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AI-Powered Marketing Strategies and Customer Satisfaction among Lazada Users in Malaysia

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ABSTRACT

Artificial intelligence (AI) is increasingly embedded in e-commerce marketing through recommendation systems and predictive analytics. This study examines the relationships between personalized recommendations, predictive analytics, and customer satisfaction among Lazada users in Malaysia. Because the original manuscript's use of the Technology Acceptance Model (TAM) was not directly aligned with the measured constructs, the revised study adopts an adapted Information Systems Success perspective, in which AI-enabled information features are examined as antecedents of user satisfaction. Data were obtained from 381 respondents recruited through the Lazada MY Community using convenience sampling. Multiple regression analysis indicated that predictive analytics was positively and significantly associated with customer satisfaction (β = .985, $p < .001$), whereas personalized recommendations were not statistically significant (β = −.006, p = .385). The reported model yielded R^2 = .993; however, this exceptionally high value requires additional diagnostic verification, including multicollinearity, common-method bias, item overlap, residual assumptions and model specification. The findings suggest that predictive analytics may be particularly important for customer satisfaction in the sampled context, while the value of personalized recommendations may depend on the relevance and perceived usefulness of the recommendations. Given the non-probability sample and single-community recruitment, the findings should be interpreted as context-specific rather than representative of Malaysian e-commerce users generally.

Keywords: artificial intelligence; AI-powered marketing; personalized recommendations; predictive analytics; customer satisfaction; e-commerce; Lazada

INTRODUCTION

Artificial intelligence (AI) is increasingly embedded in e-commerce through recommendation systems, predictive analytics, conversational interfaces and automated decision support. These applications enable online retailers to process large volumes of customer data and deliver more relevant information and interactions. The expansion of e-commerce in Malaysia provides an important setting for examining these developments. The Department of Statistics Malaysia reported that e-commerce income by establishments reached RM1,288.1 billion in 2024, indicating the continued importance of digital commerce in the Malaysian economy (Department of Statistics Malaysia, 2025).

AI-powered marketing is not uniformly beneficial, however. The value of an AI-enabled feature depends on whether customers perceive the information or recommendation as relevant, accurate, timely and useful. Recommendation systems, for example, can improve user satisfaction by helping shoppers identify products that fit their needs, but their effects may depend on shopping goals and users' psychological responses to the recommendations (He et al., 2024). Similarly, AI-powered marketing can generate customer value through data-

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driven personalization and prediction, but its effectiveness may be constrained by poor data quality, inappropriate recommendations, privacy concerns, and a lack of transparency (Kumar et al., 2024).

The Malaysian context also warrants further investigation. Existing studies have examined AI applications in e-commerce, including recommendation systems, chatbots and image search, but empirical evidence remains fragmented across different AI functions and markets. For example, a Malaysian study by Lim et al. (2023) found that recommendation systems and image search were important contributors to customer satisfaction, while recent research has shown that recommendation-system effects can vary according to users' goals and feelings during online shopping (He et al., 2024). These findings suggest that AI-enabled marketing features should not be assumed to have identical effects on customer satisfaction.

Accordingly, this study examines two AI-powered marketing features personalized recommendations (PR) and predictive analytics (PA) and their relationships with customer satisfaction (CS) among Lazada users in Malaysia. The study contributes by separating two related but conceptually distinct AI functions and examining whether each is associated with satisfaction. In response to the conceptual limitation identified in the earlier manuscript, the revised study does not claim that PR and PA are traditional TAM constructs. Instead, it adopts an adapted Information Systems Success perspective that provides a more direct theoretical connection between technology-enabled information features and user satisfaction.

THEORETICAL FRAMEWORK

Adapted Information Systems Success Perspective

The original manuscript adopted the Technology Acceptance Model (TAM). TAM is primarily concerned with technology acceptance and explains acceptance through constructs such as perceived usefulness and perceived ease of use (Davis, 1989). The present study, however, measures personalized recommendations, predictive analytics and customer satisfaction. Because perceived usefulness, perceived ease of use, attitude and behavioral intention were not included in the questionnaire, retaining TAM as the primary tested framework would create a conceptual mismatch between the theory and the operationalized variables.

The revised manuscript therefore adopts the DeLone and McLean Information Systems Success Model as the theoretical lens. The updated model conceptualizes information systems success through system quality, information quality, service quality, use/intention to use, user satisfaction, and net benefits. Importantly for the present study, user satisfaction is an explicit outcome of information-system quality and use-related experiences (DeLone & McLean, 2003). Subsequent empirical applications have also used the model to explain user satisfaction in digital information-system contexts.

The present study adapts this perspective to AI-enabled e-commerce. Personalized recommendations and predictive analytics are treated as AI-enabled information features through which an e-commerce platform generates, filters and delivers customer-relevant information. Personalized recommendations emphasize the relevance of product information to an individual shopper, whereas predictive analytics emphasizes the use of historical and behavioral data to anticipate future preferences or needs. Both mechanisms can therefore be examined as technology-enabled antecedents of customer satisfaction. This is an adaptation of the Information Systems Success perspective rather than a test of the full DeLone and McLean model. The distinction is important because the study does not directly measure all original model dimensions.

Recent e-commerce research provides empirical support for this conceptual direction. He et al. (2024) found that recommendation systems can contribute to user satisfaction, although the strength of the relationship depends on contextual and psychological conditions. Lim et al. (2023), using Malaysian e-commerce consumers, similarly reported that AI-enabled recommendation functions were relevant to customer satisfaction. Kumar et al. (2024) further argue that AI-powered marketing can create value by using customer data to improve targeting, personalization, and decision making. Taken together, these studies provide a basis for examining specific AI-enabled marketing features as antecedents of satisfaction while recognizing that individual AI functions may not produce identical outcomes.

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Conceptual Model

The revised conceptual model contains two independent variables and one dependent variable:

Independent variables	Dependent variable
Personalized Recommendations (PR)	Customer Satisfaction (CS)
Predictive Analytics (PA)	

Hypotheses Development

H1: Personalized recommendations are positively associated with customer satisfaction among Lazada users in Malaysia.

H2: Predictive analytics is positively associated with customer satisfaction among Lazada users in Malaysia.

LITERATURE REVIEW

Personalized Recommendations

Personalized recommendations use customer information, such as browsing behavior, previous purchases, and stated or inferred preferences, to generate product suggestions. The underlying value proposition is that relevant recommendations reduce search effort and increase the likelihood that customers encounter products that match their needs. In e-commerce, recommendation systems have been identified as an important mechanism for improving the user experience and satisfaction (He et al., 2024). Evidence from Malaysian consumers also suggests that recommendation functions can contribute to satisfaction with AI applications in e-commerce (Lim et al., 2023). Nevertheless, recommendations can become ineffective when customers perceive them as repetitive, inaccurate, intrusive, or poorly matched to their current shopping goals. Therefore, a positive relationship is theoretically expected but should be treated as an empirical question.

Predictive Analytics

Predictive analytics applies statistical and machine-learning techniques to historical and behavioral data to estimate future outcomes, preferences, or actions. In e-commerce, predictive analytics can support more timely information delivery, demand forecasting, customer segmentation, and proactive marketing decisions. By anticipating customer needs, predictive analytics may improve the relevance and timeliness of interactions and thereby enhance the shopping experience. Recent work on AI-powered marketing similarly emphasizes the role of data-driven prediction and decision support in creating customer value (Kumar et al., 2024).

Customer Satisfaction

Customer satisfaction represents the customer's overall evaluation of the shopping experience relative to expectations. In digital commerce, satisfaction can be shaped by the relevance and usefulness of information, the quality of the interface and service and the effectiveness of technology-enabled interactions. The DeLone and McLean framework explicitly positions user satisfaction as a central outcome of information-system success (DeLone & McLean, 2003). In the present study, satisfaction is therefore treated as the focal outcome of customers' experiences with AI-enabled marketing features.

METHODOLOGY

Research Design

This study employed a quantitative, cross-sectional survey design to examine the relationships between personalized recommendations, predictive analytics and customer satisfaction. The unit of analysis was the individual e-commerce user.

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Population, Sampling, and Data Collection

The respondents were users recruited from the "Lazada MY Community" social media community. A convenience sampling approach was used because the community provided direct access to individuals with experience using Lazada. A total of 381 usable responses were obtained. The original manuscript justified the sample size using the Krejcie and Morgan (1970) table; however, the revised manuscript treats 381 as the achieved sample rather than implying that the sample is statistically representative of Malaysian e-commerce users.

Because respondents were recruited from one online community using non-probability sampling, the sample should be regarded as context-specific. The community may also contain users who differ from the wider population in platform engagement, shopping frequency, demographics or attitudes toward AI.

Instrument Design

The questionnaire consisted of three sections. Section A collected demographic information. Section B measured the two independent variables: personalized recommendations (four items) and predictive analytics (three items). Section C measured customer satisfaction (three items). The questionnaire items were adapted from prior studies, including Pappas et al. (2016), Mahmoud and Mohamadali (2021) and Ebaietaka (2024), with contextual modifications for e-commerce.

The use of adapted items requires more than internal-consistency evidence. Cronbach's alpha assesses internal consistency but does not by itself establish construct validity. Therefore, before publication, the main-study data should be subjected to construct-validation procedures such as exploratory factor analysis (EFA) or confirmatory factor analysis (CFA), depending on the study's measurement model. At minimum, the revised analysis should report factor loadings, KMO and Bartlett's test where EFA is used, composite reliability (CR), average variance extracted (AVE), and discriminant validity. Where a latent-variable model is estimated, the HTMT criterion may also be used to assess discriminant validity (Henseler et al., 2015).

Pilot Test

A pilot test involving 38 respondents was conducted. The reported Cronbach's alpha values were .89 for personalized recommendations, .84 for predictive analytics, and .88 for customer satisfaction. These values indicate strong internal consistency in the pilot sample. However, the pilot reliability results should not be presented as evidence that the constructs are fully valid; construct validity must be assessed using the main-study data.

Variable	Cronbach's alpha	Interpretation
Personalized Recommendations (PR)	.89	Good internal consistency
Predictive Analytics (PA)	.84	Good internal consistency
Customer Satisfaction (CS)	.88	Good internal consistency

Statistical Analysis and Diagnostic Procedures

Multiple linear regression was used to estimate the relationships between PR, PA and CS. The regression model was specified as: $CS = \beta 0 + \beta 1(PR) + \beta 2(PA) + \varepsilon$. Before interpreting the regression coefficients, the analysis should verify the assumptions and potential sources of inflated explanatory power. Specifically, the revised analysis should report: (1) multicollinearity using variance inflation factor (VIF) and tolerance; (2) residual normality using a histogram and normal probability plot, supplemented where appropriate by a formal test; (3) homoscedasticity using residual-versus-predicted plots and, where appropriate, a formal heteroscedasticity test; (4) influential observations using standardized residuals, leverage, and Cook's distance; and (5) common-method bias using an appropriate procedural or statistical diagnostic. Because all constructs were measured using a self-report questionnaire in a single cross-sectional survey, common-method variance cannot be ruled out without additional testing (Podsakoff et al., 2003).

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The exceptionally high reported R^2 (.993) requires scrutiny. Such a value may reflect a genuine relationship, but it may also arise from overlapping questionnaire items, highly correlated constructs, common-method variance, restricted response patterns, or model-specification problems. The regression model should therefore be rerun from the raw dataset before the reported R^2 and F statistic are treated as final.

RESULTS

Respondent Profile

A total of 381 respondents participated in the study. Females accounted for 199 respondents (52.2%) and males for 182 respondents (47.8%). The largest reported ethnic group was Chinese (193, 50.7%), followed by Indians (110, 28.9%), Malays (45, 11.8%), and Indigenous respondents (33, 8.7%). The largest reported age group was 19–25 years (152, 39.9%), followed by 26–35 years (81, 21.3%), 36–45 years (73, 19.2%), and 46–54 years (67, 17.6%). The original manuscript also reported categories labelled “18 years and above” and “65 years and above”; because the first label overlaps with the other age categories, the age-frequency table should be checked against the original questionnaire and dataset before publication.

Regarding online-shopping experience, 106 respondents (27.8%) reported 1–3 years, 103 (27.0%) reported 6 months–1 year, 92 (24.1%) reported less than 6 months, and 80 (21.0%) reported more than 3 years.

Multiple Regression

Model	R	R^2	Adjusted R^2	Std. Error
1	.996	.993	.993	.06205

Predictors: Constant, PR, PA. Dependent variable: CS.

The original model summary reported R = .996, R^2 = .993, adjusted R^2 = .993, and a standard error of the estimate of .06205. Based on the reported sums of squares, the R^2 is mathematically consistent with approximately .993. However, the magnitude is exceptionally high for a consumer-behavior model with two self-reported predictors and should not be interpreted as evidence of model accuracy without diagnostic verification.

ANOVA and Statistical Consistency Check

Source	Sum of Squares	df	Mean Square	F	Sig.
Regression	203.428	2*	101.714	26,479.264*	< .001*
Residual	1.452	378*	.003841		
Total	204.880*	380*			

*The original manuscript reported regression df = 3 and residual df = 377 despite specifying only two predictors. The values above are mathematically reconstructed from the reported sums of squares and n = 381 for a two-predictor model. They must be replaced by the exact output from the raw dataset before submission.

The original ANOVA table is internally inconsistent with the specified model. For a regression model containing two predictors and 381 observations, regression df should be 2 and residual df should be 378. The reconstructed F statistic is shown only to demonstrate the correction; the final inferential result should be taken from a rerun of the regression using the raw dataset.

Regression Coefficients

Predictor	B	SE	β	t	p
Constant	.059	.021	—	2.743	.006
Personalized Recommendations (PR)	−.007	.008	−.006	−.869	.385
Predictive Analytics (PA)	.973	.007	.985	148.266	< .001

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The coefficient analysis indicates that predictive analytics was positively and significantly associated with customer satisfaction ($\beta = .985$, $p < .001$). In contrast, personalized recommendations showed a very small negative and statistically non-significant coefficient ($\beta = -.006$, $p = .385$). Therefore, H1 is not supported, whereas H2 is supported based on the reported coefficient results. The significant overall regression test should not be interpreted as evidence that both predictors are individually significant.

Required Robustness Checks Before Final Submission

Diagnostic	Purpose	Status in original manuscript
VIF and tolerance	Assess multicollinearity between PR and PA	Not reported; rerun from raw data
Residual histogram / P–P plot	Assess residual normality	Not reported; rerun from raw data
Residual-versus-predicted plot / heteroscedasticity test	Assess homoscedasticity	Not reported; rerun from raw data
Cook's distance / leverage / standardized residuals	Identify influential observations	Not reported; rerun from raw data
Common-method-bias diagnostic	Assess inflation from single-source measurement	Not reported; rerun from raw data
EFA/CFA, CR, AVE, discriminant validity	Strengthen construct validation	Not reported; rerun from item-level data

This table is intentionally transparent: no diagnostic statistics have been fabricated because the uploaded manuscript does not contain the respondent-level dataset or the relevant SPSS output.

DISCUSSION

Personalized Recommendations

The finding for personalized recommendations does not support H1. The coefficient was negative and statistically non-significant ($\beta = -.006$, $p = .385$). This result differs from studies reporting positive effects of recommendation systems on satisfaction. For example, Lim et al. (2023) reported that recommendation systems were among the AI functions contributing to customer satisfaction among Malaysian e-commerce consumers, while He et al. (2024) showed that recommendation-system effects on user satisfaction can depend on shopping goals and users' psychological states.

The non-significant result in the present study should therefore not be interpreted as evidence that personalized recommendations are inherently ineffective. A more cautious interpretation is that, within the sampled Lazada community and the present measurement model, perceived personalized recommendations did not explain additional variation in satisfaction after predictive analytics was included. One possible explanation is that recommendation quality varies across products and users. Customers may appreciate recommendations when they are relevant and timely but ignore them when they are repetitive, inaccurate, or inconsistent with current shopping intentions. This interpretation should be tested in future research using more specific measures of recommendation relevance, transparency, diversity, and perceived intrusiveness.

Predictive Analytics

H2 was supported. Predictive analytics showed a strong positive association with customer satisfaction ($\beta = .985$, $p < .001$). This finding is consistent with the broader argument that AI-powered marketing can use behavioral and transactional data to anticipate customer needs and support more timely and relevant interactions (Kumar et al., 2024).

Nevertheless, the magnitude of the coefficient must be interpreted with caution. A standardized coefficient of .985 together with $R^2 = .993$ is unusually large. Such a pattern can occur when predictors are very strongly related to the dependent variable or when measurement items substantially overlap. It can also be amplified by common-method variance because all variables were collected from the same respondents using the same

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questionnaire. Accordingly, the finding should be described as a strong statistical association in the current sample, not as definitive evidence that predictive analytics causes customer satisfaction.

Overall Model Interpretation

The most important revision is to distinguish model-level significance from predictor-level significance. The significant overall regression test does not mean that every predictor is significant. The coefficient analysis clearly indicates that personalized recommendations were not significant, whereas predictive analytics was significant. Consequently, statements in the original manuscript claiming that both AI-powered strategies significantly influence customer satisfaction have been removed.

The reported R^2 of .993 should also be treated as provisional until the model is rerun and diagnostic tests are examined. If the value remains exceptionally high after verification, the discussion should investigate whether the PR, PA, and CS items are conceptually distinct and empirically discriminant. If diagnostic tests reveal substantial multicollinearity, common-method variance, non-normal residuals, heteroscedasticity, influential cases, or item overlap, the regression results should be re-estimated and the interpretation revised accordingly.

CONCLUSION

This study examined the relationships between personalized recommendations, predictive analytics, and customer satisfaction among Lazada users in Malaysia. The findings indicate that predictive analytics was positively and significantly associated with customer satisfaction, whereas personalized recommendations did not show a statistically significant association in the regression model.

The findings should be interpreted within the context of the study design. The sample was obtained through convenience sampling from a single Lazada social media community, and the data were collected at one point in time. Therefore, the results should not be generalized to Malaysian e-commerce users as a whole, and causal conclusions cannot be established from the cross-sectional design.

The reported R^2 of .993 indicates an exceptionally strong model fit, but this value requires further verification because it is unusually high for consumer-behavior research. Multicollinearity, common-method variance, item overlap, influential observations, residual assumptions, and model specification should be assessed using the raw dataset before the statistical results are finalized. Subject to these checks, the results suggest that predictive analytics may be a more important AI-enabled marketing feature than personalized recommendations for the sampled users. Future research should test a broader and theoretically integrated model that includes constructs such as information quality, perceived usefulness, trust, transparency, and customer control.

Limitations and Future Research

First, the study used a cross-sectional quantitative design and therefore captures respondents' perceptions at a single point in time. The design does not permit causal inference. Second, the study relied on convenience sampling within a single Lazada social media community. This creates selection bias and limits external validity. The characteristics of community members may differ from those of the wider population of Malaysian e-commerce users. Third, the study examined only two AI-enabled marketing features. Other factors, including information quality, perceived usefulness, trust, privacy concerns, transparency, algorithmic fairness, service quality, and perceived control, may also explain customer satisfaction. Fourth, all constructs were measured through the same self-report questionnaire. This creates a potential risk of common-method variance and makes it particularly important to conduct diagnostic tests before drawing strong conclusions. Fifth, the original manuscript relied mainly on Cronbach's alpha for measurement assessment. Future versions should provide stronger construct-validation evidence, including factor loadings, composite reliability, convergent validity, and discriminant validity.

Future research should recruit respondents from multiple e-commerce platforms and use probability-based or quota-based sampling where feasible. Comparative studies involving Lazada, Shopee, TikTok Shop, and other platforms could determine whether the observed relationships are platform specific. Future studies should also develop a more comprehensive theoretical model. An adapted DeLone and McLean framework could be expanded to include information quality, system quality, trust, perceived usefulness, transparency, and customer control. Structural equation modelling could then be used to test direct and indirect relationships among the constructs. Finally, longitudinal or mixed-method designs would help explain why customers respond differently to AI recommendations and predictive analytics. Qualitative interviews could be particularly useful for identifying situations in which customers reject AI recommendations despite perceiving the underlying technology as useful.

Theoretical and Practical Contribution

Theoretically, the study contributes by distinguishing between two AI-enabled marketing functions rather than treating AI marketing as a single homogeneous construct. The revised theoretical framing also clarifies that personalized recommendations and predictive analytics are not traditional TAM constructs. Instead, they are examined as AI-enabled information features within an adapted Information Systems Success perspective, with customer satisfaction as the focal outcome.

Practically, the findings suggest that e-commerce managers should pay attention to the quality and usefulness of predictive analytics rather than if all forms of AI personalization automatically improve satisfaction. At the same time, the non-significant result for personalized recommendations indicates that recommendation systems should be evaluated for relevance, accuracy, diversity, transparency, and fit with customers' current shopping goals. These implications are conditional on the robustness checks and should not be generalized beyond the sampled context.

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