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PERCEIVED AI-BASED PERSONALIZATION AND PURCHASE INTENTION TOWARD GLAD2GLOW ON SHOPEE: RELEVANCE, ENGAGEMENT, AND TRUST

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ABSTRACT

This study examines how perceived AI-based personalization influences purchase intention toward Glad2Glow on Shopee through perceived relevance, consumer brand engagement, and brand trust. A cross-sectional survey using purposive sampling produced 190 usable responses from Shopee users aged 18 - 40 in Greater Jakarta. The model was assessed using partial least squares structural equation modeling with 5,000 bootstrap subsamples. Perceived AI-based personalization was positively associated with perceived relevance and consumer brand engagement. Perceived relevance was positively associated with engagement and purchase intention, while engagement was strongly and positively associated with brand trust and purchase intention. Brand trust, however, did not independently affect purchase intention. The model explained 65.8% of purchase-intention variance. The study's novelty lies in positioning multidimensional consumer brand engagement as the focal mechanism linking AI-personalized marketplace recommendations with relational and behavioral brand outcomes. The findings suggest that e-commerce personalization creates value when relevant recommendations stimulate cognitive, emotional, and behavioral engagement.

INTRODUCTION

Artificial intelligence enables marketplaces to tailor product exposure at scale through recommendation engines and predictive analytics (Davenport et al., 2020; Huang & Rust, 2021). Consumers, however, evaluate AI through the experience it creates: personalization may improve convenience and relevance but can also appear intrusive (Aguirre et al., 2015; Puntoni et al., 2021; White et al., 2008). In e-commerce, personalized recommendations can reduce search costs and shape decisions (Tam & Ho, 2006), particularly when content and placement fit consumers' motives (Bleier & Eisenbeiss, 2015). Perceived relevance is consequently a central mechanism of personalized persuasion (Yeo et al., 2025).

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Indonesia is a pertinent context because e-commerce continues to expand nationally (Badan Pusat Statistik, 2025), while Southeast Asia's digital economy was projected to exceed USD 300 billion in gross merchandise value in 2025 (Google et al., 2025). Shopee's parent reported 13.9 billion gross orders and USD 127.4 billion in gross merchandise value in 2025 (Sea Limited, 2026). For skincare brands such as Glad2Glow, this recommendation environment can influence discovery, evaluation, and purchasing.

Research links AI personalization with relevance and purchase intention (An & Ngo, 2025), digital engagement (Teepapal, 2025), brand evaluations (Shanahan et al., 2019), and e-commerce engagement (Masoud & Kumar, 2026). Nevertheless, three gaps remain. Personalization and relevance are often treated as interchangeable although a tailored recommendation may still be unsuitable. Engagement is frequently modeled as a general response rather than as cognitive processing, affection, and activation (Hollebeek et al., 2014). Moreover, limited brand-specific marketplace research integrates personalization, relevance, multidimensional consumer brand engagement (CBE), brand trust, and purchase intention.

This study addresses these gaps among Shopee users aged 18 - 40 in Greater Jakarta who encountered Glad2Glow recommendations. It positions higher-order CBE as the focal mechanism and tests seven relationships among perceived AI-based personalization (PAIP), perceived relevance (PR), CBE, brand trust (BT), and purchase intention (PI). The study clarifies how personalized exposure becomes relational and behavioral value and whether trust contributes independently to purchase intention when relevance and engagement are considered simultaneously.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Theoretical Foundation and Hypotheses

The Stimulus–Organism–Response framework explains how environmental stimuli shape internal states and subsequent behavioral responses (Mehrabian & Russell, 1974). In this study, personalized recommendations constitute the stimulus; relevance, engagement, and trust are organismic evaluations or relational states; and purchase intention is the response.

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PAIP reflects the belief that algorithmic recommendations match one's interests or behavior. Matching content with individual needs should increase relevance (Tam & Ho, 2006), as supported by personalized-advertising research (An & Ngo, 2025) and meta-analytic evidence (Yeo et al., 2025).

H1: Perceived AI-based personalization positively influences perceived relevance.

Personalized encounters can attract attention and strengthen brand-related responses (Shanahan et al., 2019; Teepapal, 2025). AI-powered personalization has also been associated with e-commerce engagement (Masoud & Kumar, 2026). Consumers may therefore invest greater thought, feeling, and activity in Glad2Glow when Shopee appears to recognize their preferences.

H2: Perceived AI-based personalization positively influences consumer brand engagement.

CBE comprises positively valenced cognitive processing, affection, and activation during brand interaction (Hollebeek et al., 2014). Consumers allocate attention and effort to content that supports their goals; relevant digital content therefore creates value and encourages interaction (Brodie et al., 2013; Hollebeek & Macky, 2019).

H3: Perceived relevance positively influences consumer brand engagement.

Brand trust reflects confidence that a brand is reliable and capable of fulfilling expectations (Delgado-Ballester, 2004). Repeated cognitive, affective, and behavioral interaction supplies information and relational experience from which trust can develop. Online-community evidence connects engagement with trust formation and transfer (Liu et al., 2018; Samarah et al., 2022).

H4: Consumer brand engagement positively influences brand trust.

Trust reduces uncertainty because consumers expect reliable performance, thereby supporting loyalty-related behavior (Chaudhuri & Holbrook, 2001). This should be especially relevant for skincare products that cannot be physically evaluated before online purchase.

H5: Brand trust positively influences purchase intention.

Engaged consumers process more information, form stronger affective responses, and undertake activities that move them toward purchase. Engagement theory

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identifies behavioral consequences (Pansari & Kumar, 2017), while empirical research links brand engagement with loyalty and purchase intention (Gutiérrez-Rodríguez et al., 2024; Leckie et al., 2016).

H6: Consumer brand engagement positively influences purchase intention.

Relevant recommendations reduce search effort and facilitate product evaluation. Personalized advertising is more persuasive when the offer applies to the recipient (An & Ngo, 2025; Bleier & Eisenbeiss, 2015), so relevance should retain a direct behavioral role after engagement is considered.

H7: Perceived relevance positively influences purchase intention.

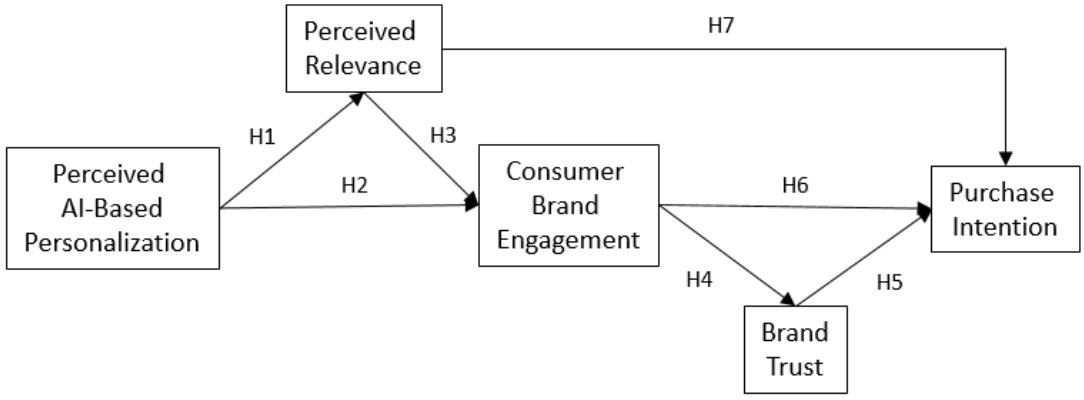


Figure 1. Conceptual research model

RESEARCH METHODOLOGY

Design, Sample, and Measurement

This quantitative, explanatory, cross-sectional study used purposive sampling and an online questionnaire. Eligible respondents were aged 18 - 40, lived in Greater Jakarta, had used and purchased through Shopee during the previous three months, knew Glad2Glow, had seen its products recommended on Shopee, and had purchased skincare during the previous six months. Participation was voluntary, anonymous, and preceded by informed consent.

All indicators used a five-point agreement scale. PAIP (four items) and PR (four items) were adapted from An and Ngo (2025); cognitive processing (three items), affection (three items), and activation (four items) were adapted from Hollebeek et al.

(2014); BT (eight items) from Delgado-Ballester (2004); and PI (five items) from Spears and Singh (2004). The questionnaire was translated and contextually adapted for Glad2Glow on Shopee.

Data Collection and Analysis

Google Forms data were collected during July 1–18, 2026 and from 223 submissions, 13 excluded the preliminary review. A secondary audit of 210 records removed ten screening failures, nine incomplete indicator sets, and one straight-line response; no duplicate email addresses or exact indicator patterns were found. The final sample was 190.

CBE was modeled as a reflective–reflective higher-order construct using a disjoint two-stage procedure: first-order dimension scores were estimated and then used as indicators of higher-order CBE (Sarstedt et al., 2019). PLS-SEM assessment followed the guidelines of Hair et al. (2022). The measurement model evaluated loadings, Cronbach's alpha, composite reliability (CR), average variance extracted (AVE), and HTMT. The structural model examined VIF, path coefficients, R^2, f^2, *t* values, *p* values, and 95% confidence intervals using 5,000 bootstrap subsamples and two-tailed testing. Discriminant validity was assessed using the heterotrait–monotrait ratio of correlations (HTMT), following Henseler et al. (2015).

RESULTS AND DISCUSSION

Sample and Measurement Model

Respondents were predominantly aged 18–24 (54.2%), female (83.2%), and students (56.3%); all Greater Jakarta areas were represented. Most had purchased through Shopee at least four times during the preceding three months (75.3%); 76.8% had purchased Glad2Glow and 46.8% were current users.

Table 1. Measurement-model reliability and convergent validity

Construct	Loading range	Cronbach's α	CR	AVE
PAIP	0.750–0.839	0.812	0.877	0.640
PR	0.859–0.904	0.906	0.935	0.781
Cognitive Processing	0.844–0.869	0.819	0.892	0.734

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Affection	0.846–0.906	0.851	0.909	0.770
Activation	0.816–0.870	0.863	0.907	0.710
Higher-order CBE	0.942–0.968	0.949	0.967	0.908
BT	0.801–0.872	0.935	0.946	0.687
PI	0.810–0.884	0.903	0.928	0.720

As shown in Table 1, all first-order indicator loadings ranged from 0.750 to 0.906. Cronbach's alpha values ranged from 0.812 to 0.935, composite reliability values from 0.877 to 0.946, and AVE values from 0.640 to 0.781. Therefore, the first-order measurement model demonstrated satisfactory indicator reliability, internal consistency reliability, and convergent validity. At the higher-order level, cognitive processing, affection, and activation loaded between 0.942 and 0.968 on CBE. Higher-order CBE achieved a Cronbach's alpha of 0.949, composite reliability of 0.967, and AVE of 0.908. The composite reliability of higher-order CBE was slightly above the conservative threshold of 0.95, reflecting the strong conceptual proximity among the three engagement dimensions.

Discriminant validity was assessed using the heterotrait–monotrait ratio of correlations (HTMT). All HTMT values were below the recommended threshold of 0.90. The highest value was observed between perceived relevance and brand trust (HTMT = 0.867), followed by perceived AI-based personalization and purchase intention (HTMT = 0.851), and perceived relevance and consumer brand engagement (HTMT = 0.850). Therefore, discriminant validity was considered acceptable, although these values indicate relatively close empirical relationships among the conceptually related constructs.

Structural Model and Hypothesis Testing

Inner VIF values ranged from 1.000 to 3.496, indicating no critical collinearity. The model explained 43.3% of PR, 71.2% of CBE, 63.7% of BT, and 65.8% of PI. Six of seven hypotheses were supported.

Table 2. Structural-model results

H	Path	β	*t*	*p*	f^2	Decision
H1	PAIP → PR	0.658	11.533	< .001	0.763	Supported

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H2	PAIP → CBE	0.395	7.324	< .001	0.307	Supported
H3	PR → CBE	0.529	9.049	< .001	0.552	Supported
H4	CBE → BT	0.798	17.722	< .001	1.752	Supported
H5	BT → PI	0.133	1.866	.062	0.015	Not supported
H6	CBE → PI	0.424	5.413	< .001	0.158	Supported
H7	PR → PI	0.311	4.293	< .001	0.084	Supported

Discussion

H1 confirms that personalized Glad2Glow recommendations become influential when consumers judge them relevant, consistent with An and Ngo (2025) and Yeo et al. (2025). H2 and H3 show that both personalization and relevance stimulate CBE, but relevance has the larger coefficient. Individualization alone is therefore insufficient; recommendations must meaningfully fit consumers' skincare needs. This supports research emphasizing valuable digital content as a foundation of engagement (Hollebeek & Macky, 2019).

H4 produced the strongest coefficient: consumers who think about, feel positively toward, and actively explore Glad2Glow are more likely to trust it. This agrees with engagement-based trust formation in online communities (Liu et al., 2018; Samarah et al., 2022) and supports CBE as the model's focal relational mechanism.

H5 was not supported. Trust remained positive but made no statistically distinct contribution to PI after relevance and engagement were included. This does not make trust unimportant; rather, trust operated more clearly as an outcome of engagement. Marketplace intentions may also depend on price, promotions, reviews, seller reputation, and delivery, qualifying the traditional trust-to-behavior relationship (Chaudhuri & Holbrook, 2001).

H6 and H7 identify two direct routes to PI. Engagement represents an experiential route through consumers' cognitive, emotional, and behavioral investment, whereas relevance represents an evaluative route through product suitability and reduced search effort. Supplementary analysis revealed significant specific indirect effects for PAIP → PR → CBE ($\beta = 0.348$, $p < .001$), PAIP → CBE → PI

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($\beta = 0.168$, $p < .001$), PAIP → PR → PI ($\beta = 0.205$, $p < .001$), and PAIP → PR → CBE → PI ($\beta = 0.148$, $p < .001$). In contrast, the indirect effect of CBE → BT → PI was not significant ($\beta = 0.106$, $p = .064$).

CONCLUSION

PAIP was associated with purchase intention toward Glad2Glow on Shopee primarily through perceived relevance and multidimensional CBE. Six hypotheses were supported: personalization increased relevance and engagement; relevance increased engagement and purchase intention; and engagement increased trust and purchase intention. Trust did not independently predict purchase intention.

Theoretically, the study separates personalization from relevance and establishes cognitive processing, affection, and activation as a higher-order engagement mechanism connecting algorithmic marketplace stimuli with relational and behavioral outcomes. The nonsignificant trust–purchase path also indicates that trust may remain relationally important without providing incremental explanatory power when relevance and engagement are modeled together.

Managerially, Shopee and Glad2Glow should assess recommendation quality through relevance and engagement rather than exposure alone. Recommendations should correspond to skincare concerns, browsing patterns, price expectations, and product interests, while ingredient explanations, reviews, demonstrations, comparisons, bundles, vouchers, and live-shopping content can stimulate the three engagement dimensions. Trust messages should be embedded in relevant and engaging experiences.

The cross-sectional, purposive, Greater Jakarta, single-brand design and reliance on intentions limit generalizability and causal inference. Future research should use experiments or longitudinal data, broader samples, multiple brands or platforms, verified purchases, and marketplace variables such as promotions, reviews, seller reputation, perceived risk, and product involvement.

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