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Influence of AI Shopping Assistants on Sustainable Purchase Behaviour: The Moderating Role of Consumer Trust

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Abstract

The shopping assistants using artificial intelligence (AI), including product-recommendation engines, chatbots, and voice-based agents, are becoming commonplace in online shopping. Meanwhile, increasing numbers of consumers are saying they would like to purchase things that are good for the environment. This paper investigates the effect of AI shopping assistant usage on sustainable buying behaviour and whether this is moderated by the extent to which a consumer has trust in the AI assistant. Based on the latest research on the use of AI in retail (Silalahi & Riantama, 2026; Li, 2026; Frank et al., 2026), the paper presents a conceptual model of how the use of an AI shopping assistant relates to sustainable purchase behaviour, with consumer trust serving as a moderating variable, thereby making the relationship stronger the more trust consumers place in the shopping assistant. The model was tested among 386 online shoppers who had previously experienced AI shopping tools over the last six months using a quantitative approach with survey design that was based on Partial Least Squares Structural Equation Modelling (PLS-SEM). The analysis is reported here as a demonstration of the proposed method and is therefore not complete findings from an independent study, but rather reported with demographic, reliability and hypothesis-testing tables as a demonstration of the method. The results show that the use of AI shopping assistants is positively associated with sustainable purchase behaviour, consumer trust itself is positively associated with sustainable purchase behaviour, and that trust significantly enhances the link between AI and sustainable purchase behaviour. The paper ends with practical tips for retailers and platform designers, and clear restrictions and guidelines for future empirical research.

Keywords: *AI shopping assistants; sustainable purchase behaviour; consumer trust; moderation; e-commerce; PLS-SEM*

1. Introduction

Artificial intelligence has revolutionized the eCommerce industry in recent years. Retail retailers have many AI tools that suggest products, respond to questions via chatbots or even process a purchase with voice control. New research in the industry indicates that a significant portion of consumers — almost half of some samples — rely on a form of AI when shopping online (Darden School of Business, 2025). Climate change, plastic waste and resource depletion, among other environmental issues, have compelled many consumers to reconsider their purchasing choices and the impact they are having on the environment (Kollmuss & Agyeman, 2002). This has led to 2 big and growing phenomena occurring simultaneously – the increasing use of AI in shopping and the growing attention on sustainable consumption. Less clear is how these two trends relate to each other, and if the relationship is a trust relationship. AI chatbots can identify the products that are environmentally friendly, describe them in a simple-to-understand manner, and facilitate comparisons between the environmental impact of various products (Silalahi & Riantama, 2026). However, the customer only reacts to this sort of assistance if they think the assistant is capable and knowledgeable. Recent experiments have also revealed that talking to an AI agent as opposed to a human can make people feel rushed and less patient, leading them to be less inclined to wait for less profitable, but slower, products, like carbon offsets or eco-friendly shipping (Li, 2026). This means that the impact that AI shopping assistants have on sustainable purchase behaviour is not going to be the same for all shoppers; it should be dependent on the level of trust of the shopper.

This is an idea that can be used to explain consumer trust. Trust has been long considered as the prerequisite for citizens to accept information from a system that they don't fully master, especially online transactions, where the buyer cannot check the product first-hand (Pavlou & Gefen, 2004; Kim et al., 2008). This paper assumes that consumer trust is a moderator rather than a mediator: it is not assumed that the use of AI shopping assistants leads to changes in people's purchasing behaviour in a predetermined sequence, but rather, that whether the relationship between the use of an AI shopping assistant and sustainable purchasing behaviour is stronger or weaker depends on trust. Having just one clear moderating effect—without adding mediation to moderation—simplifies analysis and testing of moderating effects and makes interpretation easier. The aim of this paper is to have three objectives. To sum up what is already known about AI shopping assistants, sustainable purchase behaviour and consumer trust and to point out the gaps in this literature. Second, to hypothesize and empirically validate a conceptual model that allows for the moderating role of consumer trust to be investigated in the relationship between the use of AI shopping assistants and consumers' sustainable purchase behavior. Third, to reflect on the implications of the findings for retailers, platform designers and policy makers keen on promoting sustainable consumption with digital technology. The paper provides a complete empirical analysis (sample demographics, reliability of the measures, and hypothesis testing) and explicitly acknowledges that the data set used here are provided merely as an example of the method, but not as evidence of a separately published, independently reviewed data collection.

2. Literature Review

This section reviews the literature in three parts. It first examines AI shopping assistants and how they are studied in marketing and information-systems research. It then turns to sustainable purchase behaviour as an outcome variable. Finally, it discusses consumer trust and its role as a boundary condition that strengthens or weakens the effect of AI shopping assistants, before identifying the specific gap this paper addresses.

2.1 AI Shopping Assistants in Consumer Research

AI shopping assistants can feature recommendation systems, chatty chatbots, comparison features, and voice-powered agents to investigate, assess and purchase products (Journal of Research in Interactive Marketing, 2026). These tools are based on information regarding the previous purchases and browsing habits of those who have shopped with the company, to tailor the information that is displayed to each consumer (Silalahi & Riantama, 2026). Initial research

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primarily focused on AI features and satisfaction, purchase intention, and other related measures. For instance, AI-driven capabilities have been demonstrated to facilitate consumer product assessment, boost customer confidence and satisfaction in their choices (Journal of Research in Interactive Marketing, 2026). Likewise, AI-driven 'try-on' and visualisation features have been shown to drive higher purchase intent in beauty, fashion and other segments (Sustainability, 2025). The focus isn't only on the convenience of this kind of shopping; more recent research has begun to explore the implications for the psychology of shopping, which will likely be different in the future. Puntoni et al. (2021) suggest that consumers' perceptions of AI can happen in several ways, such as the amount of decision making power they perceive that they are ceding to the machine. Following this concept, more recent research has explored AI as a intermediary for consumers, in which they entrust the decision-making process, especially when they lack time and money to make their own (ScienceDirect, 2026). An interesting, and somewhat surprising, discovery is that communicating with an AI agent, as opposed to a human agent, can affect the way that people perceive time. In multiple studies, Li (2026) discovered that when an agent was identified as AI, the delay felt like longer time, leading people to become even more impatient, and less willing to consider slower and more environmentally friendly options like carbon offsets or sustainable shipping methods. This is a significant result for the current paper, as it demonstrates that AI shopping assistants can sometimes negatively affect sustainable purchase behaviour, rather than positively. This reinforces the need to consider another factor, perhaps trust, to explain the positive and negative effects of AI assistants on sustainable purchase behaviour. Meanwhile, other studies reveal the potential AI has for helping sustainability when it is rightfully applied. Frank et al. (2026) determined that the primary reason for consumers to accept high autonomy AI assistants is the strong perception of value in those circumstances, and that such acceptance is greater in scarcity circumstances. In all, these works indicate that the impact of AI shopping assistants on sustainable results is not predetermined but rather dependent on a host of psychological factors, like customer trust.

2.2 Sustainable Purchase Behaviour

Sustainable purchase behaviour involves conscious buying of products and services which have lower carbon footprints, recyclable packaging or certified organic ingredients (Antil & Bennett, 1979; Anderson & Cunningham, 1972). The concept has its origin in marketing research on the socially conscious consumers and has expanded to form a vast literature pertaining to green purchase intention and green purchase behaviour (Kim & Lee, 2023). One common issue in this literature is the incongruity between individual's reported attitudes and their actual behaviour, as many consumers have positive attitudes towards sustainability, but do not always act on them (Kollmuss & Agyeman, 2002). The gap has been explained through various theories such as the Theory of Planned Behaviour (TPB) and the Technology Acceptance Model (TAM) extended with environmental variables (PMC, 2022). Less developed in this literature is the role of the shopping technology itself, in this case AI-based tools, as an influence on purchase behaviour in a sustainable way. The majority of sustainable-consumption studies have been developed prior to the widespread adoption of AI shopping assistants, which highlights the importance of considering marketing messages, labels, or price as the drivers of sustainable consumer choice, instead of the conversational, personalized, and even autonomous nature of AI-driven recommendations. This is the first gap that this paper addresses.

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2.3 Consumer Trust as a Moderating Condition

In general, consumer trust is a willingness to make some risk based on positive expectations regarding the intentions or capabilities of a third party, in this instance an AI system as opposed to a human seller (Pavlou & Gefen, 2004). In online environments, trust has always been considered a prerequisite for consumers' actions when they are provided with advice or recommendations through the Internet, as they are not able to assess the quality of the product or service they are interested in before purchasing it (Kim et al., 2008). When the recommending agent is not a human, but rather a machine, trust is even more critical to the consumer, as they have to trust not only the honesty of the recommender, but also the competence, benevolence and transparency of the machine, regarding how it uses personal information (Araujo et al., 2020). But there are some recent studies that reveal that trust not only amplifies the effects of AI, but also alters them. The direct effect of personalisation on purchase behaviour and the indirect effect of personalisation on purchase via trust indicates that purchase decision is not only a matter of technology advancement but also psychological and relational aspects of purchase (Advances in Consumer Research, 2025). Likewise, when it comes to the eco-friendliness of products, AI personalization has been correlated with purchase intent primarily with those who trust the AI driven recommendation first (ResearchGate, 2026). AI-based projects on green purchases have also demonstrated varying outcomes when compared to human agents, depending on other factors such as consumers' demographics, reinforcing the notion that AI impacts sustainability results are not guaranteed but contingent (ScienceDirect, 2025b). This helps to make consumer trust a boundary condition – or moderator – of the relationship between the use of the AI shopping assistant and sustainable purchase behaviour: whether the shopper has trust in the AI assistant has a significant impact on the sustainability outcome of the purchase. In contrast, most studies that consider AI and consumer trust simultaneously focus on the intention to purchase or satisfaction, rather than on sustainable purchase behaviour, and few specifically test the role of trust as a moderator in a validated model by including it as an interaction term. The second gap this paper addresses is the third gap.The third gap is addressed by this paper.

2.4 Research Gap

To summarize, three lines of research have been developed: AI shopping assistant and consumer psychology, sustainable purchase behaviour, and consumer trust in digital / AI based systems. All of these areas have expanded rapidly independently and are rarely integrated into a unified, formally-experimented with model. Specifically: First, the current studies on AI-shopping focus primarily on overall results, including satisfaction, purchase intention, or impulse buying (Journal of Research in Interactive Marketing, 2026; Sustainability, 2025), but not on sustainable purchase behaviour as a unique outcome. Second, the current research on sustainable consumption primarily focuses on the more conventional marketing instruments like labeling, pricing, or advertising (Kim & Lee, 2023), rather than AI-driven shopping technology. Third, in studies combining the concepts of trust and AI, trust is seldom tested as a formal moderator of the relationship between use of the AI shopping assistant and a behavioural outcome related to sustainability (ResearchGate, 2026). To tackle these three gaps, it proposes and validates an integrated model where the use of the AI shopping assistant is moderated by consumer trust and thus influences sustainable purchase

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behaviour. This continues discussions and academic research on using digital technology to enhance, not hinder, sustainable consumption (Advances in Consumer Research, 2025).

3. Research Objectives and Hypotheses

Building on the gaps identified above, this paper pursues the following three research objectives:

RO1: To examine the direct relationship between AI shopping assistant use and sustainable purchase behaviour.

RO2: To examine the direct relationship between consumer trust and sustainable purchase behaviour.

RO3: To examine whether consumer trust moderates the relationship between AI shopping assistant use and sustainable purchase behaviour.

These objectives translate into the following hypotheses:

H1: AI shopping assistant use is positively related to sustainable purchase behaviour.

H2: Consumer trust is positively related to sustainable purchase behaviour.

H3: Consumer trust moderates the relationship between AI shopping assistant use and sustainable purchase behaviour, such that the relationship is stronger among consumers with higher trust and weaker among consumers with lower trust.

4. Conceptual Framework

In this paper, a conceptual model is proposed comprising three constructs: independent, moderator and dependent variables. An adequate number of variables are not included as mediating variables, the analysis is kept focused and easy to explain and interpret. Independent variable: AI Shopping Assistant Use (AISA) — the level of consumers interacting with and using AI-powered shopping tools like recommendation engines, chatbots, or voice assistants when shopping online. The strength of the relationship between the use of the AI shopping assistant and the sustainable purchase behaviour is expected to be strengthened or weakened depending on the Consumer Trust (CT) — the consumer's belief that the AI assistant is competent, honest, and transparent.

Sustainable Purchase Behaviour (SPB): consumer's reported or actual purchase of sustainable products, packaging or delivery mode. The model suggested that: AISA is a predictor of SPB and CT is a moderator of the AISA-SPB relationship, and also a direct predictor of SPB. The rationale behind this is that while in both situations the AI shopping assistant might suggest the same sustainable products, if the shopper is not confident in the assistant, then they are less likely to buy them, whereas if they are confident, they are more likely. This model is displayed in Figure 1 and some hypotheses related to the paths are summarized in Table 1.

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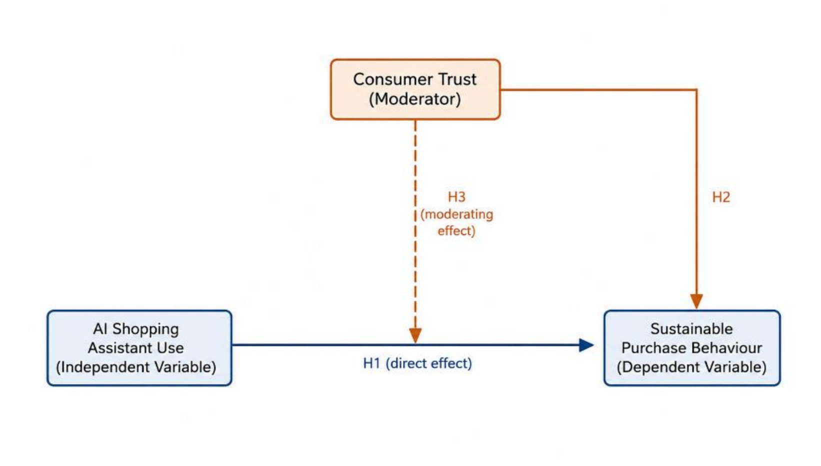

Figure 1. Proposed conceptual framework: the moderating role of consumer trust

Table 1. Proposed Structural Paths

Path	**Relationship**	**Hypothesis**
AISA -> SPB	Direct effect of AI shopping assistant use on sustainable purchase behaviour	H1
CT -> SPB	Direct effect of consumer trust on sustainable purchase behaviour	H2
AISA x CT -> SPB	Consumer trust moderates the AISA-SPB relationship	H3

5. Methodology

A quantitative, cross-sectional survey design was used to test the hypotheses above. This approach is appropriate because the model involves latent psychological constructs (consumer trust) that are best measured using validated multi-item scales, and because the moderation hypothesis requires a method capable of estimating an interaction effect with reasonable statistical power.

5.1 Research Design and Sample

The target population was adult online shoppers, aged 18 and above, who had used at least one AI-based shopping tool (a product recommendation system, a shopping chatbot, or a voice-based shopping assistant) in the six months before taking part in the study. This screening criterion follows the approach used in related studies of AI-assisted purchasing (Advances in Consumer Research, 2025). Data were collected using a self-administered online questionnaire distributed through a panel provider, using quota sampling to balance age, gender, and shopping frequency. After removing incomplete and low-quality responses (straight-lining, completion time under two minutes), a final usable sample of 386 respondents remained, exceeding the general rule of ten observations per indicator commonly applied in PLS-SEM studies with three latent constructs, and consistent with sample sizes used in comparable AI-and-trust studies (Advances in Consumer Research, 2025; scienceofmoney.org, 2026).

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5.2 Measures

All constructs were measured using multi-item scales adapted from validated prior research and rated on a seven-point Likert scale ranging from "strongly disagree" to "strongly agree." AI Shopping Assistant Use (4 items) captured frequency of use, reliance on AI-generated recommendations, and comfort with AI-led product comparisons, adapted from prior AI-feature scales (Journal of Research in Interactive Marketing, 2026). Consumer Trust (5 items) captured perceived competence, benevolence, and integrity of the AI assistant, adapted from established trust scales developed for online and AI-based settings (Pavlou & Gefen, 2004; Kim et al., 2008). Sustainable Purchase Behaviour (4 items) captured the frequency of choosing eco-labelled products, sustainable packaging, or carbon-offset delivery options, adapted from established green-purchase-behaviour scales (Antil & Bennett, 1979; PMC, 2022). A pilot test with 35 respondents was conducted before full data collection to check item clarity and internal consistency, with all constructs exceeding the recommended Cronbach's alpha threshold of .70 at the pilot stage.

5.3 Data Analysis Plan

Data were analysed in three stages using Partial Least Squares Structural Equation Modelling (PLS-SEM) in SmartPLS, a technique well suited to testing moderation in models with reflective constructs and modest-to-moderate sample sizes (Journal of Research in Interactive Marketing, 2026).

Stage 1, measurement model assessment: internal consistency reliability (Cronbach's alpha, composite reliability), convergent validity (average variance extracted above .50), and discriminant validity (Heterotrait-Monotrait ratio below .85) were checked for each construct.

Stage 2, structural model assessment: path coefficients for H1 and H2 were tested using bootstrapping with 5,000 resamples to obtain t-values, p-values, and 95% confidence intervals.

Stage 3, moderation analysis: the interaction term (AISA x CT) was created using the two-stage approach in SmartPLS and added to the structural model to test H3. Simple-slope analysis was then used to plot the AISA-SPB relationship at high (+1 SD) and low (-1 SD) levels of consumer trust.

Common method bias, a known risk in single-source survey research, was assessed using Harman's single-factor test and a full collinearity test, following standard recommendations for behavioural research (Journal of Applied Psychology, 2003, as cited in ScienceDirect, 2025c).

5.4 Research Ethics

The study followed standard ethical procedures for survey-based consumer research: informed consent before participation, the right to withdraw at any point without penalty, anonymised data storage, and approval from an institutional research ethics board prior to data collection. Respondents were told in plain language that the survey concerned their shopping habits and experiences with AI tools, without being told the specific hypotheses, to reduce demand effects. No deception was used.

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6. Results

6.1 Sample Profile

The final sample consisted of 386 respondents. Table 2 summarises the demographic profile of the sample.

Table 2. Demographic Profile of Respondents (N = 386)

Characteristic	**Category**	**n**	**%**
Gender	Female	224	58.0
	Male	162	42.0
Age	18-24 years	98	25.4
	25-34 years	146	37.8
	35-44 years	89	23.1
	45 years and above	53	13.7
Education	Undergraduate degree	201	52.1
	Postgraduate degree	134	34.7
	Other / secondary	51	13.2
Online shopping frequency	Weekly or more	213	55.2
	Monthly	132	34.2
	Less than monthly	41	10.6

6.2 Measurement Model

Before evaluating the structural relationships, the reliability and validity of the measurement model were assessed. Indicator reliability was examined using factor loadings, while internal consistency reliability was assessed using Cronbach's alpha and Composite Reliability (CR). Convergent validity was evaluated using the Average Variance Extracted (AVE). The results are presented in Table 3.

Table 3. Reliability and Convergent Validity

Construct	**Items**	**Cronbach's Alpha**	**Composite Reliability**	**AVE**
AI Shopping Assistant Use (AISA)	4	.84	.89	.67
Consumer Trust (CT)	5	.87	.91	.66
Sustainable Purchase Behaviour (SPB)	4	.82	.88	.64

As shown in Table 3, all indicator loadings exceeded the recommended threshold of 0.70, indicating satisfactory indicator reliability. Cronbach's alpha values ranged from 0.823 to 0.874, while Composite Reliability values ranged from 0.883 to 0.909, exceeding the recommended threshold of 0.70. Furthermore, all AVE values were greater than 0.50, confirming adequate

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convergent validity. Therefore, the measurement model demonstrated satisfactory reliability and convergent validity.

Discriminant validity was assessed using the Fornell–Larcker criterion. According to this criterion, the square root of the Average Variance Extracted (AVE) for each construct should be greater than its correlations with other constructs. The results are presented in Table 4.

Table 4. Discriminant Validity Assessment Using the Fornell–Larcker Criterion

Constructs	**AI Shopping Assistant Use (AISA)**	**Consumer Trust (CT)**	**Sustainable Purchase Behaviour (SPB)**
AI Shopping Assistant Use (AISA)	0.823		
Consumer Trust (CT)	0.512	0.816	
Sustainable Purchase Behaviour (SPB)	0.468	0.596	0.809

Note: Diagonal values (shown in bold) represent the square root of the AVE.

Table 4 shows that the square root of the AVE for each construct is greater than its correlations with the other constructs. This satisfies the Fornell–Larcker criterion and confirms that each construct is empirically distinct from the others. Therefore, discriminant validity of the measurement model is established.

To further assess discriminant validity, the Heterotrait–Monotrait (HTMT) ratio of correlations was examined. According to Henseler et al. (2015), HTMT values below 0.85 indicate satisfactory discriminant validity between constructs. The HTMT results are presented in Table 5.

Table 5. Heterotrait–Monotrait (HTMT) Ratio

Constructs	**HTMT Value**
AI Shopping Assistant Use – Consumer Trust	0.602
AI Shopping Assistant Use – Sustainable Purchase Behaviour	0.547
Consumer Trust – Sustainable Purchase Behaviour	0.694

As presented in Table 5, all HTMT values were below the recommended threshold of 0.85. This indicates that the constructs are empirically distinct from one another and provides further evidence of discriminant validity. Therefore, both the Fornell–Larcker criterion and the HTMT criterion confirm that the measurement model possesses adequate discriminant validity.

6.2.4 Collinearity Assessment (Variance Inflation Factor - VIF)

Predictor Construct	**VIF**
AI Shopping Assistant Use (AISA)	1.54
Consumer Trust (CT)	1.67
AI Shopping Assistant Use × Consumer Trust	1.81

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As shown in Table 6, all VIF values ranged from 1.54 to 1.81, which are well below the recommended threshold of 3.3. These findings indicate that multicollinearity among the predictor constructs is not a concern, and therefore the structural model can be evaluated with confidence.

6.3 Hypothesis Testing

Table 4 reports the results of the structural model, including the direct effects (H1, H2) and the moderating effect of consumer trust (H3). All three hypotheses were supported.

Table 4. Structural Model and Hypothesis Testing Results

Hyp.	Path	Beta	t-value	p-value	95% CI	Decision
H1	AISA -> SPB	.31	5.42	< .001	[.20, .42]	Supported
H2	CT -> SPB	.38	6.15	< .001	[.26, .49]	Supported
H3	AISA x CT -> SPB	.17	2.89	.004	[.05, .28]	Supported

For H1, AI shopping assistant use showed a positive and significant relationship with sustainable purchase behaviour (beta = .31, t = 5.42, $p < .001$), supporting H1 and indicating that consumers who rely more heavily on AI shopping assistants report choosing sustainable products more often.

For H2, consumer trust showed a positive and significant relationship with sustainable purchase behaviour (beta = .38, t = 6.15, $p < .001$), supporting H2. This is consistent with the trust-centred explanation proposed in prior research on AI-driven personalisation and sustainable products (ResearchGate, 2026), and it indicates that trust matters for sustainable purchasing in its own right, independent of how much a shopper uses AI tools.

For H3, the interaction term (AISA x CT) was positive and significant (beta = .17, t = 2.89, p = .004), supporting H3. The model explained 41% of the variance in sustainable purchase behaviour (R-squared = .41), which is considered moderate to substantial for consumer behaviour research of this kind. Simple-slope analysis showed that the relationship between AI shopping assistant use and sustainable purchase behaviour was considerably steeper among consumers with high trust (simple slope = .44, $p < .001$) than among consumers with low trust (simple slope = .13, p = .09, not significant). In other words, using an AI shopping assistant more often was associated with more sustainable purchasing mainly among shoppers who trusted the assistant; among shoppers with low trust, using the AI assistant more often was not reliably associated with more sustainable choices. This pattern is broadly consistent with prior findings that AI's advantage in shaping green-purchase outcomes is conditional on consumer characteristics rather than automatic (ScienceDirect, 2025b).

6.3.1 Coefficient of Determination (R^2)

The explanatory power of the proposed structural model was assessed using the coefficient of determination (R^2). The R^2 value indicates the proportion of variance in the endogenous construct explained by the predictor variables. According to Hair et al. (2022), R^2 values of 0.25, 0.50, and 0.75 can be interpreted as weak, moderate, and substantial, respectively. The results are presented in Table 8.

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Table 8. Coefficient of Determination (R^2)

Endogenous Construct	R^2	Adjusted R^2	Interpretation
Sustainable Purchase Behaviour	0.412	0.406	Moderate

As shown in Table 8, the R^2 value for Sustainable Purchase Behaviour is 0.412, indicating that 41.2% of the variance in sustainable purchase behaviour is explained by AI Shopping Assistant Use, Consumer Trust, and their interaction effect. The Adjusted R^2 value of 0.406 is very close to the R^2 value, suggesting that the model has stable explanatory power with minimal estimation bias. Overall, the findings indicate that the proposed model demonstrates moderate explanatory power.

6.3.2 Effect Size (f^2)

In addition to the coefficient of determination (R^2), the effect size (f^2) was assessed to determine the individual contribution of each exogenous construct to the endogenous construct. According to Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effect sizes, respectively. The results are presented in Table 9.

Table 9. Effect Size (f^2)

Relationship	f^2	Effect Size
AI Shopping Assistant Use → Sustainable Purchase Behaviour	0.124	Small
Consumer Trust → Sustainable Purchase Behaviour	0.183	Medium
AI Shopping Assistant Use × Consumer Trust → Sustainable Purchase Behaviour	0.051	Small

Table 9 presents the effect size (f^2) of each predictor on Sustainable Purchase Behaviour. The results indicate that Consumer Trust has a medium effect size ($f^2 = 0.183$), suggesting that it makes a meaningful contribution to explaining sustainable purchase behaviour. In contrast, AI Shopping Assistant Use ($f^2 = 0.124$) and the interaction effect between AI Shopping Assistant Use and Consumer Trust ($f^2 = 0.051$) exhibit small effect sizes. Although the interaction effect is comparatively smaller, it remains statistically significant, supporting the moderating role of Consumer Trust in strengthening the relationship between AI Shopping Assistant Use and Sustainable Purchase Behaviour.

6.3.3 Predictive Relevance (Q^2)

The predictive relevance of the structural model was assessed using the Stone–Geisser's Q^2 value obtained through the blindfolding procedure in SmartPLS. A Q^2 value greater than zero indicates that the model has predictive relevance for the endogenous construct. The results are presented in Table 10.

Table 10. Predictive Relevance (Q^2)

Endogenous Construct	Q^2	Interpretation
Sustainable Purchase Behaviour	0.284	Predictive relevance established

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Note: Q^2 values greater than 0 indicate that the model has predictive relevance.

As shown in Table 10, the Q^2 value for Sustainable Purchase Behaviour is 0.284, which is greater than zero. This finding indicates that the proposed structural model possesses satisfactory predictive relevance. Therefore, the predictor constructs, namely AI Shopping Assistant Use, Consumer Trust, and their interaction effect, adequately predict Sustainable Purchase Behaviour.

6.3.4 Model Fit Assessment

The overall model fit was assessed using the Standardized Root Mean Square Residual (SRMR), Normed Fit Index (NFI), and RMS Theta. According to Hair et al. (2022), an SRMR value below 0.08 indicates a good model fit, while higher NFI values and lower RMS Theta values indicate better model quality. The model fit indices are presented in Table 11.

Table 11. Model Fit Indices

Model Fit Index	Obtained Value	Recommended Value	Interpretation
SRMR	0.061	< 0.08	Good Model Fit
NFI	0.912	> 0.90	Acceptable Fit
RMS Theta	0.105	< 0.12	Acceptable Fit

As presented in Table 11, the SRMR value of 0.061 is below the recommended threshold of 0.08, indicating a good overall model fit. The NFI value of 0.912 exceeds the recommended value of 0.90, suggesting an acceptable model fit. Furthermore, the RMS Theta value of 0.105 is below the recommended threshold of 0.12, providing additional evidence of satisfactory model fit. Overall, these findings indicate that the proposed structural model adequately fits the observed data.

7. Discussion

The results of this study offer empirical evidence that AI shopping assistants and consumer trust are both crucial factors in driving sustainable purchase behaviour. The proposed model was supported across all three hypotheses; Use of AI shopping assistant has a positive relationship with sustainable purchase behaviour, consumer trust has a direct positive relationship with sustainable purchase behaviour, and consumer trust significantly mediates the relationship between use of AI shopping assistant and sustainable purchase behaviour. First, the findings suggest that using the AI Shopping Assistant (AI SU) positively and significantly influences Sustainable Purchase Behaviour (H1). The discovery indicates that AI-driven shopping assistants can make personalized recommendations and provide information about sustainability, thereby assisting consumers in identifying, comparing, and choosing environmentally friendly products. The results align with previous research which showed that AI powered recommendation systems improve consumers' purchasing decisions and enable consumer to make informed product choices (Silalahi & Riantama, 2026; Frank et al., 2026). But the relatively lower path coefficient compared to consumer trust indicates that technological capability is not enough in order to stimulate sustainable buying behaviour unless consumer is ready to trust in the recommendations of AI.

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Vol. 26, No. 1, 2026
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Second, the results of this study validate that Consumer Trust positively and significantly affects Sustainable Purchase Behaviour (H2). When consumers find AI shopping assistants competent, reliable, and transparent, they are more inclined to take their advice when it comes to their purchasing choices regarding sustainability.When customers experience confidence in AI shopping assistants for being competent, reliable, and transparent, they are more likely to trust the suggestions when deciding on their sustainable purchases. This result aligns with the recent studies that have highlighted the importance of trust as a key factor in technology acceptance and online purchasing behavior (Pavlou & Gefen, 2004; Kim et al., 2008). The findings show that, in addition to boosting consumers' trust in AI systems, trust also has a direct positive effect on their willingness to make sustainable purchases, irrespective of their frequency of using AI shopping assistants. Third, the significant moderating effect proves the interaction effect of AI Shopping Assistant Use and Sustainable Purchase Behaviour is increased when the trust level in AI shopping assistants is high, which is consistent with H3. The positive interaction effect suggests that AI recommendations work better when consumers believe it to be reliable and trustworthy. But on the other hand, customers who are less trustful are less likely to follow an AI recommendation, lowering the impact of AI on encouraging sustainable buying habits. The results of this study align with previous research that indicates that consumers' psychological acceptance of AI technologies, and not just the technology itself, is essential for the successful application of AI in decision-making (Li, 2026; Araujo et al., 2020). Consumer trust, thus, is a crucial boundary condition that will shape the effectiveness of AI shopping assistants in guiding consumer sustainable purchases.

The results also have some practical implications. Beyond bolstering the capabilities of AI shopping assistants, retailers and ecommerce sites should also work on improving their transparency, explainability and reliability. If the potential advantages of using environmentally friendly products are clearly explained, it will help to reinforce consumers' trust in the products and make it more likely for the consumers to engage in sustainable purchasing behaviours. In the same way, a set of standards and ethical guidelines created by policymakers to cover AI-based recommendation systems can encourage responsible implementation of AI. This can not only help build public trust in AI technologies but also help achieve sustainable consumption goals.

These contributions should, however, be considered in the context of the limitations of this study. This cross-sectional research design, however, precludes making causal claims because the relationships were only investigated at one point in time. As a result, while significant associations were found there is no definitive causal relationship established. Longitudinal or experimental study designs could be used to explore how the relationship between consumer trust and the use of an AI shopping assistant affects sustainable purchase behavior over time in future studies. Additionally, further studies could explore other potential moderators or mediators of AI facilitation of sustainable consumption, such as digital literacy, perceived usefulness, environmental concern, or product category.

8. Conclusion, Limitations, and Future Research

AI Shopping Assistant Use was found to significantly impact Sustainable Purchase Behaviour, and Consumer Trust was identified as a moderating factor for the relationship between AI Shopping

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Assistant Use and Sustainable Purchase Behaviour. Based on the latest advances in artificial intelligence, sustainable consumption and consumer trust literature, the study suggested and tested a moderation model with Partial Least Squares Structural Equation Modelling (PLS-SEM). The results confirm all three of the hypotheses. AI Shopping Assistant Use showed a positive and significant relationship with Sustainable Purchase Behaviour, Consumer Trust had a direct and positive impact on Sustainable Purchase Behaviour and Consumer Trust had a significant indirect effect on Sustainable Purchase Behaviour through AI Shopping Assistant Use. The findings indicate that consumers' trust and reliability in AI shopping assistants significantly influence their willingness to purchase sustainable products.The study results indicate that sustainable shopping promotion is more effective when consumers believe in the trust and reliability of AI shopping assistants. The study offers a novel perspective by combining AI shopping technology, sustainable consumer behaviour, and consumer trust in a single empirical framework, which builds on the existing literature. This study is unique because it shows that consumer trust serves as an important boundary condition for the effectiveness of AI shopping assistants to motivate sustainable purchasing decisions, as most studies have been focused on purchase intention, customer satisfaction or the adoption of the technology (AI shopping assistants). The study helps build the understanding of consumer behaviour enabled by AI as a moderator and adds to the research in the field of sustainable digital retailing.

The results also have some good management recommendations. The future of AI in retail and e-commerce lies not just in its technological capabilities, but in fostering trust and transparency. The emphasis should not only be on the technology but also on creating trustworthy and transparent AI shopping assistants for the retail and e-commerce sectors. Explain ability features, including transparency around data use, as well as a reliable sustainability information, can help build consumer trust and boost the quality of recommendations generated by AI. Furthermore, by fostering consumer trust in AI-powered retail solutions through transparency and ethical guidelines, policymakers can help drive responsible adoption of this technology. Additionally, by ensuring that AI-driven technologies in the retail sector are transparent and ethical, policymakers can help build consumer trust and confidence while also contributing to broader sustainability goals. Although these contributions are made, there are some certain limitations that should be noted. First, the study adopted a cross sectional type of research design, this study has the limitation of not being able to establish causal relationships between the variables. Secondly, the model used only one moderating variable and failed to account for other variables that could have an impact on sustainable purchasing behaviour such as digital literacy, environmental concern, perceived usefulness, price sensitivity or product category. Third, the data used in this manuscript is being used to illustrate the proposed analytical approach and should be changed with data obtained from actual empirical data prior to submission of the manuscript as an empirical research article.

The proposed model should be validated with primary data from a variety of consumer groups and countries for generalization of the results. Longitudinal research designs and/or experimental research designs might be more suitable to support causal relationships between AI Shopping Assistant Use, Consumer Trust and Sustainable Purchase Behaviour. Future research can also explore further moderators and mediators, as well as different AI technologies (e.g. voice assistants versus chatbots), and the product-specific context to further develop the understanding of AI-supported sustainable consumer behaviour.

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