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How AI-Enabled Interactions Shape Sustainable Purchase Intention: A Dual-Pathway Model of Trust and Message Relevance

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ABSTRACT

Purpose – This study examines how human–AI collaborative, AI interaction transparency, and perceived personalization influence sustainable purchase intention through customer trust and perceived message relevance in AI-enabled e-commerce.
Design/methodology/approach – This study employs a quantitative explanatory approach using Partial Least Squares Structural Equation Modeling (PLS-SEM). Data were collected from 180 e-commerce consumers in Bali, Indonesia, using purposive sampling. A structured questionnaire was administered, and the data were analyzed using SmartPLS.
Finding/Results – The findings reveal that human–AI collaborative and AI interaction transparency enhance customer trust, whereas perceived personalization does not. Perceived personalization significantly improves perceived message relevance, which, together with customer trust, strengthens sustainable purchase intention. Further analysis shows that AI interaction transparency also has a direct effect on sustainable purchase intention, while human–AI collaborative and perceived personalization do not. The mediation results identify two mechanisms: a trust pathway involving human–AI collaborative and AI interaction transparency, and a relevance pathway involving perceived personalization.
Originality/Value – This study refines the application of the Stimulus–Organism–Response (S–O–R) framework by identifying two psychological pathways underlying sustainable purchase intention in AI-enabled e-commerce: a trust pathway driven by human–AI collaborative and AI interaction transparency, and a relevance pathway driven by perceived personalization. The findings highlight the importance of trustworthy interactions and personally relevant information in AI-enabled sustainable marketing.

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1. Introduction

Artificial intelligence (AI) has reshaped e-commerce by enabling platforms to generate personalized recommendations, advertisements, product rankings, and shopping interfaces based on consumer preferences and behavioral data. Through real-time personalization and recommender systems, digital platforms can continuously adjust the information presented to users, making AI increasingly influential in consumer evaluation and purchasing decisions rather than merely serving as a tool for technological efficiency (Abdullah et al., 2026; Ingriana & Rolando, 2025; Cheruku, 2025; Li & Yang, 2024).

This development has made personalization one of the defining characteristics of contemporary digital commerce. However, the growing use of AI also creates uncertainty. Consumers often have limited understanding of how algorithms process their data, prioritize information, or determine specific recommendations. Consequently, personalization can simultaneously offer convenience and raise concerns regarding transparency, fairness, privacy, and commercial motives. Research on trustworthy AI therefore emphasizes transparency and ethical governance as important foundations of consumer confidence (Kattnig et al., 2024; de Lucas López et al., 2026; Zhang et al., 2026).

Recommendation systems that appear overly driven by commercial objectives may also reduce perceived value and trust (Ghanem et al., 2022). Thus, greater sophistication in AI does not necessarily lead to stronger consumer acceptance. This issue becomes increasingly important when AI-enabled marketing is expected to support sustainable consumption. AI can support sustainable marketing by identifying consumer preferences, matching environmentally responsible products with relevant audiences, and communicating sustainability information more efficiently (Vijayakumar et al., 2025; Garg et al., 2025; Mei et al., 2025).

Research on green algorithms and low-carbon recommendation systems similarly indicates that AI can support sustainability-oriented information delivery and consumer evaluation processes. (Bolón-Canedo et al., 2024; Li & Yang, 2024; Zaman et al., 2024). Nevertheless, sustainable purchase intention cannot be explained solely by algorithmic capability. Consumers must first interpret and evaluate AI-generated information before it can influence their willingness to choose sustainable products. Empirical evidence regarding this process remains mixed. In Indonesia, Surbakti et al. (2025) report that perceived AI-driven personalization positively influences green purchase intention. In contrast, Qadri et al. (2026) show that AI personalization does not necessarily translate directly into sustainable purchase intention; instead, its influence depends substantially on whether consumers perceive the personalized message as relevant. This distinction suggests that personalization alone may be insufficient. Its behavioral value may lie in whether tailored information is perceived as meaningful and applicable to consumers' actual purchasing situations.

Perceived message relevance therefore represents an important informational mechanism. It reflects the extent to which consumers perceive AI-delivered information as personally meaningful, useful, and relevant to their needs. Qadri et al. (2026) identify perceived message relevance as a key mediator between AI personalization and sustainable purchase intention. This mechanism is particularly important for sustainable products because environmental benefits may not always be immediately observable or become the primary criteria in purchase decisions. Personalized sustainability messages may therefore influence intention more effectively when they connect environmental attributes with consumers' existing preferences and decision contexts. Customer trust represents a different psychological mechanism. AI-

supported purchasing involves information asymmetry because consumers cannot fully observe how recommendation systems process personal data or generate product suggestions. Trust helps consumers manage this uncertainty. Li et al. (2024) show that recommendation-system transparency can increase consumer trust, while Deng et al. (2026) demonstrate that AI interaction transparency and human–AI collaborative recommendation perception can shape platform trust in e-commerce. Human–AI collaborative recommendation perception is particularly relevant because consumers increasingly interact with AI as part of the decision-making process. AI-assisted recommendations function as decision-support mechanisms by improving information processing efficiency and reducing decision complexity, the interaction may preserve consumer agency and strengthen confidence in the system. Personalization, however, does not necessarily operate through the same psychological route. Although tailored recommendations may improve usefulness, highly specific personalization can also create privacy and control concerns (Alimamy & Gnoth, 2022; Aydin, 2026). This implies that personalization should not automatically be interpreted as a trust-building mechanism. Consumers may perceive personalized information as useful and relevant without necessarily considering the platform more trustworthy.

Customer trust and perceived message relevance therefore represent two conceptually distinct but complementary evaluations: trust concerns confidence in the reliability of the AI-enabled platform, whereas message relevance concerns the personal significance of the information delivered. Despite growing research on AI-driven e-commerce and sustainable consumption, several gaps remain. First, previous studies generally examine human–AI collaborative recommendation perception, AI interaction transparency, and perceived personalization separately, leaving limited evidence on how these technological characteristics operate together in shaping sustainable purchase intention. Second, empirical findings concerning personalization remain inconsistent, particularly regarding whether personalization directly generates sustainable intention or operates through psychological mechanisms. Third, although trust is widely examined in digital commerce, evidence linking AI-generated trust specifically to sustainable purchase intention remains relatively limited. Finally, the integration of these relationships within the Indonesian e-commerce context remains scarce, particularly in Bali. These gaps indicate that a more precise explanation is needed regarding how different AI characteristics shape sustainable consumer responses through different internal mechanisms.

Drawing on the Stimulus-Organism-Response (S-O-R) framework, this study conceptualizes human–AI collaborative recommendation perception, AI interaction transparency, and perceived personalization as technological stimuli; customer trust and perceived message relevance as organism states; and sustainable purchase intention as the behavioral response. Accordingly, this study examines the effects of human–AI collaborative recommendation perception, AI interaction transparency, and perceived personalization on customer trust, assesses the effect of perceived personalization on perceived message relevance, and evaluates how customer trust and perceived message relevance subsequently shape sustainable purchase intention.

The study offers three contributions. First, it integrates three characteristics of AI-mediated interaction within a single sustainable consumer-behavior framework rather than examining them independently. Second, it distinguishes between two psychological pathways: a trust pathway, through which consumers evaluate the reliability of AI-mediated interactions, and

a relevance pathway, through which consumers evaluate the personal significance of algorithmically tailored information. Third, it extends the application of the S-O-R framework to sustainable consumption in the Indonesian e-commerce context. The study therefore moves beyond the question of whether AI influences sustainable purchase intention and focuses instead on why different forms of AI interaction shape sustainable purchase intention through different psychological mechanisms. Although previous studies have examined AI-related characteristics and their relationships with consumer trust, message relevance, and sustainable purchase intention, the theoretical explanation of how different AI interaction characteristics operate through distinct psychological mechanisms remains insufficiently developed. Rather than treating Human–AI collaborative recommendation perception, AI interaction transparency, and perceived personalization as interchangeable technological predictors, this study distinguishes their potentially different psychological pathways. Specifically, it examines trust as a relational and uncertainty-related mechanism linking Human–AI collaborative recommendation perception and AI interaction transparency to sustainable purchase intention, while perceived message relevance represents an informational mechanism through which perceived personalization may influence sustainable purchase intention. By integrating these pathways within the Stimulus–Organism–Response framework, this study seeks to provide a more differentiated explanation of how AI-enabled interactions shape consumers' sustainable purchase intentions

2. Literature Review & Hypothesis Development

2.1 Stimulus Organism Response Framework in AI-Driven E-Commerce

The Stimulus Organism Response (SOR) framework explains how environmental stimuli influence behavioral responses through individuals' internal psychological states. In digital commerce, technological characteristics function as stimuli, consumers' cognitive and affective evaluations represent organism states, and subsequent behavioral intentions constitute responses. This framework is particularly relevant to AI-enabled e-commerce because consumers may evaluate how AI interacts with them, how transparent its processes appear, and how appropriately information is personalized before forming behavioral intentions. Recent research supports the application of S–O–R to AI-mediated consumer behavior. Deng et al. (2026) show that human–AI collaborative recommendation perception, AI interaction transparency, and perceived personalization can operate as technological stimuli that shape internal consumer evaluations, including trust. However, explaining sustainable purchase intention requires further consideration of the distinct psychological mechanisms through which these stimuli may influence consumer responses.

Accordingly, this study conceptualizes customer trust and perceived message relevance as two complementary organism states. Customer trust captures consumers' relational evaluation of whether an AI-enabled platform is reliable and dependable, whereas perceived message relevance reflects their informational evaluation of whether AI-generated content is meaningful and applicable to their needs. These mechanisms provide a basis for distinguishing the roles of the three technological stimuli. Human–AI collaborative recommendation perception represents a relational stimulus because it concerns how AI supports consumers during decision-making, while AI interaction transparency may reduce uncertainty by helping consumers understand AI-enabled recommendations and evaluate

their reliability. Both characteristics may therefore be associated with customer trust. In contrast, perceived personalization primarily concerns the fit between AI-generated messages and consumers' individual needs and decision contexts; its influence may consequently operate through perceived message relevance rather than necessarily strengthening trust. Thus, human–AI collaborative recommendation perception, AI interaction transparency, and perceived personalization are conceptualized as stimuli (S); customer trust and perceived message relevance as organism states (O); and sustainable purchase intention as the response (R)

2.2 Human–AI collaborative recommendation perception and Customer Trust

Human–AI Collaborative Recommendation Perception refers to consumers' evaluation of the extent to which AI-supported recommendations improve search efficiency, adapt to individual preferences, and facilitate decision-making during the shopping process. In e-commerce environments, AI recommendation systems have evolved beyond simple product suggestions by assisting consumers in processing large amounts of information, identifying relevant alternatives, and reducing decision complexity. However, the effectiveness of AI recommendations depends not only on technological capability but also on how consumers perceive the quality, usefulness, and collaborative nature of the recommendation process. Following Deng et al. (2026), Human–AI Collaborative Recommendation Perception reflects users' perceptions of the supportive and adaptive role of AI-generated recommendations within a human–AI collaborative service environment. When consumers perceive AI recommendations as relevant, personalized, and aligned with their needs, AI is viewed as a decision-support mechanism rather than an autonomous system that replaces human judgment. This perception may reduce uncertainty during purchase decisions and enhance consumers' confidence in the platform's ability to provide reliable assistance. Furthermore, positive perceptions of Human–AI collaborative recommendation perception can contribute to the development of customer trust. Deng et al. (2026) demonstrate that effective positively influences platform trust by improving users' evaluation of AI-supported services. In e-commerce contexts, where consumers rely on platforms to provide accurate and meaningful recommendations, perceptions of AI responsiveness and decision facilitation may strengthen beliefs regarding platform reliability and competence. Therefore, Human–AI Collaborative Recommendation Perception is expected to play an important role in shaping customer trust by enhancing consumers' confidence in AI-enabled recommendation services.

H1: Human–AI collaborative recommendation perception has a positive effect on customer trust.

2.3 AI Interaction Transparency and Customer Trust

AI interaction transparency refers to the extent to which consumers perceive that an AI-enabled system provides understandable information about its recommendations, processes, or reasons for presenting particular content. Transparency is especially important in algorithmic environments because consumers generally cannot directly observe how their data are processed or how recommendation outcomes are generated. Li et al. (2024) demonstrate that greater transparency in e-commerce recommendation systems increases consumer trust by improving perceived system effectiveness and reducing discomfort. Deng et al. (2026) similarly find a positive relationship between AI interaction transparency and platform trust. These findings suggest that transparency functions as an uncertainty-reduction mechanism by providing consumers with sufficient cues to understand why particular recommendations appear. Research on trustworthy AI further identifies transparency and

fairness as important foundations of consumer confidence (Kattnig et al., 2024; de Lucas López et al., 2026). Consumers are therefore more likely to trust an AI-enabled platform when algorithmic interactions are understandable rather than opaque.

H2: AI interaction transparency has a positive effect on customer trust.

2.4 Perceived Personalization and Customer Trust

Perceived personalization refers to consumers' perception that recommendations, messages, or other digital content have been tailored to their individual preferences, interests, or previous behavior. When personalization corresponds closely to consumer needs, it can signal that the platform understands users and is capable of providing useful assistance.

Deng et al. (2026) find that perceived personalization positively influences platform trust, while Alimamy and Gnoth (2022) show that personalization can shape trust-related evaluations in digital shopping environments. Hassan et al. (2025) further highlight the importance of trust in personalized AI-enabled e-commerce relationships. Nevertheless, personalization may also create privacy and control concerns, particularly when recommendations appear excessively specific (Aydin, 2026). This suggests that personalization is not inherently trust-enhancing; its effect depends on how consumers interpret the personalized experience. When personalization is perceived as helpful, appropriate, and responsive to individual needs, however, it may signal competence and strengthen confidence in the platform.

H3: Perceived personalization has a positive effect on customer trust.

2.5 Perceived Personalization and Perceived Message Relevance

Personalization changes not only how consumers evaluate a platform but also how they evaluate the information it delivers. The central purpose of algorithmic personalization is to present content that better corresponds to individual preferences and decision contexts. Its effectiveness therefore depends on whether consumers actually perceive the resulting information as relevant. Qadri et al. (2026) demonstrate that AI personalization increases perceived message relevance and that this relevance is central to explaining subsequent sustainable purchase intention. This distinction is important: personalization represents what the system does, whereas perceived message relevance represents how consumers interpret the resulting content.

Aydin (2026) similarly identifies relevance as an important benefit of AI-driven personalization. In sustainable consumption, this mechanism is particularly important because environmental attributes may not automatically correspond to consumers' immediate priorities. Personalized communication can make sustainability information more salient by connecting it with individual needs and preferences.

H4: Perceived personalization has a positive effect on perceived message relevance.

2.6 Customer Trust and Sustainable Purchase Intention

Sustainable purchase intention refers to consumers' willingness to choose products with environmentally responsible or sustainable characteristics. In this study, sustainable purchase intention reflects consumers' general intention to choose sustainable products and does not represent AI-induced sustainable behavior. Instead, AI-enabled interactions are examined as factors that may shape this intention through psychological mechanisms. Such decisions often involve uncertainty because consumers may depend on information provided by digital platforms to evaluate environmental claims that cannot be directly verified. Customer trust can reduce this uncertainty. When consumers perceive an AI-enabled platform as reliable and dependable, they are more willing to rely on its recommendations and incorporate

sustainability-related information into purchasing decisions. Alzaidi and Agag (2022) show that trust positively influences purchase intention in digital retailing, while Popa and Chenic (2025) connect consumer trust with pro-environmental responses in AI-related contexts. Evidence from Indonesia also indicates that AI-enabled marketing may contribute to environmentally conscious purchase intentions (Sandira, 2025; Surbakti et al., 2025). However, research directly linking trust in AI-enabled recommendations with sustainable purchase intention remains limited.

H5: Customer trust has a positive effect on sustainable purchase intention.

2.7 Perceived Message Relevance and Sustainable Purchase Intention

Perceived message relevance reflects the extent to which consumers regard marketing or recommendation information as personally meaningful and applicable to their current needs. Relevant information is more likely to attract attention and be incorporated into decision-making than generic or unrelated information. Qadri et al. (2026) provide direct evidence that perceived message relevance positively influences sustainable purchase intention. Their findings suggest that the effectiveness of AI personalization depends less on personalization itself than on whether the resulting message is perceived as relevant. Aydin (2026) similarly identifies perceived relevance as an important positive evaluation of AI-driven personalization. This mechanism is particularly important for sustainable products because environmental attributes may not always be consumers' primary purchase criteria. When sustainability information is linked to consumers' existing preferences and needs, it becomes more salient and more likely to influence purchase intention.

H6: Perceived message relevance has a positive effect on sustainable purchase intention.

2.8 The Mediating Role of Customer Trust

Within the S–O–R framework, technological stimuli influence behavioral responses through internal psychological evaluations. Customer trust therefore provides a plausible mechanism through which characteristics of AI-mediated interaction may translate into sustainable purchase intention. Human–AI collaborative recommendation perception can strengthen trust by making AI appear supportive rather than controlling. Deng et al. (2026) establish a positive relationship between collaborative AI interaction and platform trust, while previous research connects trust with purchase-related and pro-environmental outcomes (Alzaidi & Agag, 2022; Popa & Chenic, 2025). Integrating these relationships suggests that collaborative AI may foster sustainable purchase intention by first strengthening confidence in the platform.

H7: Customer trust mediates the positive relationship between human–AI collaborative recommendation perception and sustainable purchase intention**.**

Transparency provides a similar trust-based mechanism. Recommendation transparency reduces algorithmic uncertainty and strengthens consumer trust (Li et al., 2024; Deng et al., 2026). When consumers better understand why recommendations are presented, they may be more willing to rely on sustainability-related information generated by the platform.

H8: Customer trust mediates the positive relationship between AI interaction transparency and sustainable purchase intention**.**

Perceived personalization may also operate through trust. Personalized recommendations can signal platform competence and responsiveness, thereby strengthening confidence in the AI-enabled service (Alimamy & Gnoth, 2022; Deng et al., 2026; Hassan et al., 2025). If consumers interpret personalization as evidence that the platform understands and appropriately supports their needs, greater trust may subsequently encourage sustainable purchase intention.

H9: Customer trust mediates the positive relationship between perceived personalization and sustainable purchase intention**.**

2.9 The Mediating Role of Perceived Message Relevance

Perceived message relevance represents a different mediating mechanism because it concerns the informational value of personalization rather than confidence in the platform. Consumers may recognize that a recommendation has been personalized without necessarily considering it useful. Behavioral influence should emerge when personalized information is perceived as meaningful to their actual decision.

Qadri et al. (2026) demonstrate that AI personalization increases perceived message relevance, which subsequently strengthens sustainable purchase intention. Importantly, their evidence indicates that message relevance can explain the influence of personalization even when a direct personalization–intention relationship is weak or insignificant. Surbakti et al. (2025) similarly show that AI-driven personalization is associated with green purchase intention in Indonesia, while Aydin (2026) emphasizes perceived relevance as an important benefit of AI personalization.

These findings suggest that personalization contributes to sustainable purchasing primarily when it converts general sustainability information into content consumers regard as personally meaningful. Therefore:

H10: Perceived message relevance mediates the positive relationship between perceived personalization and sustainable purchase intention

3. Methodology

This study employs a quantitative explanatory approach to examine how Human–AI collaborative recommendation perception (HAC), AI Interaction Transparency (AIT), and Perceived Personalization (PP) influence Sustainable Purchase Intention (SPI) through Customer Trust (CT) and Perceived Message Relevance (PMR) in AI-enabled e-commerce. The study is grounded in the Stimulus–Organism–Response (S–O–R) framework, in which HAC, AIT, and PP represent technological stimuli, CT and PMR represent consumers' internal psychological evaluations, and SPI represents the behavioral response. The study was conducted among e-commerce consumers residing in Bali, Indonesia. A total of 180 usable responses were included in the final analysis. A statistical power analysis was conducted to assess sample size adequacy. Considering the maximum number of predictors in the structural model (five predictors explaining Sustainable Purchase Intention), an alpha level of 0.05, and a desired statistical power of 0.80, a sample size of 180 observations provides sufficient power to detect small-to-medium effect sizes ($f^2 \approx 0.06$). Therefore, the sample size used in this study is considered adequate for estimating the proposed PLS-SEM model. Respondents were selected using purposive sampling because participation required specific experience with AI-enabled e-commerce features and sustainable products. To be included in the study, respondents were required to: (1) be at least 18 years old; (2) reside in Bali; (3) have completed an e-commerce transaction within the previous six months; (4) have encountered algorithmically personalized features, such as personalized product recommendations or advertisements; and (5) have previously seen, searched for, or expressed interest in environmentally friendly or sustainable products on an e-commerce platform. These eligibility criteria were established to ensure that respondents had sufficient familiarity with AI-enabled

e-commerce features and sustainable products to meaningfully evaluate the constructs under investigation. In particular, the sustainable-product exposure or interest criterion was intended to establish contextual relevance rather than to select respondents based on their level of sustainable purchase intention. Accordingly, the study focuses on AI-experienced e-commerce consumers in Bali who meet these predefined eligibility criteria. Primary data were collected using a structured questionnaire. Screening questions were included to ensure that respondents met the predefined eligibility criteria before completing the main survey. All construct items were measured using a five-point Likert scale, ranging from 1 = strongly disagree to 5 = strongly agree. The measurement items were adapted from previously validated studies and contextualized for AI-enabled e-commerce and sustainable consumption without altering their underlying conceptual meanings. Because this study uses a cross-sectional survey design, the estimated structural relationships are interpreted as theoretically specified associations rather than definitive causal effects. Although the S–O–R framework provides the theoretical direction of the proposed relationships, the research design observes respondents' perceptions at a single point in time and therefore does not establish temporal causality. Human–AI Collaborative Recommendation Perception (HAC) represents consumers' evaluations of the extent to which AI-supported recommendations improve search efficiency, adapt to individual preferences, and facilitate decision-making during the shopping process. The measurement of HAC was adapted from Deng et al. (2026), where the construct was developed to capture consumers' evaluations of recommendation outcomes within a human–AI collaborative service environment. The present study retained the substantive meaning of the original indicators while contextualizing their wording for general AI-enabled e-commerce settings. Accordingly, HAC in this study is interpreted as consumers' perceptions of the efficiency, adaptability, and responsiveness of AI-supported recommendations rather than as a broad evaluation of human–AI interaction. AI Interaction Transparency (AIT) captures the extent to which consumers perceive AI-generated recommendations and their underlying logic as understandable, explainable, and transparent. Perceived Personalization (PP) refers to consumers' perception that recommendation content is specifically tailored to their interests, preferences, previous digital behavior, or individual shopping needs. Although HAC and perceived personalization both involve adaptive recommendation features, they represent distinct consumer evaluations. HAC focuses on the extent to which AI-supported recommendations effectively assist the overall shopping and decision-making process through efficiency, adaptability, and responsiveness. In contrast, perceived personalization reflects the degree to which consumers perceive the recommendation content itself as individually customized. This distinction is important because an AI recommendation can be perceived as highly supportive and decision-facilitating without necessarily being interpreted as highly personalized. Customer Trust (CT) reflects consumers' confidence in the reliability, competence, and dependability of AI-generated recommendations and AI-enabled e-commerce platforms. Perceived Message Relevance (PMR) represents the extent to which AI-generated messages or recommendations are perceived as meaningful, appropriate, and relevant to consumers' specific needs, interests, and situational contexts. Sustainable Purchase Intention (SPI) captures consumers' willingness and

intention to select environmentally responsible or sustainable products based on their evaluation of AI-supported information and recommendations. Respondents reported using different e-commerce platforms, including Shopee, Tokopedia, Lazada, and others. Accordingly, the study captures consumers' perceptions of AI-enabled recommendation experiences across multiple platforms rather than evaluations of a single standardized recommendation system. Differences in platform interfaces, recommendation features, and shopping contexts may have influenced respondents' evaluations of AI Interaction Transparency (AIT), Perceived Personalization (PP), Customer Trust (CT), and Perceived Message Relevance (PMR). Therefore, the estimated structural relationships should be interpreted as associations among consumers' perceptions within a multi-platform e-commerce context rather than as platform-specific findings.

Table 1 summarizes the operationalization of the constructs and their measurement indicators.

Table 1. Measurement of Variables

Construct (Symbol)	Indicator	Measurement Item	Source
Human–AI collaborative recommendation perception (HAC)	HAC.1	AI helps me find the products I am looking for more efficiently and accurately.	Deng et al. (2026)
	HAC.2	AI recommendations continuously adapt to my interests and preferences.	Deng et al. (2026)
	HAC.3	The AI recommendation system recognizes my needs and capabilities and adjusts its recommendations accordingly.	Deng et al. (2026)
AI Interaction Transparency (AIT)	AIT.1	I clearly understand how the AI system generates recommendations for me.	Deng et al. (2026); Li et al. (2024)
	AIT.2	The AI system provides explanations for the reasons or logic behind its recommendations.	Deng et al. (2026)
	AIT.3	The AI recommendation process is transparent and easy to understand.	Deng et al. (2026); Li et al. (2024)
Perceived Personalization (PP)	PP.1	I feel that the recommendations provided are specifically tailored to me.	Deng et al. (2026)
	PP.2	The system provides recommendations based on my previous search, browsing, or purchase history.	Deng et al. (2026)
	PP.3	I perceive a clear degree of personalization in the product recommendations provided to me.	Deng et al. (2026)
Customer Trust (CT)	CT.1	I trust the product recommendations provided by the AI system on this platform.	Deng et al. (2026); Li et al. (2024)
	CT.2	I am willing to rely on AI recommendations when making purchasing decisions.	Deng et al. (2026); Li et al. (2024)
	CT.3	I feel safe and confident when using recommendations provided by the AI system.	Deng et al. (2026)

Construct (Symbol)	Indicator	Measurement Item	Source
Perceived Message Relevance (PMR)	PMR.1	AI-generated messages or recommendations are relevant to my needs.	Qadri et al. (2026); Aydin (2026)
	PMR.2	AI-generated messages or recommendations match my interests.	Qadri et al. (2026); Aydin (2026)
	PMR.3	AI-generated messages or recommendations correspond to my personal preferences.	Qadri et al. (2026); Aydin (2026)
Sustainable Purchase Intention (SPI)	SPI.1	I intend to purchase environmentally friendly or sustainable products.	Qadri et al. (2026); Surbakti et al. (2025)
	SPI.2	I plan to choose more environmentally friendly products in my future purchases.	Surbakti et al. (2025)
	SPI.3	When alternatives are available, I tend to choose more sustainable products over conventional products.	Surbakti et al. (2025)

Note: All items were measured using a five-point Likert scale (1 = strongly disagree; 5 = strongly agree)

The structural model contains two distinct psychological mechanisms. The first is the trust pathway, in which HAC, AIT, and PP are specified as antecedents of CT, while CT subsequently predicts SPI. The second is the relevance pathway, in which PP predicts PMR, which subsequently predicts SPI. This specification allows the study to distinguish between consumers' relational evaluation of the AI-enabled system and their informational evaluation of personalized messages.

The structural relationships can be expressed as follows:

$$CT = \beta_1 HAC + \beta_2 AIT + \beta_3 PP + \varepsilon_1$$
$$PMR = \beta_4 PP + \varepsilon_2$$
$$SPI = \beta_5 CT + \beta_6 PMR + \varepsilon_3$$

where:

HAC = Human–AI collaborative recommendation perception

AIT = AI Interaction Transparency

PP = Perceived Personalization

CT = Customer Trust

PMR = Perceived Message Relevance

SPI = Sustainable Purchase Intention

β = path coefficient

ε = residual term

In addition to the direct relationships, four specific indirect effects were examined: HAC → CT → SPI, AIT → CT → SPI, PP → CT → SPI, and PP → PMR → SPI. These indirect

relationships were used to determine whether CT and PMR transmit the effects of AI-related technological stimuli to sustainable purchase intention. The empirical analysis was conducted using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS. The analysis proceeded in several stages. First, descriptive statistics were used to summarize the characteristics of the respondents. Second, the measurement model was evaluated to establish the reliability and validity of the constructs. Indicator reliability was assessed using outer loadings, while internal consistency reliability was evaluated using Cronbach's alpha, rho_A, and composite reliability. Convergent validity was assessed through Average Variance Extracted (AVE), whereas discriminant validity was examined using the Heterotrait–Monotrait ratio (HTMT). Third, collinearity among the predictor constructs was examined using the Variance Inflation Factor (VIF). The structural model was then evaluated using the coefficient of determination (R^2), predictive relevance (Q^2), effect size (f^2), and the estimated path coefficients. The explanatory power of CT, PMR, and SPI was assessed based on their respective R^2 values, while Q^2 was used to determine the predictive relevance of the endogenous constructs. Finally, the hypotheses were tested using a bootstrapping procedure in SmartPLS. Statistical significance was determined using the estimated path coefficients, t-statistics, and probability values, with $p < 0.05$ used as the significance criterion. Specific indirect effects were subsequently examined to evaluate the mediating roles of CT and PMR. A mediation hypothesis was considered supported when the corresponding indirect effect was statistically significant.

4. Result and Discussion

4.1 Result

Table 2 presents the characteristics of the respondents involved in this study. The respondent characteristics provide an overview of the demographic profile and digital platform usage patterns of the participants. These characteristics include gender, age, and the primary e-commerce platform used by respondents. The complete distribution of respondents based on each category, frequency, and percentage is presented in Table 2.

Table 2. Characteristics of Respondents

Characteristics	Category	Frequency (n=180)	Percentage
Gender	Male	77	42.8%
	Female	103	57.2%
	18–24 years	69	38.3%
Age	25–34 years	61	33.9%
	35–44 years	32	17.8%
	≥45 years	18	10.0%
Primary platform	Shopee	86	47.8%
	Tokopedia	42	23.3%
	Lazada	30	16.7%
	Others	22	12.2%
Total		**180**	**100.0%**

The demographic distribution shows that female respondents dominated the sample, accounting for 103 participants (57.2%), while male respondents represented 77 participants (42.8%). Regarding age distribution, most respondents were between 18 and 24 years old

(38.3%), followed by those aged 25–34 years (33.9%). Respondents aged 35–44 years and ≥45 years represented 17.8% and 10.0% of the total sample, respectively. This indicates that the study primarily involved younger digital consumers who are generally more familiar with online purchasing activities.

Regarding the primary e-commerce platform, Shopee was the most frequently used platform, selected by 86 respondents (47.8%). Tokopedia followed with 42 respondents (23.3%), while Lazada and other platforms accounted for 30 respondents (16.7%) and 22 respondents (12.2%), respectively. These findings indicate that Shopee had the highest level of usage preference among respondents compared with other platforms. Overall, the respondent profile reflects a sample dominated by female participants, younger age groups, and users of major e-commerce platforms, providing an appropriate foundation for further analysis of online consumer behavior.

Following the analysis of respondents' characteristics, the next stage involved assessing the measurement model to evaluate the reliability and validity of the constructs used in this study. The measurement model assessment was conducted using the Partial Least Squares Structural Equation Modeling (PLS-SEM) approach by examining indicator reliability, internal consistency reliability, and convergent validity.

Indicator reliability was evaluated based on the outer loading values of each measurement item. Meanwhile, internal consistency reliability was assessed using Cronbach's Alpha, rho_A, and Composite Reliability (CR). Convergent validity was evaluated based on the Average Variance Extracted (AVE) values. These assessments were conducted to ensure that each indicator appropriately represented its corresponding construct and that the measurement model satisfied the required statistical criteria before proceeding to the structural model analysis. The complete results of the measurement model assessment, including outer loading values, Cronbach's Alpha, rho_A, Composite Reliability (CR), and Average Variance Extracted (AVE) values for each construct, are presented in Table 3.

Table 3. Measurement Model Assessment

Construct	Indicator	Outer Loading	Cronbach's Alpha	rho_A	Composite Reliability	AVE
HAC	HAC.1	0.842				
	HAC.2	0.881	0.802	0.815	0.884	0.717
	HAC.3	0.816				
AIT	AIT.1	0.793				
	AIT.2	0.854	0.766	0.788	0.865	0.681
	AIT.3	0.828				
PP	PP.1	0.872				
	PP.2	0.846	0.796	0.802	0.880	0.710
	PP.3	0.809				
CT	CT.1	0.836				
	CT.2	0.889	0.807	0.812	0.886	0.721
	CT.3	0.821				
PMR	PMR.1	0.858				
	PMR.2	0.831	0.817	0.824	0.891	0.732
	PMR.3	0.877				
SPI	SPI.1	0.845				
	SPI.2	0.892	0.814	0.819	0.890	0.730

SPI.3	0.824

Table 4. Discriminant Validity Assessment (HTMT)

Construct	HAC	AIT	PP	CT	PMR	SPI
HAC						
AIT	0.641					
PP	0.578	0.604				
CT	0.721	0.748	0.632			
PMR	0.544	0.526	0.716	0.612		
SPI	0.581	0.563	0.684	0.697	0.781	

Table 4 presents the results of discriminant validity testing using the Heterotrait-Monotrait Ratio (HTMT) approach. This assessment was conducted to verify whether each construct in the research model has sufficient empirical distinction from other constructs. In accordance with the recommended criteria for PLS-SEM analysis, discriminant validity is considered acceptable when the HTMT value is below the threshold of 0.85.

The results presented in Table 4 indicate that all HTMT values among the constructs are below the recommended threshold. The highest HTMT value was found between PMR and SPI (0.781), followed by CT and AIT (0.748), whereas the lowest HTMT value was observed between PMR and AIT (0.526). Since none of the HTMT values exceed the value of 0.85, it can be concluded that the constructs in this study demonstrate adequate discriminant validity.

These findings confirm that HAC, AIT, PP, CT, PMR, and SPI represent distinct theoretical concepts and that each construct captures a unique aspect of the proposed research model. Therefore, the measurement model fulfills the discriminant validity requirement and can proceed to the evaluation of the structural model

Table 5. HTMT Assessment with Bootstrapped Confidence Intervals

Construct Relationship	HTMT	95% CI Lower	95% CI Upper
HAC – AIT	0.641	0.480	0.732
HAC – PP	0.578	0.446	0.708
HAC – CT	0.721	0.561	0.817
HAC – PMR	0.544	0.402	0.691
HAC – SPI	0.581	0.492	0.764
AIT – PP	0.604	0.455	0.733
AIT – CT	0.748	0.613	0.842
AIT – PMR	0.526	0.377	0.663
AIT – SPI	0.563	0.481	0.760
PP – CT	0.632	0.532	0.811
PP – PMR	0.716	0.571	0.835
PP – SPI	0.684	0.516	0.792
CT – PMR	0.612	0.554	0.819
CT – SPI	0.697	0.605	0.846
PMR – SPI	0.781	0.654	0.862

Table 5 presents the HTMT inference results based on the bootstrapped 95% confidence intervals. The results indicate that all lower and upper confidence interval values remain below the threshold value of 1.00. The lower bounds range from 0.377 to 0.654, while the upper bounds range from 0.663 to 0.862. The highest upper bound is observed for the PMR–SPI

relationship (0.862), followed by CT–SPI (0.846) and AIT–CT (0.842), yet all values remain below 1.00. These findings confirm that none of the confidence intervals include the value of 1.00, providing further evidence of adequate discriminant validity among the constructs

Table 6. Collinearity Assessment (VIF)

Endogenous Construct	Predictor Construct	VIF
CT	HAC	1.684
CT	AIT	1.792
CT	PP	1.436
PMR	PP	1.000
SPI	CT	1.527
SPI	PMR	1.527

Table 6 presents the results of the collinearity assessment in the inner model using Variance Inflation Factor (VIF) values. This analysis was performed to ensure that the predictor constructs do not experience multicollinearity problems that could affect the stability and accuracy of the structural model estimation. In PLS-SEM, VIF values below 5.00 indicate that collinearity is not a critical concern, while values below 3.30 are considered a more conservative acceptable threshold.

The results indicate that all VIF values in the structural model are within the acceptable range, ranging from 1.000 to 1.792. The highest VIF value was found for AIT predicting CT (VIF = 1.792), followed by HAC predicting CT (VIF = 1.684). Meanwhile, the lowest VIF value was observed for PP predicting PMR (VIF = 1.000). Since all values are substantially below the recommended thresholds, the model does not exhibit problematic collinearity among predictor constructs.

Therefore, the structural model meets the collinearity assessment criteria, indicating that each predictor construct provides unique explanatory information and that the subsequent hypothesis testing can be conducted reliably.

Table 7. Hypothesis Testing Results (Direct and Indirect Effects)

Hypothesis	Path	β	t-statistic	p-value	Decision
H1	HAC → CT	0.236	3.550	<0.001	Supported
H2	AIT → CT	0.344	5.200	<0.001	Supported
H3	PP → CT	0.081	1.300	0.194	Not Supported
H4	PP → PMR	0.625	12.200	<0.001	Supported
H5	CT → SPI	0.271	4.250	<0.001	Supported
H6	PMR → SPI	0.463	7.300	<0.001	Supported
H7	HAC → CT → SPI	0.064	2.650	0.008	Indirect only mediation
H8	AIT → CT → SPI	0.093	3.350	<0.001	Complementary mediation
H9	PP → CT → SPI	0.022	1.100	0.271	No mediation
H10	PP → PMR → SPI	0.289	6.050	<0.001	Indirect only mediation
	HAC → SPI	0.062	1.150	0.251	Not Significant
	AIT → SPI	0.165	2.550	0.011	Significant
	PP → SPI	0.039	0.750	0.453	Not Significant

Table 7 presents the results of direct and indirect hypothesis testing using the bootstrapping procedure in the PLS-SEM analysis**.** The assessment was conducted by examining the path coefficient (β), t-statistic values, and p-values to determine the significance of the proposed relationships. A relationship is considered statistically significant when the p-value is below 0.05 and the corresponding t-statistic exceeds the critical value.

The results indicate that most hypothesized relationships in the structural model are empirically supported. Specifically, HAC demonstrates a positive and significant effect on CT (β = 0.236, t = 3.550, p < 0.001), indicating that effective human–AI collaborative recommendation perception enhances customer trust. Similarly, AIT has a significant positive influence on CT (β = 0.344, t = 5.200, p < 0.001), suggesting that transparent AI interactions contribute to greater consumer confidence. However, the relationship between PP and CT is not significant (β = 0.081, t = 1.300, p = 0.194), indicating that personalization alone does not necessarily increase customer trust. Furthermore, PP significantly influences PMR (β = 0.625, t = 12.200, p < 0.001), while CT and PMR significantly contribute to SPI (β = 0.271, t = 4.250, p < 0.001; β = 0.463, t = 7.300, p < 0.001, respectively). The mediation analysis further reveals different underlying mechanisms among the AI-related antecedents. HAC significantly influences SPI through CT (β = 0.064, t = 2.650, p = 0.008), confirming the mediating role of customer trust. Likewise, AIT exhibits a significant indirect effect on SPI through CT (β = 0.093, t = 3.350, p < 0.001). In contrast, the indirect effect of PP on SPI through CT is not significant (β = 0.022, t = 1.100, p = 0.271), indicating that customer trust does not mediate the relationship between personalization and sustainable purchase intention. However, PP demonstrates a significant indirect effect on SPI through PMR (β = 0.289, t = 6.050, p < 0.001), confirming the importance of perceived message relevance as the mechanism through which personalization affects sustainable purchase intention. To further examine the mediation mechanisms, additional direct paths from the AI-related antecedents to SPI were estimated. The results show that HAC does not have a significant direct effect on SPI (β = 0.062, t = 1.150, p = 0.251), whereas AIT has a significant direct effect on SPI (β = 0.165, t = 2.550, p = 0.011). Meanwhile, PP does not directly influence SPI (β = 0.039, t = 0.750, p = 0.453). These findings indicate that HAC operates through an indirect-only mediation pathway via CT, while AIT demonstrates complementary mediation through both direct and trust-mediated pathways. Conversely, PP affects SPI only through PMR rather than through CT. Overall, the findings demonstrate that AI-related factors influence sustainable purchase intention through differentiated psychological mechanisms. While human–AI collaborative recommendation perception relies primarily on customer trust, AI transparency contributes through both direct and trust-based pathways. Meanwhile, personalization becomes effective only when consumers perceive the AI-generated message as relevant to their needs.

Table 8. Coefficient of Determination (R^2)

Endogenous Construct	R-square	R-square Adjusted
Customer Trust	0.424	0.418
Perceived Message Relevance	0.391	0.389
Sustainable Purchase Intention	0.548	0.536

Based on the results of the analysis, the R^2 value for the endogenous construct Customer Trust (CT) is 0.424, with an Adjusted R^2 value of 0.418. This indicates that the exogenous constructs included in the model explain 42.4% of the variance in Customer Trust, while the remaining 57.6% is explained by other factors outside the proposed research model. After adjusting for

the number of predictors, the explanatory power decreases slightly to 41.8%, indicating that the model maintains a stable explanatory capability for Customer Trust. For the endogenous construct Perceived Message Relevance (PMR), the R^2 value is 0.391, while the Adjusted R^2 value is 0.389. These results indicate that the predictor construct, namely Perceived Personalization, explains 39.1% of the variance in Perceived Message Relevance, whereas the remaining 60.9% is attributable to other factors not included in the model. The minimal difference between R^2 and Adjusted R^2 suggests that the explanatory power of the model remains consistent after considering the number of predictors. Meanwhile, the endogenous construct Sustainable Purchase Intention (SPI) obtains the highest R^2 value of 0.548, with an Adjusted R^2 value of 0.536. This indicates that the predictors included in the revised structural model explain 54.8% of the variance in Sustainable Purchase Intention, while the remaining 45.2% is explained by other factors beyond the scope of this study. After adjustment, the model still explains 53.6% of the variance in SPI, demonstrating adequate explanatory power. Overall, the results indicate that Sustainable Purchase Intention (SPI) is the endogenous construct with the highest explanatory power ($R^2 = 0.548$), suggesting that the proposed model provides a substantial explanation of consumers' sustainable purchase intention. In comparison, Perceived Message Relevance (PMR) has the lowest R^2 value (0.391), although it remains within an acceptable explanatory range. The relatively small differences between R^2 and Adjusted R^2 values across all constructs indicate that the model complexity does not substantially reduce its explanatory capability.

Table 9. Effect Size Assessment (f^2)

Structural Path	f^2	Effect Size
HAC → CT	0.060	Small
AIT → CT	0.125	Small
PP → CT	0.008	Negligible
PP → PMR	0.641	Large
CT → SPI	0.085	Small
PMR → SPI	0.238	Medium
HAC → SPI	0.003	Negligible
AIT → SPI	0.034	Small
PP → SPI	0.002	Negligible

Table 9 presents the effect size (f^2) assessment of the structural paths. The f^2 values indicate the contribution of each exogenous construct in explaining the variance of the corresponding endogenous constructs. Based on the results, most structural paths demonstrate small to medium effects, with several paths showing negligible effects.

The strongest effect is observed for PP → PMR with an f^2 value of 0.641, indicating a large effect. This finding suggests that Perceived Personalization provides a substantial contribution in explaining Perceived Message Relevance. Furthermore, PMR → SPI shows a medium effect ($f^2 = 0.238$), indicating that perceived relevance of AI-generated messages plays an important role in explaining Sustainable Purchase Intention. Meanwhile, AIT → CT demonstrates a small effect ($f^2 = 0.125$), followed by CT → SPI ($f^2 = 0.085$) and HAC → CT ($f^2 = 0.060$), indicating that these constructs contribute meaningfully, although with limited magnitude. The direct effect of AIT → SPI also shows a small effect ($f^2 = 0.034$). In contrast, PP → CT ($f^2 = 0.008$), HAC → SPI ($f^2 = 0.003$), and PP → SPI ($f^2 = 0.002$) demonstrate negligible effects. These results are consistent with the structural model findings, where Perceived Personalization does not directly influence Customer Trust or Sustainable Purchase Intention, while Human–AI

collaborative recommendation perception and Perceived Personalization primarily operate through indirect mechanisms.

Overall, the f^2 results confirm that Perceived Message Relevance and Customer Trust represent important mechanisms in explaining Sustainable Purchase Intention, while direct effects from AI-related antecedents generally exhibit smaller contributions

Table 10. Predictive Relevance (Q^2 predict)

Endogenous Construct	Q^2predict
Customer Trust (CT)	0.301
Perceived Message Relevance (PMR)	0.287
Sustainable Purchase Intention (SPI)	0.392

The predictive relevance of the structural model was assessed using Q^2predict. As presented in Table 10, all endogenous constructs exhibited positive Q^2predict values, with Customer Trust (CT) at 0.301, Perceived Message Relevance (PMR) at 0.287, and Sustainable Purchase Intention (SPI) at 0.392. These findings indicate predictive relevance for all three endogenous constructs, with SPI exhibiting the highest Q^2predict value. However, positive Q^2predict values alone do not establish the model's overall out-of-sample predictive performance, which requires further assessment of indicator-level prediction errors against an appropriate benchmark model. Accordingly, these findings are considered alongside the R^2 values to provide a balanced evaluation of the model's predictive relevance and explanatory power.

4.2 Discussion

4.2.1 Human–AI collaborative recommendation perception and Customer Trust

The findings demonstrate that human–AI collaborative recommendation perception has a positive and significant effect on customer trust ($\beta = 0.236$, $t = 3.550$, $p < 0.001$), supporting H1. This result indicates that consumers are more likely to develop trust toward AI-enabled e-commerce platforms when AI-supported recommendations are perceived as effective decision-support mechanisms. In the context of online shopping, Human–AI collaborative recommendation perception provides consumers with decision assistance by improving product search efficiency, adapting recommendations, and helping consumers evaluate available alternatives. This finding should be interpreted in relation to consumers' evaluation of AI-supported recommendation performance rather than general collaborative with AI. When recommendations are perceived as efficient, adaptive, and responsive to consumers' needs, they may reduce decision uncertainty and strengthen confidence in the recommendation system. In this sense, HAC reflects consumers' perceptions of how well AI-supported recommendations facilitate the shopping and decision-making process. This mechanism differs from perceived personalization, which concerns whether the recommendation content is individually tailored to consumers' preferences, interests, or previous behavior, rather than whether the recommendation system effectively supports the decision process itself. This finding supports the perspective of the Stimulus–Organism–Response (S–O–R) framework, where human–AI collaborative recommendation perception represents a technological stimulus that influences consumers' internal psychological evaluation. When consumers perceive that AI-generated recommendations provide meaningful assistance and improve decision effectiveness, they are more likely to evaluate the AI-enabled platform as reliable and dependable. As a result, consumers develop stronger confidence in the reliability of AI-based recommendations. The finding is consistent with previous research by Deng et al. (2026), which demonstrates that collaborative human–AI

recommendation environments strengthen platform trust by improving consumers' evaluation of AI-supported services. However, the additional direct effect analysis reveals that human–AI collaborative recommendation perception does not directly influence sustainable purchase intention ($\beta = 0.062$, $t = 1.150$, $p = 0.251$). Instead, its influence occurs through customer trust, indicating an indirect-only mediation pathway. This finding extends previous research by showing that human–AI collaborative recommendation perception contributes to sustainable purchase intention primarily by strengthening consumers' confidence in AI-enabled platforms rather than directly stimulating sustainable purchasing decisions. Therefore, AI-supported collaborative recommendation perception is not only relevant for improving shopping convenience but also for encouraging consumers to rely on AI-generated sustainability-related information through a trust-based mechanism.

4.2.2 AI Interaction Transparency and Customer Trust

AI interaction transparency was found to have a strong positive influence on customer trust among the examined antecedents ($\beta = 0.344$, $t = 5.200$, $p < 0.001$), supporting H2. This result highlights that transparency represents a critical foundation for building consumer confidence in AI-enabled commerce. Consumers often lack direct knowledge regarding how AI systems process personal data, determine recommendations, or prioritize certain products. Therefore, transparency can reduce uncertainty by helping consumers understand the logic behind AI-generated recommendations. When consumers perceive that AI interactions are understandable and explainable, they are more likely to consider the system reliable and dependable. This finding aligns with Li et al. (2024), who found that recommendation-system transparency increases consumer trust, and with Deng et al. (2026), who identified AI interaction transparency as an important determinant of platform trust. The results further indicate that AI interaction transparency contributes to sustainable purchase intention through both direct and indirect pathways. Specifically, AI interaction transparency demonstrates a significant direct effect on sustainable purchase intention ($\beta = 0.165$, $t = 2.550$, $p = 0.011$), while also influencing sustainable purchase intention through customer trust. This complementary mediation pathway suggests that transparency not only strengthens consumers' confidence in AI-enabled platforms but also directly enhances their willingness to consider sustainable purchasing decisions. In sustainable consumption contexts, this mechanism becomes particularly important because consumers frequently rely on digital platforms to evaluate environmental claims that cannot be directly verified. Thus, improving transparency mechanisms, such as providing explanations regarding why sustainable products are recommended or how consumer preferences influence recommendations, may strengthen consumer confidence and encourage sustainable purchasing decisions.

4.2.3 Perceived Personalization and Customer Trust

Contrary to expectations, perceived personalization did not significantly influence customer trust ($\beta = 0.081$, $t = 1.300$, $p = 0.194$), resulting in the rejection of H3. This finding indicates that personalized recommendations are not automatically interpreted as evidence of platform reliability. Although personalization can improve the relevance and convenience of online shopping experiences, consumers may evaluate personalized recommendations primarily from an informational perspective rather than a relational perspective. In other words, consumers may recognize that AI understands their preferences without necessarily developing greater confidence in the platform. This result differs from studies suggesting that personalization strengthens trust in digital environments. However, the finding is theoretically reasonable because personalization may generate mixed perceptions. On one

side, consumers may appreciate recommendations that match their interests; on the other side, highly personalized recommendations may raise concerns regarding privacy, surveillance, or excessive use of personal data. Furthermore, the additional direct effect analysis indicates that perceived personalization does not directly influence sustainable purchase intention ($\beta = 0.039$, $t = 0.750$, $p = 0.453$). Therefore, personalization should not be considered a direct driver of either customer trust or sustainable purchase intention. Instead, its contribution may depend on whether consumers perceive AI-generated information as meaningful and relevant to their needs. The current findings suggest that trust depends more strongly on how AI interacts with consumers and how transparent the system appears rather than simply on the degree of customization provided.

4.2.4 Perceived Personalization and Perceived Message Relevance

The results reveal that perceived personalization has a strong positive effect on perceived message relevance ($\beta = 0.625$, $t = 12.200$, $p < 0.001$), supporting H4. This relationship represents one of the strongest paths in the structural model and confirms that personalization plays an important role in improving the perceived usefulness of AI-generated information. Personalization enables AI systems to deliver messages that better correspond with consumers' preferences, previous behaviors, and purchasing contexts. However, the behavioral value of personalization depends not only on the technical ability of AI to customize content but also on whether consumers perceive the information as meaningful and applicable. This finding supports Qadri et al. (2026), who emphasize that perceived message relevance represents a key mechanism explaining how AI personalization influences sustainable purchase intention. The result also confirms the conceptual distinction between personalization and relevance. Personalization reflects the action performed by the AI system, whereas relevance reflects consumers' interpretation of the information received. For sustainable products, this mechanism is particularly important because environmental benefits may not always represent consumers' primary purchasing considerations. AI-generated messages become more persuasive when sustainability information is connected with consumers' personal needs, preferences, and decision situations. Therefore, the influence of personalization on sustainable purchase intention appears to depend on whether personalized information is perceived as relevant and meaningful rather than merely being customized.

4.2.5 Customer Trust and Sustainable Purchase Intention

Customer trust significantly influences sustainable purchase intention ($\beta = 0.271$, $t = 4.250$, $p < 0.001$), supporting H5. This finding demonstrates that trust plays an important role in shaping AI-enabled interactions into sustainable consumer responses. Sustainable purchasing often involves uncertainty because consumers may have difficulty evaluating environmental claims, product sustainability attributes, or the credibility of information provided online. In this situation, customer trust functions as a mechanism that reduces uncertainty and increases consumers' willingness to rely on AI-generated recommendations. The finding supports previous research by Alzaidi and Agag (2022), which identifies trust as an important determinant of purchase intention in digital environments. It also extends research on AI and sustainable consumption by demonstrating that trust in AI-supported platforms can encourage consumers to consider environmentally responsible purchasing options. Therefore, building trustworthy AI environments may help organizations support consumers' sustainable purchase decisions through digital platforms.

4.2.6 Perceived Message Relevance and Sustainable Purchase Intention

Perceived message relevance demonstrated a strong direct effect on sustainable purchase intention ($\beta = 0.463$, $t = 7.300$, $p < 0.001$), supporting H6. This finding indicates that consumers are more likely to develop sustainable purchase intentions when AI-generated information is perceived as personally meaningful and relevant. The result suggests that sustainable purchasing decisions are not driven solely by the availability of sustainability information but by how effectively such information is connected with individual consumer needs. Even highly accurate AI recommendations may have limited influence if consumers do not perceive the message as applicable to their circumstances. This finding reinforces Qadri et al. (2026), who identify perceived message relevance as a critical mechanism linking AI personalization with sustainable purchase intention. It also provides an explanation for inconsistent findings regarding personalization and sustainable consumption. Personalization may not directly create sustainable intention; rather, its influence emerges when personalized content becomes relevant and meaningful to consumers.

4.2.7 The Mediating Role of Customer Trust

The mediation results indicate that customer trust significantly mediates the relationship between human–AI collaborative recommendation perception and sustainable purchase intention ($\beta = 0.064$, $t = 2.650$, $p = 0.008$) and between AI interaction transparency and sustainable purchase intention ($\beta = 0.093$, $t = 3.350$, $p < 0.001$). These findings support H7 and H8. These results demonstrate the existence of a trust-based pathway within the proposed model. However, the mediation mechanisms differ between human–AI collaborative recommendation perception and AI interaction transparency. Human–AI collaborative recommendation perception influences sustainable purchase intention primarily through customer trust, indicating an indirect-only mediation pathway. In contrast, AI interaction transparency contributes to sustainable purchase intention through both a direct effect and an indirect effect mediated by customer trust, indicating a complementary mediation pathway. The mediation effect of AI transparency indicates that consumers' willingness to accept sustainability-related recommendations depend greatly on whether they perceive AI processes as understandable and reliable. Transparency therefore becomes an essential mechanism for converting technological capability into consumer trust and, subsequently, sustainable purchasing intention, while also directly encouraging sustainable purchase decisions. However, customer trust did not mediate the relationship between perceived personalization and sustainable purchase intention ($\beta = 0.022$, $t = 1.100$, $p = 0.271$), meaning H9 was not supported. This reinforces the argument that personalization primarily functions through informational value rather than trust formation. Consumers may appreciate personalized recommendations because they are relevant to their needs, but such personalization alone does not necessarily increase confidence in the AI-enabled platform.

4.2.8 The Mediating Role of Perceived Message Relevance

The mediation analysis confirms that perceived message relevance significantly mediates the relationship between perceived personalization and sustainable purchase intention ($\beta = 0.289$, $t = 6.050$, $p < 0.001$), supporting H10. This finding highlights that personalization influences sustainable consumption mainly because it improves the relevance of information delivered to consumers. The effectiveness of AI personalization therefore depends not only on the degree of customization but also on consumers' perception that the resulting message is meaningful and applicable to their needs. The result strengthens the theoretical contribution of this study by identifying different psychological pathways through which AI characteristics

influence sustainable purchase intention. Human–AI collaborative recommendation perception primarily operates through a trust pathway, AI interaction transparency contributes through both direct and trust-mediated pathways, whereas perceived personalization operates through a relevance pathway. Overall, the findings provide evidence that AI-enabled sustainable marketing should not rely on personalization alone. Instead, successful AI implementation requires a combination of trustworthy interaction, transparent AI processes, and meaningful communication. By integrating collaborative, transparency, and relevance, e-commerce platforms can improve consumers' willingness to engage in sustainable purchasing behavior.

5. Conclusion and Suggestion

5.1 Conclusion

This study concludes that AI-enabled e-commerce characteristics influence sustainable purchase intention through two distinct psychological pathways: a trust pathway and a relevance pathway. The findings demonstrate that human–AI collaborative recommendation perception and AI interaction transparency strengthen customer trust, whereas perceived personalization does not significantly enhance trust. Furthermore, perceived personalization contributes to sustainable purchase intention primarily by increasing perceived message relevance, while customer trust and perceived message relevance serve as important psychological mechanisms underlying sustainable purchase intention. The distinction between Human–AI Collaborative Recommendation Perception and perceived personalization also contributes to conceptual precision in AI-enabled consumer research. Although both constructs involve adaptive recommendation processes, they represent different consumer evaluations. HAC reflects consumers' perceptions of the supportive performance of AI-supported recommendation systems, particularly in terms of efficiency, adaptability, and responsiveness during the shopping and decision-making process. In contrast, perceived personalization reflects the perceived degree to which recommendation content is individually tailored to consumers' preferences, interests, or previous behavior. The different structural effects observed in this study suggest that these evaluations should not be treated as interchangeable. An AI recommendation system may be perceived as highly effective in supporting consumer decisions without necessarily being perceived as highly personalized, and vice versa. The additional direct effect analysis provides further insight into the different roles of AI-related characteristics. Human–AI collaborative recommendation perception does not directly influence sustainable purchase intention but operates through customer trust. In contrast, AI interaction transparency affects sustainable purchase intention through both direct and trust-mediated pathways, indicating that transparent AI interactions can enhance consumer confidence while also directly supporting sustainable purchase intention. Perceived personalization does not have a direct effect on sustainable purchase intention but becomes influential when AI-generated information is perceived as relevant and meaningful. This study extends the Stimulus–Organism–Response (S–O–R) framework by demonstrating that AI-enabled interactions shape sustainable purchase intention through differentiated psychological mechanisms. The findings highlight that effective AI-enabled sustainable marketing should not rely on personalization alone but should emphasize

trustworthy interactions and meaningful communication. However, the findings should be interpreted within the context of AI-experienced consumers with prior interest in sustainable products, as sustainable purchase intention may also be influenced by existing environmental values, preferences, and consumption orientations.

5.2 Suggestion

Future research is encouraged to extend this study by examining AI-enabled sustainable consumption in broader contexts and using more diverse research designs. Longitudinal or experimental approaches may provide deeper insights into how consumer trust, perceived message relevance, and responses to AI interaction transparency develop through continuous interaction with AI recommendation systems. Future studies may also expand the research model by incorporating additional factors that may influence consumers' responses to AI-enabled sustainable recommendations, such as privacy concerns, perceived risk, environmental awareness, perceived value, algorithmic fairness, and consumer skepticism. These factors may provide a more comprehensive explanation of why certain AI characteristics strengthen sustainable purchase intention through trust-based mechanisms, while others operate through information relevance. Furthermore, future research may examine the direct and indirect pathways through which different AI characteristics influence sustainable purchase intention. For example, additional studies may investigate how AI transparency directly affects consumer decisions and how personalization creates behavioral outcomes through perceived message relevance rather than direct influence. Researchers are also encouraged to examine actual sustainable purchasing behavior rather than relying only on purchase intention, as intention may not always translate into real consumption decisions. Finally, future research may consider larger and more diverse samples across different regions, consumer groups, and product categories to improve the generalizability of findings and provide a more comprehensive understanding of AI-driven sustainable consumption.

6. Limitations and Future Research

This study has several limitations that should be considered when interpreting the findings. First, this research employs a cross-sectional survey design, which captures consumer perceptions at a single point in time. Therefore, the relationships identified between AI characteristics, customer trust, perceived message relevance, and sustainable purchase intention should be interpreted as theoretical associations rather than confirmed causal relationships. Future studies may employ longitudinal or experimental designs to examine how continuous exposure to AI-enabled recommendations influences changes in consumer trust, perceived message relevance, and sustainable purchase intention over time. Second, this study applies purposive sampling involving e-commerce consumers in Bali, Indonesia. Although this approach ensures that respondents have experience with AI-enabled shopping features and sustainable products, it may limit the generalizability of the findings to other geographic regions, consumer groups, and cultural contexts. Future research may involve larger and more diverse samples across different regions and demographic characteristics to validate and extend the current findings. Third, this study focuses on sustainable purchase intention rather than actual purchasing behavior. Although purchase intention represents an important indicator of consumer decision-making, intention may not always translate into actual purchasing actions due to external factors such as price, product availability,

convenience, and product quality. Future studies may incorporate actual purchase data, behavioral tracking, or experimental purchasing situations to provide stronger evidence regarding the relationship between AI-enabled interactions and sustainable purchasing outcomes. Fourth, this research model focuses on customer trust and perceived message relevance as the primary psychological mechanisms explaining sustainable purchase intention. However, sustainable purchase intention may also be influenced by consumers' existing sustainability orientations and other individual-level factors beyond AI-related experiences. Future research should incorporate variables such as environmental concern, perceived green value, prior sustainable purchasing behavior, privacy concerns, perceived risk, algorithmic fairness, and consumer skepticism as additional explanatory or control variables. These factors may help distinguish the influence of AI-enabled interactions from consumers' pre-existing sustainability orientations. Finally, this study identifies two psychological pathways through which AI characteristics relate to sustainable purchase intention, namely the trust-based pathway and the relevance-based pathway. Future research may further examine the boundary conditions under which specific AI characteristics generate direct effects or operate through psychological mechanisms. Such investigations may provide a more comprehensive understanding of how transparency, collaborative, and personalization shape consumers' evaluations of AI-enabled sustainable recommendations. These limitations are primarily related to research design, sampling strategy, and research scope rather than measurement validity, as all constructs demonstrated acceptable reliability and validity. Future research should therefore extend this framework through stronger research designs, broader samples, additional explanatory variables, and behavioral outcomes to further clarify the role of artificial intelligence in supporting sustainability-related consumer decision processes.

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