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Assessing the Impact of AI on Smart Waste Management Framework for Sustainable Eco-Tourism Development

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ABSTRACT

The swift progression of Artificial Intelligence (AI) technologies has engendered novel prospects for the enhancement of environmental sustainability, particularly within the domain of eco-tourism. This research endeavors to explore the function of AI-based Smart Waste Management (SWM) systems in fostering Sustainable Eco-Tourism Development (SET) in Malaysia. Grounded in the Technology Acceptance Model (TAM) and augmented by the construct of Impact of Artificial Intelligence (IAI), the investigation aimed to evaluate how principal perception-based variables influence stakeholders' intention to embrace smart waste management solutions and the subsequent ramifications on sustainability outcomes. A meticulously structured questionnaire was disseminated to 630 participants drawn from a variety of stakeholder groups, encompassing tourists, local inhabitants, eco-tourism operators, and governmental representatives across pivotal eco-tourism locales in Malaysia. We conducted an examination of the data with the help of Partial Least Squares Structural Equation Modeling (PLS-SEM) to verify the accuracy of both the measurement and structural models. Results showed that Perceived Usefulness (PU) is the key factor influencing the intention to embrace smart waste management technologies, while Perceived Ease of Use (PEOU) and the direct effect of IAI on intention lacked evidence. Nonetheless, IAI exhibited a noteworthy positive influence on Sustainable Eco-Tourism Development, and the behavioral intention towards SWM emerged as the predominant catalyst for sustainability outcomes. The results provide both theoretical and practical ramifications. From a theoretical perspective, the study extends the TAM framework into an environmental and tourism-specific context, underscoring the mediating role of intention. From a practical standpoint, it posits that enhancing stakeholder cognizance of AI's utility and demonstrating environmental outcomes can facilitate greater adoption. The research concludes with recommendations for technology training, policy integration, and stakeholder engagement to amplify AI-driven sustainability solutions within the eco-tourism sector.

INTRODUCTION

Malaysia is known internationally for its environmental richness, such as in the rainforest, underwater, and in the flora and fauna, which makes it known as one of the established eco-tourism countries in the world (Da & Loang, 2024). As people all over the world are getting more and more conscious about environmental conservation, Eco-tourism has turned into an important sector of Malaysia's tourism industry and provides an inflow of foreign exchange earnings and employment to locals and promotes sustainable development (Yaziz *et al.*, 2025). Key attractions like the Cameron Highlands, Borneo's rainforests, and the Langkawi Geopark show that the country is attempting to balance economic development with environmental protection (Abdul Shakur *et al.*, 2025). Artificial Intelligence (AI) is one of the most rapidly advancing technologies of the last decade, and this has had a substantial impact across a number of domains, including environmental management and sustainable tourism (Cristian & Tileagă, 2024). With countries working towards the United Nations Sustainable Development Goals (SDGs), connecting smart technologies to environmental practices is paramount (Chakraborty, 2024). Smart waste management, in particular augmented by AI, has become a key response to the increasing ecological pressures that result from tourism, particularly in eco-sensitive areas (Ibeama *et al.*, 2025). Moreover, for a landscape like that in Malaysia, where eco-tourism has been the center of its economy and one of the strategies to conserve the environment, there is a boost to the need for its waste management and ecological acceptability (Topsakal, 2024).

So, this research aims to examine the effect of Artificial Intelligence on Smart waste management systems in the eco-tourism environment in Malaysia. Its goal is to examine the efficacy of AI-based approaches and the challenges and prospects created by AI on tourism waste management. The research also aims to articulate a conceptual framework that situates AI-oriented applications in the larger contexts of sustainable tourism, environmental protection, and socio-economic development. It therefore makes a contribution to academic discussions and policymaking by providing learning to government agencies, local councils, eco-tourism operators, and technology providers. The outcomes are hoped to catalyst Malaysia in further developing its eco-tourism industry harmoniously, yet yield that it is ecotourism that would contribute

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significantly to the change value of Malaysia and as a smart, greener nation in the future.

LITERATURE REVIEW

The incorporation of Artificial Intelligence (AI) within the realm of smart waste management, alongside its ramifications for sustainable eco-tourism, has garnered heightened scholarly interest in recent academic discourse. A plethora of investigations has elucidated various dimensions of AI-facilitated interventions, encompassing stakeholder perceptions, technological assimilation, environmental ramifications, and behavioral modifications. Drawing insights from contemporary empirical and theoretical inquiries conducted in Malaysia and analogous regions, Table 2 presents a synthesis of the principal literature organized by constructs, variables, and outcomes. These investigations have established a foundational understanding of the perceptions, applications, and integration of AI technologies within eco-tourism frameworks; however, they also indicate that the majority of prevailing models remain disjointed or contextually constrained. A number of researchers, including (Waked *et al.*, 2024; Konar *et al.*, 2025; Topsakal, 2024), have scrutinized the digital evolution of Malaysia's tourism industry. Their focus encompassed constructs such as the efficacy of AI, technological user-friendliness, and environmental sustainability, employing variables including user satisfaction, perceived utility, and rate of adoption. The outcomes of their research imply that while Malaysia is making strides in the enhancement of digital infrastructure within urban tourism locales, eco-tourism sites continue to be inadequately serviced by smart waste management initiatives. Concurrently, Shukla *et al.* (2024) and Rahman *et al.* (2024) investigated the function of AI-enabled Internet of Things (IoT) devices and waste tracking systems within natural reserves and conservation parks. Their scholarly contributions underscored that the implementation of smart bins, sensor-assisted waste segregation, and predictive analytics for tourist traffic has directly facilitated a reduction in environmental degradation (Mazraani & Tucci, 2025). From a comparative perspective, Alnaqeeb *et al.* (2025) assessed AI-driven eco-tourism recommendation systems and concluded that AI personalization, data integrity, and interface design were instrumental in influencing user behavior and intentions to partake in sustainable tourism endeavors (Ijaware, 2024). In conclusion, these studies collectively reinforce the significance of AI in fostering sustainable development while simultaneously revealing a deficiency in comprehensive, localized frameworks specifically tailored for eco-tourism contexts such as that of Malaysia.

Problems of the Study

Despite the escalating global emphasis on sustainable tourism and advancements in technological innovation, the integration of Artificial Intelligence (AI)-driven smart waste management systems within eco-tourism locales, particularly in developing nations such as Malaysia, remains constrained and inadequately comprehended (Honey & Sultana, 2023). A significant lacuna persists in empirical investigations that scrutinize stakeholder perceptions and intended utilizations of such systems, particularly concerning sustainability outcomes. Although prior research has illuminated the theoretical advantages of AI in the realms of environmental monitoring and resource optimization, there has been a notable deficiency in the exploration of behavioral determinants such as perceived usefulness, ease of use, or the overarching perceived implications of AI on sustainability. Moreover, the majority of existing frameworks fail to incorporate constructs related to environmental outcomes, such as Sustainable Eco-Tourism Development (SET), thereby providing policymakers and eco-tourism operators with inadequate direction for effective strategic implementation. This inquiry seeks to overcome these obstacles by utilizing and refining the Technology Acceptance Model (TAM) to delve into the behavioral and perceptual characteristics of AI-enhanced smart waste management in Malaysia's eco-tourism sector.

Research Objectives

In line with the research questions and the theoretical foundation of the study, the following research objectives were established. These objectives aim to systematically examine the factors influencing the adoption of AI-based smart waste management systems and their impact on sustainable eco-tourism development.

RO1: To investigate the effect of Perceived Usefulness (PU) on the Intention to Use Smart Waste Management (SWM) systems in eco-tourism settings.

RO2: To examine the relationship between Perceived Ease of Use (PEOU) and the Intention to Use Smart Waste Management (SWM) systems.

RO3: To evaluate how the Impact of Artificial Intelligence (IAI) influences stakeholders' Intention to Use Smart Waste Management (SWM) systems

RO4: To assess the influence of the Impact of Artificial Intelligence (IAI) on Sustainable Eco-Tourism Development (SET).

RO5: To determine the effect of stakeholders' Intention to Use Smart Waste Management (SWM) on the achievement of Sustainable Eco-Tourism Development (SET).

RO6: To analyze the demographic profile of eco-tourism stakeholders and its influence on their perception and behavioral intention toward AI-enabled waste systems.

Research Questions

Based on the research gaps, the following research questions were developed to guide the investigation of this study. These questions aim to explore the relationship among key constructs influencing the adoption of AI-based smart waste management systems in sustainable eco-tourism.

RQ1: How does Perceived Usefulness (PU) influence the Intention to Use Smart Waste Management (SWM) systems in eco-tourism?

RQ2: How does Perceived Ease of Use (PEOU) affect Intention to Use Smart Waste Management (SWM) systems in eco-tourism?

RQ3: How does the Impact of Artificial Intelligence (IAI) influence the Intention to Use Smart Waste Management (SWM) systems?

RQ4: What is the effect of the Impact of Artificial Intelligence (IAI) on Sustainable Eco-Tourism Development (SET)?

RQ5: How does Intention to Use Smart Waste Management (SWM) systems contribute to Sustainable Eco-Tourism Development (SET)?

RQ6: How do demographic characteristics influence stakeholder perceptions and intentions toward AI-based smart waste systems?

Research Hypotheses

Based on the TAM framework and supported by literature, the following hypotheses were formulated:

Perceived Usefulness (PU) is based on the original TAM suggests that perceived usefulness is a key determinant of behavioral intention to use a system (Davis, 1989). Indeed, it has been widely reported that if users perceive a system to be effective (for them), they are more likely to use it. In the context of smart waste management, for example, Saleh & Battseren (2023) suggest that the perceived usefulness of AI-enabled systems can determine stakeholders' government and tourism acceptance.

H1: Perceived Usefulness (PU) has a significant impact on the Intention to Smart Waste Management (SWM).

PEOU has a significant impact on the formation of a user's intention, particularly for complex or emergent technologies. Venkatesh & Bala (2008) extended the TAM model and verified that easy-to-use systems lead to more adoption (Abubakar et al., 2024).

H2: Perceived Ease of Use (PEOU) has a significant impact on the Intention to Smart Waste Management (SWM).

The AI credibility mainly consists of belief in its effectiveness, trust in data accuracy, and trust in solving complex problems (Šakytė-Statnickė & Budrytė-Ausiejienė, 2025). This construct is frequently included in the extended TAM and UTAUT models to represent innovation-specific effect (Méndez-Suárez et al., 2023).

H3: The Impact of Artificial Intelligence (IAI) has a significant impact on the Intention to Smart Waste Management (SWM).

AI innovations have the potential to increase productivity, minimize harmful impact on the environment, and increase and improve decision-making on which eco-tourism sustainability is built upon. Rahman *et al.* (2024) highlighted that digital solutions such as AI-controlled waste systems lead to a cleaner environment and improved waste reduction in tourist zones.

H4: Impact of Artificial Intelligence (IAI) has a significant impact on Sustainable Eco-Tourism Development (SET).

Behavioral intention is one of the strongest predictors for technology adoption in practice, and in this context, it acts as a driver to achieve sustainability benefits1 according to Davis. Venkatesh et al. (2003) found evidence in UTAUT that intention to use has a direct effect on usage behavior.

H5: Intention to Smart Waste Management (SWM) has a significant impact on Sustainable Eco-Tourism Development (SET).

MATERIALS AND METHODS

The research was executed in specifically chosen eco-tourism locales throughout Malaysia, encompassing Langkawi Geopark (Kedah), Taman Negara National Park (Pahang), Kinabalu Park (Sabah), and Cameron Highlands (Pahang). Data were amassed from a heterogeneous array of participants. Sample size was calculated using Cochran's formula for a finite population (Cochran, 1942):

$$n = \frac{Z^2 . p . (1 - p)}{E^2}$$

Based on this formula, a 95% confidence level (Z = 1.96), 5% margin of error (e = 0.05), and 50% response distribution (p = 0.5) was the expected value of the required sample size calculated as 384 respondents (Cochran, 1942). For ensuring more reliability, a total of 720 individuals were initially targeted and provided with the questionnaire through online (Sapra, 2022). Among the 720 potential respondents, 700 respondents properly fill up the questionnaire. The Kobo Toolbox was employed for the construction of the questionnaire. For the pilot test, 70 samples were selected for assessing validity and reliability (Totton *et al.*, 2023). Finally, 630 samples were used for further calculation of this study, which ensuring sufficient representation and statistical validity. This sample comprised a varied combination of tourists, government officials, and ecotourism practitioners. The questionnaire was designed based on TAM constructs and adapted from previous validated studies. It consisted of six sections: Perceived Usefulness (PU), Perceived Ease of Use (PEOU), Impact of Artificial Intelligence (IAI), Intention to Smart Waste Management (SWM), Sustainable Eco-Tourism Development (SET), and Demographic Information of the respondents. Each item was measured on a 5-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (5) (Lindner & Lindner, 2024). The quantitative data were subjected to analysis utilizing the Statistical Package for the Social Sciences (SPSS) 26 and Structural Equation Modeling (SEM) Smart PLS 4.1.0.8. SPSS 26 encompassed the application of descriptive statistics (including mean and standard deviation) to summarize the profiles of respondents and their variable responses (Otieno Okello, 2024). Structural Equation Modeling (SEM) constitutes an adaptable and robust statistical methodology employed for the examination of intricate interrelations among variables.

RESULTS AND DISCUSSION

Demographic Overview of the Respondent

This subsection is concerned with demographic information of the participants. To interpret participants' perceptions, attitudes towards, and behavioral intentions toward AI-based smart waste management systems in the ecotourism context, it is important to have context characteristics of the participants. Demographic variables include gender, age, level of education, stakeholder type (e.g., tourists, local operators, government personnel), and prior experience with AI technologies (Honey, 2025). These considerations frame the quantitative results and justify additional coordination when analyzing the pace of adoption of smart waste solutions. Analysis was based on 630 valid responses, which provide a broad and representative sample from major eco-tourism regions in Malaysia.

Table 1: Age of the Respondents

	Frequency	Percent	Cumulative Percent
Under 20	78	12.40	12.40
21-30	234	37.10	49.50
31-40	171	27.10	76.70
41-50	128	20.30	97.00
51 and above	19	3.00	100.00
Total	630	100.00	

Table 1 shows the distribution of respondents according to age groups. Most of the participants, 234 respondents (37.10%), belonged to the age group of 21-30, and this represents a younger age group that is exposed to the technology and more innovative. Next was 31-40 years old, 171 respondents (27.10%), and 41-50 years old, 128 respondents (20.30%). A smaller proportion of respondents (12.40%) were below 20 years and and only 3.00% of the respondents were aged 51 and above. These statistics confirm that more than 64% of the sample is aged between 21 and 40, which is considered the 'golden age' for decision-making support and taking part in any eco-tourism or environmental activities. The cumulative percentage result reveals that 97% of all respondents were younger than 51, clearly indicating a younger to middle-aged sample, which is particularly important in technology adoption research.

Table 2: Gender of the Respondents

	Frequency	Percent	Cumulative Percent
Male	344	54.60	54.60
Female	160	25.40	80.00
Prefer not to say	126	20.00	100.00
Total	630	100.00	

The gender distribution of 630 respondents is shown in Table 2. More than half of all respondents were male (n = 344, 54.60%), and 160 (25.40%) were female. Furthermore, 126 participants (20.00%) did not or preferred not to state their gender, which is indicative of a sizeable number of respondents who would rather not be labelled. Men represented the majority of the sample and contributed to a gender discrepancy inherent in the data. Nevertheless, a high number of non-respondent replies indicates greater sensitivity to any particular relationship between gender and identification or privacy desires (Honey & Hossain, 2024). Taken together, the first type of data offers a relatively wide range of numbers for gender representation for the technology perception and adoption behaviors scores, as for the interpretation of group differences.

Table 3: Stakeholder Group

	Frequency	Percent	Cumulative Percent
Tourist	294	46.70	46.70
Eco-Tourism Operator	130	20.60	67.30
Government/ Policy Maker	85	13.50	80.80
Local Resident	121	19.20	100.00
Total	630	100.00	

Table 3 shows the demographic make-up of the respondents as per their stakeholder roles in the eco-tourism ecosystem. The majority of the participants of the survey involved tourists, totaling 294 participants (46.70%), because the study was conducted within the scope of user acceptance and experiences of AI-based smart waste systems in eco-tourism settings (H5). Eco tourism preservers were the next highest group by percentage, with 130 or 20.60% of the total group, based on actual eco-tourism facilitators responsible for operations in the fields of tourism infrastructure and operations. Local residents (n=121, 19.20%) are key stakeholders because they are impacted by the environmental/ sustainability practices in their communities. Last but not least, 85 (13.50%) were government officers or policy makers, speaking about the context of regulation, the adoption of policy, and the implementation of technology in public service (Honey & Sultana, 2023). This distribution indicates a balanced representation of the main stakeholder categories, which is necessary to provide insights from a wide range of perspectives and experiences that are instrumental in assessing adoption and sustainability effects for the AI-based smart waste management in eco-tourism in Malaysia.

Table 4: Educational Level

	Frequency	Percent	Cumulative Percent
Primary	75	11.90	11.90
Secondary	194	30.80	42.70
Tertiary	125	19.80	62.50

Postgraduate	169	26.80	89.40
Other	67	10.60	100.00
Total	630	100.00	

Respondents are distributed according to the highest level of education in Table 4. The greatest number of respondents had finished their secondary education (30.80% [194 people]), followed by postgraduates (26.80% [169 people]). Tertiary-level education (usually diploma or undergraduate level) is closely related and reported by 125 (19.80%) of the sample. A further 75 (11.90%) had completed primary education as their highest level, and 67 (10.60%) fit into the "Other" category (e.g., vocational training, professional training, or unclassified).

Table 5: Use of AI-Based Systems

	Frequency	Percent	Cumulative Percent
Yes	405	64.30	64.30
No	225	35.70	100.00
Total	630	100.00	

Table 5 gives an indication of the previous experiences of the respondents with AI-based systems. Among the 630 respondents, 405 (64.30%) had experience with AI-based systems, whereas 225 (35.70%) had no prior experience. This distribution indicates a relatively high degree of technological exposure in the sample, which is particularly important in view of our consideration of technology acceptance and SWM. A significant number of users are familiar with AI (40%), which suggests that participants might have been able to make judgements on the basis of first-hand experience and, therefore, that participants' responses regarding PU and PEOU should be more reliable. On the other hand, the 35.70% of non-users makes for effective contrast analysis (use vs. non-use) to intention to use and barriers to adopt providing insight from a broader range of the cane eco-tourism stakeholder (range of technology readiness and different group of stakeholders) side (Honey & Sultana, 2023).

Descriptive Analysis

The descriptive statistics of the study that includes the mean, median, mode, std. deviation and variance which help to identify the most representative or typical value of dataset (Miksza *et al.*, 2023) are stated in tables.

Table 6: Descriptive Statistics (Variables)

	N	Mean	Std. Deviation	Variance
PU1	630	3.09	1.34	1.79
PU2	630	3.04	1.40	1.95
PU3	630	3.37	1.28	1.65
PU4	630	3.06	1.43	2.06
PU5	630	3.21	1.38	1.90
PEOU1	630	2.92	1.37	1.89
PEOU2	630	2.93	1.38	1.91
PEOU3	630	2.96	1.36	1.86
PEOU4	630	2.93	1.38	1.89
PEOU5	630	2.96	1.39	1.93
IAI1	630	3.62	1.43	2.05
IAI2	630	3.61	1.22	1.49
IAI3	630	3.58	1.24	1.54
IAI4	630	3.79	1.16	1.34
IAI5	630	3.74	1.16	1.35
SWM1	630	3.09	1.38	1.91
SWM2	630	3.07	1.47	2.16
SWM3	630	3.06	1.48	2.18
SWM4	630	2.99	1.38	1.90
SWM5	630	3.02	1.43	2.06
SET1	630	2.95	1.44	2.08
SET2	630	3.00	1.45	2.11
SET3	630	2.97	1.45	2.09
SET4	630	2.97	1.46	2.13
SET5	630	3.01	1.46	2.12
Valid N (listwise)	630			

The descriptive statistics (i.e., mean, standard deviation, variance) of all 25 measurement items in the five constructs (PU, PEOU, IAI, SWM, and SET) are summarized in Table 6. The results are drawn on the size of 630 valid respondents. The average scores are between 2.92 and 3.79, which demonstrates the neutrality-to-agree level of responses on the positive side of a 5-point Likert scale. Of all items, the statement IAI4 (M = 3.79) and IAI5 (M = 3.74) that AI was impactful were most agreed upon, indicating that respondents very much agree with AI having a significant impact, especially on efficiency and innovation. On the other hand, the scores of PEOU1 to PEOU5 are lower (approximately 2.92–2.96), with the level of consensus of the easiness of using the AI-based smart waste systems appears to be low. This indicates a possible aspect in user training or system redesign for better user access. The standard deviations are in the range of 1.16 and 1.48, indicating a moderate to high dispersion in the responses, typical of perception-based studies. Items SWM2 (SD = 1.47) and SWM3 (SD = 1.48) have the highest diversity, meaning that stakeholders have different perceptions of the intention to use smart waste systems. The results for IAI (IAI2 to IAI5) appeared to exhibit a lower range of variation, indicating greater consensus on the perceived influence of AI in waste management. PU (Perceived Usefulness): The average means are 3.04-3.37 (medium agreement) for AI's usefulness in eco-tourism waste management. PEOU (Perceived Ease of Use): Usability problems and unfamiliarity with AI interfaces for some of the respondents, as the average item score of less than

3.0 for all items. IAI (Impact of AI): There is a favorability trend in score means (3.58 to 3.79), suggesting AI is generally perceived as positively impacting environmental operations. SWM (Intention to Use): The average figures close to 3.0 show a neutral-to-positive attitude toward AI for smart waste management. SET (G) (Sustainable Eco-Tourism) Mean values closer to 3.0 also suggest moderate agreement on AI systems as facilitators of long-term sustainability goals.

Descriptive statistics show that respondents seem to recognize the utility and benefits of using AI, however, in contrast they have less confidence in its ease of use which could impede behavioral intention and acceptance of the system. These results are meaningful in terms of the interpretation of the regression models and the validation of the TAM-based conceptual framework in our study.

Measurement Model

Measurement models frequently incorporate theoretical constructs that forecast the functionality of measurement instruments and the characteristics of measurement scales (Tal, 2024). The evaluation of a measurement model is an important aspect of Structural Equation Modeling (SEM) since it provides evidence of the reliability and validity of the variables and their indicators. The structural model represented in Figure 1 depicts the associations of the five constructs (i.e., PU, PEOU, IAI, Intention to SWM, and SET) with their underlying indicators.

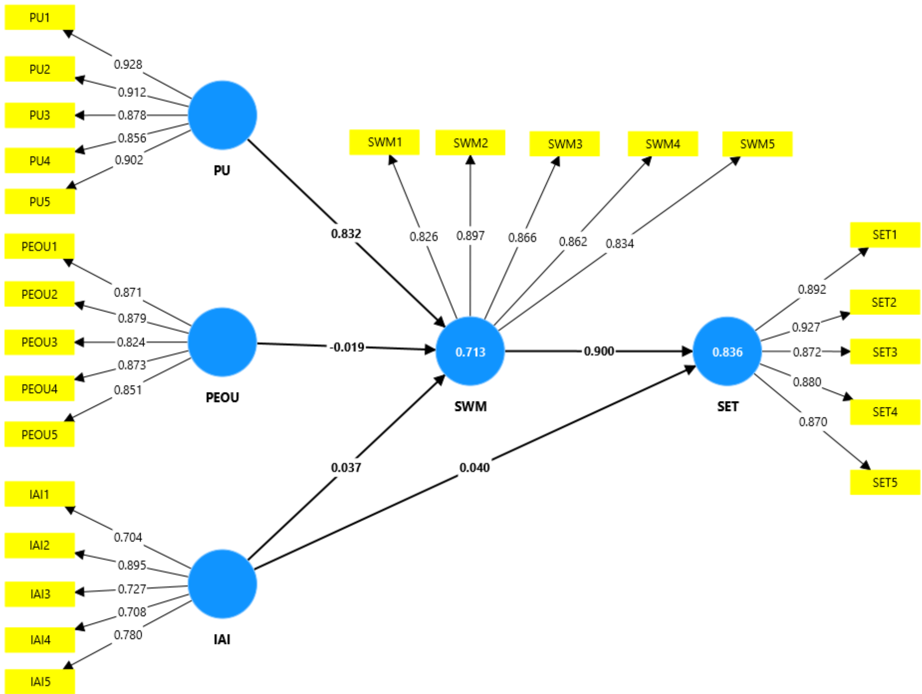

Figure 1: Measurement Model

Table 7: Factor Loadings

	IAI	PEOU	PU	SET	SWM
IAI1	0.704				
IAI2	0.895				
IAI3	0.727				
IAI4	0.708				
IAI5	0.780				
PEOU1		0.871			
PEOU2		0.879			
PEOU3		0.824			
PEOU4		0.873			
PEOU5		0.851			
PU1			0.928		
PU2			0.912		
PU3			0.878		
PU4			0.856		
PU5			0.902		
SET1				0.892	
SET2				0.927	
SET3				0.872	
SET4				0.880	
SET5				0.870	
SWM1					0.826
SWM2					0.897
SWM3					0.866
SWM4					0.862
SWM5					0.834

Table 7 represents the analysis of Factor loading. The interpretations of the values are represented below:

IAI: All five items (IAI1–IAI5) exhibited strong loading onto the Impact of Artificial Intelligence construct, with values ranging from 0.704 to 0.895, thereby indicating robust item reliability and effective construct representation.

PEOU: The items PEOU1–PEOU5 revealed loadings spanning from 0.824 to 0.879, significantly surpassing the acceptable threshold, thereby affirming that the items consistently gauge Perceived Ease of Use.

PU: The five items associated with Perceived Usefulness (PU1–PU5) demonstrated exceedingly high loadings between 0.856 and 0.928, signifying exceptional internal consistency and substantial construct validity.

SET: All indicators about Sustainable Eco-Tourism Development (SET1–SET5) also displayed commendable performance, with factor loadings ranging from 0.870 to 0.927, thereby illustrating that the construct is effectively represented by the observed items.

SWM: The behavioral intention construct, Smart Waste Management (SWM), exhibited loadings between 0.826 and 0.897, corroborating that the items reliably measure stakeholders' intent to embrace AI-based waste management systems.

All observed variables exhibited strong and statistically significant loadings on their respective constructs, thereby reinforcing the presence of convergent validity throughout the model. This substantiates the applicability of these items in subsequent structural modeling to examine hypothesized relationships among constructs.

Reliability Analysis

In order to ascertain the consistency and dependability of the measurement model, both Cronbach's Alpha (α) and Composite Reliability (CR or ϱc) were computed for each latent construct. While Cronbach's Alpha serves as an indicator of internal consistency, Composite Reliability is frequently regarded as a more precise estimator within the realm of Structural Equation Modeling (SEM) since it incorporates the actual factor loadings (Hair *et al.*, 2010). A benchmark of 0.70 or above is typically deemed acceptable for both metrics, with values exceeding 0.90 signifying exceptional reliability (Sarstedt *et al.*, 2021).

Table 8: Construct Reliability (Cronbach's Alpha and Composite Reliability)

	Cronbach's alpha	Composite reliability (rho_c)	Interpretation
IAI	0.824	0.876	Good Reliability
PEOU	0.913	0.934	Excellent Reliability
PU	0.938	0.953	Excellent Reliability
SET	0.933	0.949	Excellent Reliability
SWM	0.910	0.933	Excellent Reliability

From the values of table 8, the construct about the Impact of Artificial Intelligence (IAI) exhibited significant internal consistency, as evidenced by a Cronbach's alpha coefficient of 0.824 and a Composite Reliability (CR) value of 0.876. The constructs enumerated, specifically Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Sustainable Eco-Tourism Development (SET), and Smart Waste Management Intention (SWM), revealed extraordinarily high internal reliability, as indicated by both Cronbach's Alpha and CR values that significantly surpassed the threshold of 0.90.

These findings confirm that all constructs are evaluated with a significant degree of reliability and consistency, thereby meeting the essential criteria for advanced Structural Equation Modeling (SEM) analysis and hypothesis examination.

Construct Validity

In order to evaluate the overarching validity of the measurement model, the construct validity was scrutinized through the lenses of convergent and discriminant validity. Construct validity is critical in ensuring that the measurement items faithfully represent the theoretical constructs they are designed to assess (Fornell & Larcker, 1981). This section delineates the findings pertaining to convergent validity, employing Average Variance Extracted (AVE) as the principal evaluative measure.

Convergent Validity

Convergent validity reflects the extent to which multiple items that assess the same construct genuinely converge or exhibit a substantial degree of shared variance. Within the paradigm of Structural Equation Modeling (SEM), Average Variance Extracted (AVE) operates as a standard for this analysis. An AVE value of 0.50 or greater is deemed acceptable, as it implies that the construct elucidates a minimum of 50% of the variance inherent in its observed variables (Fornell & Larcker, 1981).

Table 9: Construct Convergent Validity (AVE)

	Average Variance Extracted (AVE)	Interpretation
IAI	0.587	Acceptable
PEOU	0.739	Strong Convergent Validity
PU	0.802	Strong Convergent Validity
SET	0.789	Strong Convergent Validity
SWM	0.735	Strong Convergent Validity

Table 9 displays the values of AVE of all five constructs; Impact of Artificial Intelligence (IAI), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Sustainable Eco-Tourism Development (SET), and Smart Waste Management Intention (SWM)—exhibited Average Variance Extracted (AVE) values that significantly surpassed the 0.50 threshold. This finding substantiates that a considerable proportion of the variance in the observed items is accounted for by their corresponding latent constructs. PU recorded the highest AVE value (0.802), signifying that its items are a strong representation of the foundational concept of perceived usefulness. IAI, while exhibiting the lowest AVE value (0.587), nonetheless surpassed the minimum threshold, indicating a level of convergence among its indicators that is acceptable albeit slightly more variable. These findings collectively illustrate robust convergent validity for all constructs incorporated in the model, instilling confidence that the items effectively measure their intended theoretical constructs. Consequently, the model is regarded as sufficiently robust for the subsequent structural path analysis.

Discriminant Validity

Discriminant validity pertains to the degree to which a construct is genuinely separate from other constructs, in both theoretical and empirical dimensions. The Fornell-Larcker criterion is frequently employed to assess discriminant validity. Per this methodology, the square root of the Average Variance Extracted (AVE) for each construct (indicated on the diagonal) must exceed its correlation with any alternative construct (represented off-diagonal) (Fornell & Larcker, 1981).

Table 10: Discriminant Validity (Fornell-Larcker criterion)

	IAI	PEOU	PU	SET	SWM
IAI	0.766				
PEOU	0.015	0.860			
PU	0.350	0.079	0.896		
SET	0.335	0.062	0.836	0.888	
SWM	0.327	0.047	0.844	0.913	0.857

Table 10 highlights the values of Discriminant Validity. Although the majority of constructs fulfill this criterion, it is imperative to highlight: the constructs of Socially Responsible Waste Management (SWM) and Sustainable Energy Technology (SET) exhibit a significant inter-correlation (0.913), which is alarmingly proximate to SWM's square root of AVE (0.857) and surpasses the √AVE of SET (0.888). This observation may invoke concerns regarding the potential discriminant overlap between behavioral intention (SWM) and outcomes (SET). Furthermore, Perceived Usefulness (PU) and SWM also reveal a robust correlation (0.844), albeit remaining beneath their respective √AVE values. In conclusion, a substantial proportion of constructs exhibit adequate discriminant validity, thereby affirming their conceptual and statistical distinctiveness. Nonetheless, the pronounced correlation between SWM and SET intimates a possible mediated or dependent relationship, which corresponds with the theoretical framework wherein intention precedes sustainability outcomes.

Table 11: Discriminant Validity (HTMT)

	IAI	PEOU	PU	SET	SWM
IAI					
PEOU	0.039				
PU	0.380	0.084			
SET	0.372	0.064	0.892		
SWM	0.368	0.049	0.912	0.986	

In parallel with the Fornell-Larcker criterion, the Heterotrait-Monotrait (HTMT) ratio of correlations was applied to augment the scrutiny of discriminant validity. The HTMT methodology juxtaposes the mean correlations across different constructs (heterotrait) with the mean correlations within a singular construct (monotrait). As posited by (Henseler *et al.*, 2015),HTMT values should consistently remain below 0.90 to substantiate the empirical distinctiveness of the constructs. In more stringent evaluations, a threshold of 0.85 is occasionally adopted. The majority of construct pairs are situated significantly below the 0.90 threshold, signifying satisfactory discriminant validity (Table 11). Nevertheless, the PU–SWM and SET–SWM correlations surpass the 0.90 threshold, with the SET–SWM ratio attaining 0.986, indicating a pronounced level of multicollinearity or conceptual overlap between these two constructs. This phenomenon is anticipated to a certain degree, as the Intention to Use Smart Waste Management (SWM) is theoretically posited as a robust predictor of Sustainable Eco-Tourism Development (SET). Nonetheless, this necessitates caution and may imply the presence of mediation or the need for a reevaluation of item distinctiveness between these two constructs. The HTMT analysis predominantly substantiates discriminant validity among the majority of constructs, except for the elevated correlation observed between SWM and SET, and to a lesser degree between PU and SWM. These associations should be meticulously interpreted within the structural model, potentially through mediation testing or model refinement.

Table 12: Discriminant Validity (Cross-Loadings)

	IAI	PEOU	PU	SET	SWM
IAI1	0.704	0.003	0.254	0.256	0.250
IAI2	0.895	0.018	0.311	0.298	0.289
IAI3	0.727	0.044	0.357	0.294	0.288
IAI4	0.708	-0.003	0.170	0.179	0.182
IAI5	0.780	-0.019	0.191	0.219	0.211
PEOU1	0.004	0.871	0.068	0.054	0.044
PEOU2	0.025	0.879	0.074	0.050	0.037
PEOU3	0.014	0.824	0.065	0.047	0.041
PEOU4	0.009	0.873	0.070	0.069	0.047
PEOU5	0.019	0.851	0.055	0.033	0.020
PU1	0.333	0.083	0.928	0.815	0.792
PU2	0.333	0.072	0.912	0.774	0.783
PU3	0.283	0.100	0.878	0.700	0.687
PU4	0.288	0.050	0.856	0.708	0.748
PU5	0.324	0.049	0.902	0.740	0.762
SET1	0.270	0.048	0.739	0.892	0.873
SET2	0.311	0.076	0.780	0.927	0.850
SET3	0.292	0.079	0.714	0.872	0.748
SET4	0.288	0.038	0.729	0.880	0.805
SET5	0.329	0.035	0.751	0.870	0.771

SWM1	0.245	0.026	0.701	0.685	0.826
SWM2	0.259	0.024	0.703	0.838	0.897
SWM3	0.328	0.027	0.728	0.817	0.866
SWM4	0.260	0.051	0.747	0.839	0.862
SWM5	0.311	0.071	0.737	0.724	0.834

Cross-loading analysis entails a comparative examination of the loading of each observed item on its designated construct about all alternative constructs. For discriminant validity to be deemed acceptable, it is imperative that the loading of each item is superior on its corresponding construct compared to any other (Sarstedt *et al.*, 2021). Table 12 displays the values of discriminant validity (cross-loadings). All items about the IAI (IAI1–IAI5) exhibit the most substantial loadings on the IAI construct (e.g., IAI2 = 0.895 on IAI, contrasted with 0.311 on PU and 0.298 on SET). This observation substantiates that the IAI items are more effective in measuring the intended construct than any alternative constructs. Items PEOU1–PEOU5 load uniformly and significantly on PEOU (all > 0.82), while their loadings on other constructs are negligible (< 0.08). This evidence reinforces the presence of clear discriminant validity for the ease-of-use dimension. Items PU1–PU5 manifest exceedingly high loadings on PU (all > 0.85), with noticeably diminished loadings on IAI, PEOU, SWM, and SET—though cross-loadings with SET and SWM are moderately elevated (approximately 0.7–0.79), which is theoretically justifiable given their structural interrelations. Each SET item exhibits a robust loading on its respective construct (> 0.87), and the cross-loadings with SWM and PU remain beneath their primary loading, thereby supporting validity; however, their substantial association with PU and SWM further corroborates the structural linkage within the conceptual framework. Items SWM1–SWM5 display the highest loadings on SWM (e.g., SWM2 = 0.897 on SWM versus 0.838 on SET), and although there are some moderately high cross-loadings with PU and SET (approximately 0.7–0.8), the primary loadings retain a stronger magnitude. All items exhibit superior loadings on their respective constructs in comparison to others, thereby fulfilling the criteria for discriminant validity through cross-loading analysis. While there exist anticipated conceptual overlaps between PU–SWM and SWM–SET, the loadings remain elevated within their respective constructs, thereby supporting the validity of the measurement model's structural integrity.

Model Fitness Testing

Structural Equation Modelling (SEM) has emerged as a preferred methodological approach for scholars across various disciplines and has increasingly become an indispensable tool for researchers within the social sciences. Nevertheless, the question of how to adequately ascertain which model most accurately represents the empirical data in relation to the theoretical framework, commonly referred to as model fit, remains a topic of contention (Yuan, 2005). In evaluating the structural model's adequacy, a range of vital fit indices were analyzed: Chi-square (χ^2), RMSEA, GFI, AGFI, NFI, and CFI were considered carefully. These metrics as a whole determine the degree of correspondence between the theoretical model and the empirical data. The saturated model and the estimated model yielded identical values, indicating a high degree of internal consistency between the measurement and structural elements (Hu & Bentler, 1999a).

Table 13: Fitness Indices

Measures	Authors	Description	Good Fit Value
Model chi-square (χ2)	(L. Hu & Bentler, 1999; Barrett, 2007)	The Chi-Square statistic represents the conventional metric for assessing the comprehensive fit of a model and evaluates the extent of deviation between the sample covariance matrices and the matrices derived from the fitted model. An effective model fit would yield a result that is not statistically significant at a threshold of 0.05.	p-value>0.05
Root means square error of approximation (RMSEA)	(MacCallum *et al.*, 1996; McQuitty, 2004)	The RMSEA tells us how well the model, with unknown but optimally chosen parameter estimates would fit the populations covariance matrix. In recent years it has become regarded as 'one of the most informative fit indices.	RMSEA<0.08
Goodness-of-fit statistic (GFI) and the adjusted goodness-of-fit statistic (AGFI)	(Tabachnick, 2007; Sharma *et al.*, 2005)	The Goodness-of-Fit statistic (GFI) was created by Jöreskog and Sorbom as an alternative to the Chi-Square test and calculates the proportion of variance that is accounted for by the estimated population covariance. Related to the GFI is the AGFI which adjusts the GFI based upon degrees of freedom, with more saturated models reducing fit. Thus, more parsimonious models are preferred while penalised for complicated models. In addition to this, AGFI tends to increase with sample size.	GFI0.95 AGFI0.90

Normed-fit index (NFI)	(Ryan *et al.*, 2023)	An NFI above 0.90 or 0.95 suggests an adequate model, though its usefulness in Latent Class Analysis may be limited.	NNFI ≥ 0.95
CFI (Comparative fit index)	(S & Mohana sundaram, 2024)	The Comparative Fit Index (CFI) is a fit index used in Structural Equation Modeling (SEM) that assesses model fit by comparing the specified model to a baseline model. A CFI value above 0.90 typically indicates good fit.	CFI ≥ 0.95

Table 13 presents a Model Fit Summary, comparing the Saturated Model and the Estimated Model using key goodness-of-fit indices (J. F. Hair *et al.*, 2010). The overall model fit statistics affirm that the structural model aligns satisfactorily with the observed data. Specifically: the Chi-square statistic (0.096) is markedly low, signifying a minimal divergence between the observed and model-implied covariances. The RMSEA (0.073) resides within the acceptable interval (less than 0.08), suggesting an adequate approximation of the model (Hu & Bentler, 1999a). All additional indices (GFI, AGFI, NFI, and CFI) surpass the widely acknowledged threshold of 0.90, thereby confirming robust model performance and a commendable overall fit. These findings furnish substantial empirical evidence that supports the continuation of path coefficient analysis and hypothesis testing.

Table 14: Model Fit Summery

Measures	Saturated Model	Estimated Model
$\chi 2$	0.096	0.096
RMSEA	0.073	0.073
GFI	0.92	0.92
AGFI	0.91	0.91
NFI	0.97	0.96
CFI	0.96	0.96

Hypothesis Testing

To investigate the interrelations among constructs within the proposed structural model, path coefficients (β), standard deviations, t-statistics, and p-values were systematically assessed for each hypothesis through the application of Partial Least Squares Structural Equation Modeling (PLS-SEM) (Hair *et al.*, 2010). The findings delineated in Table 15 elucidate whether the posited paths achieve statistical significance, adhering to a conventional significance threshold of $p < 0.05$.

Table 15: Summary of Hypothesis Test Results

Hypothesis	Beta Coefficient ()	Standard Deviation (SD)	T Statistics	P values	Results
H1: PU -> SWM	0.832	0.018	45.133	0.000	Supported
H2: PEOU -> SWM	-0.019	0.024	0.812	0.417	Not Supported
H3: IAI -> SWM	0.037	0.023	1.627	0.104	Not Supported
H4: IAI -> SET	0.040	0.017	2.337	0.019	Supported
H5: SWM -> SET	0.900	0.011	84.993	0.000	Supported

From the analysis of the above table the interpretation of the hypothesis is:

H1 is robustly substantiated: Perceived Usefulness (PU) emerges as a profoundly significant predictor of stakeholders' intention to utilize smart waste management systems (β = 0.832, $p < 0.001$), aligning with the principles of the Technology Acceptance Model (TAM).

H2 and H3 lack empirical support: Perceived Ease of Use (PEOU) and Impact of AI (IAI) do not exhibit a statistically significant direct effect on SWM intention, indicating that their influences may operate indirectly or be mediated by other variables.

H4 is validated: IAI demonstrates a modest yet significant direct impact on Sustainable Eco-Tourism Development (SET), suggesting that observable AI applications (for instance, sensors and smart bins) enhance perceived sustainability outcomes.

H5 is strongly confirmed: SWM intention serves as a potent and statistically significant predictor of SET (β = 0.900, $p < 0.001$), signifying that when stakeholders express a readiness to adopt AI-driven waste systems, it precipitates tangible enhancements in sustainability. Among the five hypotheses subjected to empirical scrutiny, three (H1, H4, H5) garnered statistical validation, affirming the model's efficacy in forecasting behavioral intention and sustainability results. The outcomes accentuate the pivotal significance of Perceived Usefulness and behavioral intention (SWM) in facilitating AI adoption and promoting eco-tourism sustainability.

Final Validated Model

The final validated model underwent evaluation predicated upon the strength, reliability, and significance of the associations between latent constructs and their corresponding observed variables, employing the outer loadings and bootstrapping results delineated in Table 16. All items attained statistically significant outer loadings ($p < 0.001$), thereby substantiating the robustness of the measurement model. These findings are congruent with contemporary research that underscores the essential function of precisely defined success factors and quality metrics within organizational and technological paradigms (Hair & Alamer, 2022; Sarstedt *et al.*, 2023). The elevated T-statistics (all exceeding 29) further substantiate the reliability of these interrelations, thereby reinforcing the proposed model.

Table 16: Outer Loadings

	Beta Coefficient ()	Standard deviation (STDEV)	T statistics	P values
IAI1 <- IAI	0.704	0.026	26.619	0.000
IAI2 <- IAI	0.895	0.009	102.628	0.000
IAI3 <- IAI	0.727	0.029	24.831	0.000
IAI4 <- IAI	0.708	0.038	18.604	0.000
IAI5 <- IAI	0.780	0.035	22.518	0.000
PEOU1 <- PEOU	0.871	0.161	5.398	0.000
PEOU2 <- PEOU	0.879	0.176	4.982	0.000
PEOU3 <- PEOU	0.824	0.178	4.619	0.000
PEOU4 <- PEOU	0.873	0.163	5.356	0.000
PEOU5 <- PEOU	0.851	0.188	4.521	0.000
PU1 <- PU	0.928	0.009	101.791	0.000
PU2 <- PU	0.912	0.011	85.895	0.000
PU3 <- PU	0.878	0.012	70.984	0.000
PU4 <- PU	0.856	0.016	51.930	0.000
PU5 <- PU	0.902	0.012	77.773	0.000
SET1 <- SET	0.892	0.012	74.822	0.000
SET2 <- SET	0.927	0.009	102.995	0.000
SET3 <- SET	0.872	0.016	56.079	0.000
SET4 <- SET	0.880	0.014	60.837	0.000
SET5 <- SET	0.870	0.017	51.395	0.000
SWM1 <- SWM	0.826	0.018	46.254	0.000
SWM2 <- SWM	0.897	0.010	87.084	0.000
SWM3 <- SWM	0.866	0.014	62.294	0.000
SWM4 <- SWM	0.862	0.014	61.095	0.000
SWM5 <- SWM	0.834	0.019	44.573	0.000

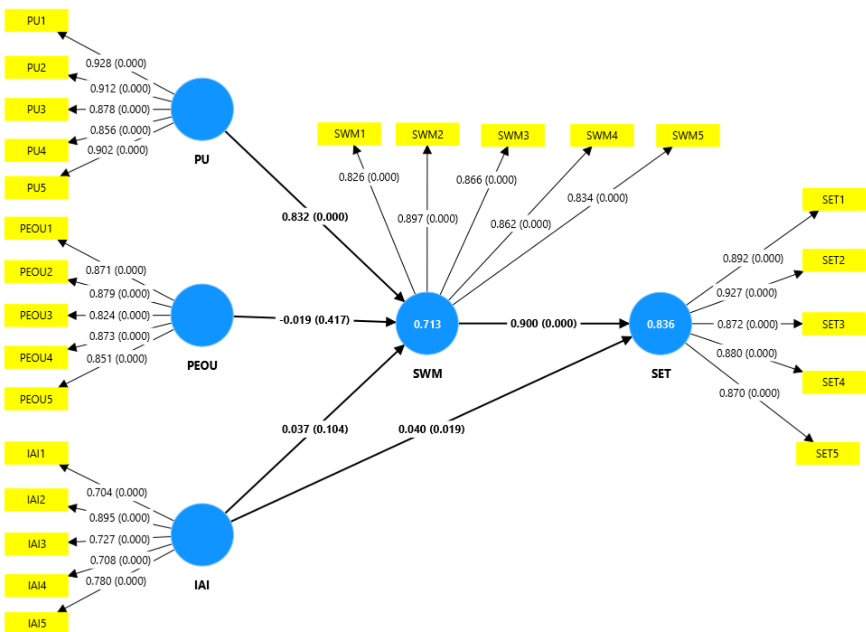

Figure 2: Validated Model

The final validated model of constructs PU, PEOU, IAI, SWM and SET are presented in figure 6.

Each latent construct: Impact of Artificial Intelligence (IAI), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), Smart Waste Management Intention (SWM), and Sustainable Eco-Tourism Development (SET) was quantified utilizing five reflective indicators. All outer loadings surpassed the recommended minimum threshold of 0.70 (Hair *et al.*, 2017), thereby exhibiting strong indicator reliability. Specifically: IAI loadings ranged from 0.704 to 0.895, with the most pronounced value observed in IAI2 ($\beta = 0.895$, $t = 102.63$), thereby affirming strong internal consistency in the measurement of AI's impact perception. PEOU loadings ranged from 0.824 to 0.879, indicating reliable performance despite marginally elevated standard deviations attributable to perceptual variability. PU loadings were remarkably high (0.856 to 0.928) with minimal standard errors and exceedingly high t-statistics (e.g., PU1 = t = 101.79), thereby affirming its pivotal role in shaping behavioral intention. SET indicators loaded within the range of 0.870 to 0.927, exhibiting consistently elevated t-values (e.g., SET2 = t = 102.99), thereby supporting the construct's efficacy in measuring sustainability outcomes. SWM loadings ranged from 0.826 to 0.897, thereby confirming that the items effectively encapsulate the intention to utilize AI-based smart waste systems.

All outer loadings were statistically significant at $p < 0.001$, with t-statistics significantly exceeding the critical threshold of 1.96. This provides substantial empirical evidence that the observed indicators reliably reflect their respective latent constructs and bolsters the structural relationships corroborated through the hypothesis testing procedure. Consequently, the measurement model is deemed valid, reliable, and structurally robust, fulfilling all established thresholds for outer loadings, internal consistency (Cronbach's Alpha and Composite Reliability), convergent validity (AVE), and discriminant validity (as assessed via Fornell-Larcker, HTMT, and cross-loadings). These validations substantiate the applicability of the model for further theoretical elucidation and practical policy recommendations.

Findings

Based on the comprehensive analysis and interpretation of data gathered from 630 respondents representing a diverse array of eco-tourism stakeholders in Malaysia, the following salient findings were discerned:

1. Perceived Usefulness (PU) emerged as the most pivotal factor in influencing stakeholders' intention to utilize AI-based smart waste management (SWM) systems. This finding supports the validity of the Technology Acceptance Model (TAM) within the framework of sustainable eco-tourism.
2. Perceived Ease of Use (PEOU) was found to have no significant effect on behavioral intention regarding SWM, indicating that stakeholders may prioritize outcomes over usability considerations, likely attributable to enhanced digital literacy and previous exposure to AI-based systems.
3. The Impact of Artificial Intelligence (IAI) did not exert a direct influence on the intention to adopt SWM; however, it exhibited a significant positive effect on Sustainable Eco-Tourism Development (SET), underscoring the broader perceived value of AI in fostering environmental enhancement and operational transparency.
4. The intention to adopt smart waste management (SWM) demonstrated the most substantial and significant effect on the attainment of sustainable eco-tourism outcomes, thereby affirming that behavioral intention serves as a critical mediator in the nexus between technology and sustainability.
5. The measurement and structural models exhibited strong reliability, validity, and model fit, thereby confirming the appropriateness of the extended TAM framework for the analysis of technology-driven environmental initiatives within the eco-tourism sector.

Recommendations

Based on the empirically validated results of the study, the subsequent recommendations are put forth for consideration by policymakers, tourism operators, and technology developers. Communication and training methodologies should be oriented towards elucidating the concrete advantages of artificial intelligence systems such as enhanced cleanliness, operational efficiency, and positive environmental impacts—rather than merely prioritizing user-friendliness. To bolster behavioral intentions, governmental bodies and tourism authorities ought to implement pilot initiatives and instructional programs that illustrate the successful application of AI-enabled waste management in eco-tourism regions. Tourism operators should incorporate AI technologies, such as intelligent waste receptacles, data visualization dashboards, and mobile platforms, in a manner that clearly underscores their sustainability impact, thereby fostering increased trust and engagement among stakeholders. Given that the perceived ease of use was assessed to be relatively low, it is advisable to provide specialized training for local communities and eco-operators to ensure they possess the confidence and proficiency required to effectively engage with AI tools. Local governmental entities should incorporate intelligent waste management systems within eco-tourism development regulations, sustainability certification processes, and public funding strategies, to promote widespread adoption. Collaborative partnerships between technology developers, environmental agencies, and tourism boards are critical to co-create contextually appropriate, user-centric AI solutions that align with both ecological imperatives and stakeholder requirements.

Limitations

The investigation was conducted exclusively within the context of eco-tourism in Malaysia. While the outcomes are pertinent to this specific environment, they may not be extrapolated to eco-tourism paradigms in alternative cultural, regulatory, or geographic contexts. Data were gathered at a singular temporal point, thereby constraining the capacity to evaluate causal relationships or to observe the evolution of behavioral patterns over an extended duration. The examination depended on the self-reported attitudes and aims of participants, which could potentially be influenced by social desirability bias or misinterpretation, particularly in assessing sustainability-related constructs. Despite 64.3% of respondents possessing prior exposure to AI systems, the remaining cohort may have misinterpreted technical elements, thereby affecting their evaluations of constructs such as perceived ease of use or the impact of AI. The investigation did not incorporate moderating variables such as age, levels of digital literacy, or types of stakeholders (e.g., tourist versus policymaker), which could have illuminated more nuanced insights into adoption behaviors.

CONCLUSION

This research makes a significant contribution to the expanding corpus of literature concerning AI-driven intelligent waste management within the realm of sustainable eco-tourism, by empirically substantiating an augmented Technology Acceptance Model (TAM) within the context of Malaysia. The results elucidate that Perceived Usefulness serves as the most robust predictor of stakeholders' intent to engage with smart waste systems, while behavioral intention is identified as a pivotal mediating factor in the attainment of sustainable tourism outcomes. Furthermore, the influence of AI is shown to positively affect perceived sustainability, thereby emphasizing the environmental legitimacy of AI technologies in the domains of waste and resource management. From an academic angle, the application of Intelligent AI (IAI) within the TAM framework significantly contributes to the discourse on eco-tourism and sustainability, particularly relevant to the context of rising markets. From a practical viewpoint, the findings yield actionable insights for tourism operators, technology developers, and governmental agencies aiming to implement advanced environmental technologies in both protected and natural environments.

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