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The Effect of AI-Based Recommendations on Embedded Finance Use in E-Commerce through Trust Mediation among Generation X in Jakarta

Selvia De Wana¹, Riwandari Juniasti², Amri Sinuraya^{3*}

¹Universitas Kristen Indonesia, Jakarta, Indonesia, sildewana@gmail.com

²Universitas Kristen Indonesia, Jakarta, Indonesia, riwandari.juniasti@uki.ac.id

³Universitas Kristen Indonesia, Jakarta, Indonesia, amrisinuraya@gmail.com

*Corresponding Author: amrisinuraya@gmail.com³

Abstract: Artificial intelligence increasingly shapes how e-commerce platforms recommend integrated financial services, yet evidence concerning Generation X remains limited. This methodological study examines the relationships among perceived AI-based recommendation quality, trust, and embedded finance use, while also distinguishing recommendation quality from exposure frequency. A structured synthetic dataset of 300 observations representing Generation X e-commerce users in Jakarta was analysed using partial least squares structural equation modelling with 10,000 bootstrap subsamples. AI-based recommendations were positively related to embedded finance use ($\beta = 0.514$) and trust ($\beta = 0.444$), while trust was positively related to use ($\beta = 0.240$); all paths had $p < 0.001$. The indirect effect through trust was significant ($\beta = 0.107$), indicating complementary partial mediation, and the model explained 43.1% of the variance in use. A contextual cross-tabulation showed that recommendation exposure frequency was not associated with purchase response ($p = 0.818$). The study's novelty lies in showing that, for digitally experienced Generation X profiles, perceived relevance and accuracy matter more than repeated exposure, while trust strengthens but does not dominate the relationship. Empirical validation with linked respondent-level data remains necessary.

Keywords: AI-based recommendation, trust, embedded finance, Generation X, PLS-SEM.

INTRODUCTION

E-commerce has evolved from a transaction channel into a digital ecosystem that combines product discovery, recommendations, payments, financing, and financial services. Expanding internet access and digital payments in Indonesia have reinforced this integration (Badan Pusat Statistik, 2025; Bank Indonesia, 2026). Within this ecosystem, embedded finance allows users to access e-wallets, digital instalments, Buy Now Pay Later, or banking services without leaving the primary platform. Although this integration offers convenience, it also

raises concerns regarding data protection, fee transparency, credit risk, and algorithmic accountability (Otoritas Jasa Keuangan, 2024).

AI-based recommender systems form an important bridge between behavioural data and financial service offers displayed at the point of transaction. These systems can use search history, clicks, purchases, preferences, and usage context to select recommendations considered relevant. Algorithmic studies show that user ratings can generate product predictions and recommendations (Syah, 2020). Technical performance alone, however, does not guarantee user acceptance. Recommendation-system transparency can influence perceived effectiveness, discomfort, and trust (Li et al., 2024).

Trust becomes particularly important when recommendations concern financial services because users' decisions involve money, security, personal data, and repayment obligations. Research on recommendation agents indicates that personalisation and familiarity can develop trust and encourage adoption (Komiak & Benbasat, 2006; Wang & Benbasat, 2005). In Indonesian e-commerce, interface quality, information, security, and privacy are also related to satisfaction and trust (Dhiranty et al., 2017), while e-trust contributes to e-satisfaction and e-loyalty among Shopee customers (Kuska et al., 2024).

Technology-adoption theories explain acceptance through usefulness, ease of use, and performance expectancy (Davis, 1989; Venkatesh et al., 2003). Studies of Indonesian digital financial services show that perceived usefulness, perceived ease of use, security, risk, and trust are associated with intention and continued use (Ikhsan et al., 2025; Kornitasari et al., 2024; Melianthi & Darma, 2024; Panasea & Erliani, 2021; Sudarsono et al., 2024). System effectiveness and perceived risk are also relevant to consumer interest in ShopeePay (Budiman et al., 2025).

Three gaps remain. First, recommender-system research commonly focuses on products, whereas recommendations of financial services inside e-commerce have rarely been examined as an integrated model. Second, trust is often treated as a direct predictor, while its mediating mechanism between recommendation quality and embedded finance use requires contextual examination. Third, digital-payment studies frequently use general, Generation Z, or multigenerational samples. Generation X encountered much digital technology after reaching adulthood and may therefore evaluate it pragmatically through utility, accuracy, security, and provider credibility (Agustin et al., 2025; Barus et al., 2026; Yunus et al., 2025).

The study's novelty lies in integrating four dimensions of AI-based recommendations—relevance, personalisation, perceived accuracy, and transparency—with four trust dimensions and embedded finance use in a mediation model focused on Generation X. It also separates exposure frequency from perceived recommendation quality. This distinction is important because repeated exposure may not generate a response when recommendations are irrelevant, opaque, or provide no concrete value. Explainable AI further highlights the need for users to understand why a recommendation appears and what its consequences are (Shin, 2021).

Accordingly, this study examines the effect of AI-based recommendations on embedded finance use, the effect of recommendations on trust, the effect of trust on use, and the mediating role of trust. These objectives are translated into four hypotheses.

1. H1: AI-based recommendations have a positive effect on embedded finance use.
2. H2: AI-based recommendations have a positive effect on trust.
3. H3: Trust has a positive effect on embedded finance use.
4. H4: Trust mediates the effect of AI-based recommendations on embedded finance use.

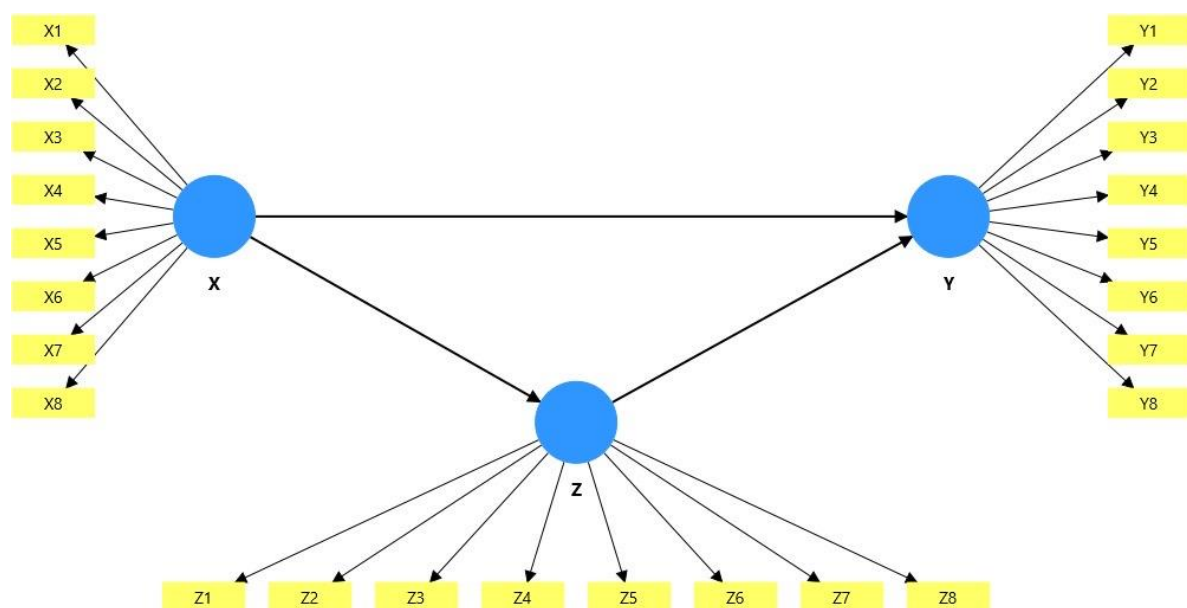
METHODS

This study adopts a quantitative explanatory cross-sectional design. The analysis is organised as a methodological study using a structured synthetic dataset of 300 observations representing Generation X e-commerce user profiles born between 1965 and 1980 in Jakarta.

This positioning is essential: the results demonstrate the coherence of the proposed model and PLS-SEM procedure rather than population prevalence estimates. A subsequent empirical implementation must use actual respondent answers and auditable data-collection documentation.

The profile file contains unique IDs, year of birth, age, region, gender, education, occupation, primary platform, duration of e-commerce use, transaction frequency, recommendation exposure, and purchasing after a recommendation. Quality checks identified 300 unique IDs with no missing values or duplicates, and all age-birth-year pairs were consistent. All profiles met the five available screening criteria: Generation X, Jakarta domicile, e-commerce use, prior exposure to automatic recommendations, and understanding of recommendation features. The profile did not contain embedded-finance type or intensity and could not be linked by respondent ID to the PLS-SEM indicator output; consequently, profile analyses are used only as aggregate context.

The reflective measurement model comprises 24 indicators. AI-Based Recommendations (X) are measured through relevance, personalisation, perceived accuracy, and transparency; Trust (Z) through reliability, security, credibility, and integrity; and Embedded Finance Use (Y) through actual use, frequency of use, continued use, and preference for use. Each dimension is represented by two indicators measured on a five-point Likert scale. Figure 1 presents the structural model before estimation.



Source: Research model, prepared by the author (2026).

Figure 1. PLS-SEM structural model before estimation

The model was analysed using SmartPLS 4 (Ringle et al., 2024). Measurement-model evaluation followed Hair et al. (2019, 2020, 2021): outer loadings were preferably above 0.70; Cronbach's alpha, rho_A, and composite reliability above 0.70; and average variance extracted above 0.50. Discriminant validity was assessed using the heterotrait-monotrait ratio with a conservative 0.85 threshold (Henseler et al., 2015). The structural model was assessed through VIF, R², adjusted R², f², SRMR, NFI, path coefficients, and direct and indirect effects.

Significance was examined using nonparametric bootstrapping with 10,000 subsamples, two-tailed tests, a 5% significance level, and 95% confidence intervals. Mediation was determined from the significance and directions of the direct and indirect effects (Nitzl et al., 2016). In a separate contextual analysis, the association between recommendation-exposure frequency and purchasing after a recommendation was evaluated using a continuity-corrected

chi-square test and Cramer's V. Out-of-sample predictive ability was not evaluated because PLSpredict results were unavailable; this assessment is required in subsequent empirical validation (Shmueli et al., 2019).

RESULTS AND DISCUSSION

Respondent and E-Commerce Profile

Table 1. Main characteristics of the observation profiles

Characteristic	Category	n	%
Age	46-50; 51-55; 56-61 years	103; 83; 114	34.3; 27.7; 38.0
Gender	Women; men	165; 135	55.0; 45.0
Largest regions	East; South; West Jakarta	90; 66; 66	30.0; 22.0; 22.0
Education	High school; diploma; bachelor's; postgraduate	60; 42; 138; 60	20.0; 14.0; 46.0; 20.0
Occupation	Employee/professional; entrepreneur; public sector; household manager; other	105; 60; 45; 45; 45	35.0; 20.0; 15.0; 15.0; 15.0

Source: Structured synthetic dataset (n = 300), processed by the author (2026).

The profiles ranged from 46 to 61 years, with a mean age of 53.37 years, SD 4.55, and median 54. The 56-61 group was the largest (38.0%), followed by ages 46-50 (34.3%) and 51-55 (27.7%). Women represented 55.0% and men 45.0%. Eighty per cent had diploma to postgraduate education, while 70.0% were employees or professionals, entrepreneurs, or public-sector employees. The composition represents a relatively educated and economically active urban profile; generalisation to the entire Generation X population therefore requires caution.

Shopee was the primary platform for 45.0% of profiles and Tokopedia for 25.0%. Seventy per cent had used e-commerce for more than five years; the average duration was 7.06 years, SD 3.25, median seven years, and range one to twelve years. Eighty per cent transacted at least three times per month, 60.0% often saw automatic recommendations, and 69.7% showed a purchase after a recommendation. Platform shares describe dataset composition, not market share.

Table 2. Purchase response by recommendation-exposure frequency

Recommendation exposure	Purchased	Did not purchase	Total	% purchased
Sometimes	85	35	120	70.8
Often	124	56	180	68.9
Total	209	91	300	69.7

Source: Structured synthetic dataset (n = 300), processed by the author (2026).

Among profiles that often encountered recommendations, 124 of 180 observations (68.9%) showed purchasing after a recommendation. Among those encountering recommendations sometimes, the proportion was 85 of 120 (70.8%). The continuity-corrected chi-square test produced $\chi^2(1) = 0.053$, $p = 0.818$, and Cramer's V = 0.013. Exposure frequency was therefore not meaningfully associated with purchase response. Repetition is not a substitute for relevance, accuracy, and transparency. Sentiment evidence on digital financial services similarly indicates that user responses depend on the context of benefits and risks rather than the feature's mere presence (Mahayani et al., 2020).

Measurement Model Evaluation

Table 3. Descriptive statistics of construct dimensions

Construct	Dimension	Mean	SD
X	Relevance	4.230	0.597
X	Personalisation	4.067	0.639
X	Perceived accuracy	4.173	0.640
X	Transparency	3.957	0.674
Z	Reliability	3.908	0.627
Z	Security	3.845	0.656
Z	Credibility	3.917	0.624
Z	Integrity	3.725	0.651
Y	Actual use	4.237	0.586
Y	Frequency of use	4.185	0.578
Y	Continued use	4.215	0.616
Y	Preference for use	4.050	0.628

Source: Analytical output, processed by the author (2026).

Relevance had the highest mean within X (4.230), followed by perceived accuracy (4.173), personalisation (4.067), and transparency (3.957). Within Trust, credibility was highest (3.917) and integrity lowest (3.725). Contextual value and recommendation precision were therefore more prominent than confidence in information integrity. Within Y, actual use had a mean of 4.237 and continued use 4.215. These mean comparisons describe score tendencies and do not establish temporal or causal ordering.

Table 4. Reliability and convergent validity

Construct	Loading range	Cronbach's alpha	rho_A	rho_C	AVE
AI-based recommendations	0.782-0.827	0.923	0.924	0.937	0.649
Trust	0.730-0.839	0.908	0.914	0.926	0.609
Embedded finance use	0.753-0.806	0.902	0.903	0.921	0.593

Source: PLS Algorithm output, processed by the author (2026).

All 24 indicators had outer loadings between 0.730 and 0.839. Cronbach's alpha, rho_A, and rho_C exceeded 0.70, while AVE ranged from 0.593 to 0.649. Indicator reliability, internal consistency, and convergent validity were therefore supported. HTMT values were 0.480 for X-Z, 0.677 for X-Y, and 0.510 for Z-Y, all below 0.85. The Fornell-Larcker criterion was also satisfied because each construct's square root of AVE exceeded its associated interconstruct correlations.

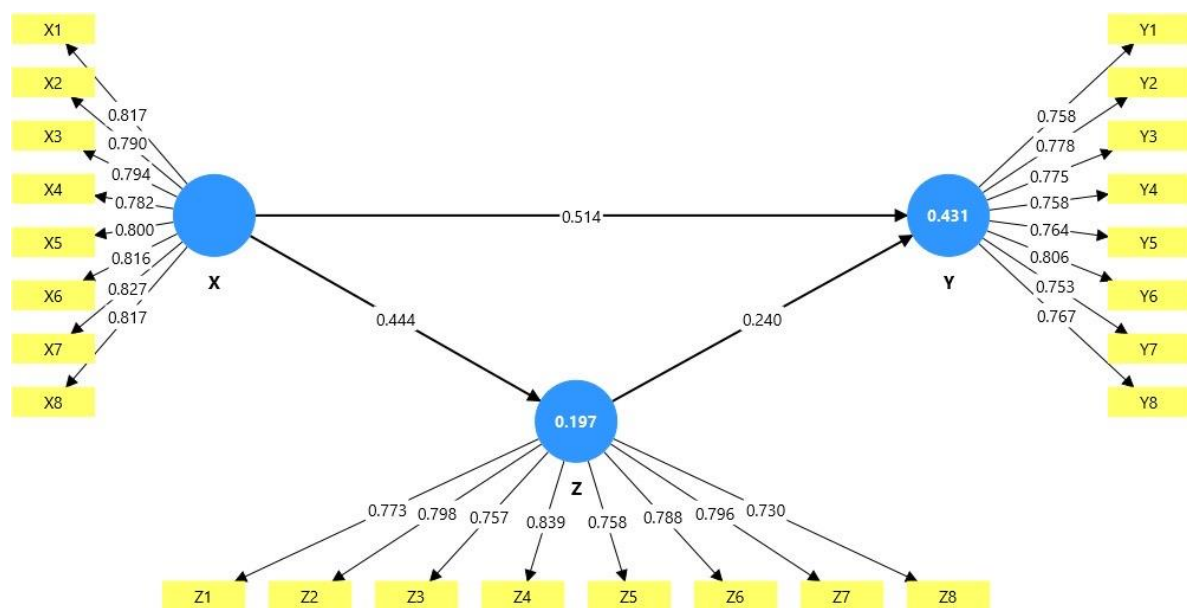
Structural Model and Hypothesis Testing

Table 5. Structural-model evaluation summary

Measure	Construct/path	Value	Interpretation
R ²	Trust	0.197	19.7% of variance explained by X
R ²	Embedded finance use	0.431	43.1% of variance explained by X and Z
f ²	X → Z	0.245	Medium effect
f ²	X → Y	0.373	Large effect
f ²	Z → Y	0.081	Small effect
VIF	All paths	1.000-1.245	No collinearity concern
SRMR; NFI	Estimated model	0.045; 0.922	Adequate fit

Source: SmartPLS 4 output, processed by the author (2026).

VIF values of 1.000-1.245 indicate no collinearity concern. AI-based recommendations explained 19.7% of the variance in Trust. Together, AI-based recommendations and Trust explained 43.1% of the variance in Embedded Finance Use. X had a large effect on Y ($f^2 = 0.373$), X had a medium effect on Z ($f^2 = 0.245$), and Z had a small effect on Y ($f^2 = 0.081$). SRMR of 0.045 and NFI of 0.922 support adequate model fit, although assessment should primarily focus on measurement quality, explanatory power, effect sizes, and prediction.



Source: SmartPLS 4 PLS Algorithm output, processed by the author (2026).

Figure 2. Estimated PLS-SEM model
Table 6. Hypothesis-testing results

Hypothesis	Path	β	t	p	95% CI	Decision
H1	X → Y	0.514	11.164	<0.001	0.423-0.603	Supported
H2	X → Z	0.444	9.149	<0.001	0.349-0.539	Supported
H3	Z → Y	0.240	4.832	<0.001	0.145-0.338	Supported
H4	X → Z → Y	0.107	4.383	<0.001	0.062-0.156	Supported

Source: Bootstrapping with 10,000 subsamples, processed by the author (2026).

H1 was supported because $X \rightarrow Y$ was positive and significant ($\beta = 0.514$; $t = 11.164$; $p < 0.001$; 95% CI [0.423, 0.603]). Recommendations perceived as relevant, personal, accurate, and transparent were associated with greater embedded finance use. Its f^2 indicates that recommendation quality is the most substantive predictor in the model. This result is consistent with technology-acceptance research that positions usefulness and ease of use as foundations of adoption (Davis, 1989; Venkatesh et al., 2003), while extending it by treating financial recommendation quality as a contextual stimulus.

H2 was also supported ($\beta = 0.444$; $t = 9.149$; $p < 0.001$; 95% CI [0.349, 0.539]). The result reinforces evidence that personalisation, familiarity, and transparency can develop trust in recommendation agents (Komiak & Benbasat, 2006; Li et al., 2024; Wang & Benbasat, 2005). The R^2 of 0.197 for Trust nevertheless means that most of its variance lies outside the model. Provider reputation, security, service experience, privacy, financial literacy, and perceived risk may provide additional explanations (Ikhsan et al., 2025; Kornitasari et al., 2024).

H3 was supported with a smaller coefficient ($\beta = 0.240$; $t = 4.832$; $p < 0.001$; 95% CI [0.145, 0.338]). Trust remained positively associated with use but was not the dominant factor. This finding is consistent with digital-payment studies in which trust operates alongside perceived usefulness, perceived ease of use, security, and facilitating conditions (Melianthi & Darma, 2024; Sudarsono et al., 2024). Users may therefore perceive sufficient practical value to use a service even when confidence in information integrity is not maximal.

The Mediating Role of Trust

Table 7. Direct, indirect, and total effects

Effect type	Coefficient	p	Interpretation
Direct $X \rightarrow Y$	0.514	<0.001	Significant
Indirect $X \rightarrow Z \rightarrow Y$	0.107	<0.001	Significant
Total $X \rightarrow Y$	0.621	-	Positive
VAF	17.2%	-	Limited partial mediation

Source: SmartPLS 4 output, processed by the author (2026).

The specific indirect effect $X \rightarrow Z \rightarrow Y$ was 0.107 and significant ($t = 4.383$; $p < 0.001$; 95% CI [0.062, 0.156]). Because the direct effect $X \rightarrow Y$ remained significant and both effects had the same direction, Trust operated as a complementary partial mediator. The total effect was 0.621 and VAF approximately 17.2%. H4 was supported, although the mediating contribution was limited. This interpretation follows the principle that mediation classification should rest on the significance and directions of the direct and indirect effects rather than VAF alone (Nitzl et al., 2016).

Substantively, AI-based recommendations may relate to use through two concurrent mechanisms. A direct mechanism emerges when a recommendation provides concrete value, such as a suitable payment method, clearer costs, or a more practical transaction. An indirect mechanism emerges when consistency, security, credibility, and integrity develop trust. The partial mediation pattern is consistent with digital-payment research showing a mediating role for trust, while indicating that trust is not the only route to acceptance (Melianthi & Darma, 2024; Rachbini et al., 2019).

Novelty and Implications

The principal novelty is the distinction between the amount and the quality of recommendations. Frequent exposure did not produce a higher purchase-response proportion

than occasional exposure, whereas perceived recommendation quality had the strongest path to use. This produces a sharper proposition: for digitally experienced Generation X profiles, recommendations need not become more frequent; they should become more relevant, accurate, explainable, secure, and controllable. Earlier work similarly portrays Generation X as pragmatic users of digital payments whose responses depend on benefits and risks (Agustin et al., 2025; Barus et al., 2026; Yunus et al., 2025).

For e-commerce and fintech developers, the practical priority is to improve the timing and context of recommendations, explain why a service is offered, display costs and risks transparently, and provide an option to reject personalisation. Explainable AI can be implemented through brief statements such as 'recommended based on the payment methods you frequently use' without disclosing sensitive data (Shin, 2021). For credit services such as BNPL, the system should consider repayment capacity and avoid design patterns that encourage excessive use.

CONCLUSION AND RECOMMENDATIONS

Conclusion

The model shows that AI-based recommendations are positively related to embedded finance use and trust, while trust is positively related to use. Trust partially and complementarily mediates this relationship, but the direct recommendation-to-use path remains dominant. The model explains 43.1% of the variance in use. At the dimension level, relevance and perceived accuracy are most prominent; at the profile level, recommendation-exposure frequency is not associated with purchase response. The study's central contribution is therefore not a claim that more recommendations are always more effective. It shows that recommendation quality and concrete value matter more for Generation X profiles, while trust strengthens the relationship without dominating it.

Limitations

The analysis uses a structured synthetic dataset; its coefficients must not be treated as population estimates or actual empirical evidence. The profile file does not record embedded-finance type or intensity and cannot be linked by ID to the PLS-SEM indicators. The cross-sectional design does not establish temporal order, while use remains a designed self-report construct rather than objective transaction logs. PLSpredict results are unavailable, so out-of-sample predictive performance cannot be concluded.

Recommendations

Subsequent empirical research should collect actual responses from Generation X participants, use consistent anonymous IDs across profile and indicator data, record embedded-finance types and transaction intensity, and add perceived risk, financial literacy, privacy concern, and explainability. Longitudinal or experimental designs are required to examine changes in trust following usage experience. PLSpredict and comparison with a linear benchmark should assess predictive ability. In practice, providers should prioritise relevance, accuracy, transparency, security, and user control rather than increasing exposure frequency.

Author Contribution

The sole author was responsible for conceptualisation, theoretical-framework development, model specification, analysis, interpretation, manuscript preparation, scholarly revision, and approval of the final article.

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