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Breaking Borders with Bots: A Cross-National Study on How Generative AI Personalization Drives Impulse Buying in Global Social Commerce

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Abstract

The growing application of artificial intelligence (AI) in digital commerce has transformed how consumers interact with online shopping platforms, evaluate personalised recommendations, and develop purchasing intentions. This study aimed to investigate the correlation between AI-driven personalisation, perceived usefulness, responsiveness, transparency, platform trust, and consumer purchase intention, with a specific focus on the mediating role of platform trust. Employing a quantitative research design, this study utilised cross-sectional data from 248 respondents based in Indonesia. Using Python-based statistical libraries, descriptive statistics, reliability and validity assessments, multiple regression, bootstrapping, predictive analysis, and robustness checks were performed. The results showed that the proposed models accounted for 44.3% of the variance in platform trust and 51.6% of the variance in purchase intention. AI personalisation was significantly and positively related to platform trust ($\beta = 0.523$, $p < 0.001$), with platform trust emerging as the strongest predictor of purchase intention ($\beta = 0.450$, $p < 0.001$). Although the direct relationship between personalisation and purchase intention was not statistically significant, the indirect relationship was statistically significant ($\beta = 0.236$, 95% CI [0.168, 0.310]). Additionally, there was a positive relationship between perceived usefulness, transparency, and purchase intention, but not with responsiveness. The findings indicate that trust is a crucial explanatory factor in AI-driven purchasing situations. However, limitations regarding the dataset and the single-country sample require cautious interpretation. Further research using cross-national observations is needed to examine generative AI-specific personalisation and actual impulse-buying behaviour.

Keywords: *AI-driven personalisation, social commerce, platform trust, purchase intention, consumer behaviour, mediation analysis, digital commerce*

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1. INTRODUCTION

Social commerce has changed how consumers discover products and make purchasing decisions. Social sites make a combination of entertainment, suggestions, conversations and shopping as you browse. Products can be presented to consumers via videos or comments and they are not necessarily in the mindset to purchase. Impulsive buying urges are related to brand-engagement motivations (Moghddam et al., 2024), while Xu et al. (2024) discovered that social learning might explain this form of behaviour. Product information and social cues thus work in tandem. Notably, there is a connection between viewing content and purchasing, enabling opportunities for impulse purchases (Bernstein & Guo, 2025). Socialcommerce factors related to consumers include social influence and shopping convenience, as stated by Sadiq et al., (2025). These have been enhanced with artificial intelligence (AI) for personalized product suggestions, search, and promotional content. Automated recommendations for increased relevance and search effort reduction. That's not the same approach that Generative AI will take however, as it will create conversational answers and personal explanations instead of just choosing from existing products. Kamoonpuri and Sengar (2025) examined the intention to use genAI shopping chatbots, demonstrating the importance of considering interactive services distinct from other types of services. Generative AI Chatbot characteristics and consumer trust are linked to a study of consumer trust in online grocery shopping (Chakraborty et al., 2024). Thus, traditional recommendation systems cannot be considered as alternatives to generative AI systems.

Whether consumers view AI-powered services as reliable can be influenced by their usefulness and responsiveness. Clear suggestions can make comparisons easier, unclear explanations or not informing of personal information used may lead to uncertainty. The timely answers can make the shopping assistance more dependable but it doesn't mean that it is more accurate with speed. Responsiveness was found to be correlated with trust in sellers for Instagram users and perceived price fairness with trust-related purchase intentions (Senali et al., 2024). A correlation between personalised recommendations, and satisfaction/trust was found by Hassan et al. (2025). Ali and Sunela (2026) investigated the relationships of personalisation, usefulness, transparency, and purchase intention with mediation by trust in Pakistan. Consumers can therefore assess not only technical performance but also information practices of the platform. The use of GenAI in advertising has the potential to improve the value of perceived personalisation, while also creating a privacy issue (Nusir et al., 2026). Personalisation can be different with regard to purchase intention and impulse buying. The former is an indication of willingness to purchase whilst the latter is an indication of impulsiveness or an unplanned purchase. Personalisation is linked to the hedonic value along with personalisation is linked to utilitarian value in the minds of Indian shoppers and hedonic value is linked to impulsive buying urges, as stated by Shamim and Misra (2025). Moghddam et al., (2024), also established a correlation between social-commerce engagement and the similar proclivities. Purchase intention should not be considered as evidence for impulse purchasing.

The nature of these relationships can be influenced by the national context, due to variations in privacy expectations, online trust and familiarity with automated services. Among the studies on consumers of social commerce, research has correlated information sharing, social support, perceived risk, and purchasing intention among millennials (Tseng et al., 2025). A longitudinal study associated trust, perceived privacy, and shopping value with social-commerce purchase intentions over time (Laradi et al., 2024). In Lebanon and Türkiye, Dia et al. (2026) found that personalisation was associated with purchase intention indirectly through relevance, usefulness, privacy concerns, and trust. Cross-national claims nevertheless require comparable measures and respondents from the countries being compared.

This study examines the relationships among AI personalization, consumer perceptions, platform trust, and purchase intention through the following research questions. The study is guided by the following five research questions:

- How is perceived AI personalization associated with consumers' purchase intention in digital commerce?
- How are perceived usefulness, responsiveness, and transparency associated with platform trust?

- What is the relationship between platform trust and consumers' purchase intention?
- Does platform trust statistically mediate the relationship between perceived AI personalization and purchase intention?
- How do the observed relationships compare with published international evidence on AI-supported personalization, consumer trust, and purchasing behaviour?

2. LITERATURE REVIEW

Social commerce has redefined how consumers shop, as it combines social, entertainment, product discovery and online shopping into one. When users are in the research phase, they're often exposed to promotional messages and product recommendations when they're using social media. In such an environment, people are likely to make impulsive purchasing decisions as the impact of attractive products and social influence is constant (Moghddam et al., 2024). Social learning is another factor affecting consumer decisions as it is based on what other customers experience, review and do when buying products. Embedding product exploration and purchase into the same platform is also linked to consumer trust and impulsive buying (Han, 2023). Djafarova & Bowes (2021) also found that ads, social media influencers and user-generated content can inspire impulsive buying among Gen Z consumers. These have sparked a greater interest from businesses for artificial intelligence (AI) solutions that can help tailor consumer interactions and make digitally-based marketing efforts more effective.

Through AI, personalisation includes analyzing consumer choices, browsing trends, and purchase histories to offer recommendations tailored to their personal interests. Personalised recommendations can help minimize information-search efforts and enhance the perceived relevance of digital shopping experiences (Hassan et al., 2025). AI technologies are also useful in marketing activities with consumer segmentation, targeted recommendations and personalised communication (Huang & Rust, 2021). These can help to develop customer trust when the advice given meets what they may have expected from them, and when they can be of assistance. But personalisation isn't always well received as the collection of a lot of information can lead to the concern of surveillance and privacy (Magano & Rebelo, 2026). Consumer problems of AI are possible problems in data collection, automated classification and decreasing consumer control in decision making processes (Puntoni et al., 2021). Studies have shown that personalised recommendations can enhance the link between consumer trust, satisfaction, and loyalty (Hassan et al., 2025). The implications of these insights are that for AI personalisation to be successful, a strong foundation of consumer acceptance and service relevance for digital platforms is needed.

As the Generative AI model has evolved, personalization has been taken up a notch in a conversational manner, with some of its applications being conversational shopping assistants, automated product explanations, and context-specific recommendations. These technologies enable consumers to get personalized information and compare products via the use of natural language communication. The study by Kamoonpuri and Sengar (2025) investigated the perception and behavioral responses of consumers when using generative AI chatbots during their shopping journeys, underscoring their growing importance in retail environments. In the study of online consumers in China, positive correlation between chatbot interactivity, perceived humanness and trust in AI-supported shopping services have also been found (Ding & Najaf, 2024). The willingness of consumers to accept these services hinges on the accuracy, completeness, and usefulness of the information they produce for shopping (Iranmanesh et al., 2025). The reliability and accuracy of the recommendations made by chatbots have also been linked to technological trust and consumers' acceptance of automated recommendations (Zhang et al., 2024). Foroughi et al. (2025) have identified trust, performance expectancy, and perceived convenience as important factors that are associated with the adoption of ChatGPT to obtain shopping information. These results suggest that personalised communication isn't enough to adopt generative AI.

Perceived usefulness is consumers' perceptions that AI powered services make shopping easier and help them make shopping decisions. Automated recommendations can curb the time spent searching, and if customers get valuable information regarding the product relevant to their search, they may react positively (Iranmanesh et al., 2025). Another consideration is responsiveness, as prompt communication can enhance perception of assistance with

shopping. But, a consumer must also consider how correct and reliable the automated responses are. Consumer decision confidence and satisfaction are linked to information credibility, comprehensiveness, and timeliness for generative AI shopping assistants (Tafesse & Sandhu, 2026). According to evidence based on AI (Artificial Intelligence) advertising research, two factors – perceived usefulness and recommendation relevance – attribute to the relationship between personalisation and purchasing intentions (Dia et al., 2026). The consistency, usefulness, and uptake of such services is therefore key, and overall it must be shown to either be more useful or more frequent than simply the difference in the number of personalised messages transmitted.

Consumers might not be fully aware of the processes involved in collecting personal data or making recommendations by AI systems, making transparency an important concern. While transparency can help to increase consumer understanding, its impact on trust might vary depending on AI communication contexts (Magano & Rebelo, 2026). Credibility of information and perceived risk of privacy have also been found to play a role in the formation of consumer trust in the context of social-commerce (Tseng, 2023). Generative AI research has found that anthropomorphic communication can enhance purchasing intentions by using social presence and trust (Wang et al., 2025). Disclosing AI involvement, however, can hinder some of the impacts of human-like communication (Wang et al., 2025). The study revealed that detailed explanations of AI recommendations can enhance perceived trust and privacy concerns, while also impacting purchasing intentions, which depend on the level of information shared (Zhang & Ramasamy, 2026). Pakistani study has also indicated that while transparency does not always result in significant indirect linkages with purchase intention, it influences purchase intention through trust (Ali & Sunela, 2026). The differences suggest that transparency and personalisation need to be investigated separately as consumer perceptions.

Platform trust is the confidence that consumers have in the reliability, integrity and dependability of digital shopping services. Trust is especially important in situations where consumers rely on automatic recommendations whose decision-making mechanisms they don't grasp. Trust and satisfaction among consumers have been found to have positive links to consumer loyalty in previous studies in the context of AI-supported e-commerce (Hassan et al., 2025). The role of trust has also been recognized as a big mediator between perceived personalisation and purchase intention, among online consumers in Pakistan (Ali & Sunela, 2026). Recent reports indicate that the recommendations given by explainable AI can improve consumer trust, which in turn is linked to an increase in purchase intention (Tiwari & Namdeo, 2026). However, the personalised advertising has an indirect effect on purchase intention as revealed by Dia et al. (2026) through relevance, usefulness, privacy concern and trust. Based on these findings, the platform trust is considered as a potential statistical mediator between AI personalisation and consumer purchase intention.

Impulse buying and purchase intention are similar but conceptually different forms of consumer behaviour. While purchase intention is an aroused predisposition to buy a product, impulse buying represents a sudden urge to buy. Personalised AI services can lead to impulsive purchasing and encourage consumers to buy products that they would not otherwise have considered because they are being made more enjoyable and appealing (Shamim & Misra, 2025). Hedonic value is established as an important predictor of impulsive urges to buy, but utilitarian value alone does not always elicit the same urge to buy process (Shamim & Misra, 2025). Meanwhile, studies involving social media influencers have also shown that consumers' impulsive shopping tendencies correspond to credibility and trust when viewing and interacting with the promotional content that social media celebrities post (Shamim et al., 2024). Marketing activities, consumer engagement, and social learning may cause impulsive buying within social-commerce settings (Xu et al., 2024). The results indicate that there is a need to differentiate planned purchase intention from unplanned purchases.

While research into AI personalisation continues to grow, results vary from consumer markets to digital shopping experiences. Cross-national evidence indicates that personalisation does not necessarily influence purchase intention directly, as its relationship may depend on usefulness, relevance, and trust (Dia et al., 2026). Privacy concerns may also complicate consumers' evaluations of highly personalised recommendations (Magano & Rebelo, 2026). A study involving 635 Generation Z consumers in Vietnam similarly identified personalisation, privacy concerns, and trust as interconnected factors associated with online purchasing decisions (Ngo & Nguyen, 2026). The present study examines perceived AI personalisation,

usefulness, responsiveness, transparency, platform trust, and purchase intention using secondary respondent-level data reported from Indonesia. It investigates direct associations and the statistical mediating role of platform trust. International findings provide a broader basis for interpretation, while the available data do not permit direct testing of generative AI exposure, actual impulse buying, or cross-national differences.

3. METHODOLOGY

3.1 Research Design

The study adopted a quantitative, explanatory research design using secondary cross-sectional data. It examined the relationships among perceived AI personalisation, usefulness, responsiveness, transparency, platform trust, and consumer purchase intention. The research focused on identifying statistical associations and the mediating role of platform trust in AI-supported digital commerce.

3.2 Data Source and Sample

A secondary data that was publicly available and included 248 respondent data that were recorded as consumers in digital commerce in Indonesia was used. Twenty-two questionnaire indicators in total were included which related to six constructs. Records were filtered for blanking-outs, duplicate identifiers and invalid responses.

3.3 Measurement of Variables

The study examined six constructs: AI personalisation, perceived usefulness, responsiveness, transparency, platform trust, and purchase intention. Questionnaire responses were measured using five-point Likert scales ranging from 1 (strongly disagree) to 5 (strongly agree). Composite scores were calculated from the corresponding indicators.

3.4 Data Analysis Techniques

Analytical procedures were performed using Python based statistical analysis. Descriptive statistics as well as Cronbach's alpha, indicator loadings, average variance extracted, HTMT ratios, and Fornell–Larcker comparisons were used to examine the measurement properties. The direct relationships were assessed by regression analysis, and the indirect relationships and confidence intervals were estimated by bootstrapping. Variance inflation factors, sensitivity analysis and cross validation were also explored for multicollinearity, effect sizes and predictive performance.

3.5 Data Quality and Research Limitations

There were some similar response-frequency distributions between indicators, which were identified by data screening and raised concerns about data provenance and data independence in measurement. Thus, the analysis was exploratory. As it was a one reported national context, no cross-national comparison was made. Measurements considered general AI personalisation and purchase intention, not generative AI exposure or actual impulse buying. Thus, the results were explained in terms of statistical relationships, not causal relationships.

4. RESULTS

4.1 Data Screening and Demographic Profile

Data from 248 respondents were analyzed quantitatively from a secondary dataset which was originally reported from Indonesia. The dataset included 22 measurement indicators which covered six constructs, namely, perceived AI personalisation (PP), perceived usefulness (PU), AI responsiveness (AIR), AI transparency (AIT), platform trust (PT), and purchase intention (PI). A preliminary screening of the questionnaires revealed no missing responses, respondent IDs, or out-of-range values. All 5456 item-level responses were thus kept in the analysis.

Table 1:. Demographic characteristics of respondents (N = 248)

Characteristic	Category	f	%
Gender	Female	139	56.0%
	Male	109	44.0%
Age	25–34 years	112	45.2%
	18–24 years	79	31.9%
	35–44 years	38	15.3%
	45 years and above	19	7.7%
Shopping platform	Shopee	87	35.1%
	Tokopedia	65	26.2%
	TikTok Shop	41	16.5%
	Lazada	37	14.9%
	Other platforms	18	7.3%

The gender distribution of respondents was 56.0% for women and 44.0% for men. The age distribution was found to be predominantly the 25 – 34 age group (45.2%) followed by the 18 – 24 age group (31.9%). Among shopping platforms, Shopee (35.1%), Tokopedia (26.2%), TikTok Shop (16.5%) as well as Lazada (14.9%) and other platforms (7.3%) were the most common platforms reported. These differences represent differences in intranational attributes and not necessarily in separate country samples.

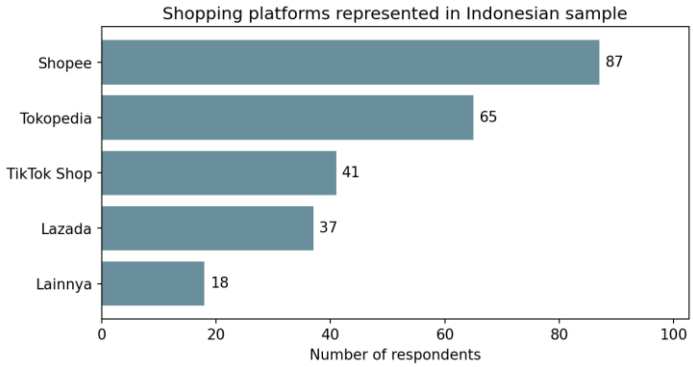


Figure 1:. Respondents by main shopping platform.

4.2 Descriptive Statistics and Internal Consistency

The average score of each construct was used to calculate descriptive data. Mean values ranged between 3.007 and 3.008 and were near the midpoint of the scale. The standard deviations ranged from 1.015 to 1.100, reflecting some variation in contestants' reported evaluations. The Cronbach's alpha was between 0.779 and 0.906, with AI responsiveness having the lowest value and platform trust having the highest value. The composite reliability of the exploratory factor-based constructs varied from 0.778 to 0.906, and the average variance extracted (AVE) was between 0.539 and 0.711.

Table 2:. Construct descriptives and exploratory measurement reliability

Scale	Items	N	Mean	SD	Alpha	FA CR	FA AVE
PP	4	248	3.008	1.017	0.850	0.849	0.585
PU	4	248	3.007	1.015	0.848	0.847	0.582
AIR	3	248	3.008	1.019	0.779	0.778	0.539
AIT	3	248	3.008	1.056	0.828	0.827	0.615
PT	5	248	3.008	1.044	0.906	0.906	0.660
PI	3	248	3.008	1.100	0.881	0.881	0.711

PP = perceived personalisation; PU = perceived usefulness; AIR = AI responsiveness; AIT = AI transparency; PT = platform trust; PI = purchase intention. CR and AVE are based on exploratory single-factor estimates, not SmartPLS.

Cronbach's alpha values for all six items were ≥ 0.70 indicating acceptable internal consistency. Purchase intention had the highest standard deviations of the means scores (SD = 1.100) and usefulness had the lowest (SD = 1.015). Since the wording of the constructs is very similar, do not assume that the consumer attitudes reflected in the constructs are the same without a source-check.

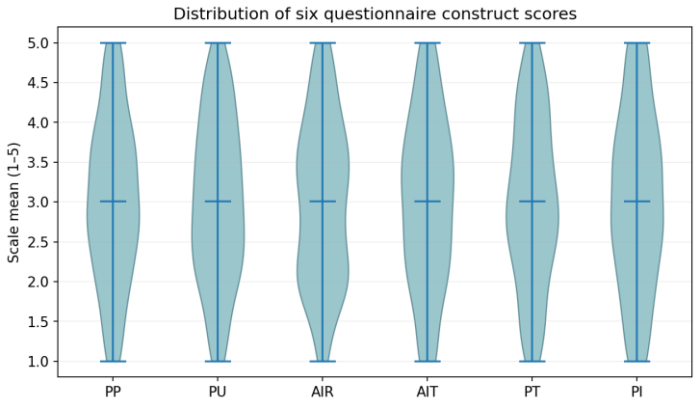


Figure 2:. Distributions of the six composite scores.

4.3 Exploratory Indicator Loadings and Convergent Validity

Table 3:. Exploratory single-factor loadings and communalities

Item	Scale	FA loading	Communality
PP1	PP	0.726	0.527
PP2	PP	0.797	0.635
PP3	PP	0.761	0.579
PP4	PP	0.775	0.600
PU1	PU	0.711	0.506
PU2	PU	0.763	0.582
PU3	PU	0.764	0.584
PU4	PU	0.809	0.655
AIR1	AIR	0.754	0.569
AIR2	AIR	0.703	0.494
AIR3	AIR	0.744	0.554
AIT1	AIT	0.767	0.589
AIT2	AIT	0.758	0.574
AIT3	AIT	0.826	0.682
PT1	PT	0.710	0.503
PT2	PT	0.846	0.716

PT3	PT	0.834	0.695
PT4	PT	0.826	0.683
PT5	PT	0.839	0.703
PI1	PI	0.794	0.631
PI2	PI	0.840	0.706
PI3	PI	0.893	0.797

The exploratory indicator loadings ranged from 0.703 (AIR2) to 0.893 (PI3). All estimated loadings exceeded 0.70, with AIR2 having the smallest loading. The corresponding communalities ranged from 0.494 to 0.797. AVE was above 0.50 for every construct, with purchase intention obtaining the highest value (0.711) and AI responsiveness the lowest (0.539). These findings are consistent with acceptable convergent measurement properties in an exploratory single-factor assessment. They do not constitute confirmatory loadings from a latent-variable PLS-SEM model.

4.4 Discriminant Validity Assessment

Discriminant validity was screened using heterotrait–monotrait (HTMT) ratios and Fornell–Larcker comparisons. Following table presents the complete HTMT matrix. The largest off-diagonal ratio was observed between platform trust and purchase intention (0.711), followed by personalisation and platform trust (0.697). All off-diagonal values were below 0.85.

Table 4:. HTMT ratios among construct item sets

Scale	PP	PU	AIR	AIT	PT	PI
PP	1.000	0.292	0.163	0.361	0.697	0.507
PU	0.292	1.000	0.123	0.415	0.431	0.593
AIR	0.163	0.123	1.000	0.265	0.222	0.166
AIT	0.361	0.415	0.265	1.000	0.382	0.496
PT	0.697	0.431	0.222	0.382	1.000	0.711
PI	0.507	0.593	0.166	0.496	0.711	1.000

The square roots of AVE appear on the diagonal with interconstruct correlations off the diagonal. Each diagonal value exceeded the corresponding correlations in its row and column. For example, the square root of AVE for platform trust was 0.812, exceeding its correlation with purchase intention (0.635) and perceived personalisation (0.612). The two screening approaches were therefore consistent with distinguishable construct scores, although the single-factor exploratory basis and the source-data warning remain relevant.

Table 5:. Fornell–Larcker screening matrix

Scale	PP	PU	AIR	AIT	PT	PI
PP	0.765	0.248	0.133	0.303	0.612	0.439
PU	0.248	0.763	0.081	0.348	0.378	0.513
AIR	0.133	0.081	0.734	0.213	0.187	0.137
AIT	0.303	0.348	0.213	0.784	0.331	0.423
PT	0.612	0.378	0.187	0.331	0.812	0.635
PI	0.439	0.513	0.137	0.423	0.635	0.843

Diagonal: square root of factor-based AVE. Off-diagonal: correlations among composite mean scores.

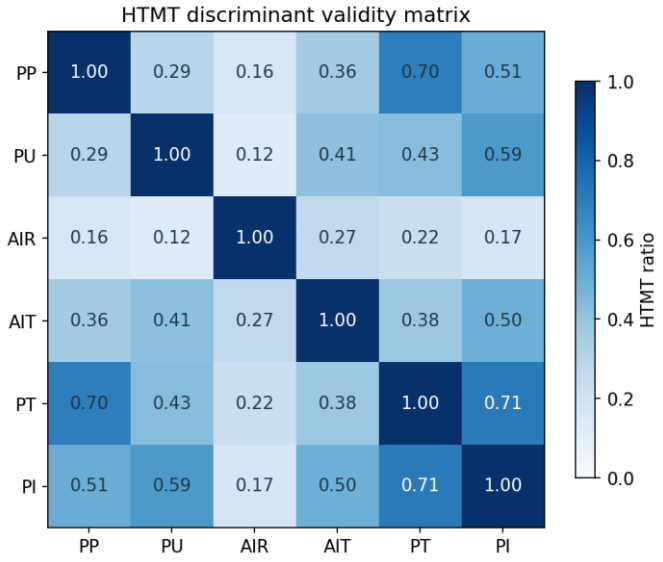


Figure 3: HTMT ratios across the six construct groups.

4.5 Structural Associations and Explained Variation

Two standardised composite-score ordinary least-squares regressions were estimated using heteroskedasticity-robust HC3 standard errors. The first model regressed platform trust on personalisation, usefulness, responsiveness, and transparency. The second regressed purchase intention on these four predictors together with platform trust. The trust equation explained 44.3% of observed score variation ($R^2 = 0.443$; adjusted $R^2 = 0.434$), whereas the purchase-intention equation explained 51.6% ($R^2 = 0.516$; adjusted $R^2 = 0.506$). Both overall regression tests were statistically significant ($p < 0.001$).

Table 6:. Composite regression explanatory performance

Outcome	N	R^2	Adj. R^2	Robust F	p
PT	248	0.443	0.434	59.28	<0.001
PI	248	0.516	0.506	54.62	<0.001

This table reports adjusted standardised coefficients. Personalisation was positively associated with trust (β = 0.523, p < 0.001), as was perceived usefulness (β = 0.213, p < 0.001). Associations of responsiveness and transparency with trust were positive but statistically uncertain. For purchase intention, platform trust had the largest adjusted coefficient (β = 0.450, p < 0.001). Usefulness (β = 0.273, p < 0.001) and transparency (β = 0.167, p = 0.001) were also positively associated with purchase intention. The adjusted direct coefficient for personalisation was small (β = 0.046, p = 0.431), while responsiveness was not statistically distinguishable from zero (β = −0.011, p = 0.804).

Table 7:. Direct associations from standardised HC3 composite regressions

Path	β	SE HC3	t/z	p	95% CI
PP → PT	0.523	0.049	10.61	<0.001	0.427 to 0.620
PU → PT	0.213	0.050	4.24	<0.001	0.115 to 0.312
AIR → PT	0.083	0.053	1.55	0.121	-0.022 to 0.187
AIT → PT	0.081	0.055	1.48	0.140	-0.026 to 0.189
PP → PI	0.046	0.059	0.79	0.431	-0.069 to 0.161
PU → PI	0.273	0.049	5.58	<0.001	0.177 to 0.369
AIR → PI	-0.011	0.044	-0.25	0.804	-0.097 to 0.076
AIT → PI	0.167	0.052	3.23	0.001	0.066 to 0.269
PT → PI	0.450	0.057	7.87	<0.001	0.338 to 0.563

The coefficients represent adjusted associations between observed scale scores; they are not SmartPLS latent-variable path coefficients.

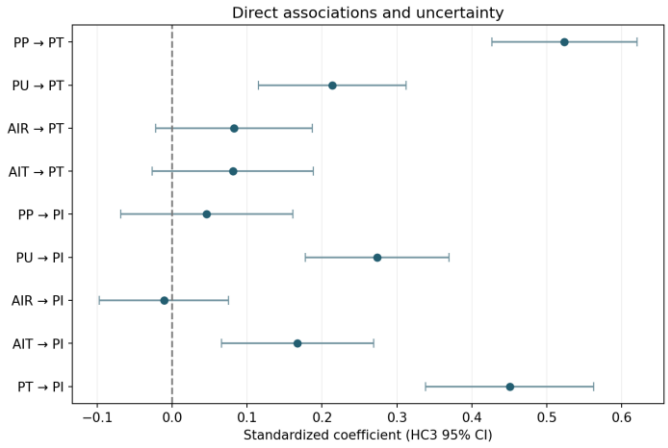


Figure 4:. Robust 95% confidence intervals for the nine adjusted direct coefficients.

4.6 Effect Sizes and Multicollinearity

Variance inflation factors ranged from 1.053 to 1.796 across the two regression equations, indicating no serious linear multicollinearity. Predictor-specific f^2 estimates identified personalisation as the strongest contributor to the trust equation ($f^2 = 0.433$). For purchase intention, trust had the largest f^2 value (0.233), followed by usefulness (0.124) and transparency (0.046). By contrast, personalisation's adjusted direct contribution to the purchase-intention model was small ($f^2 = 0.003$).

Table 8:. Effect sizes and variance inflation factors

Path	f^2	VIF
PP → PT	0.433	1.136
PU → PT	0.070	1.167
AIR → PT	0.012	1.053
AIT → PT	0.009	1.245
PP → PI	0.003	1.628
PU → PI	0.124	1.249
AIR → PI	<0.001	1.066
AIT → PI	0.046	1.256
PT → PI	0.233	1.796

f^2 = (full-model R^2 − reduced-model R^2)/(1 − full-model R^2). Values refer to observed-score regressions.

4.7 Bootstrap Analysis of Indirect Associations

Indirect associations through platform trust were estimated from 4,000 respondent-level bootstrap resamples using percentile confidence intervals. The indirect personalisation–purchase intention coefficient was positive (β = 0.236; 95% CI [0.168, 0.310]). The corresponding

indirect usefulness coefficient was also positive (β = 0.096; 95% CI [0.048, 0.152]). Intervals for responsiveness and transparency crossed zero, providing insufficient evidence of a nonzero indirect association for those predictors in the supplied dataset.

Table 9:. Bootstrapped indirect associations through platform trust

Indirect path	Estimate	Boot SD	95% low	95% high	CI excludes zero
PP → PT → PI	0.236	0.036	0.168	0.310	Yes
PU → PT → PI	0.096	0.027	0.048	0.152	Yes
AIR → PT → PI	0.037	0.024	-0.008	0.086	No
AIT → PT → PI	0.037	0.025	-0.013	0.089	No

The total personalisation–purchase intention coefficient was estimated at 0.282 (95% bootstrap CI [0.173, 0.384]), despite its small adjusted direct coefficient (β = 0.046). This pattern was consistent with a statistical indirect relationship through trust. However, temporal ordering could not be observed in the cross-sectional data, so this analysis should not be interpreted as proving a causal mediation process.

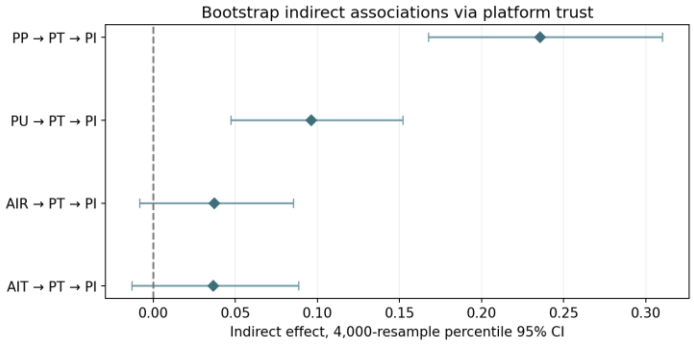


Figure 5:. Bootstrap 95% confidence intervals for indirect paths through trust.

4.8 Internal Predictive Assessment

Repeated five-fold cross-validation (10 repetitions) was used to assess out-of-fold prediction of the two observed outcomes. Compared with a training-mean benchmark, prediction errors were lower for both fitted models. Platform-trust RMSE decreased from 1.048 to 0.798, with cross-validated Q^2 = 0.420; purchase-intention RMSE decreased from 1.103 to 0.785, with cross-validated Q^2 = 0.493. These values indicate useful internal prediction of the observed composite scores relative to the specified benchmark.

Table 10:. Repeated cross-validated predictive performance

Outcome	Model MAE	Model RMSE	Baseline MAE	Baseline RMSE	CV Q^2
PT	0.652	0.798	0.867	1.048	0.420
PI	0.630	0.785	0.918	1.103	0.493

Repeated five-fold CV × 10. CV Q^2 is based on out-of-fold model and training-mean benchmark sums of squares; it is not SmartPLS PLSpredict or CVPAT.

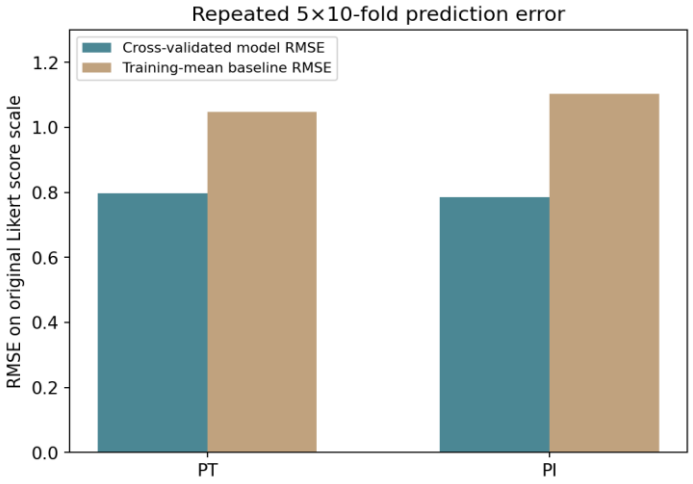


Figure 6:. Out-of-fold RMSE compared with the training-mean benchmark.

4.9 Robustness and Common-Method Screening

Sensitivity analyses compared the full purchase-intention regression with an estimation excluding 13 observations exceeding the Cook's-distance threshold (4/248) and a Huber robust regression using the full sample. The adjusted trust coefficient remained positive in all three specifications (β = 0.450, 0.469 and 0.474, respectively). Usefulness remained positive and responsiveness stayed close to zero. The direction and broad size of the main coefficients were therefore not materially changed by these checks.

Table 11:. Sensitivity of coefficients in the purchase-intention equation

Predictor	Full model	Exclude influential cases	Huber robust
PP	0.046	0.054	0.052

PU	0.273	0.306	0.299
AIR	-0.011	-0.026	-0.016
AIT	0.167	0.175	0.168
PT	0.450	0.469	0.474

The diagnostic for a limited common method applied to all 22 standardised indicators showed that 35.7% of the variance was explained by the first principal component, which was not rotated. This was not indicative of the 50% descriptive level commonly used, but it was not possible to rule out common method bias using a one-factor screen. The available measurements did not allow marker-variable and method-factor tests.

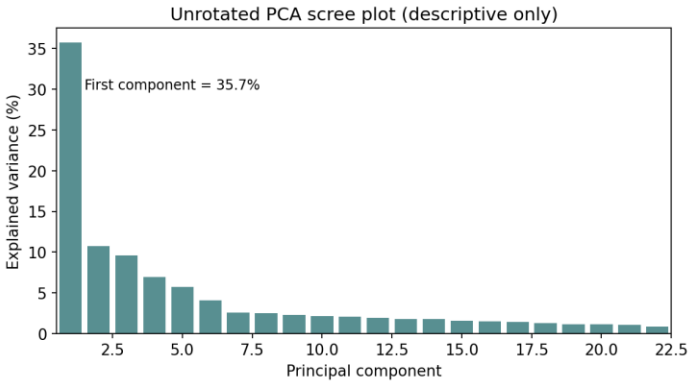


Figure 7:. Principal-component scree plot across 22 indicators.

4.10 Exploratory Within-Sample Group Comparisons

Personalisation, platform trust and purchase intention differences between shopping platforms, gender groups and age categories were assessed using exploratory Kruskal–Wallis tests. All nine unadjusted tests were > .05. The smallest p value was 0.078 for purchase intention by Primary shopping platform. These findings do not demonstrate population-level equivalence and no adjustments were made for multiple testing.

Table 12:. Exploratory Kruskal–Wallis comparisons

Grouping	Outcome	Groups	H	Unadjusted p
primary_platform	PP	5	4.07	0.396
	PT	5	5.22	0.265
	PI	5	8.41	0.078
gender	PP	2	0.10	0.750
	PT	2	0.92	0.337
	PI	2	1.47	0.225
age_group	PP	4	1.26	0.740
	PT	4	3.07	0.381
	PI	4	1.48	0.687

Tests are within the Indonesian dataset. Results do not constitute cross-national multigroup analysis.

5. DISCUSSION

The findings of the present study provide empirical evidence regarding the relationships between AI-driven personalisation, platform trust, perceived usefulness, transparency, and consumer purchase intention in digital commerce. Based on 248 respondent records, the regression models explained 44.3% of the variance in platform trust ($R^2 = 0.443$) and 51.6% of the variance in purchase intention ($R^2 = 0.516$). These results indicate that the selected consumer perceptions were jointly associated with a substantial proportion of the variation in purchasing intentions. Comparable findings were reported in a Pakistani study involving 112 social media consumers, where AI personalisation and trust-related variables explained 38.0% of consumer trust and 57.0% of purchase intention (Hanif et al., 2026). Although the present study demonstrated higher explanatory power for trust, the Pakistani study reported slightly greater explanatory power for purchase intention. Another investigation involving 156 Pakistani online shoppers explained 34.0% of the variation in purchase intention through AI recommendations, trust, and ease-of-use-related relationships (Razzaq et al., 2025). These differences suggest that explanatory performance depends on the included predictors, consumer characteristics, and statistical specifications rather than personalisation alone.

One of the strongest findings concerned the positive association between perceived AI personalisation and platform trust ($\beta = 0.523$, $p < 0.001$). The effect size of the corresponding effect was also considerable ($f^2 = 0.433$), indicating that personalisation has made a significant contribution to the explanatory power of the trust model. This finding aligns well with the study by Sarwar & Malik (2025), which conducted a comparison of 376 Generation Z consumers in Pakistan and United Kingdom and found that AI-driven personalisation is associated positively with consumer trust with ($\beta = 0.497$, $p < 0.001$). On the other hand, a study in Pakistan explored the link between personalisation and consumer trust, revealing a strong positive relationship ($\beta = 0.617$, $p < 0.001$) (Hanif et al.,

2026). These estimates have all been derived using different models but consistently with positive directions, indicating that personalised recommendations can have an impact on a consumer's level of confidence in a digital shopping content. When consumers feel that automated suggestions align with their likes and dislikes, they can see the services as proof of competence and reliability of the platform.

Although there is a high correlation between personalisation and trust, the adjusted direct effect of this on purchase intention was not statistically significant (β = 0.046, p = 0.431). This finding suggests that after controlling for usefulness, responsiveness, transparency and trust, personalised recommendations were not significantly related to a higher purchase intention. In a cross-national study of 802 Lebanese (n = 394) and Turkish (n = 408) social media users, a similar result occurred as personalisation did not show a direct significant relationship with purchase intention for Lebanese or Turkish users (Dia et al., 2026). Contrasting evidence, however, was reported in the context of 112 Pakistani consumers in which personalisation still had a significant direct relationship with purchase intention (β = 0.264, p = 0.008) (Hanif et al., 2026). Another study, that was conducted amongst Generation Z consumers from Pakistan and Britain, also found a positive and significant personalisation–purchase intention coefficient equal to β = 0.693 (Sarwar & Malik, 2025). These competing results could be due to differences in scope of consumers, methods of measurement, or the use of intermediate measures. Based on the results of the current study, it appears as though the sole consideration of personalised recommendations is not sufficient to explain consumers' purchasing intentions when the consumer's evaluation of the platform is taken into account.

The largest adjusted estimate in the prediction of purchase intention was the effect of platform trust (β = 0.450; $p < 0.001$; $f^2 = 0.233$). Its positive relationship shows that consumers who indicated high confidence in the platform also showed high intentions to purchase. Similar findings were found in Pakistan that consumer trust showed positive relationship with purchase intention, $\beta = 0.552$ and $p<0.001$ (Hanif et al., 2026). Moreover, after controlling for the effect of demographic variables, there was a positive relationship between trust and purchase intention in Lebanon (β = 0.259) and Türkiye (β = 0.247) (Dia et al., 2026). These coefficients were lower than the estimate from the present study but the relationships were still in the same direction. Because the belief-satisfaction-loyalty link was not found, the authors believed that trust was the most effective predictor of customer satisfaction in online retail and concluded that it had a positive effect on customer satisfaction and customer trust (Hassan et al., 2025). Because satisfaction and loyalty are different from purchase intention, these coefficients are not comparable as predictors of this outcome. The research results, however, validate the overall conclusion that the element of trust is related to positive reactions in consumers concerning services with the support of the AI.

Results from the mediation analyses also evidenced the relationship between personalisation and purchase intention. The indirect association (via platform trust) was estimated to be positive and statistically significant (β = 0.236, 95% CI [0.168, 0.310]); however, the adjusted direct association was not statistically significant. This pattern was found to be consistent with a statistical relationship that was indirect-only and therefore indicated that trust was playing a significant role in the observed relationship between personalisation and purchasing intentions. Similar results were observed among the consumers of social media in Pakistan, with an indirect path coefficient from personalisation to purchase intention through trust of β = 0.340 ($p < 0.001$) (Hanif et al., 2026). Another Pakistani investigation reported a positive indirect effect of 0.20, with a 95% confidence interval of [0.11, 0.33] (Razzaq et al., 2025). The latter estimate was reported on a different coefficient scale, preventing a strict numerical comparison. However, the positive indirect estimates across these studies suggest that consumer trust may represent an important statistical pathway linking personalised shopping experiences with purchase intention. The cross-sectional nature of the present analysis does not establish that personalisation first increased trust and subsequently caused purchasing behaviour.

Perceived usefulness also showed positive associations with both platform trust ($\beta = 0.213$, $p < 0.001$) and purchase intention ($\beta = 0.273$, $p < 0.001$). Its effect size for purchase intention was $f^2 = 0.124$, making usefulness the second-largest adjusted predictor after platform trust. These findings suggest that practical benefits, including relevant information and reduced searching effort, may be associated with consumers' willingness to buy. It was also found to have a positive relationship with trust (β = 0.397, β = 0.421) and with purchase intention (β = 0.276, β =

0.183) in the descriptive models after controlling for the demographics in Lebanon and Türkiye, respectively (Dia et al., 2026). The coefficient of the current purchase-intention was especially well aligned with the Lebanese estimate, but the models used were different. By contrast, the adjusted relationships of AI responsiveness with trust (β = 0.083, p = 0.121) and purchase intention (β = −0.011, p = 0.804) were not significant. This indicates that, for the sample available, consumers' assessments of usefulness were more related to purchasing intentions than their assessments of responsiveness.

The results with regard to transparency showed a different pattern. AI transparency was found to have a significant direct link to purchase intention (β = 0.167, p = 0.001) and not in the adjusted relationship with platform trust (β = 0.081, p = 0.140). Its indirect association through trust was also insignificant (β = 0.037, 95% CI [−0.013, 0.089]). This indicates that there may be additional trust pathways that are related to transparency that have not been measured and therefore may also relate to purchasing intention. Ali & Sunela (2026) have observed similar evidence amongst the Pakistani e-commerce consumers with the mediation of trust between the perceived personalisation and purchase intention being significant but not significant for the corresponding transparency relationship. Based on the present results, it can thus be assumed that providing clearer information about services supported by AI is associated with more favourable purchasing intentions, but not necessarily with an additional measurable association through the platform trust. The lack of a consistent relationship between transparency and studies may be attributed to differences in understanding and measurement.

The internal statistical properties of the measurement assessments were generally acceptable. The Cronbach's alpha values are between 0.779 and 0.906, and the average variance extracted values are between 0.539 and 0.711. The results of the internal consistency revealed that platform trust had the highest score (α = 0.906) and the lowest was purchase intention (α = 0.881). Hassan et al. (2025) obtained 0.849 reliability coefficient for personalised recommendations, 0.857 for trust, 0.866 for satisfaction and 0.926 for loyalty in their Egyptian study with 729 consumers. The personalisation reliability coefficient in the present study (α = 0.850) was nearly identical to the Egyptian estimate, although the questionnaire items and estimation procedures were not necessarily equivalent. The variance inflation factors were between 1.053 and 1.796, and the highest HTMT ratio was observed 0.711, which is below the commonly used 0.85. Such results agreed with acceptable exploratory measurement separation and low predictor collinearity. However, both measures of reliability and validity have been computed using exploratory factor analysis and composite scores instead of confirmatory PLS-SEM estimation.

The predictive evaluation also has obtained positive results. Five-fold cross validation was performed and the values of Q2 as 0.420 for platform trust and 0.493 for purchase intention were obtained. The purchase-intention model achieved a root mean square error (RMSE) of 0.785, compared with 1.103 for the training-mean benchmark. These results suggest that the selected variables provided better internal prediction than the specified baseline. Sensitivity analysis produced similar estimates for the trust–purchase intention relationship across ordinary regression (β = 0.450), exclusion of influential observations (β = 0.469), and Huber robust regression (β = 0.474). Hassan et al. (2025) found that personalised chatbot recommendations helped to enhance the explanatory power of the model by about 5% and demonstrated a negative moderation coefficient for the trust–satisfaction relationship (β = −0.085) through a comparable study using PLS-SEM. This said, the cross-validation statistics presented here was calculated using the composite-score regression and might not be equated with the PLSpredict or CVPAT statistics calculated by the use of SmartPLS.

The results also needed to be interpreted in the context of impulse buying as this is the reason for the general research question but was not directly assessed in the data gathered. Purchase intention indicates the supposed intention to purchase, and impulse purchase is defined as an unplanned urge or purchase. In a study of 325 Indian online shoppers, it was found that there is a positive and significant relationship between AI personalisation and hedonic and utilitarian perceived value, and hedonic perceived value was linked to impulsive buying urges, but the same was not found for utilitarian perceived value (Shamim & Misra, 2025). Social commerce research has also found a connection between entertainment and brand-related needs and impulsive buying behaviors (Moghddam et al., 2024). Findings suggest that, in addition to the usefulness and trust relationships that were examined, there are additional mechanisms that may play a role in emotional enjoyment and spontaneous purchase.

Consequently, the positive associations identified in the present analysis should not be interpreted as evidence that generative AI caused impulse buying.

International comparisons provide further context but cannot substitute for direct cross-national testing. The Lebanese–Turkish investigation found that ten of eleven structural relationships did not differ significantly between the two countries, whereas perceived relevance was more strongly associated with purchase intention in Türkiye ($\beta = 0.401$) than Lebanon ($\beta = 0.164$), with a difference of 0.237 ($p = 0.010$) (Dia et al., 2026). In comparison, the Pakistani–British study of 376 Generation Z consumers reported no statistically significant country-moderation effect ($p > 0.05$) (Sarwar & Malik, 2025). These findings demonstrate that cross-national differences may vary according to the particular relationship examined and the populations studied. The present dataset comprised one reported Indonesian sample, making it inappropriate to claim that its regression relationships differed significantly from those of other countries simply because their published coefficients were numerically different.

6. CONCLUSION

The study investigated the correlation between AI-based personalisation, perceived usefulness, responsiveness, transparency, platform trust and consumer purchase intention by using secondary data from the respondents in Indonesia who were 248 people. Results showed that personalisation and perceived usefulness had positive relationship with platform trust and platform trust showed the highest positive relationship with purchase intention ($\beta = 0.450$, $p < 0.001$). The regression models accounted for 44.3% of the variance in platform trust and 51.6% of the variance in purchase intention. Personalisation was indirectly linked to purchase intention via platform trust, which was statistically significant ($\beta = 0.236$), but was not directly linked to purchase intention ($\beta = 0.033$). These results indicate that when it comes to purchase intentions, personalised shopping experiences are linked with consumer confidence with digital platforms. There are also positive links between perceived usefulness and transparency with purchase intention, while for responsiveness, it was found that it was not significantly related to purchase intention when accounting for the effect of perceived usefulness and transparency. The study adds to the literature of consumer responses to AI-assisted digital commerce by capturing the trust factor as being relevant. The generalisability and causal interpretation of the results were, however, constrained by the single-country sample, unresolved data-provenance issues and due to the cross-sectional design. The future research will focus on validated cross-national databases, generative AI-specific experiences, and true impulse purchasing to determine if these relationships hold true in other markets of consumers.

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