AI for Sustainable Hospitality: Guest Perceptions of Green Technologies in Certified Hotels in the Philippines

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Abstract: The hospitality industry faces mounting pressure to integrate sustainable practices in response to climate change, resource scarcity, and growing environmental awareness among travellers. Artificial Intelligence (AI) has emerged as a promising tool for enabling green innovations in hotels, particularly those certified under sustainability programs such as ANAHAW, ASEAN Green Hotel Standard, Green Key, and LEED. This study examines guest perceptions of AI-driven green technologies in certified hotels in the Philippines, focusing on awareness, perceived usefulness, and support for eco-friendly initiatives. Using a quantitative, descriptive–correlational approach and Structural Equation Modelling (SEM), data were collected from 350 domestic and international tourists who had recently stayed in certified hotels. Findings reveal that while guests demonstrated moderate to high awareness of AI-enabled green practices, awareness alone did not significantly predict either perceived usefulness or behavioural support. Instead, perceived usefulness emerged as the strongest determinant of support, influencing intentions to revisit, recommend, and pay a premium for environmentally sustainable accommodations. These results highlight the importance of making AI features more visible and directly linked to guest experiences rather than relying solely on awareness. Beyond confirming the predictive strength of TAM, this study contributes originality by extending TAM, in combination with S-O-R and TPB, to the context of AI-enabled sustainability initiatives in certified hotels, offering new insights into guest behaviour in a developing economy. The findings provide practical guidance for hotel managers, certification bodies, and policymakers in aligning technological adoption with sustainability objectives while advancing the hospitality industry's role in sustainable development.

1 INTRODUCTION

The hospitality industry faces growing pressure to adopt sustainable practices in response to climate change, resource scarcity, and consumer concern for the environment. While tourism supports economies, it also contributes to environmental strain through high energy use, water consumption, and waste [1]. With travelers becoming more eco-conscious, hotels are expected to lead sustainability initiatives by adopting green technologies [2], [3]. Artificial Intelligence (AI) plays an important role in this shift, offering applications such as smart thermostats, occupancy-based lighting, predictive maintenance, and real-time monitoring that reduce emissions, improve efficiency, and enhance guest experiences [4]–[7].

Certification programs such as ANAHAW, ASEAN Green Hotel Standard, Green Key and LEED set structured benchmarks for eco-friendly operations in the Philippines [8]–[10]. Certified hotels are expected not only to meet infrastructure standards but also to integrate innovations like AI to complement traditional green practices and meet evolving guest expectations [11]. However, much of the existing literature focuses on managerial or operational perspectives [12], with limited research on guest awareness, perceived usefulness, and support for AI-enabled sustainability, especially in developing economies with resource constraints [13], [14]. Understanding guest perspectives is crucial, as positive perceptions strongly shape behavioral intentions and long-term support for green initiatives [15], [16].

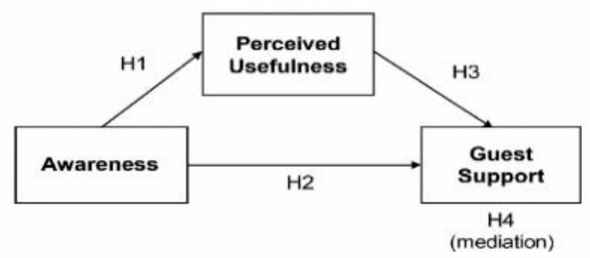

Figure 1: Conceptual framework of the study on harnessing AI for sustainable hospitality: guest perceptions of green technologies in certified hotels in the Philippines.

To address this gap, the study investigates guest perceptions of AI-enabled green technologies in certified sustainable hotels in the Philippines, focusing on awareness, perceived usefulness, and support. Using Structural Equation Modeling (SEM), it analyzes the relationships among these constructs to inform hotel managers, policymakers, and technology providers. The study also contributes to sustainable tourism development while supporting global frameworks such as the United Nations Sustainable Development Goals [10].

2 THEORETICAL FRAMEWORK

This study draws on three complementary theories: the Technology Acceptance Model (TAM), the Stimulus–Organism–Response (S-O-R) model, and the Theory of Planned Behavior (TPB). TAM, developed by Davis [18], explains how perceptions of usefulness drive technology adoption and has been applied in hospitality to AI-based systems such as smart energy management and eco-efficient innovations [5], [18]. The S-O-R model [29] illustrates how external stimuli influence internal states and behaviors; in this study, awareness serves as the stimulus, perceived usefulness the organism, and guest support the response [17], [15]. TPB [26] further highlights how attitudes, norms, and control beliefs shape intentions, with positive views of AI-driven sustainability expected to increase revisit intentions, recommendations, and willingness to pay more [22], [21]. Unlike earlier hospitality research that applied TAM mainly to guest-facing technologies, this study situates it within AI-enabled sustainability practices in certified hotels, an underexplored area in developing economies. By integrating TAM with S-O-R and TPB, the model moves beyond traditional adoption studies to link awareness, usefulness, and pro-environmental intentions, underscoring the study's originality as illustrated in Figure 1.

3 CONCEPTUAL FRAMEWORK

The conceptual framework combines TAM, S-O-R, and TPB to explain how guests respond to AI-enabled sustainability practices in certified hotels. In this model, awareness of AI-driven green technologies is treated as the external stimulus, influencing the internal evaluation of perceived usefulness, which then shapes support behaviors such as revisiting, recommending, and willingness to pay more. Beyond these direct effects, perceived usefulness is expected to act as a mediator between awareness and guest support. To test these relationships, Structural Equation Modeling (SEM) is used to examine both direct and indirect pathways among awareness, perceived usefulness, and guest support.

Hypotheses:

- H1: Guest awareness positively influences the perceived usefulness of AI-driven green technologies.
- H2: Perceived usefulness positively influences guest support for sustainability initiatives in certified hotels.
- H3: Guest awareness positively influences guest support for sustainability initiatives.
- H4: Perceived usefulness mediates the relationship between awareness and support.

4 METHODOLOGY

This study employed a quantitative descriptive–correlational design, utilizing Structural Equation Modeling (SEM) to test both direct and mediating relationships among awareness, perceived usefulness, and guest support. Respondents consisted of domestic and international tourists who had stayed in ANAHAW, Green Key, LEED, or ASEAN Green Hotel Standard-certified hotels within the last 12 months. Participants were selected through purposive sampling, with at least 300 respondents targeted to satisfy SEM requirements [26].

Data were collected using a structured questionnaire adapted from validated scales, covering demographics, awareness, perceived usefulness, and guest support, all measured on a 5-point Likert scale. Reliability and validity were established through Cronbach's alpha, composite reliability, and AVE. To ensure diversity, respondents were recruited through a combination of approaches. On-site surveys were conducted in partnership with certified hotels, where staff invited guests during or after their stay to participate by scanning a QR code. At the same time, online surveys were distributed through booking platforms and travel-related social media groups that catered to domestic and international travelers. While this method broadened the reach of the study, it may also explain why a notable proportion of respondents answered "not sure" to certification-related items, as some guests may have stayed in certified hotels without being aware of the specific certification label. Data analysis included descriptive statistics, SEM modeling with AMOS/SmartPLS, and bootstrapped mediation testing, with model fit indices (CFI, TLI, RMSEA, SRMR) applied following [27]. Ethical standards, including compliance with the Philippine Data Privacy Act of 2012, were strictly observed as shown in Table 1.

Internal reliability was established with Cronbach's alpha values above the .70 threshold for Awareness (α = .893) and Perceived Usefulness (α = .839). Composite reliability (CR) values were also strong: Awareness (CR = .895), Perceived Usefulness (CR = .891), and Guest Support (CR = 1.000). Convergent validity was supported with Average Variance Extracted (AVE) values exceeding .50 for Awareness (AVE = .683) and Perceived Usefulness (AVE = .671). Guest Support, modeled as a higher-order construct, demonstrated acceptable composite reliability (CR = 1.000, AVE = 1.000). Some items (AAGT4, PUADGT4, RI1, and WPM1) exhibited weaker factor loadings. These were retained to preserve the breadth of content validity across awareness, perceived usefulness, and guest support. However, their weaker contributions may have reduced the overall strength of the measurement model. Future studies are encouraged to refine or replace these items to further enhance reliability and construct validity as shown in Table 2.

5 RESULTS AND DISCUSSION

The sample was largely composed of Millennials (50.29%) and Gen X (33.43%), indicating a predominance of working-age adults typically more exposed to sustainability and digital innovations as shown in Table 3. Most respondents were male (67.14%) and earned between ₱20,001–₱40,000 monthly. While 31.14% reported staying in a certified green hotel, nearly half (49.14%) had not, and 19.71% were unsure. A majority (68.00%) were unfamiliar with certification labels such as ANAHAW, Green Key, LEED, and ASEAN Green Hotel, reflecting earlier findings that travelers are eco-conscious but often unaware of specific certification.

Descriptive statistics revealed a high overall awareness of AI-driven green technologies (M = 3.65, SD = 0.77). Guests were most aware of AI applications in waste management systems (M = 4.09, SD = 0.85) and smart sustainability technologies (M = 3.89, SD = 0.99). However, awareness was only moderate regarding the use of AI in monitoring energy and water consumption (M = 2.69, SD = 1.37). This aligns with prior work showing that consumers tend to notice visible and service-related AI applications but are less aware of technical and back-end sustainability functions [5].

As shown in Table 4, respondents reported a high level of perceived usefulness (M = 4.18, SD = 0.57). The highest agreement was with the statement that AI-based sustainability initiatives are innovative and valuable (M = 4.37, SD = 0.60). Respondents also strongly agreed that AI improves operational efficiency (M = 4.23, SD = 0.75). This finding resonates with prior studies which indicate that perceived usefulness is the most critical factor influencing user acceptance of AI and green hotel technologies [28], [29].

Table 5 highlights that guest support was found to be high overall (M = 4.08, SD = 0.43). The strongest support was expressed for booking AI-enabled hotels (M = 4.24, SD = 0.74) and considering AI practices worthwhile investments (M = 4.10, SD = 0.78). This result supports earlier evidence that guests are willing to support sustainability initiatives if they perceive them as valuable and beneficial, even when these involve higher costs [30], [21].

Table 1: Factor loadings and internal reliability and convergent validity.

Construct	Item	Mean	SD	Factor Loading		Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)
				Initial	Final			
Awareness	AAGT1	3.794	0.912	0.732	0.740	0.893	0.895	0.683
	AAGT2	4.091	0.847	0.710	0.762			
	AAGT3	3.791	1.028	0.884	0.837			
	AAGT4	2.689	1.366	0.225	-			
	AAGT5	3.886	0.993	0.916	0.949			
Perceived Usefulness	PUADGT1	4.077	0.625	0.788	0.783	0.839	0.891	0.671
	PUADGT2	4.231	0.749	0.871	0.877			
	PUADGT3	4.189	0.700	0.784	0.791			
	PUADGT4	4.023	0.941	0.635	-			
	PUADGT5	4.374	0.595	0.794	0.821			
Guest Support	RI1	4.094	0.600	0.461	-	1.000	1.000	1.000
	RI2	4.237	0.739	0.543	-			
	ReI1	3.960	0.679	0.674	-			
	ReI2	4.091	0.773	0.744	1.000			
	WPM1	3.971	0.696	0.509	-			
	WPM2	4.097	0.780	0.603	-			

Table 2: Demographic profile.

Variable	Category	Frequency	Percentage
Age	Gen Z	50	14.29%
	Millennial/ Gen Y	176	50.29%
	Gen X	117	33.43%
	Boomer/Baby Boomer	7	2.00%
Gender	Male	235	67.14%
	Female	113	32.29%
	Prefer not to say	2	0.57%
Monthly Income	Below ₱20,000	8	2.29%
	₱20,001–₱40,000	196	56.00%
	₱40,001–₱60,000	109	31.14%
	₱60,001–₱80,000	37	10.57%
Hotel Stay Frequency	Once	170	48.57%
	2-3 times	132	37.71%
	4-5 times	30	8.57%
	More than 6 times	18	5.14%
Green Hotel Stay	Yes	49	14.00%
	No	2	0.57%
	Not Sure	299	85.43%
Certifications	ANAHW	101	28.86%
	Green Key	130	37.14%
	LEED	44	12.57%
	Not sure	75	21.43%

Table 3: Descriptive statistics of guest awareness of AI-driven Green Technologies.

Item	Statement	M	SD	Interpretation
AAGT1	I am aware that the hotel I stayed in uses AI to conserve energy.	3.79	0.91	High Awareness
AAGT2	I know that AI technologies are used in hotel waste management systems.	4.09	0.85	High Awareness
AAGT3	The hotel provided information about its AI-based sustainability features.	3.79	1.03	High Awareness
AAGT4	I am familiar with the use of AI in monitoring energy and water consumption in hotels.	2.69	1.37	Moderate Awareness
AAGT5	I actively notice smart technologies aimed at promoting sustainability in the hotels I visit.	3.89	0.99	High Awareness
Overall	Guest awareness of AI-driven green technologies (construct level)	3.65	0.77	High Awareness
Note. Responses were measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).				

Table 4: Descriptive statistics of perceived usefulness of AI-driven green technologies.

Item	Statement	M	SD	Interpretation
PUADGT1	AI technologies in hotels contribute significantly to environmental sustainability.	4.08	0.63	High Usefulness
PUADGT2	I believe AI systems improve the hotel’s operational efficiency.	4.23	0.75	Very High Usefulness
PUADGT3	The use of AI in the hotel enhanced my comfort and overall experience.	4.19	0.70	High Usefulness
PUADGT4	AI-driven sustainability features (e.g., smart thermostats) made me feel that the hotel cares for nature.	4.02	0.94	High Usefulness
PUADGT5	I find AI-based sustainability initiatives in hotels to be innovative and valuable.	4.37	0.60	Very High Usefulness
Overall	Perceived usefulness of AI-driven green technologies (construct level)	4.18	0.57	High Usefulness
Note. Responses were measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).				

Table 5: Descriptive statistics of guest support for AI-driven green initiatives

Item	Statement	M	SD	Interpretation
RI1	I would stay in this hotel again because of its AI-driven green technologies.	4.09	0.60	High Support
RI2	I prefer to book hotels that implement AI-powered sustainability practices.	4.24	0.74	Very High Support
ReI1	I would recommend this hotel to others because of its environmental sustainability practices.	3.96	0.68	High Support
ReI2	I am likely to promote this hotel to my peers due to its use of innovative green technologies.	4.09	0.77	High Support
WPM1	I am willing to pay a higher price to stay in a hotel that uses AI to promote environmental goals.	3.97	0.70	High Support
WPM2	I consider AI-supported green practices a worthwhile investment, even if the room cost is higher.	4.10	0.78	High Support
Overall	Guest support for AI-driven green initiatives (construct level)	4.03	0.62	High Support
Note. Responses were measured on a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).				

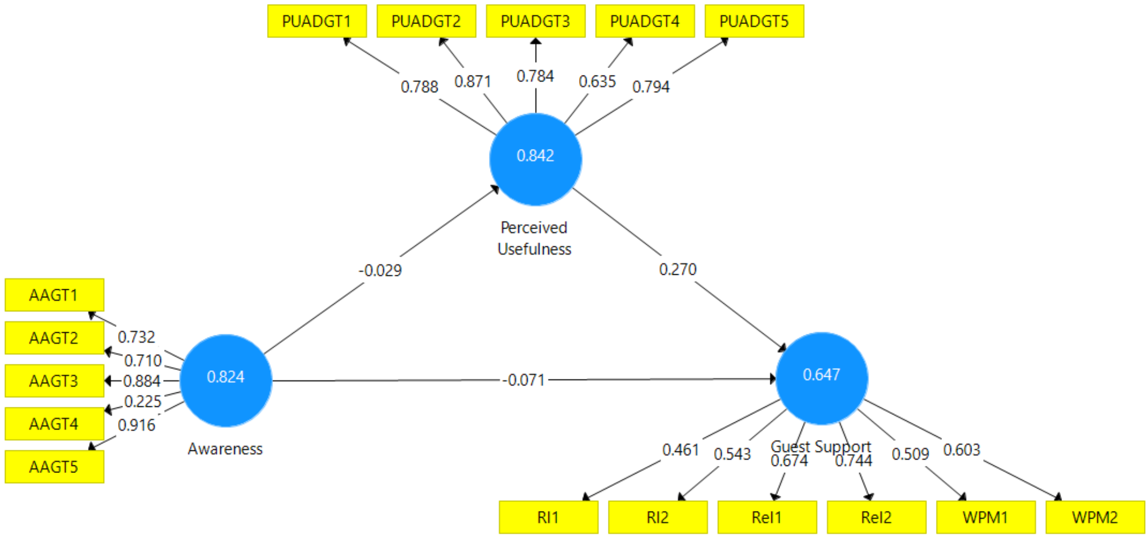

Figure 2: Structural equation modeling results: output loading of factors.

The measurement model was evaluated in terms of factor loadings, reliability, and validity (see Figure 2 and Table 5). For the Awareness construct, four items (AAGT1, AAGT2, AAGT3, AAGT5) were retained with loadings ranging from .740 to .949, while AAGT4 was dropped due to a weak loading (.225). The Perceived Usefulness construct retained four items (PUADGT1, PUADGT2, PUADGT3, PUADGT5) with loadings between .783 and .877; PUADGT4 was removed due to a low loading (.635). All six items of Guest Support (RI1, RI2, ReI1, ReI2, WPM1, WPM2) were retained, with loadings from .461 to .744, though RI1 and WPM1 showed weaker contributions.

Table 6: Fornell-Larcker criterion.

	Aware-ness	Guest Support	Perceived Usefulness
Awareness	0.826		
Guest Support	-0.046	1.000	
Perceived Usefulness	-0.015	0.245	0.819

Table 7: Heterotraiet-Monotrait Ratio (HTMT).

	Aware-ness	Guest Support	Perceived Usefulness
Awareness			
Guest Support	0.029		
Perceived Usefulness	0.046	0.257	

As shown in Table 6, the Fornell–Larcker criterion confirmed discriminant validity, with the square root of each AVE (Awareness = .826; Perceived Usefulness = .819; Guest Support = 1.000) exceeding the inter-construct correlations. Furthermore, the HTMT ratios (Table 7) were well below the conservative threshold of .85 (Awareness–Support = .029; Awareness–Usefulness = .046; Usefulness–Support = .257), providing additional evidence of discriminant validity.

The path coefficients of the structural model are presented in Figure 2. Awareness was not found to significantly predict Perceived Usefulness ($\beta = –.029$) nor Guest Support ($\beta = –.071$). In contrast, Perceived Usefulness had a positive and meaningful effect on Guest Support ($\beta = .270$). These findings suggest that while respondents are generally aware of AI-driven green technologies, this awareness does not directly enhance perceptions of usefulness or support for green initiatives. Instead, Perceived Usefulness serves as the critical driver of Guest Support. The SEM results indicate that awareness alone is insufficient to encourage guest support for AI-driven sustainability initiatives. Guests are more likely to revisit, recommend, or pay more for certified green hotels when they perceive AI technologies as useful in enhancing sustainability, operational efficiency, and their overall hotel experience. Thus, hotels should not only raise awareness but also highlight the practical benefits of AI applications to strengthen guest support [18].

Table 8: Hypothesis testing.

Path Direct Effect	β	t-Value	p-Value	Remarks
H1: Awareness □ Guest Support	-0.031	0.651	0.515	Not Significant
H2: Awareness □ Perceived Usefulness	0.008	0.182	0.855	Not Significant
H3: Perceived Usefulness □ Guest Support	0.249	5.094	0.000	Significant
Note: p < 0.001; Bootstrap resampling with 5,000 subsamples was used to generate estimates.				

Table 8 presents the results of hypothesis testing for the direct effects. The path from awareness to guest support (H1) was not significant (β = –0.031, t = 0.651, p = .515), indicating that awareness of AI-driven green technologies did not directly influence guest support. Similarly, the path from awareness to perceived usefulness (H2) was also nonsignificant (β = 0.008, t = 0.182, p = .855). These results suggest that awareness alone was insufficient to explain variations in either usefulness perceptions or support. In contrast, perceived usefulness demonstrated a significant positive effect on guest support (H3; β = 0.249, t = 5.094, p < .001), confirming that guests who perceived AI-driven green technologies as useful were more likely to support sustainability initiatives. This pattern aligns with prior studies showing that perceived usefulness is often a stronger determinant of behavioral support compared to awareness [18], [32]. Overall, the non-significant paths involving awareness highlight that awareness alone does not meaningfully shape guest perceptions or behaviors, underscoring the need for further analysis of this finding in the discussion.

Table 9: Indirect effects.

Relationship	Indirect Effect			Bootstrapped Confidence Interval		Decision
	β	t-Value	p-Value	95% LL	95% UL	
H4: Awareness □ Perceived Usefulness □ Guest Support	0.063	0.176	0.860	0.035	0.039	Not Mediated
Note: p < 0.001, LL: Lower level, UL: Upper level						

Table 9 summarizes the mediation analysis. The indirect path from awareness through perceived usefulness to guest support (H4) was not significant (β = 0.063, t = 0.176, p = .860), with confidence intervals crossing zero (LL = 0.035, UL = 0.039). This indicates that perceived usefulness did not mediate the relationship between awareness and guest support. Thus, even though usefulness was a significant direct predictor of support, awareness did not contribute indirectly through usefulness. These findings suggest that increasing awareness alone may not be sufficient to foster guest support unless it simultaneously enhances perceived usefulness.

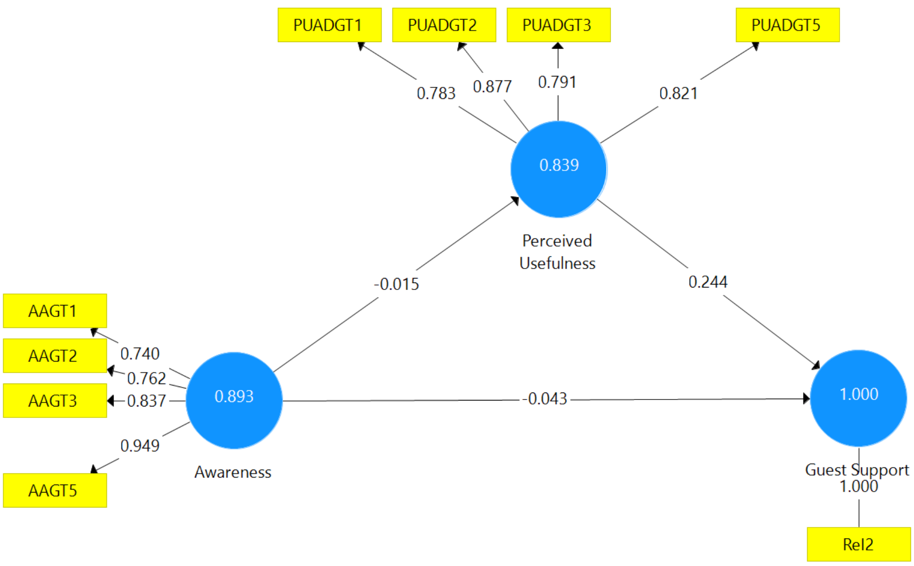

Figure 3: Final SEM model.

Figure 3 illustrates the structural equation model (SEM) of the main hypothesis. The model depicts the direct, indirect, and nonsignificant paths among awareness, perceived usefulness, and guest support. The visual representation reinforces the statistical findings: awareness paths to both guest support and perceived usefulness were weak, whereas perceived usefulness had a stronger direct effect on guest support (β = 0.244). The model also shows strong outer loadings of perceived usefulness items (ranging from 0.783 to 0.877), indicating reliable measurement of this construct. Awareness items also loaded well, particularly AAGT5 (0.949). However, the weak structural paths confirm that awareness was not a robust driver of usefulness or support.

Table 10: Associated R-square adjusted and R-square.

Construct	R Square	R Square Adjusted
Guest Support	0.062	0.056
Perceived Usefulness	0.000	-0.003

Table 10 reports the coefficient of determination (R^2) values. Guest support had an R^2 of .062 (adjusted R^2 = .056), meaning the predictors explained about 6.2% of the variance in guest support. Perceived usefulness had an R^2 of .000 (adjusted R^2 = –.003), indicating that awareness explained virtually no variance in usefulness. Following [33] guidelines, these effect sizes are weak, suggesting that the structural model had limited explanatory power. While perceived usefulness still emerged as a meaningful predictor of guest support, the low R^2 values indicate that the model did not fully capture the complexity of guest behavior. Additional factors such as trust in sustainability claims, perceived value of green initiatives, or environmental concern may contribute to a stronger explanatory framework. This limitation is acknowledged, and future studies are encouraged to incorporate these variables to enhance predictive power and provide a more comprehensive understanding of guest support for AI-enabled sustainability practices.

Table 11: Predictive relevance.

Construct	SSO	SSE	Q^2 (=1-SSE/SSO)
Awareness	1400	1400.00	
Guest Support	350	335.57	0.041
Perceived Usefulness	1400	1403.35	-0.002

Table 11 presents the predictive relevance (Q^2) values obtained through blindfolding. Guest support yielded a positive Q^2 value of .041, suggesting small predictive relevance. However, perceived usefulness had a negative Q^2 value (–.002), indicating no predictive relevance. Awareness also produced no predictive relevance. These results reinforce the earlier conclusion that awareness contributed little to predicting guest perceptions or support, while usefulness provided some predictive power for guest support.

Table 12: Model Fit.

Index	Saturated Model	Estimated Model
SRMR	0.062	0.062
d_ULS	0.171	0.171
d_G	0.121	0.121
Chi-Square	239.778	239.778
NFI	0.834	0.834

Table 12 displays model fit indices. The standardized root mean square residual (SRMR) value of .062 fell below the threshold of .08, indicating an acceptable fit [18]. The normed fit index (NFI) was .834, suggesting moderate fit but not reaching the conventional .90 cutoff [34] The chi-square value (χ^2 = 239.778) was statistically significant, which is expected given the sensitivity of chi-square to sample size. Overall, the fit indices suggest that the model was adequate but not strong, consistent with the low explanatory and predictive power of the constructs.

6 CONCLUSIONS

This study examined guest perceptions of AI-driven green technologies in certified hotels in the Philippines and found that while awareness was moderate to high, it did not significantly influence guest support. Instead, perceived usefulness emerged as the strongest driver of revisit intentions, recommendations, and willingness to pay a premium, showing that guests respond more when they see clear benefits such as efficiency, comfort, and innovation. The findings affirm the relevance of TAM in a sustainability context and add originality by integrating TAM with S-O-R and TPB to frame guest behavior in certified hotels within a developing economy. At the same time, the low explanatory power of the model highlights its limitations and signals the need to include other factors – such as trust, perceived value, and environmental concern – in future research. Overall, the study offers balanced insights by recognizing both the strengths and constraints of the model, while providing practical and policy guidance for advancing sustainable hospitality.

7 RECOMMENDATIONS

The study recommends that hotel operators make AI-enabled sustainability initiatives more visible and directly tied to the guest experience by highlighting certifications, explaining green technologies during check-in, and using in-room displays to show their benefits in real time. Policymakers and certification bodies are likewise encouraged to strengthen standards by not only setting infrastructural requirements but also promoting clear, guest-centered communication of technological advancements to bridge awareness gaps. Finally, future research should consider additional constructs such as trust, perceived value, and environmental concern, and adopt longitudinal and cross-cultural approaches to improve the generalizability of findings.

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REFERENCES

[1] S. Gössling and C. M. Hall, Sustainable Tourism: A Global Perspective. London, U.K.: Routledge, 2019.

[2] D. Buhalis and D. Leung, "Smart hospitality – Interconnectivity and sustainability," International Journal of Hospitality Management, vol. 71, pp. 41–50, 2018, doi: 10.1016/j.ijhm.2017.11.011.

[3] V. Filimonau and D. De Coteau, "Food waste management in hospitality operations: A critical review," Tourism Management, vol. 71, pp. 234–245, 2019.

[4] S. Ivanov, C. Webster, and K. Berezina, "Adoption of robots and service automation in tourism and hospitality," Tourism Management Perspectives, vol. 30, pp. 1–9, 2019, doi: 10.1016/j.tmp.2018.11.008.

[5] I. Tussyadiah, "A review of research into automation in tourism: Launching the Annals of Tourism Research curated collection on artificial intelligence and robotics in tourism," Annals of Tourism Research, vol. 81, Art. 102883, 2020, doi: 10.1016/j.annals.2020.102883.

[6] Z.-X. Li, Y. Liu, and R. Ernst, "A dynamic 2000–540 Ma Earth history: From cratonic amalgamation to the age of supercontinent cycle," Earth-Science Reviews, vol. 238, Art. 104336, pp. 1–45, 2023, doi: 10.1016/j.earscirev.2023.104336.

[7] B. L. Chua et al., "Green hotels: The state of green hotel research and future directions," International Journal of Hospitality Management, 2022.

[8] Department of Tourism, National Green Certification Guidelines (ANAHAW). Republic of the Philippines, 2020. [Online]. Available: https://beta.tourism.gov.ph

[9] ASEAN Secretariat, ASEAN Green Hotel Standard. Jakarta, Indonesia, 2021. [Online]. Available: https://asean.org/book/asean-green-hotel-standard.

[10] World Tourism Organization, Sustainable Development of Tourism. Madrid, Spain: UNWTO, 2023. [Online]. Available: https://www.unwto.org/sustainable-development.

[11] J. J. Kim and H. Han, "Hotel service innovation with smart technologies: Exploring consumers' readiness and behaviors," Sustainability, vol. 14, no. 10, Art. 5746, 2022, doi: 10.3390/su14105746.

[12] S. Ivanov and C. Webster, "Adoption of robots and service automation in tourism," Tourism Management Perspectives, vol. 23, pp. 2–11, 2017, doi: 10.1016/j.tmp.2017.04.001.

[13] D. Gursoy, O. H. Chi, L. Lu, and R. Nunkoo, "Consumers' acceptance of artificially intelligent (AI) device use in service delivery," International Journal of Information Management, vol. 49, pp. 157–169, 2019, doi: 10.1016/j.ijinfomgt.2019.03.008.

[14] B. S. Nayak, S. Bhattacharya, and P. Nguyen, "Sustainability in tourism in emerging economies," Sustainable Development, vol. 30, no. 1, pp. 112–124, 2022, doi: 10.1002/sd.2223.

[15] H. Chen, G. Zhang, and P. K. C. Lee, "Guest perceptions of hotel sustainability initiatives and green technologies: A structural model of eco-friendly behavioral intentions," Journal of Hospitality Marketing & Management, vol. 30, no. 3, pp. 325–343, 2021, doi: 10.1080/19368623.2020.1819643.

[16] Y. Zhang et al., "Work on sustainability perceptions and consumer behavior," 2022.

[17] U. Gretzel, M. Sigala, Z. Xiang, and C. Koo, "Smart tourism: Foundations and developments," Electronic Markets, vol. 30, no. 1, pp. 7–18, 2020, doi: 10.1007/s12525-020-00419-1.

[18] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," MIS Quarterly, vol. 13, no. 3, pp. 319–340, 1989, doi: 10.2307/249008.

[19] C. Koo, J. Ham, and N. Chung, "Examining the impact of smart technology in green hotels on guest satisfaction and behavioral intention," Journal of Sustainable Tourism, vol. 29, no. 9, pp. 1405–1423, 2021, doi: 10.1080/09669582.2020.1855434.

[20] L. Wang, Q. Zhang, M.-J. Ye, P. P. W. Wong, and Y. Gong, "Green hotels visit intention among young adults: Integrating the familiarity, novelty, trust, perceived risk, and theory of planned behaviour," Humanities and Social Sciences Communications, vol. 11, Art. 1390, 2024.

[21] B. S. Al-Romeedy et al., “Reimagining sustainability: The power of AI and intellectual capital in hospitality,” Journal of Hospitality & Tourism, 2024.

[22] J. S. Lee, L. T. Hsu, H. Han, and Y. Kim, “Understanding how consumers view green hotels: How a hotel’s green image can influence behavioral intentions,” Journal of Sustainable Tourism, vol. 31, no. 2, pp. 324–342, 2020, doi: 10.1080/09669582.2019.1705464.

[23] H. Han, L. T. Hsu, and C. Sheu, “Application of the theory of planned behavior to green hotel choice: Testing the effect of environmental values and perceived usefulness,” Tourism Management, vol. 71, pp. 47–56, 2019, doi: 10.1016/j.tourman.2018.09.006.

[24] I. Rahman et al., “Corporate social responsibility and environmental sustainability in hospitality,” Journal of Hospitality & Tourism Management, vol. 31, pp. 83–91, 2017.

[25] A. Mehrabian and J. A. Russell, An Approach to Environmental Psychology. Cambridge, MA, USA: MIT Press, 1974.

[26] I. Ajzen, “The theory of planned behavior,” Organizational Behavior and Human Decision Processes, vol. 50, no. 2, pp. 179–211, 1991, doi: 10.1016/0749-5978(91)90020-T.

[27] J. F. Hair, G. T. M. Hult, C. Ringle, and M. Sarstedt, A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM), 3rd ed. Thousand Oaks, CA, USA: Sage Publications, 2021.

[28] L. T. Hu and P. M. Bentler, “Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives,” Structural Equation Modeling, vol. 6, no. 1, pp. 1–55, 1999, doi: 10.1080/10705519909540118.

[29] Y. Duan, J. S. Edwards, and Y. K. Dwivedi, “Artificial intelligence for decision making in the era of Big Data – Evolution, challenges and research agenda,” International Journal of Information Management, vol. 48, pp. 63–71, 2019, doi: 10.1016/j.ijinfomgt.2019.01.021.

[30] F. Xu, F. W. Kellermanns, L. Jin, and J. Xi, “Family support as social exchange in entrepreneurship: Its moderating impact on entrepreneurial stressors–well-being relationships,” Journal of Business Research, vol. 120, pp. 59–73, 2020.

[31] H. Han and H. J. Yoon, “Hotel customers’ environmentally responsible behavioral intention: Impact of key constructs on decision in green consumerism,” International Journal of Hospitality Management, vol. 45, pp. 22–33, 2015, doi: 10.1016/j.ijhm.2014.11.004.

[32] V. Venkatesh, M. G. Morris, G. B. Davis, and F. D. Davis, “User acceptance of information technology: Toward a unified view,” MIS Quarterly, vol. 27, no. 3, pp. 425–478, 2003, doi: 10.2307/30036540.

[33] J. Cohen, Statistical Power Analysis for the Behavioral Sciences, 2nd ed. Hillsdale, NJ, USA: Lawrence Erlbaum Associates, 1988.

[34] P. M. Bentler and D. G. Bonett, “Significance tests and goodness-of-fit in the analysis of covariance structures,” Psychological Bulletin, vol. 88, no. 3, pp. 588–606, 1980, doi: 10.1037/0033-2909.88.3.588.