the Effect of AI Algorithm Personalization on Fashion Purchased Decisions Among Generation Z in Indonesia: the Mediating Role of Perceived Value and Privacy Risk in Tiktok Shop

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Abstract: *Artificial intelligence–driven personalization increasingly shapes consumers' online shopping experiences, yet its effects may arise through competing evaluations of value and privacy risk. Drawing on the Stimulus–Organism–Response framework, this study examines the influence of AI algorithm personalization on purchase decisions, with perceived value and perceived privacy risk as mediating mechanisms. A quantitative approach was applied, and the proposed relationships were tested using Partial Least Squares–Structural Equation Modeling. The findings show that AI personalization positively influences purchase decisions, perceived value, and perceived privacy risk. Both mediators significantly affect purchase decisions and transmit the effect of personalization, although perceived value exerts the stronger mediating role. The positive association between privacy risk and purchase decisions also indicates a privacy paradox, whereby consumers remain willing to transact despite heightened privacy concerns. This study extends personalization research by integrating benefit- and risk-based evaluations within a single explanatory model. Managerially, the findings suggest that firms should combine relevant personalization with transparent data practices to strengthen consumer value and trust.*

INTRODUCTION

The rapid advancement of artificial intelligence (AI) has significantly transformed consumer behavior in digital environments, particularly within social commerce platforms. One of the most notable developments is the increasing use of algorithmic personalization, which enables platforms to recommend products based on users' preferences, behaviors, and interactions. This shift has fundamentally changed how consumers discover products, moving from active searching to passive discovery driven by algorithmic recommendations. As a result, AI-powered personalization has become a critical factor influencing consumer decision-making processes in online shopping contexts (Srivastava & Gurme, 2026; Zhao et al., 2025).

In the context of Generation Z, who are highly engaged with digital platforms and social media, personalization plays an even more significant role. Previous studies have shown that Generation Z consumers tend to value personalized experiences, social influence, and convenience when interacting with digital platforms (Salam et al., 2024). Short-form video platforms such as TikTok Shop have created an immersive and interactive shopping environment, where product discovery is often driven by algorithmic feeds and live-streaming content. This environment encourages faster decision-making and increases the likelihood of spontaneous or impulse purchases (Hu et al., 2025).

Several empirical studies have confirmed the positive impact of AI-driven personalization on consumer behavior. AI-powered recommendation systems have been found to enhance purchase intention by improving perceived relevance, usefulness, and engagement (Khanh et al., 2025; Ruiz-Viñals et al., 2024). Furthermore, personalization can strengthen consumer trust and influence purchasing decisions through improved accuracy and user experience (Guerra-Tamez et al., 2024). However, while these studies emphasize the benefits of AI personalization, they often overlook the potential risks associated with the use of personal data.

The increasing reliance on AI-driven systems has also raised concerns regarding data privacy and security. Consumers are becoming more aware that personalized recommendations are generated through the collection and processing of their personal data. This awareness may lead to privacy concerns, which can negatively affect consumer trust and decision-making (M. Chen & Chen, 2025; Mutambik et al., 2023). According to Privacy Calculus Theory, consumers tend to evaluate the trade-off between perceived benefits and perceived risks when deciding whether to engage with digital platforms or share personal information (M. Chen & Chen, 2025). Thus, while personalization offers convenience and efficiency, it may simultaneously trigger concerns about privacy, creating a paradox in consumer behavior.

To better understand this phenomenon, the Stimulus–Organism–Response (S-O-R) framework provides a comprehensive theoretical foundation. In this context, AI-driven personalization can be conceptualized as a stimulus that influences internal consumer evaluations (organism), such as perceived value and perceived privacy risk, which in turn shape behavioral responses, including purchase decisions (Iskamto, 2021; Khanh et al., 2025). Perceived value reflects the benefits consumers experience, such as efficiency, relevance, and enjoyment, while perceived privacy risk represents concerns related to data misuse, lack of control, and security issues.

Despite the growing body of literature, several research gaps remain. First, many previous studies have examined either the positive effects of personalization (e.g., perceived value, usefulness, trust) or the negative aspects (e.g., privacy concerns) separately, rather than integrating both perspectives within a single (Ojokoh et al., 2025; Utami & Aimin, 2026). Second, most studies focus on general e-commerce platforms, with limited attention to social commerce platforms such as TikTok Shop, which rely heavily on algorithm-driven content and real-time interaction (Deng et al., 2024). Third, empirical research focusing on Generation Z consumers in emerging markets, particularly Indonesia, remains relatively limited.

Therefore, this study aims to examine the effect of AI algorithm personalization on fashion purchase decisions among Generation Z in Indonesia, with a particular focus on the mediating roles of perceived value and perceived privacy risk. By integrating both benefit and risk perspectives through a dual-pathway model, this research seeks to provide a more comprehensive understanding of consumer decision-making in social commerce environments.

This study employs a quantitative research approach using a cross-sectional survey method.

Data are collected from Generation Z consumers in Indonesia who actively use TikTok Shop and have experience purchasing fashion products through the platform. The data are analyzed using Structural Equation Modeling–Partial Least Squares (SEM-PLS) to examine both direct and indirect relationships among variables. The findings of this study are expected to contribute to the development of digital marketing strategies by offering insights into how businesses can balance personalization effectiveness with consumer privacy concerns.

LITERATURE REVIEW

Artificial Intelligence (AI) Personalization in Social Commerce

Artificial Intelligence (AI) personalization refers to the use of algorithmic systems to tailor content, product recommendations, and user experiences based on individual preferences, behaviors, and interaction patterns. In social commerce environments, AI-driven personalization plays a crucial role in enhancing consumer engagement by delivering relevant and timely product recommendations (Srivastava & Gurme, 2026). These systems utilize data analytics and machine learning techniques to continuously adapt to user behavior, thereby improving the accuracy and relevance of recommendations.

Previous studies have demonstrated that AI-powered personalized recommendations significantly influence consumer responses, including engagement, trust, and purchase intention (Hu et al., 2025; Zhao et al., 2025). Within short-form video platforms, algorithmic feeds enable rapid product discovery, which reduces search effort and enhances user experience. As a result, personalization not only improves efficiency but also increases the likelihood of spontaneous purchasing behavior among Generation Z consumers (Hu et al., 2025).

Furthermore, AI personalization has been shown to strengthen brand trust and positively affect purchasing decisions when consumers perceive the recommendations as accurate and relevant (Guerra-Tamez et al., 2024). However, the effectiveness of personalization depends on how consumers interpret the benefits and risks associated with the use of their personal data.

Stimulus-Organism-Response (S-O-R) Theory

The Stimulus–Organism–Response (S-O-R) theory, originally proposed by Mehrabian and Russell (1974) in (Khanh et al., 2025), provides a foundational framework for understanding consumer behavior in response to environmental stimuli. The theory posits that external stimuli (S) influence internal psychological states (O), which subsequently lead to behavioral responses (R).

In the context of digital and social commerce, AI-driven personalization can be conceptualized as a technological stimulus that affects consumers' internal evaluations, such as perceived value and perceived risk, ultimately shaping their purchase decisions. This framework has been widely applied in studies examining online consumer behavior and technology adoption (Khanh et al., 2025).

Recent research has extended the S-O-R model by incorporating dual appraisal mechanisms, where both positive (e.g., perceived value) and negative (e.g., perceived risk) evaluations coexist and jointly influence behavioral outcomes (Syamsuar & Witarsyah, 2025). This dual-pathway perspective is particularly relevant in AI-driven environments, where technological benefits are often accompanied by potential risks.

Perceived Value

Perceived value is defined as the consumer's overall assessment of the benefits received from a product or service relative to the costs incurred. In the context of AI personalization, perceived value reflects the extent to which consumers perceive personalized recommendations as useful, efficient, and enjoyable.

AI-driven personalization enhances perceived value by improving product relevance, reducing search time, and providing a more convenient and engaging shopping experience (Hu et al., 2025). Additionally, personalized recommendations allow consumers to explore products that align with their preferences and lifestyle, thereby increasing satisfaction and decision confidence.

Empirical evidence suggests that perceived value plays a significant role in influencing purchase intention and decision-making in digital environments (Syamsuar & Witarsyah, 2025). When consumers perceive high value from personalized recommendations, they are more likely to proceed with purchase decisions. Therefore, perceived value serves as a key psychological mechanism linking AI personalization to consumer behavior.

Perceived Privacy Risk (Privacy Concern)

Perceived privacy risk refers to the level of concern consumers have regarding the collection, use, and potential misuse of their personal data. In AI-driven personalization systems, the use of user data to generate recommendations may raise concerns about data security, surveillance, and lack of control.

Studies have shown that while personalization enhances user experience, it simultaneously increases awareness of data tracking and privacy risks (Y. Chen et al., 2024). Consumers may perceive that excessive data collection leads to higher transaction costs, discomfort, and vulnerability to data misuse. This concern can negatively affect their willingness to engage with digital platforms or complete transactions.

Privacy Calculus Theory explains that consumers evaluate the trade-off between perceived benefits and perceived risks before making decisions related to data disclosure and platform usage (M. Chen & Chen, 2025). Supporting this perspective, prior research indicates that privacy concerns significantly influence consumer behavior in social commerce, often acting as a barrier to purchase (Mutambik et al., 2023; Xiao et al., 2020)

Thus, perceived privacy risk represents a critical inhibiting factor in AI-driven environments, particularly when consumers feel that the benefits of personalization do not outweigh the associated risks.

Purchase Decision

Purchase decision refers to the consumer’s process of selecting, deciding, and completing the purchase of a product. In digital commerce, this process is influenced by multiple factors, including information availability, perceived value, trust, and perceived risk.

AI-driven personalization has been found to significantly influence purchase decisions by increasing the relevance and attractiveness of product recommendations (Ruiz-Viñals et al., 2024). Additionally, improved user experience and trust resulting from accurate recommendations further enhance consumers’ likelihood of making a purchase (Guerra-Tamez et al., 2024).

However, purchase decisions are not solely driven by positive factors. Negative perceptions, such as privacy concerns, can reduce consumer confidence and discourage transaction completion. Therefore, understanding both facilitating and inhibiting factors is essential for explaining consumer decision-making in social commerce.

Research Framework and Hypothesis Development

The research model developed in this study is based on the integration of the Stimulus–

Organism–Response (S-O-R) theory and Privacy Calculus Theory, which are widely used to explain consumer behavior in digital environments. In this framework, AI algorithm personalization is conceptualized as a technological stimulus that influences consumers' internal psychological evaluations, which subsequently shape their behavioral responses.

Specifically, AI-driven personalization is expected to generate both positive and negative cognitive evaluations. On the one hand, personalization enhances perceived value by improving efficiency, relevance, and overall shopping experience. On the other hand, it may increase perceived privacy risk due to concerns regarding data collection, surveillance, and potential misuse of personal information.

Perceived value and perceived privacy risk are positioned as mediating variables that explain the mechanism through which AI personalization affects purchase decisions. Perceived value represents the benefit pathway that encourages consumer purchasing behavior, while perceived privacy risk represents the risk pathway that may inhibit such behavior.

The conceptual framework illustrated in Figure 1 proposes that AI algorithm personalization influences purchase decisions both directly and indirectly through perceived value and perceived privacy risk. This dual-pathway model provides a more comprehensive understanding of how consumers evaluate and respond to AI-driven recommendations in social commerce platforms such as TikTok Shop.

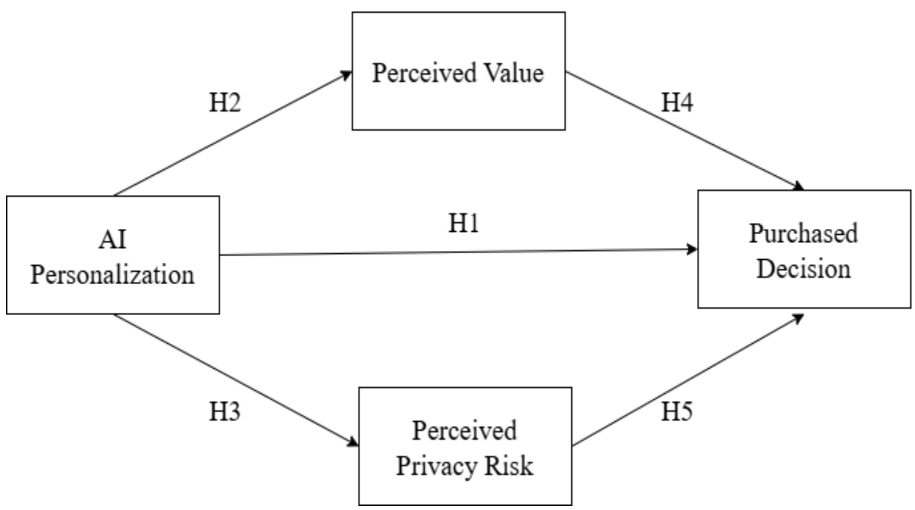

Figure 1. Research Framework

The hypothesis in this study is formulated based on theoretical arguments and empirical findings from prior research.

AI Personalization and Purchase Decision

AI-driven personalization enables digital platforms to deliver relevant product recommendations tailored to user preferences and behavior. This capability reduces search effort and enhances decision-making efficiency, thereby increasing the likelihood of purchase decisions. Prior studies have shown that personalized recommendation systems positively influence consumer purchasing behavior by improving relevance and user experience (German Ruiz-Herrera et al., 2023; Khanh et al., 2025).

H1: AI algorithm personalization positively influences purchase decisions.

AI Personalization and Perceived Value

Personalized recommendation systems enhance consumers' perceived value by providing relevant, timely, and useful product suggestions. This leads to greater efficiency in product discovery and improves overall shopping experience. Empirical evidence suggests that AI personalization significantly increases perceived usefulness and value among users (Hu et al., 2025).

H2: AI algorithm personalization positively influences perceived value.

AI Personalization and Perceived Privacy Risk

Despite its benefits, AI personalization relies heavily on the collection and processing of user data, which may increase consumers' awareness of privacy issues. As personalization becomes more sophisticated, users may perceive higher levels of data tracking and surveillance, leading to increased privacy concerns (Y. Chen et al., 2024).

H3: AI algorithm personalization positively influences perceived privacy risk.

Perceived Value and Purchase Decision

Perceived value reflects the extent to which consumers believe that the benefits of a product or service outweigh the costs. When consumers perceive high value from personalized recommendations, they are more likely to proceed with purchase decisions. Previous studies confirm that perceived value significantly enhances purchase intention and decision-making (REENA & UDITA, 2020; Syamsuar & Witarsyah, 2025).

H4: Perceived value positively influences purchase decisions.

Perceived Privacy Risk and Purchase Decision

Perceived privacy risk represents consumers' concerns about data misuse, lack of control, and security issues. Higher levels of privacy concern may reduce trust and discourage consumers from completing transactions. Research in social commerce contexts indicates that privacy concerns negatively affect consumer behavior and purchase decisions (Culnan, 1996; Joanna Ciendy Inasa Putri & Mohammad Khusnu Milad, 2025; Mutambik et al., 2023).

H5: Perceived privacy risk negatively influences purchase decisions.

Mediation Role of Perceived Value

AI personalization may indirectly influence purchase decisions through perceived value. When consumers perceive high value from personalized recommendations, they are more likely to make purchasing decisions. This suggests that perceived value acts as a positive mediating mechanism (Syamsuar & Witarsyah, 2025)

H6: Perceived value mediates the relationship between AI personalization and purchase decisions.

Mediation Role of Perceived Privacy Risk

Conversely, AI personalization may also indirectly influence purchase decisions through perceived privacy risk. Increased privacy concerns may weaken the positive effect of personalization on purchase decisions, indicating a negative mediating role (M. Chen & Chen, 2025; Joanna Ciendy Inasa Putri & Mohammad Khusnu Milad, 2025; Utami & Aimin, 2026).**H7: Perceived privacy risk negatively mediates the relationship between AI personalization and purchase decisions.**

RESEARCH METHOD

Research Design

This study employed a quantitative explanatory research design to examine the causal relationships among AI algorithm personalization, perceived value, perceived privacy risk, and purchase decision. A survey approach was utilized as it enables the collection of standardized data from a relatively large number of respondents and is appropriate for testing structural relationships using Partial Least Squares Structural Equation Modeling (PLS-SEM).

Population and Sample

The population of this study consists of Generation Z consumers in Indonesia who actively use TikTok and have been exposed to AI-driven personalized product recommendations on TikTok Shop. Indonesia was selected as the research setting due to the rapid growth of social commerce and the widespread adoption of TikTok as a digital shopping platform among young consumers.

A purposive sampling technique was applied to ensure that respondents possess relevant experience with the research context. The inclusion criteria required respondents to: (1) belong to Generation Z, (2) actively use TikTok, (3) have been exposed to personalized product recommendations on TikTok Shop, and (4) have experience purchasing fashion products through the platform.

The minimum sample size targeted in this study is 200 respondents, which meets the recommended requirements for PLS-SEM analysis. Following the 10-times rule, the minimum sample size should be at least ten times the maximum number of structural paths directed at a latent construct. In this study, the maximum number of arrows pointing to a construct is three; therefore, the minimum required sample size is 30 respondents. The targeted sample size exceeds this threshold and is considered adequate for structural model estimation.

Data Collection Technique

Data were collected through an online questionnaire distributed via digital platforms such as social media and messaging applications. To ensure respondent relevance, a screening question was included at the beginning of the questionnaire to confirm that respondents have prior experience using TikTok Shop and have been exposed to AI-based personalized product recommendations.

All items were measured using a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). The questionnaire items were adapted from prior validated studies to ensure content validity and reliability.

Operational Variables

The variables examined in this study include AI algorithm personalization as the independent variable, perceived value and perceived privacy risk as mediating variables, and purchase decision as the dependent variable.

AI algorithm personalization is defined as the extent to which TikTok Shop provides relevant, accurate, and adaptive product recommendations based on users' preferences and behavior. Perceived value refers to the overall benefits perceived by consumers from personalized recommendations, including efficiency, usefulness, and enjoyment. Perceived privacy risk reflects consumers' concerns regarding the collection, use, and potential misuse of personal data. Purchase decision represents the consumer's tendency to select and complete the purchase of fashion products after receiving personalized recommendations. The operational definitions and measurement indicators of each variable are presented in Table 1.

Table 1. Operational Variables

Variable	Code	Questionnaire Indicators	Sources
AI Algorithm Personalization	X1	TikTok Shop displays product recommendations that match my interests.	Srivastava & Gurme (2026)
	X2	The recommendations I see are relevant to my needs and preferences.	Hu et al. (2025)
	X3	Product recommendations are based on my previous browsing or purchase behavior.	Zhao et al. (2025)
	X4	Personalized recommendations help me find products more easily.	Pham et al. (2025)
	X5	The recommendation system adapts to my preferences over time.	Guerra-Tamez et al. (2024)
	X6	I feel that TikTok Shop understands my preferences well.	Ruiz-Viñals et al. (2024)
Perceived Value	M11	Personalized recommendations make shopping more efficient.	Dedy Syamsuar & Witarsyah (2025)
	M12	I find personalized recommendations useful in choosing products.	Hu et al. (2025)
	M13	Personalized recommendations improve my overall shopping experience.	Deng et al. (2024)
	M14	I feel satisfied with the recommendations provided by TikTok Shop.	Pham et al. (2025)
	M15	Personalized recommendations save me time when shopping.	Zhao et al. (2025)
	M16	Overall, personalized recommendations provide valuable benefits to me.	Utami & Aimin (2026)
Perceived Privacy Risk	M21	I am concerned about how my personal data is collected by TikTok Shop.	Chen et al. (2024)
	M22	I worry that my personal information may be misused.	Mutambik et al. (2023)
	M23	I feel that my privacy is at risk when receiving personalized recommendations.	Xiao et al. (2020)
	M24	I am uncomfortable with how my data is used for recommendations.	Ojokoh et al. (2025)
	M25	I feel that I have limited control over my personal data.	Chen & Chen (2025)
	M26	Personalized recommendations increase my concerns about data security.	Utami & Aimin (2026)
Purchase Decision	Y1	I am likely to purchase products recommended on TikTok Shop.	Ruiz-Viñals et al. (2024)
	Y2	I often decide to buy products after seeing personalized recommendations.	Hu et al. (2025)
	Y3	Personalized recommendations influence my final purchase decision.	Pham et al. (2025)
	Y4	I feel confident when purchasing products recommended by TikTok Shop.	Guerra-Tamez et al. (2024)
	Y5	I am willing to try new products based on personalized recommendations.	Zhao et al. (2025)
	Y6	Overall, personalized recommendations encourage me to make purchases.	Dedy Syamsuar & Witarsyah (2025)

Common Method Bias

Given that the data were collected using a self-report questionnaire, common method bias was assessed using Harman's single-factor test. The results indicate that the first factor accounts for less than 50% of the total variance, suggesting that common method bias is not a serious concern.

Additionally, full collinearity variance inflation factor (VIF) values were examined. All VIF values were below the threshold of 5.0, indicating the absence of significant common method bias.

Data Analysis Technique

Data analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with the assistance of SmartPLS software. This technique was selected due to its suitability for analyzing complex models involving mediation effects and multiple latent variables. The analysis was conducted in two main stages (Dash & Paul, 2021; Ghazali & Yaacob, 2025):

1. Measurement Model Evaluation (Outer Model): This stage assesses the validity and reliability of the constructs, including convergent validity, discriminant validity, and composite reliability.
2. Structural Model Evaluation (Inner Model): This stage evaluates the relationships between variables by analyzing path coefficients, coefficient of determination (R^2), and hypothesis testing using the bootstrapping method.
3. Mediation Analysis: This stage examines the indirect effects of AI personalization on purchase decisions through perceived value and perceived privacy risk.

Statistics Descriptive

Descriptive statistics were used to provide an overview of respondent characteristics and the general distribution of the study variables. A total of 260 respondents participated in this research, consisting of Generation Z consumers in Indonesia who actively use TikTok Shop for purchasing fashion products.

Table 2. Demography of Respondent Based on Gender

Gender	Frequency	Percentage
Male	95	36.5%
Female	165	63.5%
Total	260	100%

Source: Analyzed Data

In terms of gender, the sample is dominated by female respondents (63.5%), indicating that female consumers are more actively engaged in TikTok Shop, particularly in the context of fashion-related purchases. This suggests that purchasing decisions influenced by AI personalization may be more prominently represented among female users.

Table 3. Demography of Respondent Based on Occupation

Occupation	Frequency	Percentage
Student	120	46.3%
Employee	108	41.5%
Entrepreneur	32	12.3%
Total	260	100%

Source: Analyzed Data

Most respondents are students (46.2%), followed by employees (41.5%). This reflects the characteristics of Generation Z, who are predominantly in the early stages of their careers or still pursuing higher education and are highly active in digital platforms such as TikTok.

Table 4. Demography of Respondent Based on Monthly Spending on TikTok Shop

Spending	Frequency	Percentage
< Rp100.000	49	18.8%
Rp100.00-Rp500.000	163	62.7%
>Rp500.000	48	18.5%
Total	260	100%

Source: Analyzed Data

Most respondents (62.7%) reported spending between Rp100,000 and Rp500,000 on TikTok Shop, indicating a moderate level of purchasing activity. This suggests that TikTok Shop is frequently used for routine or impulsive purchases rather than high-value transactions.

Table 5. Demography of Respondent Based on Domicile

Region	Frequency	Percentage
Greater Jakarta (Jakarta, Bogor, Depok, Tangerang, Bekasi)	85	32.7%
West Java	31	11.9%
Central Java & Yogyakarta	39	15.0%
East Java	78	30.0%
Other Region	27	10.4%
Total	260	100%

Source: Analyzed Data

Most respondents are in Greater Jakarta (32.7%) and East Java (30.0%), which are major urban and digital economic centers in Indonesia. This distribution indicates that the study captures consumer behavior in regions with high exposure to digital commerce and social media platforms. Additionally, the presence of respondents from various other regions enhances the diversity and generalizability of the findings.

To further assess the general tendencies of the constructs, descriptive analysis was conducted on AI personalization, perceived value, perceived privacy risk, and purchase decision.

The results indicate that respondents generally perceive AI personalization positively, as reflected in their active engagement with TikTok Shop and moderate spending levels. This suggests that personalized recommendations are effective in facilitating product discovery and influencing consumer behavior.

Furthermore, the dominance of moderate spending patterns indicates that consumers derive functional and experiential value from personalized recommendations, particularly in supporting efficient and convenient shopping experiences. However, the variation in spending behavior also suggests the presence of different levels of risk perception among users.

Overall, the descriptive findings highlight that Generation Z consumers in Indonesia are highly engaged with AI-driven social commerce platforms, where purchasing behavior is shaped by a combination of perceived benefits and potential concerns.

Measurement Model Evaluation

Before testing the proposed hypotheses, it is necessary to ensure that all research instruments meet the criteria of validity and reliability (Hair et al., 2017). This step is essential to confirm that each indicator can accurately and consistently measure its corresponding construct. Therefore, the evaluation of the measurement model (outer model) is conducted through validity and reliability testing.

To assess whether all instruments are valid, convergent validity is evaluated using factor loadings and the Average Variance Extracted (AVE). An indicator is considered valid if it has a factor loading value greater than 0.70, although values above 0.50 are still acceptable in exploratory research (Hair et al., 2017). Table 6 shows the factor loading result.

Table 6. Factor Loading Result

Variable	Indicator	Factor Loading
AI Algorithm Personalization	X1	0.847
	X2	0.846
	X3	0.848
	X4	0.870
	X5	0.869
	X6	0.836
Perceived Value	M11	0.848
	M12	0.855
	M13	0.801
	M14	0.827
	M15	0.869
	M16	0.828
Perceived Privacy Risk	M21	0.815
	M22	0.860
	M23	0.855
	M24	0.864
	M25	0.829
	M26	0.849
Purchase Decision	Y1	0.802
	Y2	0.842
	Y3	0.806
	Y4	0.851
	Y5	0.865
	Y6	0.852

Source: Analyzed Data

The results show that all indicators have loading factor values ranging from 0.801 to 0.870, which exceed the minimum threshold of 0.70. This indicates that all measurement items are valid and capable of explaining their respective constructs. Thus, all variables in this study demonstrate strong convergent validity. Table 7 shows AVE results.

Table 7. AVE Result

Variable	AVE
AI Algorithm Personalization	0.727
Perceived Value	0.703
Perceived Privacy Risk	0.715
Purchase Decision	0.700

Source: Analyzed Data

All constructs have AVE values above 0.50, indicating that each latent variable has adequate convergent validity. Based on the results of the previous tests, all indicators have demonstrated factor loading and Average Variance Extracted (AVE) values that meet the recommended thresholds. This indicates that all measurement instruments in this study are valid in terms of convergent validity.

After establishing convergent validity, the next step in evaluating the measurement model is to assess discriminant validity. Discriminant validity ensures that each construct is empirically distinct from other constructs in the model (Hair et al., 2017). In this study, discriminant validity is evaluated using two approaches: the Fornell–Larcker criterion and the Heterotrait-Monotrait ratio (HTMT).

The Fornell–Larcker criterion states that the square root of the AVE of each construct should be greater than its correlations with other constructs. This indicates that a construct shares more variance with its indicators than with other constructs. Table 8 shows Fornell-Larcker result:

Table 8. Fornell-Larcker Criterion

Variable	AI Algorithm Personalization	Perceived Value	Perceived Privacy Risk	Purchase Decision
AI Algorithm Personalization	0.853	0.549	0.434	0.712
Perceived Value	0.549	0.839	0.264	0.640
Perceived Privacy Risk	0.434	0.264	0.846	0.546
Purchase Decision	0.712	0.640	0.546	0.837

Source: Analyzed Data

The results show that the square root of AVE for each construct (ranging from 0.837 to 0.853) is higher than its correlations with other constructs. Therefore, the Fornell–Larcker criterion is satisfied, indicating adequate discriminant validity. In addition to the Fornell–Larcker criterion, discriminant validity is also assessed using the HTMT ratio. A HTMT value below 0.90 indicates that discriminant validity has been established (Hair et al., 2017). Table 9 shows the result of HTMT value.

Table 9. HTMT Results

Construct	HTMT Value
AI Algorithm Personalization ↔ Purchase Decision	0.774
AI Algorithm Personalization ↔ Perceived Value	0.594
AI Algorithm Personalization ↔ Perceived Privacy Risk	0.467
Perceived Value ↔ Purchase Decision	0.699
Perceived Privacy Risk ↔ Purchase Decision	0.593
Perceived Privacy Risk ↔ Perceived Value	0.286

Source: Analyzed Data

All HTMT values are below the threshold of 0.90, indicating that each construct is empirically distinct from the others. This confirms that the model meets the discriminant validity requirement.

Furthermore, to ensure the internal consistency of each construct, a reliability test was conducted. Reliability in this study was assessed using Cronbach's Alpha and Composite Reliability (CR). A construct is considered reliable if it has a Cronbach's Alpha value of ≥ 0.70 and a Composite Reliability value of ≥ 0.70 (Hair et al., 2017).

Therefore, this reliability test aims to confirm that the indicators within each construct can produce consistent and stable results. The results of the reliability test are presented in Table 10.

Table 10. Reliability Test Results

Variable	Cronbach's Alpha	Composite Reliability
AI Algorithm Personalization	0.925	0.941
Perceived Value	0.915	0.934
Perceived Privacy Risk	0.920	0.938
Purchase Decision	0.914	0.933

Source: Analyzed Data

All constructs show Cronbach's Alpha and Composite Reliability values above 0.70, indicating strong internal consistency and reliability. Overall, the measurement model demonstrates excellent validity and reliability. All indicators meet the criteria for convergent and discriminant validity, and all constructs are proven to be reliable. Therefore, the measurement model is appropriate and can be used for further structural model analysis.

Structural Model Evaluation

The structural model analysis was conducted to examine the hypothesized causal relationships among AI Algorithm Personalization, Perceived Value, Perceived Privacy Risk, and Purchase Decision. This analysis aims to evaluate the strength and significance of the relationships between constructs based on the proposed research model. Figure 2 presents the structural model of this study, illustrating the relationships between exogenous and endogenous variables.

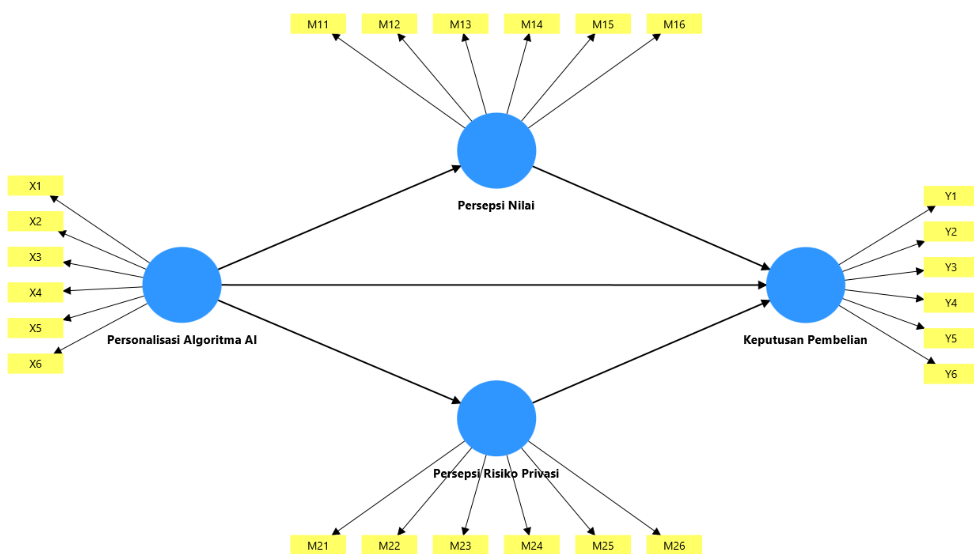

Figure 2. SEM Diagram

The coefficient of determination (R^2) measures the model's explanatory power, indicating how much variance in the endogenous constructs is explained by the exogenous variables.

Table 11. R^2 Results

Variable	R^2
Purchase Decision	0.660
Perceived Value	0.302
Perceived Privacy Risk	0.188

Source: Analyzed Data

The results show that Purchase Decision has an R^2 value of 0.660, indicating that 66.0% of its variance is explained by Perceived Value Perceived Privacy Risk, and AI Algorithm Personalization. This can be considered moderate to substantial explanatory power. Meanwhile, Perceived Value has an R^2 value of 0.302, indicating moderate explanatory power, and Perceived Privacy Risk has an R^2 value of 0.188, indicating weak to moderate explanatory power.

Next, the effect size (f^2) assesses the impact of each exogenous construct on endogenous constructs. According to Jacob Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. Table 12 shows the effect size results.

Table 12. Effect Size Results

Relationship	f^2	Effect Size
Perceived Value → Purchase Decision	0.245	Medium
Perceived Privacy Risk → Purchase Decision	0.188	Medium
AI Algorithm Personalization → Purchase Decision	0.287	Medium
AI Algorithm Personalization → Perceived Value	0.432	Large
AI Algorithm Personalization → Perceived Privacy Risk	0.232	Medium

Source: Analyzed Data

The results indicate that AI Algorithm Personalization has a strong effect on Perceived Value (f^2 = 0.432), while other relationships show moderate effect sizes. This suggests that AI personalization plays a crucial role in shaping perceived value.

The hypothesis testing was conducted to examine the proposed relationships among variables. Path coefficients were used to indicate the strength and direction of the relationships between constructs. The significance of each hypothesis was evaluated using t-statistics, where a value greater than 1.96 indicates significance at the 5% level (Hair et al., 2017). Table 13 presents the results of the direct effect hypothesis testing.

Table 13. Hypothesis Results of Direct Effect

Hypothesis	Relationship	Coefficient	t-statistics	Result
H1	AI Algorithm Personalization → Purchase Decision	0.401	8.683	Significant
H2	AI Algorithm Personalization → Perceived Value	0.549	14.203	Significant
H3	AI Algorithm Personalization → Perceived Privacy Risk	0.434	8.000	Significant
H4	Perceived Value → Purchase Decision	0.346	7.626	Significant
H5	Perceived Privacy Risk → Purchase Decision	0.281	7.431	Significant

Source: Analyzed Data

Based on the structural model results, hypothesis testing was conducted using path coefficients and t-statistics. A relationship is considered significant when the t-statistic exceeds 1.96 (Hair et al., 2017). The results of direct effect testing are summarized in Table 13.

The results indicate that AI algorithm personalization has a positive and significant effect on purchase decision (β = 0.401; t = 8.683). This suggests that higher levels of personalization provided by AI systems lead to stronger consumer purchase decisions. Therefore, H1 is supported.

AI algorithm personalization also shows a positive and significant influence on perceived value (β = 0.549; t = 14.203). This implies that personalized recommendations enhance consumers' perception of value. Thus, H2 is supported.

The findings reveal that AI algorithm personalization has a positive and significant effect on perceived privacy risk (β = 0.434; t = 8.000). This indicates that while personalization improves user experience, it simultaneously increases concerns regarding privacy. Hence, H3 is supported.

Perceived value has a positive and significant effect on purchase decision (β = 0.346; t = 7.626). This means that consumers who perceive higher value are more likely to make purchasing decisions. Therefore, H4 is supported.

Interestingly, perceived privacy risk also demonstrates a positive and significant effect on purchase decision (β = 0.281; t = 7.431). This suggests that despite privacy concerns, consumers may still proceed with purchases, possibly due to perceived benefits outweighing the risks. Thus, H5 is supported.

Furthermore, the indirect effects were examined to assess the mediating roles of perceived value and perceived privacy risk in the relationship between AI algorithm personalization and purchase decision. The results of the indirect effect analysis are presented in Table 14.

Table 14. Hypothesis Results of Indirect Effect

Relationship	Coefficient	t-statistics	Result
AI Algorithm Personalization → Perceived Value → Purchase Decision	0.190	6.822	Significant
AI Algorithm Personalization → Perceived Privacy Risk → Purchase Decision	0.122	6.058	Significant

Source: Analyzed Data

The results show that perceived value significantly mediates the relationship between AI algorithm personalization and purchase decision (β = 0.190; t = 6.822). This indicates that AI-driven personalization enhances consumers' perceived value, which subsequently leads to stronger purchase decisions. Therefore, perceived value acts as an important mediating mechanism in this relationship.

The findings also reveal that perceived privacy risk significantly mediates the relationship between AI algorithm personalization and purchase decision (β = 0.122; t = 6.058). This suggests that AI personalization increases consumers' awareness of privacy risks, which in turn influences their purchasing decisions. Thus, perceived privacy risk also serves as a significant mediator.

Discussion

This study aims to analyze the influence of AI algorithm personalization on purchase decisions, both directly and indirectly through perceived value and perceived privacy risk. Overall, the findings provide strong empirical support for the proposed model, as all hypothesized relationships are statistically significant.

From a theoretical perspective, the results are consistent with the Stimulus-Organism-Response (S-O-R) framework by Mehrabian & Russell (1974) in (Khanh et al., 2025). In this study, AI algorithm personalization functions as a *stimulus* that shapes internal cognitive evaluations (*organism*), namely perceived value and perceived privacy risk, which subsequently influence consumer behavioral responses (*response*) in the form of purchase decisions.

First, the findings reveal that AI algorithm personalization has a positive and significant effect on purchase decisions. This suggests that personalized recommendations generated by AI systems are effective in enhancing consumers' decision-making processes. This result is in line with previous (ANMAÇ, 2023; Hussain, 2025), which found that personalization improves user experience and increases the likelihood of purchase by delivering more relevant and tailored information.

Second, AI algorithm personalization significantly influences perceived value. This finding indicates that when consumers receive personalized content, they perceive higher functional and emotional benefits. This result supports the theory of perceived value, which states that consumers evaluate products or services based on the trade-off between benefits and costs. Prior studies (Syamsuar & Witarsyah, 2025) also confirm that personalization enhances perceived value by increasing relevance, convenience, and satisfaction.

Third, the results show that AI algorithm personalization has a positive and significant effect on perceived privacy risk. This implies that while personalization offers benefits, it simultaneously raises concerns about data collection and privacy. This finding is consistent with earlier research (Mutambik et al., 2023; Xiao et al., 2020), which suggests that personalized services often trigger privacy concerns due to the use of personal data.

Interestingly, perceived privacy risk is found to have a positive and significant effect on purchase decisions. This result may appear counterintuitive, as risk is generally expected to reduce purchase intention. However, this finding can be explained by the privacy paradox phenomenon, where consumers continue to engage in transactions despite being aware of privacy risks. In this context, consumers may perceive that the benefits of personalization outweigh the potential risks, leading them to proceed with their purchase decisions.

Furthermore, perceived value has a positive and significant effect on purchase decisions, confirming its role as a key determinant of consumer behavior. This finding aligns with previous studies (Deng et al., 2024; Madhuri et al., 2024), which highlight that higher perceived value leads to stronger purchase intentions and actual buying behavior.

The mediation analysis provides additional insights into the underlying mechanisms. Both perceived value and perceived privacy risk significantly mediate the relationship between AI algorithm personalization and purchase decisions. However, the indirect effect through perceived value is stronger than through perceived privacy risk. This suggests that while privacy concerns exist, the positive evaluation of value plays a more dominant role in shaping consumer decisions. This finding reinforces prior research (Handoko & Rahayu, 2026), which emphasizes that perceived value often outweighs perceived risk in digital consumption contexts.

Overall, this study contributes to the literature by integrating AI personalization, perceived value, and privacy risk within a single framework. The findings highlight that consumer decision-making in AI-driven environments is shaped by a dual mechanism: benefit maximization (perceived value) and risk evaluation (perceived privacy risk). Nevertheless, the dominance of perceived value suggests that consumers tend to adopt a rational-benefit approach when interacting with personalized systems.

CONCLUSION

This study aims to examine the effect of AI algorithm personalization on purchase decisions, both directly and indirectly through perceived value and perceived privacy risk. Based on the empirical findings, it can be concluded that the research objectives have been successfully achieved.

The results demonstrate that AI algorithm personalization has a significant positive influence on purchase decisions, indicating its important role in shaping consumer behavior in digital environments. In addition, AI personalization significantly affects both perceived value and perceived privacy risk, confirming that personalized systems simultaneously generate benefits and concerns for consumers.

Furthermore, perceived value and perceived privacy risk are found to significantly influence purchase decisions. While perceived value enhances consumers’ willingness to purchase, perceived privacy risk interestingly also shows a positive effect, suggesting that consumers tend to tolerate privacy concerns when the perceived benefits are substantial.

The mediation analysis reveals that both perceived value and perceived privacy risk act as significant mediators in the relationship between AI algorithm personalization and purchase decisions. However, perceived value plays a more dominant role, indicating that benefit-driven evaluations are more influential than risk considerations in the decision-making process.

Overall, this study confirms that AI algorithm personalization is a key driver of purchase decisions, operating through both direct and indirect pathways. These findings highlight the importance for businesses to optimize personalization strategies while maintaining transparency and managing consumer privacy concerns to enhance trust and maximize perceived value.

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