“ChatGPT adoption disposition and sustainable travel planning intention in a non-random international sample”

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CHATGPT ADOPTION DISPOSITION AND SUSTAINABLE TRAVEL PLANNING INTENTION IN A NON-RANDOM INTERNATIONAL SAMPLE

Abstract

Tourism decision-making increasingly relies on digital assistants, yet the mechanism through which conversational AI may support sustainable travel planning remains unclear. The purpose of this study was to examine whether ChatGPT adoption disposition is associated with sustainable travel planning intention and whether this association operates through ChatGPT relationship engagement and AI-assisted travel-planning experience. A quantitative cross-sectional survey was conducted online between January and March 2025 among adults from Tunisia, France, Italy, Germany, and other countries who had previously used ChatGPT to search for environmentally responsible travel information. From 234 questionnaires initially received, 48 were excluded after screening and quality control, leaving 186 valid responses. Partial Least Squares Structural Equation Modeling was used to test the measurement model, structural paths, mediation effects, and dummy-coded country controls, with France as the reference category. The results show that attitude ($\beta = 0.421$, $p < 0.001$), subjective norms ($\beta = 0.353$, $p < 0.001$), and perceived behavioral control ($\beta = 0.297$, $p < 0.001$) are positively associated with ChatGPT adoption disposition. The direct path from ChatGPT adoption disposition to sustainable travel planning intention is not significant ($\beta = 0.080$, $p = 0.734$). However, two indirect effects are significant: through ChatGPT relationship engagement ($\beta = 0.250$, $p < 0.001$) and through AI-assisted travel-planning experience ($\beta = 0.124$, $p < 0.001$). Country controls are non-significant. The study concludes that ChatGPT is more relevant as an experiential and relational facilitator than as a direct driver of sustainable travel intention, within the limits of a pooled non-probability international sample.

Keywords ChatGPT, artificial intelligence, tourism, sustainability, engagement, experience, intention

JEL Classification M31, L83, Q56, M30

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INTRODUCTION

Tourism remains a strategic sector of the global economy, but it also generates environmental pressure through transportation emissions, energy consumption, waste production, and ecosystem degradation (Gössling et al., 2022; UNWTO, 2023). Sustainable tourism research therefore increasingly focuses on how consumers identify, evaluate, and select environmentally responsible travel options such as eco-certified accommodation, lower-impact transportation, and sustainability-oriented tourism activities (Dolnicar, 2020; Han et al., 2010; Verma et al., 2019).

At the same time, tourism decision-making has become deeply platform-mediated. Travelers use online travel agencies, review communities, recommendation systems, and digital assistants to search for information, compare alternatives, and structure travel decisions (Buhalis & Law, 2008; Gretzel et al., 2015; Xiang et al., 2015). Digital environments may reduce search costs, but they may also increase information overload and uncertainty, particularly when sustainability claims are difficult to verify (Lemon & Verhoef, 2016; Pappas et al., 2014).

Generative artificial intelligence adds a new layer to this digital decision architecture. Conversational systems such as ChatGPT can generate contextual recommendations, simplify information search, and provide personalized explanations during travel planning (Dwivedi et al., 2023; Huang & Rust, 2021; Kasneci et al., 2023). In sustainable tourism contexts, such systems may help travelers identify eco-certified hotels, low-carbon mobility options, and responsible activities. Yet the behavioral mechanism through which ChatGPT may support sustainable travel planning remains insufficiently specified.

Two conceptual cautions are necessary. First, a cross-sectional survey cannot establish causal influence; it can only test theoretically grounded associations among constructs. Second, an international non-probability sample should not be treated as cross-cultural evidence unless measurement invariance and group-specific comparisons are conducted. Accordingly, this study does not claim causal effects or country-level generalizability. It investigates a pooled non-random international sample and interprets the findings as evidence of associations within this empirical frame.

The scientific problem addressed in this article concerns the insufficient understanding of how conversational AI becomes relevant in sustainable travel planning. Existing research has examined digital tourism platforms, AI-enabled services, and sustainable travel intentions, but less is known about whether ChatGPT-related adoption disposition translates into sustainability-oriented planning intention directly or through relational and experiential mechanisms. This issue is particularly important because conversational AI may provide information, but responsible travel planning also depends on user engagement, perceived experience quality, and the ability to interpret sustainability-related recommendations.

1. LITERATURE REVIEW

Sustainable travel planning involves choosing tourism options that reduce negative environmental impacts while maintaining the social and economic value of tourism activities (Han et al., 2010; Verma et al., 2019). Although many travelers express environmental concern, they frequently face cognitive and informational barriers when they try to identify genuinely sustainable alternatives. These barriers include limited comparability of sustainability claims, uncertainty about eco-labels, and difficulty evaluating the environmental consequences of travel choices (Dolnicar, 2020; Sigala, 2016).

Digital technologies have become central to this decision process. Online tourism platforms and recommendation systems structure how travelers search, compare, and choose services (Buhalis & Law, 2008; Gretzel et al., 2015). Artificial intelligence can further modify this process by personalizing recommendations, accelerating information processing, and simulating interactive advisory functions (Huang & Rust, 2021; Pantano et al., 2021). In tourism, AI can act as a planning assistant rather than a simple information repository (Ivanov & Webster, 2019; Majid et al., 2024).

The Theory of Planned Behavior provides the theoretical basis for explaining adoption disposition toward ChatGPT in this study. According to Ajzen (1991), behavioral intention is shaped by attitude, subjective norms, and perceived behavioral control. In the present context, attitude refers to the consumer's favorable evaluation of ChatGPT as a tool for sustainable travel information search. Subjective norms represent perceived social pressure from peers, professional circles, and online communities. Perceived behavioral control captures the individual's perceived ability to use ChatGPT and assess the relevance of the information received.

Consistent with TPB and technology adoption research, favorable attitudes toward intelligent systems should be associated with stronger adoption disposition (Venkatesh & Davis, 2000; Dwivedi et al., 2023; Han et al., 2024). Similarly, social influence may matter because generative AI remains a relatively new technology, and consumers may rely on peers and communities to evaluate its le-

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gitimacy. Perceived behavioral control should also matter because users who feel competent in interacting with AI tools are more likely to integrate them into travel planning.

ChatGPT adoption disposition is defined here as the respondent's self-reported propensity, willingness, and intention to use ChatGPT as a sustainable travel-planning assistant. This construct does not measure objective system-use frequency extracted from platform logs. The term "ChatGPT adoption disposition" is used to align the construct label with the questionnaire items, which capture propensity, willingness, and intention rather than objective platform-use frequency.

ChatGPT adoption disposition may be associated with sustainable travel planning intention because conversational AI can reduce search effort and make sustainable options more visible. Nevertheless, this relationship is expected to be limited if AI recommendations remain purely informational. Sustainable travel choices often require motivational involvement, perceived relevance, and confidence in the planning process. For this reason, the direct relationship between ChatGPT adoption disposition and sustainable travel planning intention is tested but interpreted cautiously as an association rather than a causal effect.

ChatGPT relationship engagement refers to relational attachment, loyalty, and continuance involvement with ChatGPT as an AI planning assistant. This construct is narrower than generic consumer engagement. It does not represent engagement with a brand, a tourism platform, or an online community. It captures the user's relational involvement with the AI assistant during sustainable travel planning. This definition aligns with the item content measuring attachment, loyalty, and continued use intention (Brodie et al., 2011; Hollebeek et al., 2019; Vivek et al., 2012).

Conversational AI can strengthen relationship engagement by providing interactive, personalized, and responsive exchanges. When users perceive the AI assistant as useful and relevant, they may develop stronger involvement with the planning process. Relationship engagement, in turn, is expected to increase sustainable travel planning intention because engaged consumers are more likely to process information deeply and translate planning support into behavioral intention (Harrigan et al., 2017; So et al., 2012).

AI-assisted travel-planning experience refers to the perceived enjoyment, interest, satisfaction, and personalization of the ChatGPT interaction during sustainable trip planning. This construct is labeled "AI-assisted travel-planning experience" because the items measure enjoyment, interest, satisfaction, and personalization during ChatGPT-assisted sustainable trip planning, rather than navigation, payment, booking, checkout, or interaction with an online store.

Positive AI-assisted travel-planning experiences can reduce cognitive effort and increase perceived relevance during sustainable travel search. Prior customer experience research shows that experiential quality, personalization, and satisfaction can strengthen consumer intentions in digital environments (Rose et al., 2012; Lemon & Verhoef, 2016; Chen et al., 2021; Tuomi et al., 2025). In the present context, this experience is expected to mediate the relationship between ChatGPT adoption disposition and sustainable travel planning intention.

Accordingly, the purpose of this study is to examine whether ChatGPT adoption disposition is associated with sustainable travel planning intention and whether this association operates through ChatGPT relationship engagement and AI-assisted travel-planning experience. Based on the preceding theoretical arguments, the following hypotheses are proposed:

H1: *Attitude is positively associated with ChatGPT adoption disposition for sustainable travel planning.*

H2: *Subjective norms are positively associated with ChatGPT adoption disposition for sustainable travel planning.*

H3: *Perceived behavioral control is positively associated with ChatGPT adoption disposition for sustainable travel planning.*

H4: *ChatGPT adoption disposition is positively associated with sustainable travel planning intention.*

H5: *ChatGPT adoption disposition is positively associated with ChatGPT relationship engagement.*

H6: *ChatGPT relationship engagement is positively associated with sustainable travel planning intention.*

H7: *ChatGPT adoption disposition is positively associated with AI-assisted travel-planning experience.*

H8: *AI-assisted travel-planning experience is positively associated with sustainable travel planning intention.*

H9: *ChatGPT relationship engagement mediates the association between ChatGPT adoption disposition and sustainable travel planning intention.*

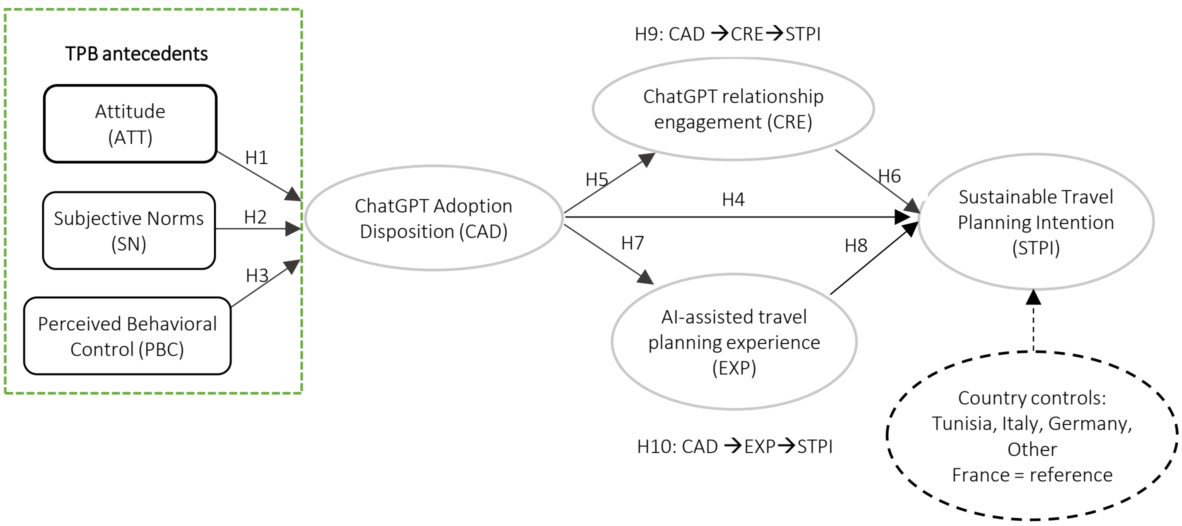
H10: *AI-assisted travel-planning experience mediates the association between ChatGPT adoption disposition and sustainable travel planning intention.*

Figure 1 summarizes the proposed conceptual model. Attitude, subjective norms, and perceived behavioral control are modeled as antecedents of ChatGPT adoption disposition. ChatGPT adoption disposition is linked to sustainable travel planning intention both directly and indirectly through ChatGPT relationship engagement and AI-assisted travel-planning experience. Given the international composition of the sample, country background is included as a control variable through dummy coding, with France used as the reference category and Tunisia, Italy, Germany, and Other countries modeled as binary controls. Country is not treated as a substantive hypothesis but as a control variable.

2. METHODOLOGY

This study adopts a quantitative cross-sectional design to test associations among TPB antecedents, ChatGPT adoption disposition, ChatGPT relationship engagement, AI-assisted travel-planning experience, and sustainable travel planning intention. A cross-sectional design is appropriate for examining perceptions and intentions at a single point in time, but it does not allow causal inference (Creswell, 2009).

The empirical context covers adults who had prior experience using ChatGPT when searching for environmentally responsible travel information. Eligible respondents had to confirm that they had used ChatGPT to search for at least one of the following: eco-certified accommodation, envi-



Note: Solid arrows represent hypothesized relationships. The dashed arrow represents dummy-coded country controls specified toward sustainable travel planning intention only. The model tests cross-sectional associations and does not establish causal influence.

Figure 1. Proposed research model

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ronmentally friendly transportation, sustainable tourism activities, green accommodation, or responsible travel information.

Data were collected online between January and March 2025. The questionnaire was distributed through digital channels where respondents with tourism, digital marketing, sustainability, and artificial intelligence-related interests were likely to be present. These channels included Facebook communities dedicated to sustainable travel, ecotourism, responsible tourism, green accommodation, and environmentally friendly tourism practices. The questionnaire was also shared through tourism-related discussion groups, LinkedIn professional networks related to tourism, digital marketing, sustainability, and AI-enabled services, as well as university and professional digital networks. The invitation explicitly targeted adult respondents with prior ChatGPT experience in sustainable travel information search.

A total of 234 questionnaires were initially received. After screening and quality control, 48 responses were excluded, resulting in a final analytical sample of 186 valid questionnaires. Exclusions were based on one or more of the following criteria: respondents were under 18 years old, had not previously used ChatGPT, had not used ChatGPT to search for environmentally responsible travel information, submitted incomplete questionnaires, provided duplicate or near-duplicate responses, or displayed careless response patterns such as straight-lining and inconsistent answers. Duplicate responses were prevented and checked through the survey platform settings where technically possible, including restriction of repeated submissions, and through post-export screening based on identical answer strings, repeated demographic profiles, and abnormal response patterns. No duplicate case was retained in the final dataset.

The sampling strategy was non-probability based and combined purposive and convenience sampling. Purposive sampling was used because the study required respondents with a specific experience: using ChatGPT in a sustainable travel-planning context. Convenience sampling was used because no sampling frame of ChatGPT users involved in sustainable travel planning was available (Saunders et al., 2019; Sekaran & Bougie, 2020).

Screening was implemented at the beginning of the questionnaire. Respondents were asked whether they were at least 18 years old, whether they had used ChatGPT before, and whether they had used ChatGPT to search for environmentally responsible travel options. Only respondents meeting these eligibility criteria were retained in the final analytical dataset.

Duplicate and careless responses were checked before analysis. After export, the dataset was examined for identical answer strings, abnormal completion patterns, inconsistent answers, and repetitive response patterns. Questionnaires presenting substantial missing values, straight-lining, or inconsistent answers were excluded during the screening and data-cleaning process. The final dataset therefore contained 186 complete and eligible responses.

Because the study relied on self-reported questionnaire data collected from a single respondent source, procedural precautions were used to reduce potential common method bias. These precautions included eligibility screening, anonymous participation, clear item wording, and post-export checks for careless or repetitive responses (Podsakoff et al., 2003).

Participation was voluntary and anonymous. The first page of the online questionnaire informed respondents about the academic purpose of the study, the eligibility criteria, the absence of personally identifying data, and their right to discontinue participation before submission. Consent was obtained by proceeding to the questionnaire after this information page. No financial incentive was offered, and the data were analyzed only in aggregated form. The dataset was collected specifically for this study and has not been used in any previous publication.

A pilot test with 20 respondents was conducted before the final data collection. The pilot test assessed item clarity, wording, completion time, and contextual relevance. Minor wording adjustments were made to ensure that the items referred clearly to ChatGPT-assisted sustainable travel planning.

The final sample included respondents from Tunisia, France, Italy, Germany, and a small group of other national contexts. These countries were not selected to support a comparative country-level design. Rather, they emerged from the online recruitment channels and professional/university networks through which respondents with relevant ChatGPT and sustainable travel-planning experience could be reached. The sample was not balanced across countries and was mainly composed of French and Italian respondents. Therefore, the study does not claim national representativeness and does not conduct cross-country comparisons. Country background was nevertheless incorporated as a control variable in the structural model to account for observable national heterogeneity in the pooled sample.

The questionnaire used five-point Likert scales ranging from 1 ("strongly disagree") to 5 ("strongly agree"). The measurement scales were adapted from prior studies and modified to fit the context of ChatGPT-assisted sustainable travel planning. Attitude, subjective norms, and perceived behavioral control were grounded in the Theory of Planned Behavior (Ajzen, 1991). ChatGPT adoption disposition was adapted from AI and technology adoption research. ChatGPT relationship engagement was adapted from engagement and relationship-oriented consumer behavior literature (Brodie et al., 2011; Hollebeek et al., 2019; Vivek et al., 2012). AI-assisted travel-planning experience was adapted from customer experience and chatbot experience research (Rose et al., 2012; Chen et al., 2021). Sustainable travel planning intention was adapted from sustainable tourism and green hotel choice research (Han et al., 2010; Verma et al., 2019). The full questionnaire appears in Appendix A.

PLS-SEM was selected because the model is prediction-oriented, includes multiple latent constructs, and investigates a recent AI-assisted sustainable tourism phenomenon (Hair et al., 2019; Hair et al., 2022; Becker et al., 2023). The analysis followed a two-stage procedure: first, assessment of the reflective measurement model; second, assessment of the structural model, including mediation analysis and country dummy controls. Since country is a nominal categorical variable, it was not coded as an ordinal metric variable. Instead, four binary dummy variables were created: Tunisia, Italy, Germany, and Other countries. France, the largest subgroup in the sample, was used as the reference category. In the SmartPLS specification, these binary controls are modeled as single-indicator control constructs linked to sustainable travel planning intention.

The adequacy of the sample size was checked through an a priori power analysis. The structural model contains up to seven predictors for the final endogenous construct when country dummy controls are included. Assuming $\alpha = 0.05$, desired

Table 1. Respondent profile

No.	Profile item	Category	Sample (N = 186)	
			Frequency	Percentage (%)
1	Gender	Male	67	36.02
		Female	119	63.98
2	Age	20-39	60	32.26
		40-59	89	47.85
		60 and above	37	19.89
3	Nationality	Tunisian	35	18.81
		French	73	39.24
		Italian	49	26.34
		German	19	10.21
		Other	10	5.37
4	Education level	High school	49	26.34
		Bachelor's degree (Bac +3)	58	31.18
		Master's degree/Engineering (Bac +6)	54	29.03
		Doctorate	25	13.44
5	Occupational category	Senior executive	47	25.26
		Middle management	52	27.95
		Professional/liberal profession	36	19.35
		Worker	51	27.41

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statistical power of 0.80, seven predictors, and a small-to-medium expected effect size of $f^2 = 0.10$, the required sample size is approximately 151 observations. The final sample of 186 respondents exceeds this threshold. However, the model remains less powered for detecting very small effects, particularly country-control effects, because the national subsamples are unevenly distributed. Consequently, small and non-significant paths are interpreted cautiously (Cohen, 1988; Hair et al., 2022; Kock & Hadaya, 2018).

Country was included as a control variable in the structural model. Because country is nominal, dummy coding was used rather than numerical ordering. France was used as the reference category because it represented the largest subgroup. Four binary controls were therefore created: Tunisia = 1 for Tunisian respondents and 0 otherwise; Italy = 1 for Italian respondents and 0 otherwise; Germany = 1 for German respondents and 0 otherwise; and Other = 1 for respondents categorized as Other and 0 otherwise. This procedure controls for national background while avoiding unsupported country-level interpretation.

Country was linked only to sustainable travel planning intention because this construct represents the final outcome of the model and the main variable for which pooled-sample interpretation could be affected by national-background heterogeneity. The objective was not to theorize country effects on each mediator, but to test whether the final intention outcome remained robust after accounting for respondents' country membership. A parsimonious control specification was preferred because the national subsamples were uneven and because country was included as a control variable rather than as a substantive predictor.

3. RESULTS

The measurement model was assessed before testing structural relationships. Table 2 reports standardized indicator loadings, composite reliability, and average variance extracted values. Composite reliability and AVE were calculated from the standardized factor loadings to ensure consistency between the reported indicators and the reliability statistics.

Table 2. Reliability and convergent validity assessment

Construct	Code	Item	Loading	Composite reliability	AVE
ChatGPT relationship engagement	CRE	CRE1	0.758	0.767	0.524
		CRE2	0.687		
		CRE3	0.725		
AI-assisted travel-planning experience	EXP	EXP1	0.823	0.885	0.659
		EXP2	0.870		
		EXP3	0.759		
		EXP4	0.792		
Sustainable travel planning intention	STPI	STPI1	0.777	0.823	0.607
		STPI2	0.773		
		STPI3	0.788		
ChatGPT adoption disposition	CAD	CAD1	0.639	0.860	0.553
		CAD2	0.751		
		CAD3	0.761		
		CAD4	0.757		
		CAD5	0.799		
Attitude	ATT	ATT1	0.841	0.883	0.715
		ATT2	0.822		
		ATT3	0.873		
Subjective norms	SN	SN1	0.696	0.750	0.500
		SN2	0.707		
		SN3	0.718		
Perceived behavioral control	PBC	PBC1	0.824	0.885	0.657
		PBC2	0.807		
		PBC3	0.799		
		PBC4	0.813		

Most standardized indicator loadings exceeded 0.70. Three items showed slightly lower loadings, namely CRE2 = 0.687, CAD1 = 0.639, and SN1 = 0.696. However, these items were retained because their loadings were close to the recommended threshold and because the corresponding constructs achieved acceptable composite reliability and AVE values. Composite reliability values ranged from 0.750 to 0.885, and AVE values ranged from 0.500 to 0.715. These values meet the recommended thresholds and support internal consistency reliability and convergent validity (Fornell & Larcker, 1981; Hair et al., 2022).

Discriminant validity was assessed using the Fornell-Larcker criterion. Table 3 reports the square root of AVE on the diagonal. For each construct, the diagonal value exceeds the correlations with the other latent variables. Discriminant validity was therefore considered satisfactory.

Table 3. Discriminant validity assessment – Fornell-Larcker criterion

	CRE	EXP	STPI	CAD	ATT	SN	PBC
CRE	0.724						
EXP	0.520	0.812					
STPI	0.330	0.490	0.779				
CAD	0.620	0.670	0.680	0.743			
ATT	0.580	0.540	0.550	0.730	0.846		
SN	0.510	0.430	0.470	0.620	0.490	0.707	
PBC	0.460	0.590	0.380	0.440	0.570	0.460	0.811

Note: Diagonal values represent the square root of the Average Variance Extracted (AVE). Off-diagonal values represent correlations between latent constructs. Discriminant validity is supported when each diagonal value is greater than the correlations in the corresponding row and column.

The structural model was then assessed using a bootstrapping procedure with 5,000 resamples. Table 4 reports the structural estimates for the hypothesized relationships.

Attitude is positively associated with ChatGPT adoption disposition ($\beta = 0.421$, $t = 6.73$, $p < 0.001$), supporting *H1*. Subjective norms are also positively associated with ChatGPT adoption disposition ($\beta = 0.353$, $t = 5.89$, $p < 0.001$), supporting *H2*. Perceived behavioral control is positively associated with ChatGPT adoption disposition ($\beta = 0.297$, $t = 4.95$, $p < 0.001$), supporting *H3*.

The direct association between ChatGPT adoption disposition and sustainable travel planning intention is not statistically significant ($\beta = 0.080$, $t = 0.34$, $p = 0.734$), leading to the rejection of *H4*. This result suggests that adoption disposition toward ChatGPT is not sufficient, by itself, to explain sustainable travel planning intention in the pooled sample.

ChatGPT adoption disposition is positively associated with ChatGPT relationship engagement ($\beta = 0.518$, $t = 8.11$, $p < 0.001$), supporting *H5*. ChatGPT relationship engagement is positively associated with sustainable travel planning intention ($\beta = 0.482$, $t = 7.54$, $p < 0.001$), supporting *H6*. ChatGPT adoption disposition is also positively associated with AI-assisted travel-planning experience ($\beta = 0.393$, $t = 6.02$, $p < 0.001$), supporting *H7*, and AI-assisted travel-planning experience is positively associated with sustainable travel planning intention ($\beta = 0.316$, $t = 5.11$, $p < 0.001$), supporting *H8*.

Country was included as a control variable using dummy coding, with France as the reference category. Table 5 reports the country dummy control effects on sustainable travel planning intention.

As shown in Table 5, all country dummy controls are statistically non-significant. Tunisia,

Table 4. Hypotheses testing results

Hypothesis	Structural relationship	Path coefficient (β)	t-value	p-value	Decision
H1	ATT → CAD	0.421	6.73	<0.001	Supported
H2	SN → CAD	0.353	5.89	<0.001	Supported
H3	PBC → CAD	0.297	4.95	<0.001	Supported
H4	CAD → STPI	0.080	0.34	0.734	Rejected
H5	CAD → CRE	0.518	8.11	<0.001	Supported
H6	CRE → STPI	0.482	7.54	<0.001	Supported
H7	CAD → EXP	0.393	6.02	<0.001	Supported
H8	EXP → STPI	0.316	5.11	<0.001	Supported
H9	CAD → CRE → STPI	0.250	4.01	<0.001	Supported
H10	CAD → EXP → STPI	0.124	3.62	<0.001	Supported

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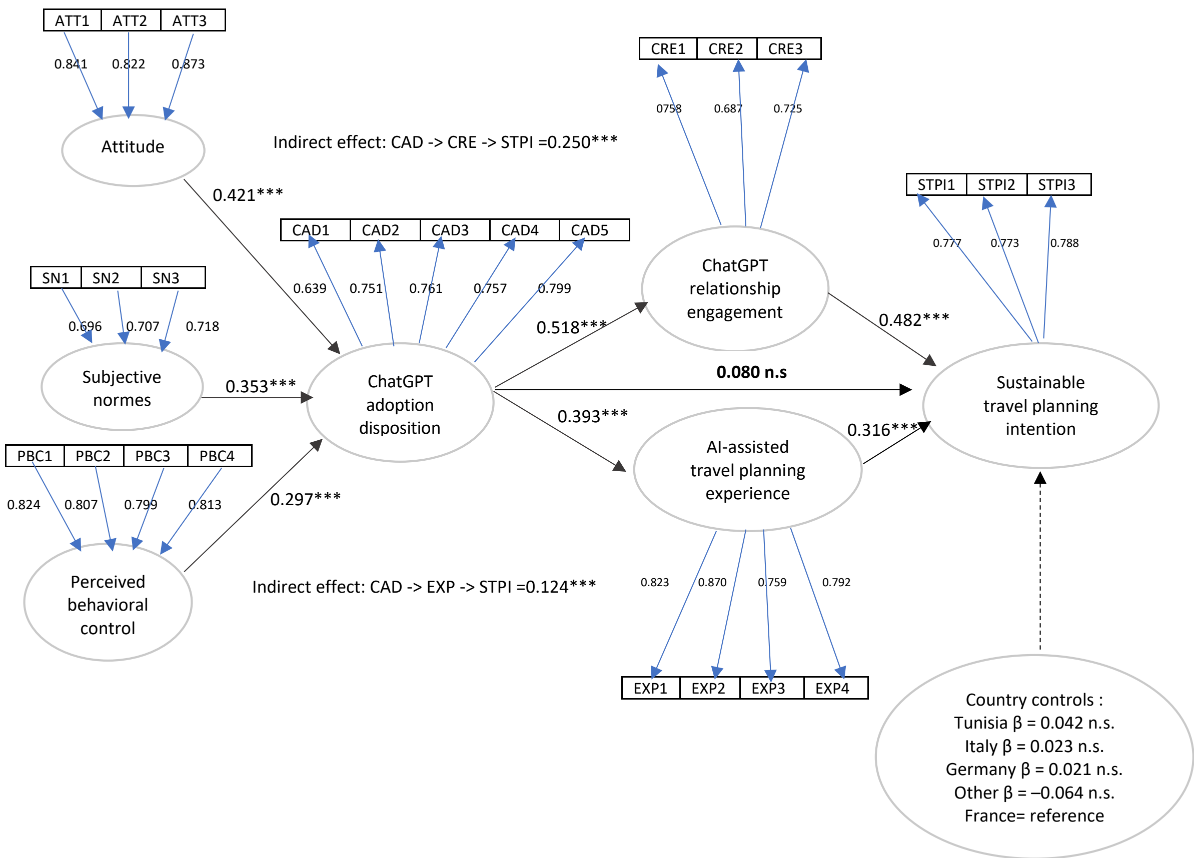
Table 5. Country dummy control effects on sustainable travel planning intention

Control path	Reference group	β	t-value	p-value	Decision
Tunisia → STPI	France	0.042	0.508	0.612	Non-significant
Italy → STPI	France	0.023	0.278	0.781	Non-significant
Germany → STPI	France	0.021	0.260	0.795	Non-significant
Other → STPI	France	–0.064	–0.818	0.414	Non-significant

Note: France is the reference group. Country controls were coded as binary dummy variables (0/1). Non-significant coefficients indicate that the corresponding country category does not differ significantly from the French reference group in sustainable travel planning intention after accounting for the main theoretical predictors. These effects are controls only and are not interpreted as country-level comparisons.

Italy, Germany, and Other country categories do not significantly differ from the French reference group in sustainable travel planning intention after the main theoretical predictors are included. Accordingly, the inclusion of country controls does not alter the substantive interpretation of the model. The effects remain interpreted at the pooled-sample level and do not provide evidence of measurement invariance or cross-national equivalence.

Indirect effects were estimated as the products of the relevant path coefficients. The indirect pathway through ChatGPT relationship engagement is β = 0.518 × 0.482 = 0.250. The indirect pathway through AI-assisted travel-planning experience is β = 0.393 × 0.316 = 0.124. Both indirect effects are statistically significant based on bootstrapping results. Because the direct path from ChatGPT adoption disposition to sustainable travel planning intention is non-significant while both in-



Note: *** $p < 0.001$; n.s. = non-significant. Dashed arrow indicates dummy-coded country controls. All country-control paths to sustainable travel planning intention were non-significant relative to the French reference category.

Figure 2. Final structural model with country controls

direct paths are significant, the results indicate indirect-only mediation in the sense proposed by Zhao et al. (2010).

These findings show that ChatGPT adoption disposition is associated with sustainable travel planning intention only when it is translated into relational engagement with the AI assistant and a positive AI-assisted planning experience. The country control analysis indicates that none of the dummy-coded country variables significantly predicts sustainable travel planning intention relative to the French reference group. This suggests that the main interpretation of the model is not substantially driven by observable country membership in the pooled sample. However, this result does not replace measurement invariance testing and does not support cross-country comparisons. The findings should therefore be interpreted as pooled-sample evidence only.

4. DISCUSSION

This study examined the association between ChatGPT adoption disposition and sustainable travel planning intention in a pooled non-random international sample. The findings first confirm the relevance of the Theory of Planned Behavior in explaining adoption disposition toward ChatGPT. Attitude, subjective norms, and perceived behavioral control are all positively associated with respondents' disposition to use ChatGPT in sustainable travel planning.

The positive association between attitude and ChatGPT adoption disposition is consistent with TPB and technology adoption literature (Ajzen, 1991; Venkatesh & Davis, 2000). Respondents who evaluate ChatGPT as useful, convenient, and relevant for sustainable travel information search are more likely to express a favorable adoption disposition. This result supports the view that positive evaluations of AI tools remain central to their uptake in consumer decision processes.

Subjective norms also matter. This suggests that social validation may shape the perceived legitimacy of generative AI in sustainable tourism planning. Since ChatGPT is still a relatively recent technology, consumers may rely on peers, online communities, and professional networks to assess whether its use is appropriate and credible. Perceived behavioral control is also significant, indicating that confidence in one's ability to use ChatGPT and judge the validity of its information is important for adoption disposition.

The non-significant direct relationship between ChatGPT adoption disposition and sustainable travel planning intention is theoretically important. It indicates that favorable disposition toward an AI assistant does not automatically translate into sustainability-oriented travel intentions. In practical terms, ChatGPT may provide information, but information access alone may be insufficient to generate responsible travel planning. Sustainable travel intentions require deeper experiential and motivational activation.

The two significant mediation paths clarify this mechanism. ChatGPT relationship engagement mediates the association between adoption disposition and sustainable travel planning intention. This suggests that relational involvement with the AI assistant – attachment, loyalty, and continuance involvement – helps transform AI adoption disposition into sustainability-oriented planning intention. AI-assisted travel-planning experience also mediates the relationship. Enjoyment, interest, satisfaction, and personalization appear to be important mechanisms through which ChatGPT becomes behaviorally relevant in sustainable tourism contexts.

The construct labels support conceptual precision. "ChatGPT adoption disposition" no longer claims to measure objective usage. "ChatGPT relationship engagement" specifies the relational and technology-focused nature of engagement. "AI-assisted travel-planning experience" replaces the inaccurate label "online shopping experience" because the items measure enjoyment, satisfaction, interest, and personalization in the ChatGPT interaction rather than navigation, payment, booking, or store interaction.

Given the non-random and uneven distribution of respondents across national groups, the international composition of the sample was treated as a methodological boundary of the study rather than as a basis for cross-country comparison. Country background was therefore included in the struc-

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tural model through dummy-coded control variables, with France used as the reference group. The results show that Tunisia, Italy, Germany, and Other country dummies are not statistically significant predictors of sustainable travel planning intention. This supports the stability of the core interpretation after controlling for observable country membership, but it should not be interpreted as evidence of cross-national equivalence, since such a claim would require formal measurement invariance testing before meaningful cross-country comparisons can be made.

Country controls were therefore specified toward the final intention variable only, as the objective was to assess the robustness of the pooled-sample interpretation rather than to theorize country effects across all mediating mechanisms.

Theoretical implications follow from this indirect-only pattern. The results suggest that AI-enabled sustainable consumer behavior should not be modeled as a simple technology-to-intention relationship. Instead, the behavioral relevance of generative AI appears to depend on experiential and relational mechanisms. This extends TPB by showing that adoption disposition can be an upstream construct whose sustainability-related consequences depend on engagement and experience pathways.

Managerially, tourism platforms and sustainable travel providers should not assume that adding AI tools will automatically increase responsible travel planning. AI interfaces must be designed to create credible, engaging, and personalized experiences. Sustainability-oriented prompts, transparent recommendation criteria, eco-label explanations, comparative environmental information, and follow-up guidance may help transform AI-assisted information search into meaningful sustainable travel planning.

CONCLUSION

This study aimed to examine whether ChatGPT adoption disposition is associated with sustainable travel planning intention and whether this association operates through ChatGPT relationship engagement and AI-assisted travel-planning experience.

The results show that attitude, subjective norms, and perceived behavioral control are positively associated with ChatGPT adoption disposition. ChatGPT adoption disposition does not have a significant direct association with sustainable travel planning intention. However, two significant indirect pathways emerge: one through ChatGPT relationship engagement and one through AI-assisted travel-planning experience. Country dummy controls were not statistically significant, indicating that observable country membership did not explain additional variance in sustainable travel planning intention relative to the French reference group after accounting for the main theoretical predictors.

These results lead to the conclusion that ChatGPT is not, by itself, a direct driver of sustainable travel intention in this pooled non-random international sample. Its relevance lies in the relational and experiential value it creates during travel planning. Conversational AI may support sustainable tourism when it increases user involvement, perceived personalization, satisfaction, and meaningful interaction with sustainability-related travel information. However, these findings should be interpreted as pooled-sample evidence and should not be generalized as evidence of cross-country equivalence or causal influence.

From a practical standpoint, tourism providers should design AI-supported planning environments around experience quality, transparency, and sustainability guidance rather than around automation alone. AI tools should help travelers understand why an option is environmentally responsible, compare alternatives, and personalize sustainable choices without overstating unsupported environmental claims. For AI-assisted sustainable travel planning to become behaviorally relevant, tourism actors should focus on trust-building, transparent recommendation criteria, eco-label explanation, and user engagement rather than on technological novelty alone.

Several limitations must be acknowledged. First, the cross-sectional design prevents causal interpretation, since the data were collected at a single point in time and do not allow the establishment of temporal precedence among the constructs. Second, the non-probability sampling strategy limits the generalizability of the findings. Although purposive and convenience sampling were appropriate for targeting respondents with prior ChatGPT experience in sustainable travel information search, the final sample cannot be considered representative of the broader population of travelers or ChatGPT users. Third, although country dummy controls were added to the model and were not statistically significant, the international sample remains uneven across national groups, and no measurement invariance or multigroup analysis was conducted. Consequently, the non-significance of country controls should be understood only as a control variable result within the pooled sample, not as evidence of cross-country equivalence or cultural invariance. Fourth, although the study reports the total number of questionnaires received and excluded, the exclusion categories were used primarily for screening and data-cleaning purposes. The study does not provide a detailed exclusion log showing the exact number of responses removed for each specific reason.

Future studies should use larger and more balanced country samples, retain full screening and exclusion logs, test measurement invariance, and compare structural paths across national contexts only after invariance conditions are met. Future research should also use longitudinal designs, platform-use data, and experimental manipulations to better assess the temporal and causal mechanisms through which ChatGPT-assisted travel planning may shape sustainable travel intentions. Future models could further incorporate trust in AI, perceived greenwashing risk, algorithmic transparency, sustainability knowledge, and perceived credibility of AI-generated recommendations.

STATEMENT ON THE USE OF ARTIFICIAL INTELLIGENCE

In preparing this manuscript, the author used ChatGPT (OpenAI) for linguistic refinement, grammar correction, stylistic polishing, and editorial organization of selected manuscript sections. The tool was not used to generate primary data, fabricate results, perform autonomous statistical analysis, or make unsupported scientific interpretations. All intellectual and scientific contributions, including conceptualization, hypothesis formulation, questionnaire design, primary data collection, data screening, PLS-SEM analysis, interpretation of results, and manuscript revision, were performed by the author. The primary data were collected from a non-random international sample including respondents from Tunisia, France, Italy, Germany, and other countries. The author critically reviewed and verified all AI-assisted linguistic suggestions and takes full responsibility for the final content and integrity of the manuscript.

AUTHOR CONTRIBUTIONS

Conceptualization: Ilhem Hammami.
Data curation: Ilhem Hammami.
Formal analysis: Ilhem Hammami.
Investigation: Ilhem Hammami.
Methodology: Ilhem Hammami.
Project administration: Ilhem Hammami.
Resources: Ilhem Hammami.
Software: Ilhem Hammami.
Supervision: Ilhem Hammami.
Validation: Ilhem Hammami.
Visualization: Ilhem Hammami.
Writing – original draft: Ilhem Hammami.
Writing – review & editing: Ilhem Hammami.

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APPENDIX A

Table A1. Measurement scales and item descriptions

Code	Measurement scale	Adapted from
CRE	ChatGPT relationship engagement	Brodie et al. (2011), Hollebeek et al. (2019), Vivek et al. (2012)
CRE1	I feel particularly attached to using ChatGPT to plan a sustainable trip.	
CRE2	I consider myself a loyal ChatGPT user when it comes to preparing environmentally friendly trips.	
CRE3	As long as ChatGPT is available, I think I will continue to use it to organize sustainable trips.	
EXP	AI-assisted travel-planning experience	Rose et al. (2012), Chen et al. (2021)
EXP1	I enjoyed my experience with ChatGPT when planning a sustainable trip.	
EXP2	The experience of using ChatGPT was interesting when planning a sustainable trip.	
EXP3	I was satisfied with the experience of using ChatGPT when planning a sustainable trip.	
EXP4	I enjoyed the personalized experience received through ChatGPT while planning a sustainable trip.	
STPI	Sustainable travel planning intention	Han et al. (2010), Verma et al. (2019)
STPI1	I would prefer to opt for sustainable tourism, even if it is more expensive than traditional tourism.	
STPI2	I choose to prioritize tourism activities that are sustainable.	
STPI3	I intend to plan a sustainable trip during my next travels because of its positive contribution to the environment.	
CAD	ChatGPT adoption disposition	Ajzen (1991), Han et al. (2024), Venkatesh and Davis (2000)
CAD1	I would be willing to recommend others to use ChatGPT to plan a sustainable trip.	
CAD2	When necessary, I will use ChatGPT to plan a sustainable trip.	
CAD3	I often use ChatGPT to search for an eco-friendly hotel, flight, or activity because of the reliability of the information it provides.	
CAD4	I intend to use ChatGPT to plan a sustainable trip.	
CAD5	I think more and more people will use ChatGPT to plan a sustainable trip.	
ATT	Attitude	Ajzen (1991), Venkatesh and Davis (2000)
ATT1	I perceive that ChatGPT is a new and unique large language model for gathering information related to sustainable travel.	
ATT2	ChatGPT offers convenience for gathering information related to sustainable travel.	
ATT3	Using ChatGPT is an exciting and enjoyable experience for gathering information related to sustainable travel.	
SN	Subjective norms	Ajzen (1991)
SN1	The people who influence my behavior think I should use ChatGPT to gather information related to sustainable travel.	
SN2	I would use ChatGPT because many of my friends use ChatGPT to gather information related to sustainable travel.	
SN3	The people around me think I should use ChatGPT to gather information related to sustainable travel.	
PBC	Perceived behavioral control	Ajzen (1991)
PBC1	It would be easy for me to use ChatGPT to gather information related to sustainable travel.	
PBC2	I feel completely in control when I use ChatGPT to gather information related to sustainable travel.	
PBC3	I can autonomously use ChatGPT features to gather information related to sustainable travel.	
PBC4	I can distinguish between valid and invalid information provided by ChatGPT about sustainable travel.	