. W., Almusharraf, A., Alfawaz, A., & Hajli, N. (2022). New trends in e-commerce research: Linking social commerce and sharing commerce: A systematic literature review. *Sustainability, 14*(23), 16024.

Bardelli, N., & Cavenaghi, P. (2024). Social sustainability in retail: Assessing the role of

digital innovation in fostering accessibility and inclusion.
Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
Hamari, J., Koivisto, J., & Sarsa, H. (2014). Does gamification work? A literature review of empirical studies on gamification. In *Proceedings of the 47th Hawaii International Conference on System Sciences* (pp. 3025–3034). IEEE. https://doi.org/10.1109/HICSS.2014.377
He, M., Pham Thi, T. D., Tran, H. M., & Duong, N. T. (2025). Consumers' intentions to use online shopping apps: A comparative analysis. *Acta Psychologica, 259*, 105414.
Huang, Z., & Benyoucef, M. (2013). From e-commerce to social commerce: A close look at design features. *Electronic Commerce Research and Applications, 12*(4), 246–259.
Huang, Y., & Suo, L. (2021). Factors affecting Chinese consumers' impulse buying decision of live streaming e-commerce. *Asian Social Science, 17*(5), 16.
Jiang, Y., Shang, J., Liu, Y., & May, J. (2015). Redesigning promotion strategy for e-commerce competitiveness through pricing and recommendation. *International Journal of Production Economics, 167*, 257–270.
Liu, X., Wan, L. C., & Mattila, A. S. (2025). Virtual influencers going head-to-head with human influencers: The impact of influencer type on trust perceptions of endorsement. *International Journal of Contemporary Hospitality Management, 37*(5), 1574–1602.
Malhotra, G., & Kharub, M. (2025). Elevating logistics performance: Harnessing the power of artificial intelligence in e-commerce. *The International Journal of Logistics Management, 36*(1), 290–321.
Pallant, J. (2020). *SPSS survival manual* (7th ed.). McGraw-Hill Education.
Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Lekakos, G. (2017). The interplay of online shopping motivations and experiential factors on personalized e-commerce: A complexity theory approach. *Telematics and Informatics, 34*(5), 730–742.
Simões, M. G. (2024). *Navigating the digital marketplace: Understanding how AI alters consumer behavior in e-commerce* (Order No. 31790128). ProQuest One Academic.
Svatosova, V. (2020). The importance of online shopping behavior in the strategic management of e-commerce competitiveness. *Journal of Competitiveness, 12*(4), 143.
Tian, X., Yan, B., Zhou, X., & Yan, Y. (2025). Impact of logistics delivery performance on consumers' future purchase behavior: Evidence from an e-commerce platform in China. *Electronic Commerce Research and Applications, 72*, 101509.
Xiang, H., Chau, K. Y., Iqbal, W., Irfan, M., & Dagar, V. (2022). Determinants of social commerce usage and online impulse purchase: Implications for business and digital revolution. *Frontiers in Psychology, 13*, 837042.
Yanchuk, V. M., Antoniuk, D. S., Tkachuk, A. G., Maestri, E., & Vizghalov, O. (2020). Integration of delivery services business cases for improvement of business and environmental sustainability of e-commerce solutions. In *ICTERI Workshops* (pp. 363–376).
Zia, S. M., Faheem, M., Raza, H., & Baig, S. (2024). Impact of contemporary logistics factors on customer satisfaction in e-commerce. *International Journal of Trends and Innovations in Business & Social Sciences, 2*(1), 38–49.