

GAMIFICATION AND AI-POWERED PERSONALIZATION IN SHOPEEFOOD CONTINUANCE INTENTION: E-TRUST MODERATION IN KUPANG

Asbi Nasar^{1*}, Ni Made Dwiyanas Rasuma Putri², Andy Noviadi³

^{1*}Politeknik Negeri Kupang, Indonesia

^{2,3}Politeknik Sahid, Indonesia

Correspondence: nasarazbii@gmail.com

Article Info	Abstract
Keywords: AI-powered personalization; continuance intention; E-Trust; gamification; online food delivery Received: September 23, 2026 Approved: September 29, 2026 Published: September 30, 2026	Online food-delivery platforms increasingly function as digital service, marketing, and culinary-product distribution channels within the hospitality industry. This study examines the relationships of gamification and AI-powered personalization with continuance intention and tests whether E-Trust moderates these relationships among ShopeeFood users in Kupang, Indonesia. A quantitative explanatory design was applied to 154 respondents selected through purposive sampling. Data were collected from June to August 2026 using a 19-item Google Forms questionnaire distributed via WhatsApp. The data were analyzed using IBM SPSS Statistics 25 through measurement-item adequacy assessment, reliability analysis, multiple linear regression, and Moderated Regression Analysis. In the direct-effect model, gamification and AI-powered personalization were positively and significantly associated with continuance intention ($p < 0.001$), and the model explained 81.8% of the variance in continuance intention. In the moderation model, gamification remained statistically significant ($p = 0.001$), whereas AI-powered personalization became nonsignificant ($p = 0.886$). The interaction between gamification and E-Trust ($p = 0.843$) and the interaction between AI-powered personalization and E-Trust ($p = 0.467$) were also nonsignificant. Thus, E-Trust did not moderate either relationship in the model tested. The findings indicate that interactive incentives were more consistently associated with continuance intention than personalized recommendations across the two model specifications. Online food-delivery providers should develop attainable and transparent rewards while improving the relevance of restaurant, menu, and promotional recommendations. Restaurant partners can support these initiatives by maintaining accurate digital product and promotional information.

How to cite:

Nasar, A., Putri, N. M. D. R., & Noviadi, A. (2026). Gamification and Ai-Powered Personalization in ShopeeFood Continuance Intention: E-Trust Moderation in Kupang. *International Journal of Travel, Hospitality and Events*, 5(3), 429-447. <https://doi.org/10.56743/ijothe.v5i3.967>

INTRODUCTION

The expansion of online food delivery (OFD) services has transformed how consumers access restaurant services and culinary products. Within the hospitality industry, OFD platforms function not only as transaction applications but also as digital service and distribution channels connecting consumers, restaurants, food businesses, and delivery partners. These platforms allow restaurants to extend their services beyond physical premises, improve the visibility of culinary products, and maintain customer relationships through digital interactions. Consumers also obtain convenient ordering processes, diverse restaurant options, flexible payment methods, and promotional benefits. Transaction-related considerations, price, and promotion therefore influence consumers' preferences when selecting OFD platforms (Hurdawaty and Dylun, 2024). As competition among platforms intensifies, their sustainability increasingly depends on retaining existing users rather than relying solely on initial adoption.

Users' willingness to maintain their relationship with a digital service is conceptualized as continuance intention. Unlike initial adoption, which is primarily influenced by expectations formed before service use, continuance intention reflects users' evaluations after obtaining direct experience with the platform. The Expectation-Confirmation Model (ECM) explains that continued use develops when users evaluate whether a system's performance and benefits correspond with their prior expectations (Bhattacharjee, 2001). A systematic literature review of 147 articles by Yan et al. (2021) demonstrates the continuing relevance of established continuance theories while identifying psychological, technological, social, and behavioral factors as major categories of antecedents to the continued use of online technologies.

The present study draws on the post-adoption perspective of ECM without claiming to test the complete original model. Confirmation, perceived usefulness, and satisfaction are not examined as separate constructs. Instead, ECM provides the underlying logic that users' evaluations of platform-related experiences can influence their intention to continue using a service. This perspective is relevant to OFD because repeated use develops through recurring experiences involving restaurant selection, promotional offers, product recommendations, payments, ordering, and delivery. Previous studies have demonstrated that performance expectancy, satisfaction, perceived value, trust, and other functional evaluations contribute to users' intentions to continue using food-ordering applications (Alalwan, 2020; Zhao and Bacao, 2020). Nevertheless, continuing developments in interactive and algorithm-supported features require further examination of platform-related mechanisms that may sustain repeated use.

One mechanism increasingly incorporated into digital platforms is gamification. Gamification refers to the application of game-like elements in non-game service environments to stimulate motivation, participation, and engagement. Within OFD platforms, these elements may include points, rewards, vouchers, challenges, and other interactive incentives. Gamification can provide extrinsic motivation through tangible benefits while creating intrinsic enjoyment through interactive and goal-oriented experiences (Hamari et al., 2014; Ryan and Deci, 2000). When users consider rewards and challenges accessible and beneficial, routine food-ordering transactions may become more engaging and provide additional reasons to revisit the platform.

Empirical evidence reinforces the relevance of gamification to application use. Bitrián et al. (2021) found that gamification enhanced user engagement by satisfying users' needs for competence, autonomy, and relatedness. Increased engagement subsequently strengthened users' intentions to use, recommend, and positively evaluate the application. Research on gamification services further indicates that perceived usefulness, enjoyment, and social influence can shape users' attitudes and continued use intentions (Hamari and Koivisto, 2015). Although these studies did not specifically investigate ShopeeFood users, they demonstrate that gamified experiences can produce motivational and behavioral outcomes extending beyond temporary enjoyment.

From a post-adoption perspective, users who repeatedly receive understandable and attainable benefits from gamified features may develop more favorable evaluations of the platform. Points, rewards, vouchers, and challenges may provide immediate value, strengthen engagement, and reinforce users' motivation to return. Conversely, gamification that is complicated, difficult to achieve, or perceived as unfair may not produce sustained engagement. The motivational and experiential value of well-designed gamification nevertheless provides a basis for expecting a positive relationship with continuance intention. Therefore, the first hypothesis is formulated as follows:

H₁: Gamification has a positive effect on continuance intention to use ShopeeFood.

In addition to gamification, OFD platforms increasingly employ algorithm-supported personalization to improve the relevance of user experiences. In this study, AI-powered personalization refers to users' perceptions of the platform's ability to use information about their preferences and previous activities to provide relevant recommendations, promotions, and product suggestions. Such personalization may reduce the effort required to search through numerous restaurants and menu items, increase information relevance, and support more efficient purchasing decisions. In the context of personalized online advertising, Bleier and Eisenbeiss (2015) demonstrated that personalization effectiveness depends on the interplay among content, timing, and placement. This finding suggests that personalization should not only match users' preferences but also be delivered within an appropriate interaction context.

Evidence from adjacent AI-enabled service contexts reinforces the potential contribution of intelligent digital features to continued use. Lee et al. (2023) found that perceived intelligence in AI-enabled mobile banking applications contributed to expectation confirmation and perceived usefulness, which subsequently increased satisfaction and continuance intention. In the context of fashion e-retail chatbots, Mpinganjira et al. (2024) similarly demonstrated that perceived chatbot intelligence positively influenced utilitarian, hedonic, and social experiential value. However, only utilitarian and hedonic experiential value positively influenced continued chatbot use intention, whereas social experiential value had a negative effect. Although these studies did not directly examine personalized recommendations in OFD services, they indicate that AI-supported features can encourage continued use when users perceive them as useful and capable of improving the digital-service experience.

In the OFD context, relevant personalized recommendations may help users identify suitable restaurants, food products, and promotional offers more efficiently. Repeated

exposure to recommendations that correspond with users' preferences may strengthen the perceived compatibility between the platform and their consumption needs. However, personalization may not uniformly produce favorable responses because users may evaluate recommendation accuracy and express concerns about the collection and use of their personal information. In the context of fashion e-retail chatbots, Mpinganjira et al. (2024) found that perceived chatbot risk, including time and privacy-information risks, significantly reduced users' utilitarian, hedonic, and social experiential value. This finding illustrates that AI-supported features can simultaneously generate perceived benefits and concerns. Nevertheless, when personalized recommendations are perceived as relevant and useful, the resulting efficiency may encourage users to continue using the platform. Accordingly, the following hypothesis is proposed:

H₂: AI-powered personalization has a positive effect on continuance intention to use ShopeeFood.

The effects of gamification and AI-powered personalization may also depend on whether users trust the platform. E-Trust reflects users' trusting beliefs regarding the ability of a digital service provider to perform reliably and act in users' interests (McKnight et al., 2002). Trust is particularly important in digitally mediated hospitality services because users cannot directly observe all processes involving payments, personal information, restaurant order processing, reward allocation, promotional mechanisms, and algorithm-supported recommendations. E-Trust may reduce perceived uncertainty and strengthen users' willingness to rely on the platform during repeated service interactions.

Recent research confirms the importance of trust in post-adoption behavior. Choi et al. (2023) found that expectation confirmation, perceived security, satisfaction, and trust significantly influenced users' continued use intention toward travel applications, whereas privacy protection did not have a significant effect. Quintus et al. (2024) further demonstrated that the antecedents and consequences of consumer trust in e-commerce may differ between advanced and emerging markets. Collectively, these findings indicate that trust remains important in digital-service relationships, although its formation and behavioral consequences may vary according to platform-related experiences and market contexts.

In this study, E-Trust is positioned as a moderating variable rather than solely as a direct predictor. A moderating variable indicates whether the strength or direction of a relationship varies across its different levels. Evidence from other digital-service contexts suggests that trust may operate as a contingent factor, although its moderating effect is not consistent across all antecedents of continuance intention. In the mobile-banking context, Nguyen and Dao (2024) found that trust positively moderated the relationship between behavioral adaptation and continuance intention but did not significantly moderate the relationship between satisfaction and continuance intention. Although these relationships differ from those examined in the present study, the mixed findings suggest that trust should not automatically be assumed to strengthen every relationship. Its moderating role must therefore be tested separately across different platform features and service contexts.

When users trust ShopeeFood, they may perceive points, rewards, vouchers, challenges, and other interactive incentives as more credible components of the platform experience. E-Trust may increase users' confidence that the platform will implement gamified

mechanisms reliably and consistently. Conversely, limited trust may cause users to question whether the incentives and their associated conditions can be relied upon, thereby weakening the relationship between gamification and continuance intention. Thus, the extent to which positive evaluations of gamification are translated into an intention to continue using ShopeeFood may depend on users' level of E-Trust. Accordingly, the following hypothesis is proposed:

H₃: E-Trust positively moderates the relationship between gamification and continuance intention, such that the positive relationship is stronger at higher levels of E-Trust.

E-Trust may also condition users' responses to AI-powered personalization. Personalized recommendations are commonly generated by processing information about users' preferences and previous activities. Although personalization can improve the relevance of restaurant recommendations, product suggestions, and promotional offers, users may remain cautious about the collection and use of the information required to generate them. The personalization–privacy paradox indicates that consumers may value personalized services while simultaneously being concerned about the disclosure and use of personal information required to provide such services (Awad and Krishnan, 2006).

When E-Trust is high, users may be more willing to rely on personalized recommendations and perceive them as relevant components of the ShopeeFood service. Trust may reduce uncertainty about the platform and strengthen users' confidence in the recommendations and promotional offers presented to them. Conversely, when E-Trust is limited, users may respond more cautiously to personalized suggestions, even when those suggestions correspond with their preferences. Therefore, the extent to which positive evaluations of AI-powered personalization are translated into continuance intention may depend on users' trusting beliefs regarding the platform. Accordingly, the following hypothesis is proposed:

H₄: E-Trust positively moderates the relationship between AI-powered personalization and continuance intention, such that the positive relationship is stronger at higher levels of E-Trust.

Research in hospitality and tourism has provided important explanations of customer retention, repurchase intention, and loyalty. Piani et al. (2024) found that electronic word of mouth and service quality contributed to repurchase intention at K Club Ubud Resort, with service quality providing the larger contribution. In the restaurant context, Omidvar and Deen (2024) demonstrated that corporate image mediated the effects of corporate social responsibility dimensions on customer retention. Pranawukir et al. (2026) further found that brand equity and perceived value mediated the relationship between integrated marketing communication and tourist loyalty in Nusa Penida. Although these studies examined different hospitality and tourism settings, their findings indicate that service evaluations, perceived value, and relational perceptions contribute to maintaining customer relationships. However, they do not explain how interactive and algorithm-supported platform features influence users' intention to continue using an online food-delivery service. The present study addresses this specific post-adoption issue by examining gamification, AI-powered personalization, and E-Trust among ShopeeFood users in Kupang.

Research on the continued use of online food-delivery services has commonly emphasized functional and post-adoption evaluations. Alalwan (2020) and Zhao and Bacao

(2020), for example, identified performance expectancy, convenience-related benefits, satisfaction, and other functional evaluations as important determinants of consumers' intentions to continue using food-ordering applications. In a related OFD setting, Hurdawaty and Dylun (2024) showed that transaction-related considerations, price, and promotion influenced consumers' platform preferences. Meanwhile, gamification research has primarily examined motivational experiences, engagement, and behavioral responses, whereas studies of AI-enabled services have emphasized perceived intelligence, usefulness, experiential value, and technology acceptance (Bitrián et al., 2021; Lee et al., 2023; Mpinganjira et al., 2024). Although these research streams provide important insights, limited attention has been given to gamification and AI-powered personalization as simultaneous predictors of continuance intention in OFD services.

A further gap concerns the contingent role of E-Trust. Choi et al. (2023) demonstrated that trust directly contributed to users' continued use intention toward travel applications. Evidence regarding trust as a moderator, however, remains more limited and relationship-specific. In the mobile-banking context, Nguyen and Dao (2024) found that trust positively moderated the relationship between behavioral adaptation and continuance intention but did not significantly moderate the relationship between satisfaction and continuance intention. These findings suggest that trust should not automatically be assumed to strengthen every antecedent of continued use. Accordingly, its moderating role needs to be examined separately for different platform features and service contexts.

Gamification and AI-powered personalization represent different mechanisms within the digital service experience. Gamification involves directly observable incentives and interactive elements, such as points, rewards, vouchers, and challenges. AI-powered personalization, by contrast, involves algorithm-supported processes that generate recommendations, promotional offers, and product suggestions based on users' preferences and previous activities. Because these mechanisms differ in how they are presented to users and in the information-processing activities underlying them, their relationships with continuance intention may not depend on E-Trust in the same way.

This study addresses this integrative and mechanism-related gap by examining gamification and AI-powered personalization within a single post-adoption model and testing E-Trust as a moderator of both relationships. Its contribution lies in comparing an explicit interactive mechanism with an algorithm-supported mechanism and evaluating whether E-Trust conditions their respective relationships with continuance intention. ShopeeFood users residing in Kupang, Indonesia, constitute the empirical setting. Kupang is treated as the research context rather than as the source of novelty, and the study does not assume that users in the city possess distinctive technological, psychological, or consumption characteristics.

Theoretically, the study draws on the post-adoption logic of the Expectation-Confirmation Model to explain how users' evaluations of platform-related experiences are associated with continuance intention, without claiming to test the complete original ECM. Empirically, it evaluates the direct relationships of gamification and AI-powered personalization with continuance intention and subsequently tests the interaction of each variable with E-Trust. Practically, the findings may assist OFD providers and restaurant

businesses in evaluating whether interactive incentives and relevant recommendations contribute to continued platform use and whether these relationships vary according to users' trust. These insights are relevant to the continuity of food-ordering services, digital restaurant marketing, and culinary-product distribution within the hospitality industry. The conceptual relationships examined in this study are presented in Figure 1.

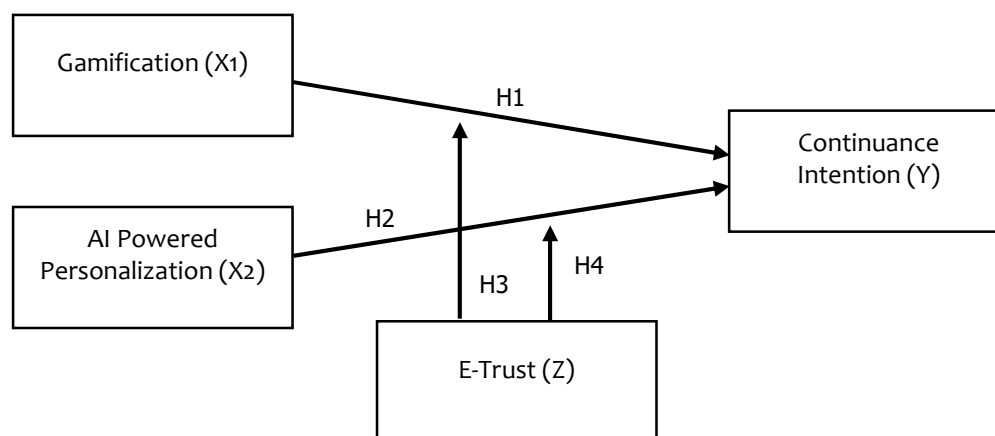


Figure 1. Conceptual Framework
 Source: Authors' conceptualization, 2026

METHODS

This study employed a quantitative explanatory design to examine the relationships of gamification and AI-powered personalization with continuance intention and to test the moderating role of E-Trust. The study involved ShopeeFood users residing in Kupang, Indonesia. The population comprised all ShopeeFood users residing in the research area. However, the population size could not be determined because no publicly accessible information was available regarding the total number of ShopeeFood users in Kupang.

Purposive sampling was employed because respondents had to satisfy specific eligibility criteria relevant to the research objectives. Respondents were eligible when they were ShopeeFood users, had completed at least one food-ordering transaction through the platform, and resided in Kupang. Data were collected from June to August 2026 through a Google Forms questionnaire distributed via WhatsApp. Before completing the questionnaire, prospective respondents received information concerning the purpose of the study, the voluntary nature of participation, and the academic use of their responses. They were required to provide consent and answer screening questions concerning their use of ShopeeFood, previous food-ordering transactions, and residence in Kupang. Only respondents who provided consent and met all eligibility criteria were included.

The data-collection period was concluded at the end of August 2026, by which time 154 eligible responses had been obtained. All 154 eligible responses were included in the analysis. Because the questionnaire contained 19 measurement items, the resulting sample represented approximately eight respondents per item and satisfied the recommendation of five to ten respondents per measurement item (Hair et al., 2019). Thus, the number of 154 represents the final research sample rather than the total population of ShopeeFood users in Kupang.

The research instrument was a structured questionnaire consisting of 19 measurement items evaluated using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Gamification was measured using six items adapted from Hamari et al. (2014) and Hamari and Koivisto (2015), covering users' evaluations of rewards, points, challenges, and interactive incentives. AI-powered personalization was measured using three items adapted from Bleier and Eisenbeiss (2015), focusing on the perceived relevance of recommendations, promotions, and product suggestions. Conceptually, E-Trust reflects trusting beliefs concerning the platform's competence, benevolence, and integrity (McKnight et al., 2002). In this study, E-Trust was operationalized using five measurement items. Continuance intention was measured using five items adapted from Bhattacharjee (2001), representing users' intention to continue using ShopeeFood for future food-ordering transactions.

The data were analyzed using IBM SPSS Statistics version 25. Measurement-item adequacy was assessed separately for each construct using the Kaiser–Meyer–Olkin (KMO) measure and factor loadings. A KMO value exceeding 0.50 was used to indicate acceptable sampling adequacy for the items within a construct, while an item was retained when its factor loading exceeded 0.40. These criteria were used to evaluate sampling adequacy and item-loading adequacy rather than to establish comprehensive construct or discriminant validity. Instrument reliability was evaluated using Cronbach's alpha, with a coefficient above 0.70 indicating acceptable internal consistency (Ghozali, 2018). Descriptive statistics were used to summarize respondents' gender, age, occupation, and frequency of ShopeeFood use.

Multiple linear regression was first employed to examine the direct relationships of gamification and AI-powered personalization with continuance intention. This model was used to test H₁ and H₂ and was expressed as follows:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \varepsilon \quad (1)$$

Moderated Regression Analysis was subsequently conducted by incorporating E-Trust and the interaction terms between E-Trust and the two independent variables. This model was used to test H₃ and H₄ and was expressed as follows:

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 Z + \beta_4 (X_1 \times Z) + \beta_5 (X_2 \times Z) + \varepsilon \quad (2)$$

In these equations, Y represents continuance intention, X₁ represents gamification, X₂ represents AI-powered personalization, Z represents E-Trust, α represents the constant, β₁–β₅ represent the regression coefficients, and ε represents the error term. The coefficient of X₁ × Z was used to determine whether E-Trust moderated the relationship between gamification and continuance intention, while the coefficient of X₂ × Z was used to determine whether E-Trust moderated the relationship between AI-powered personalization and continuance intention.

The coefficient of determination was used to evaluate the explanatory capacity of each regression model. The F-test was used to evaluate overall model significance, while the t-test was used to evaluate the individual regression coefficients. H₁ and H₂ were evaluated using the direct-effect model, whereas H₃ and H₄ were evaluated based on the statistical significance of the interaction coefficients in the moderation model.

RESULT AND DISCUSSION

Participant Characteristics

This study involved 154 ShopeeFood users residing in Kupang who met the respondent eligibility criteria. The participant characteristics were classified according to gender, age, occupation, and frequency of ShopeeFood use. The distribution of participant characteristics is presented in Table 1.

Table 1. Participant Characteristics

Characteristics	Category	Frequency	Percentage (%)
Gender	Male	59	38.3
	Female	95	61.7
Age	17-25 years	34	22.1
	26-35 years	68	44.2
	36-50 years	52	33.7
Occupation	Student	51	33.1
	Employee	103	66.9
Frequency of ShopeeFood use	1-2 times per week	121	78.6
	3 or more times per week	33	21.4
Total		154	100.0

Source: Processed data, 2026

Table 1 shows that female respondents accounted for 61.7% of the sample, while male respondents represented 38.3%. Most respondents were between 26 and 35 years old (44.2%), followed by those aged 36–50 years (33.7%) and 17–25 years (22.1%). Based on occupation, 66.9% of the respondents were employees, while 33.1% were students. Regarding usage frequency, 78.6% reported using ShopeeFood one to two times per week, whereas 21.4% used the platform three or more times per week.

Measurement-Item Adequacy

Measurement-item adequacy was assessed using the Kaiser–Meyer–Olkin (KMO) measure and factor loadings. The assessment was conducted separately for each construct. A KMO value exceeding 0.50 was used to indicate acceptable sampling adequacy for the items within a construct, while an item was retained when its factor loading exceeded 0.40. The results are presented in Table 2.

Table 2. Summary of KMO and Factor-Loading Results

Variable	KMO	Item	Factor Loading	Decision
Gamification (X ₁)	0.756	X _{1,1}	0.847	Retained
		X _{1,2}	0.805	Retained
		X _{1,3}	0.859	Retained
		X _{1,4}	0.883	Retained
		X _{1,5}	0.816	Retained
		X _{1,6}	0.906	Retained
AI-Powered Personalization (X ₂)	0.829	X _{2,1}	0.971	Retained
		X _{2,2}	0.850	Retained
		X _{2,3}	0.937	Retained
E-Trust (Z)	0.747	Z _{1,1}	0.644	Retained
		Z _{1,2}	0.960	Retained
		Z _{1,3}	0.769	Retained
		Z _{1,4}	0.938	Retained
		Z _{1,5}	0.678	Retained
Continuance Intention (Y)	0.811	Y _{1,1}	0.655	Retained
		Y _{1,2}	0.981	Retained
		Y _{1,3}	0.880	Retained
		Y _{1,4}	0.932	Retained
		Y _{1,5}	0.943	Retained

Source: Processed data, 2026

Table 2 presents the KMO values and factor-loading results obtained from separate assessments of each construct. The KMO values were 0.756 for gamification, 0.829 for AI-powered personalization, 0.747 for E-Trust, and 0.811 for continuance intention. All values exceeded the minimum criterion of 0.50, indicating acceptable sampling adequacy for the items within each construct. The factor loadings ranged from 0.805 to 0.906 for gamification, from 0.850 to 0.971 for AI-powered personalization, from 0.644 to 0.960 for E-Trust, and from 0.655 to 0.981 for continuance intention. Because all factor loadings exceeded 0.40, all measurement items were retained. These findings provide evidence of sampling adequacy and item-loading adequacy for the constructs examined. However, the results are not interpreted as evidence of comprehensive construct or discriminant validity.

Instrument Reliability

The reliability test was conducted to evaluate the internal consistency of the measurement items for each variable. A variable was considered reliable when its Cronbach's alpha coefficient exceeded 0.70. The reliability test results are presented in Table 3.

Table 3. Instrument Reliability Test Results

Variable	Cronbach's Alpha	Criterion	N of items
Gamification (X ₁)	0.922	0.7	6
AI-Powered Personalization (X ₂)	0.907	0.7	3
E-Trust (Z)	0.857	0.7	5
Continuance Intention (Y)	0.924	0.7	5

(Source: Processed data, 2026)

Table 3 shows that the Cronbach's alpha coefficients were 0.922 for gamification, 0.907 for AI-powered personalization, 0.857 for E-Trust, and 0.924 for continuance intention. All coefficients exceeded the minimum criterion of 0.70, demonstrating acceptable internal consistency for each construct. Accordingly, each construct demonstrated acceptable internal consistency, and all measurement items were retained for subsequent statistical analysis.

Direct-Effect Model

Multiple linear regression was conducted to examine the effects of gamification and AI-powered personalization on continuance intention. The regression results are presented in Table 4.

Table 4. Multiple Linear Regression Results

		Coefficients ^a		t	Sig.
Model		Unstandardized Coefficients B	Std. Error		
1	(Constant)	5.780	1.163	4.971	p<0.001
	Gamification	0.877	0.034	25.761	p<0.001
	AI-Powered Personalization	0.328	0.053	6.161	p<0.001

^a. Dependent Variable: continuance intention

Source: Processed data, 2026

Gamification was positively and significantly associated with continuance intention ($B = 0.877$, $\beta = 0.898$, $t = 25.761$, $p < 0.001$). Accordingly, H1 was supported. The positive coefficient indicates that respondents who evaluated ShopeeFood's gamification features more favorably reported stronger intentions to continue using the platform.

AI-powered personalization was also positively and significantly associated with continuance intention ($B = 0.328$, $\beta = 0.215$, $t = 6.161$, $p < 0.001$). Accordingly, H2 was supported in the direct-effect model. Respondents who perceived ShopeeFood's recommendations and promotional offers as more relevant reported stronger intentions to continue using the service.

Moderated Regression Analysis

Moderated Regression Analysis was conducted by including E-Trust and the interaction terms between E-Trust and the two independent variables. The results are presented in Table 5.

Table 5. Moderated Regression Analysis Results

		Coefficients ^a		t	Sig.
Model		Unstandardized Coefficients B	Std. Error		
1	(Constant)	0.711	8.887	0.080	0.936
	Gamification	0.875	0.262	3.334	0.001

AI-Powered Personalization	0.055	0.383	0.036	0.143	0.886
E-Trust	0.304	0.444	0.274	0.684	0.495
X ₁ .Z	0.003	0.013	0.104	0.198	0.843
X ₂ .Z	0.013	0.018	0.240	0.730	0.467

^a. Dependent Variable: continuance intention

Source: Processed data, 2026

Table 5 shows that gamification remained positively and significantly associated with continuance intention after E-Trust and the interaction terms were incorporated into the model ($B = 0.875$, $\beta = 0.896$, $t = 3.334$, $p = 0.001$). In contrast, AI-powered personalization was not statistically significant in the moderation model ($B = 0.055$, $\beta = 0.036$, $t = 0.143$, $p = 0.886$). The direct coefficient of E-Trust was also not statistically significant ($B = 0.304$, $\beta = 0.274$, $t = 0.684$, $p = 0.495$).

AI-powered personalization was statistically significant in the direct-effect model but was nonsignificant after E-Trust and the interaction terms were incorporated into the moderation model. Therefore, support for H₂ refers specifically to the predefined direct-effect model. The difference in significance across the two model specifications indicates that the direct relationship between AI-powered personalization and continuance intention should be interpreted cautiously.

The interaction between gamification and E-Trust was not statistically significant ($B = 0.003$, $\beta = 0.104$, $t = 0.198$, $p = 0.843$). Therefore, E-Trust did not moderate the relationship between gamification and continuance intention, and H₃ was not supported.

The interaction between AI-powered personalization and E-Trust was also not statistically significant ($B = 0.013$, $\beta = 0.240$, $t = 0.730$, $p = 0.467$). Therefore, E-Trust did not moderate the relationship between AI-powered personalization and continuance intention, and H₄ was not supported.

Based on the unstandardized coefficients, the moderated regression equation was formulated as follows:

$$Y = 0.711 + 0.875X_1 + 0.055X_2 + 0.304Z + 0.003(X_1 \times Z) + 0.013(X_2 \times Z) + \varepsilon \quad (3)$$

Because neither interaction coefficient was statistically significant, the results provide no statistical evidence that E-Trust functioned as a moderator of either relationship in the model tested.

Coefficient of Determination of the Direct-Effect Model

The coefficient of determination was used to assess the explanatory capacity of the direct-effect model. The Model Summary generated from the regression analysis is presented in Table 6.

Table 6. Coefficient of Determination Test for the Direct-Effect Model

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.904 ^a	0.818	0.815	1.682

^a. Predictors: (Constant), AI-Powered Personalization, Gamification

Source: Processed data, 2026

Table 6 shows that the direct-effect model produced a multiple correlation coefficient (R) of 0.904. The R Square value of 0.818 indicates that gamification and AI-powered personalization jointly explained 81.8% of the variance in continuance intention, while 18.2% remained unexplained by the model. After adjustment for the number of predictors and sample size, the adjusted R Square value was 0.815.

Coefficient of Determination of the Moderation Model

The coefficient of determination was also evaluated for the moderation model, which incorporated E-Trust and the interaction terms between E-Trust and the two independent variables. The Model Summary generated from the moderated regression analysis is presented in Table 7.

Table 7. Coefficient of Determination Test for the Moderation Model

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.905 ^a	0.820	0.814	1.690

^a. Predictors: (Constant), X₂Z, Gamification, E-Trust, AI-Powered Personalization, X₁Z

Source: Processed data, 2026.

Table 7 shows that the moderation model produced a multiple correlation coefficient (R) of 0.905. The R Square value of 0.820 indicates that gamification, AI-powered personalization, E-Trust, and the two interaction terms collectively explained 82.0% of the variance in continuance intention, while 18.0% remained unexplained by the model. After adjustment for the number of predictors and sample size, the adjusted R Square value was 0.814. Although R Square increased from 0.818 in the direct-effect model to 0.820 in the moderation model, this small increase cannot by itself be interpreted as evidence of moderation. The moderating effects were determined from the statistical significance of the interaction coefficients reported in Table 5.

Overall Significance of the Direct-Effect Model

The F-test was conducted to determine whether gamification and AI-powered personalization jointly explained continuance intention. The direct-effect model was considered statistically significant when the p-value was below 0.05. The ANOVA results are presented in Table 8.

Table 8. Simultaneous F-Test for the Direct-Effect Model

ANOVA ^a					
Model		Sum of Squares	df	Mean Square	F
1	Regression	1917.523	2	958.762	339.065
	Residual	426.977	151	2.828	
	Total	2344.500	153		

^a. Dependent Variable: Continuance Intention

^b. Predictors: (Constant), AI-Powered Personalization, Gamification

Source: Processed data, 2026.

Table 8 shows that the direct-effect model was statistically significant overall, $F(2, 151) = 339.065$, $p < 0.001$. This result indicates that gamification and AI-powered personalization jointly explained a statistically significant proportion of the variance in continuance intention. The individual relationships proposed in H1 and H2 were evaluated using the regression coefficients and t-tests presented in Table 4.

Overall Significance of the Moderation Model

The F-test was also conducted to assess the overall significance of the moderation model, which included gamification, AI-powered personalization, E-Trust, and the two interaction terms. The moderation model was considered statistically significant when the p-value was below 0.05. The ANOVA results are presented in Table 9.

Table 9. Simultaneous F-Test for the Moderation Model

ANOVA ^a					
Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	1921.751	5	384.350	134.557	$p < 0.001^b$
Residual	422.749	148	2.856		
Total	2344.500	153			

^a. Dependent Variable: Continuance Intention

^b. Predictors: (Constant), Gamification, AI-Powered Personalization, E-Trust, $X_1.Z$, $X_2.Z$

Source: Processed data, 2026.

Table 9 shows that the moderation model was statistically significant overall, $F(5, 148) = 134.557$, $p < 0.001$. This result indicates that gamification, AI-powered personalization, E-Trust, and the two interaction terms collectively explained a statistically significant proportion of the variance in continuance intention. However, the significance of the overall model does not establish the significance of the individual interaction effects. As reported in Table 5, the interaction between gamification and E-Trust was not statistically significant ($p = 0.843$), and the interaction between AI-powered personalization and E-Trust was also not statistically significant ($p = 0.467$). Therefore, H3 and H4 were not supported.

Discussions

The findings show that gamification was positively and significantly associated with continuance intention; therefore, H₁ was supported. Points, rewards, vouchers, challenges, and other interactive incentives can provide value beyond the platform's basic transactional function. When these features are perceived as understandable, achievable, and beneficial, food-ordering activities can become more engaging and provide users with additional motivation to return to the platform. This finding is consistent with Ryan and Deci (2000) motivational perspective, which explains that behavior can be maintained through intrinsic enjoyment and extrinsic benefits. It also supports Bitrián et al. (2021), who found that gamification enhanced user engagement and favorable behavioral intentions, and Hamari and Koivisto (2015), who demonstrated that perceived benefits contributed to continued

participation in gamified services. Unlike these earlier studies, the present study demonstrates the relevance of gamification to continuance intention in an online food-delivery setting.

In the direct-effect model, AI-powered personalization was positively and significantly associated with continuance intention; thus, H_2 was supported. Relevant recommendations, promotions, and product suggestions can reduce the effort required to search through numerous restaurants and menu alternatives. Repeated exposure to information corresponding with users' preferences may improve the perceived compatibility of the platform with their food-ordering needs. This finding supports Bleier and Eisenbeiss (2015), who explain that personalized content becomes more effective when its content, timing, and placement correspond with users' needs. It is also consistent with Lee et al. (2023) and Mpinganjira et al. (2024), who demonstrated that intelligent digital features can improve perceived usefulness and experiential value and thereby contribute to continued use. The present study extends these findings by demonstrating that users' perceptions of personalized recommendations are relevant to post-adoption behavior in an online food-delivery service. However, this relationship was significant only in the direct-effect model. After E-Trust and the interaction terms were incorporated, the coefficient of AI-powered personalization was no longer statistically significant. Thus, the support for H_2 should be interpreted as evidence from the direct-effect model rather than as a relationship that remained stable across all model specifications.

The positive relationships of gamification and AI-powered personalization with continuance intention are consistent with the post-adoption logic of the Expectation-Confirmation Model (Bhattacharjee, 2001). Users' intentions to maintain service use can be shaped by evaluations formed through their experiences with platform features. In this study, interactive incentives and relevant recommendations represent different sources of post-adoption value. Gamification provides explicit and observable benefits, whereas AI-powered personalization provides algorithm-supported value by improving the relevance and efficiency of restaurant and product discovery. These findings should nevertheless be interpreted as an extension of the post-adoption perspective rather than a complete test of ECM because confirmation, perceived usefulness, and satisfaction were not examined as separate constructs.

The moderation analysis showed that E-Trust did not significantly moderate the relationship between gamification and continuance intention; therefore, H_3 was not supported. This result means that the relationship between gamification and continuance intention did not differ significantly according to respondents' levels of E-Trust. One possible interpretation is that users evaluated points, vouchers, rewards, and challenges primarily according to their accessibility and immediate benefits. Because these features are relatively visible and can be directly evaluated during platform use, their motivational value may not necessarily depend on trust. Nevertheless, the result does not demonstrate that E-Trust is unimportant. It only indicates that E-Trust did not change the strength of the relationship between gamification and continuance intention in the model tested.

E-Trust also did not moderate the relationship between AI-powered personalization and continuance intention; consequently, H_4 was not supported. Although personalization involves the processing of users' preferences and previous activities, its relationship with

continuance intention did not vary significantly across different levels of E-Trust. Respondents may have evaluated personalization mainly through the relevance and practical usefulness of the recommendations received. This finding complements Nguyen and Dao (2024), who found that trust moderated some antecedents of continuance intention but not others. It reinforces the argument that trust should not automatically be assumed to strengthen every relationship in a digital-service model. Its moderating role may depend on the specific platform feature, user evaluation, and service context being examined.

The nonsignificant moderation findings provide a useful empirical insight into the conditional role of E-Trust. They indicate that E-Trust did not operate as a boundary condition for either platform mechanism examined. In the present context, users' evaluations of gamification and AI-powered personalization were associated with continuance intention, but neither relationship was contingent on E-Trust. This finding distinguishes the role of trust from users' evaluations of interactive and algorithm-supported platform features. Future research may examine whether E-Trust performs a direct or mediating role or interacts with more specific factors such as perceived privacy risk, recommendation transparency, satisfaction, and perceived fairness.

From an applied hospitality perspective, the findings provide practical direction for online food-delivery platforms and restaurant partners. Platform providers should design reward mechanisms that are attainable, transparent, and easy to understand. Gamification should provide consistent value that encourages users to explore restaurant offerings and conduct subsequent transactions. Personalization should prioritize relevant restaurant, menu, and promotional recommendations instead of exposing users to excessive or repetitive offers. Restaurant partners can support this process by maintaining accurate menu descriptions, product categories, prices, availability, photographs, and promotional information so that platform recommendations correspond more closely with consumers' needs.

The findings are also relevant to the sustainability of digital food-ordering services. Sustainability in this context refers to the continuity and viability of app-based food-ordering services rather than environmental sustainability. Continued use can help maintain digital interactions between consumers and restaurants, extend restaurant services beyond physical premises, and support the marketing and distribution of culinary products. Although E-Trust did not moderate the relationships tested, platform providers should continue to maintain trust through transparent promotional conditions, reliable transactions, responsible information management, and effective complaint handling. As a practical recommendation, platform operators and restaurant businesses could monitor repeat-order rates, reward redemption, responses to recommendations, menu-view activity, and complaint resolution when evaluating customer-retention initiatives. These applications translate the findings into service improvements without extending the conclusions to tourist behavior.

CONCLUSION

This study examined the relationships of gamification and AI-powered personalization with continuance intention and tested the moderating role of E-Trust among ShopeeFood users in Kupang. In the direct-effect model, gamification and AI-powered personalization were positively and significantly associated with continuance intention. However, after E-Trust and

the interaction terms were incorporated, only gamification remained statistically significant, while neither interaction term was significant. These findings indicate that interactive incentives were consistently associated with continuance intention across the two model specifications, whereas the relationship involving AI-powered personalization was supported only in the direct-effect model and should therefore be interpreted more cautiously.

E-Trust did not significantly moderate either the relationship between gamification and continuance intention or the relationship between AI-powered personalization and continuance intention. Accordingly, E-Trust was not statistically supported as a moderator of the two relationships in the model tested. This result does not imply that trust is irrelevant to digital food-ordering services. Rather, it indicates that the relationships of gamification and personalization with continuance intention did not vary significantly according to users' levels of E-Trust. The study therefore provides empirical insight into the post-adoption literature by indicating that E-Trust may not operate as a uniform boundary condition across different platform mechanisms.

From an applied perspective, online food-delivery platforms should develop attainable and transparent reward mechanisms while improving the relevance of restaurant, menu, and promotional recommendations. Restaurant partners can support these efforts by maintaining accurate information regarding menus, prices, product availability, photographs, and promotions. Although its moderating effects were not supported, E-Trust should continue to be maintained through reliable transactions, transparent promotional conditions, responsible information management, and effective complaint handling. These practices can support customer retention, the continuity of app-based food-ordering services, digital restaurant marketing, and the distribution of culinary products within the hospitality industry.

The findings are limited to 154 ShopeeFood users selected through purposive sampling in Kupang and are based on self-reported responses collected during a specific period. Consequently, the findings should not be generalized to all ShopeeFood users or other digital-service contexts without further examination. Future studies may include users from multiple locations, compare different online food-delivery platforms, employ longitudinal designs, and examine E-Trust as a direct or mediating variable. Further research may also consider recommendation transparency, perceived privacy risk, satisfaction, and perceived fairness to provide a more comprehensive explanation of continuance intention.

REFERENCES

- Alalwan, A. A. (2020). Mobile Food Ordering Apps: An Empirical Study of the Factors Affecting Customer E-Satisfaction and Continued Intention to Reuse. *International Journal of Information Management*, 50, 28–44. <https://doi.org/10.1016/j.ijinfomgt.2019.04.008>
- Awad, N. F., & Krishnan, M. S. (2006). The Personalization Privacy Paradox: An Empirical Evaluation of Information Transparency and the Willingness to Be Profiled Online for Personalization. *MIS Quarterly*, 30(1), 13–28. <https://doi.org/10.2307/25148715>
- Bhattacharjee, A. (2001). Understanding Information Systems Continuance: An Expectation-Confirmation Model. *MIS Quarterly*, 25(3), 351–370. <https://aisel.aisnet.org/misq/vol25/iss3/5/>

- Bitrián, P., Buil, I., & Catalán, S. (2021). Enhancing User Engagement: The Role of Gamification in Mobile Apps. *Journal of Business Research*, 132, 170–185. <https://doi.org/10.1016/j.jbusres.2021.04.028>
- Bleier, A., & Eisenbeiss, M. (2015). Personalized online advertising effectiveness: The interplay of what, when, and where. *Journal of Marketing*, 79(1), 31–50. <https://doi.org/10.1509/jm.14.0269>
- Choi, K., Wang, Y., Sparks, B. A., & Choi, S. M. (2023). Privacy or Security: Does It Matter for Continued Use Intention of Travel Applications? *Cornell Hospitality Quarterly*, 64(2), 267–282. <https://doi.org/10.1177/19389655211066834>
- Ghozali, I. (2018). *Aplikasi analisis multivariate dengan program IBM SPSS 25* (9 (ed.). Badan Penerbit Universitas Diponegoro.
- Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
- Hamari, J., & Koivisto, J. (2015). Why Do People Use Gamification Services? *International Journal of Information Management*, 35(4), 419–431. <https://doi.org/10.1016/j.ijinfomgt.2015.04.006>
- Hamari, J., Koivisto, J., & Sarsa, H. (2014). Does Gamification Work? – A Literature Review of Empirical Studies on Gamification. *Proceedings of the 47th Hawaii International Conference on System Sciences*, 3025–3034. <https://doi.org/10.1109/HICSS.2014.377>
- Hurdawaty, R., & Dylun, K. (2024). Consumer Preferences in Choosing Online Food Delivery Services in Jakarta. *International Journal of Travel, Hospitality and Events*, 3(2), 127–137. <https://doi.org/10.56743/ijothe.v3i2.370>
- Lee, J.-C., Tang, Y., & Jiang, S. (2023). Understanding Continuance Intention of Artificial Intelligence (AI)-Enabled Mobile Banking Applications: An Extension of AI Characteristics to an Expectation Confirmation Model. *Humanities and Social Sciences Communications*, 10(1), 333. <https://doi.org/10.1057/s41599-023-01845-1>
- McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). The impact of initial consumer trust on intentions to transact with a web site: A trust building model. *The Journal of Strategic Information Systems*, 11(3–4), 297–323. [https://doi.org/10.1016/S0963-8687\(02\)00020-3](https://doi.org/10.1016/S0963-8687(02)00020-3)
- Mpinganjira, M., Dlodlo, N., & Idemudia, E. C. (2024). Perceived Experiential Value and Continued Use Intention of E-Retail Chatbots. *International Journal of Retail & Distribution Management*, 52(13), 121–135. <https://doi.org/10.1108/IJRDM-04-2023-0237>
- Nguyen, G.-D., & Dao, T.-H. T. (2024). Factors Influencing Continuance Intention to Use Mobile Banking: An Extended Expectation-Confirmation Model with Moderating Role of Trust. *Humanities and Social Sciences Communications*, 11(1), 276. <https://doi.org/10.1057/s41599-024-02778-z>
- Omidvar, M., & Deen, A. (2024). Can Restaurants Achieve Customer Retention through CSR? *Journal of Applied Sciences in Travel and Hospitality*, 7(1), 1–16. <https://doi.org/10.31940/jasth.v7i1.1-16>
- Piani, N. W. O., Sari, I. G. A. M. K. K., & Mataram, I. G. A. B. (2024). Implementation of Electronic

-
- Word of Mouth and Service Quality toward Repurchase Intention at K Club Ubud Resort. *Journal of Applied Sciences in Travel and Hospitality*, 7(1), 38–51. <https://doi.org/10.31940/jasth.v7i1.38-51>
- Pranawukir, I., Haryanto, R., Awaludin, D. T., Rustaniah, & Santoso, A. (2026). Integrated Marketing Communication, Brand Equity, and Perceived Value in Shaping Tourist Loyalty: Evidence from Nusa Penida Tourism. *Journal of Applied Sciences in Travel and Hospitality*, 9(1), 73–83. <https://doi.org/10.31940/jasth.v9i1.73-83>
- Quintus, M., Mayr, K., Hofer, K. M., & Chiu, Y. T. (2024). Managing consumer trust in e-commerce: evidence from advanced versus emerging markets. *International Journal of Retail & Distribution Management*, 52(10–11), 1038–1056. <https://doi.org/10.1108/IJRDM-10-2023-0609>
- Ryan, R. M., & Deci, E. L. (2000). Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions. *Contemporary Educational Psychology*, 25(1), 54–67. <https://doi.org/10.1006/ceps.1999.1020>
- Yan, M., Filieri, R., & Gorton, M. (2021). Continuance Intention of Online Technologies: A Systematic Literature Review. *International Journal of Information Management*, 58, 102315. <https://doi.org/10.1016/j.ijinfomgt.2021.102315>
- Zhao, Y., & Bacao, F. (2020). What Factors Determining Customer Continuingly Using Food Delivery Apps During 2019 Novel Coronavirus Pandemic Period? *International Journal of Hospitality Management*, 91, 102683. <https://doi.org/10.1016/j.ijhm.2020.102683>