

Assessing the Influence of AI in Social Media on Traveler's Future Trip-Planning Behavior

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Abstract

The rapid integration of artificial intelligence (AI) into social media platforms has fundamentally transformed how travelers discover, evaluate, and plan their journeys. This study investigates the influence of AI-generated social media content on the future trip-planning behavioral intentions of frequent travelers, drawing on the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) as its theoretical foundation. Five key constructs were examined: Perceived Credibility, Perceived Usefulness, Perceived Ease of Use, Social Influence, and Digital Literacy, with Behavioral Intention serving as the dependent variable.

A quantitative research design was employed, and primary data were collected from 150 respondents through a structured online questionnaire distributed via Google Forms. Data analysis was conducted using a multi-stage approach comprising descriptive statistics, Cronbach's Alpha reliability analysis, Pearson correlation analysis, multiple linear regression (OLS), one-way ANOVA, Kruskal-Wallis, and Mann-Whitney U tests.

All five research hypotheses were supported. The integrated regression model explained 76.5% of the variance in Behavioral Intention ($R^2 = 0.765$, Adjusted $R^2 = 0.756$), demonstrating exceptional predictive validity. Perceived Usefulness ($\beta = 0.530$) and Perceived Ease of Use ($\beta = 0.382$) emerged as the dominant drivers of trip-planning intention. Demographic analyses revealed that travelers aged 35–54 exhibited the highest behavioral intention a counterintuitive finding that challenges assumptions of digital nativity. No significant gender differences were observed. Binary response items further confirmed that 84.2% of respondents found AI travel content useful for destination identification, and 79.5% indicated willingness to recommend it to others.

The study concludes that AI-generated social media content now functions as a substantive, trusted, and influential input in travelers' decision-making processes, with significant implications for tourism marketers, platform designers, and destination marketing organizations.

Keywords: Artificial Intelligence, Social Media, Trip Planning, Traveler Behavior, Technology Acceptance Model, Theory of Planned Behavior

INTRODUCTION

The global tourism industry has undergone a profound digital transformation over the past decade, driven by the proliferation of social media platforms, the democratization of user-generated content (UGC), and the rapid advancement of artificial intelligence technologies. Where travelers once relied on travel agents, printed guidebooks, and personal recommendations to plan their journeys, they now navigate an expansive digital information ecosystem populated by millions of peer reviews, destination photographs, travel vlogs, and AI-curated

recommendations accessible at their fingertips.

Social media platforms including Instagram, Facebook, YouTube, TripAdvisor, and travel blogs have emerged as primary channels through which travelers research destinations, compare accommodations, and share post-travel experiences. The volume and authenticity of user-generated content on these platforms confer a degree of credibility that traditional marketing material cannot replicate. Travelers increasingly trust the experiential narratives of fellow tourists over promotional content produced by tourism

service providers, making UGC a critical determinant of destination image, tourism demand, and trip-planning behavior.

However, the sheer volume of digital information available across social media platforms presents a significant challenge: information overload. Confronted with hundreds of thousands of reviews, ratings, and competing narratives about any given destination or service, travelers often struggle to identify reliable, relevant, and actionable insights. The presence of biased opinions, fake reviews, and contradictory information further complicates the decision-making process, creating a need for intelligent systems capable of filtering, synthesizing, and presenting social media data in a meaningful and accessible manner.

Artificial intelligence has emerged as a powerful solution to this challenge. AI technologies including machine learning algorithms, natural language processing (NLP), and sentiment analysis enable travel platforms and tourism organizations to process vast volumes of UGC rapidly, identify patterns in traveler preferences and sentiments, and generate personalized travel recommendations. By analyzing the emotional tone of reviews and synthesizing aggregate traveler feedback, AI systems can provide travelers with summarized, credible, and contextually relevant insights that support informed trip-planning decisions. Platforms such as Google Travel, TripAdvisor, and Airbnb already deploy AI-driven recommendation engines that shape the information travelers receive when planning journeys.

Despite the growing deployment of AI in tourism contexts, the academic literature has not kept pace with this technological evolution. Prior research has extensively examined the influence of electronic word-of-mouth (eWOM) and online reviews on traveler decision-making,

and a separate body of literature has explored AI adoption in tourism service delivery. However, relatively few empirical studies have specifically investigated how AI-generated analysis and curation of social media content influences travelers' future trip-planning behavioral intentions. The intersection of AI, social media, and travel decision-making represents a significant and underexplored research domain.

This study addresses that gap by examining the influence of AI-generated social media content on the trip-planning behavior of frequent travelers, drawing on an integrated TAM-TPB theoretical framework. The Technology Acceptance Model (Davis, 1989) provides a lens for understanding how travelers' perceptions of usefulness and ease of use drive technology adoption, while the Theory of Planned Behavior (Ajzen, 1991) accommodates the role of social norms and subjective influences in shaping behavioral intentions. Together, these frameworks offer a robust theoretical foundation for understanding the multi-dimensional factors that determine whether and to what extent travelers rely on AI-generated social media content when planning future trips.

The study makes several contributions to the literature. First, it provides empirical validation of the integrated TAM-TPB framework in the context of AI-mediated travel content, extending these established theories to an emerging technological phenomenon. Second, it introduces Digital Literacy as a distinct and independently significant predictor of AI content adoption, enriching existing theoretical models. Third, it challenges the assumption of digital nativity as a proxy for AI content adoption by demonstrating that mid-career and senior travelers exhibit higher behavioral intention than younger cohorts. Fourth, the findings

generate actionable strategic implications for travel brands, destination marketing organizations, and digital platform designers seeking to leverage AI content for competitive advantage.

The remainder of the paper is structured as follows: Section 3 reviews the relevant literature, Section 4 describes the research methodology, Section 5 presents data analysis and implications, Section 6 discusses findings and conclusions, Section 7 outlines the scope for future research, and Section 8 provides references.

LITERATURE REVIEW

The theoretical and empirical foundations of this study span three interconnected domains: AI in tourism, social media influence on traveler behavior, and technology acceptance.

AI in Tourism and Hospitality. Bulchand-Gidumal (2020) provided an early comprehensive review of AI's applications in travel, tourism, and hospitality, demonstrating that AI systems including chatbots and recommendation engines enable tourism platforms to analyze large volumes of consumer data and generate personalized travel options that influence destination choice. Gretzel et al. (2018) extended this line of inquiry by examining how machine learning, intelligent agents, and automated recommendation systems are reshaping interactions between travelers and tourism service providers, concluding that AI will play a vital role in shaping smart tourism and digital travel planning. More recently, López-Naranjo et al. (2025) conducted a systematic review confirming the widespread adoption of machine learning, sentiment analysis, and chatbot technologies in tourism management, and Han et al. (2025) demonstrated that AI technologies enable tourism platforms to provide personalized recommendations

that enhance service efficiency and traveler experience.

Social Media and Traveler Decision-Making. Sigala (2020) demonstrated that social media platforms empower travelers to share experiences with a global audience, significantly influencing how others perceive destinations and make travel decisions, with tourism organizations increasingly using digital analytics to enhance marketing effectiveness. Xiang et al. (2021) showed that social media data, analyzed through text mining and sentiment analysis, provides rich insights into traveler preferences and tourism demand. Hussain (2024) found that visually appealing and informative social media content strongly influences destination visitation intentions, while Wilopo et al. (2025) confirmed through structural equation modeling that social media marketing activities directly shape tourists' behavioral intentions.

Online Reviews, eWOM, and Information Quality. Filieri (2018) established that the perceived credibility, usefulness, and reliability of online travel reviews exert direct and indirect effects on travelers' purchase intentions and travel behavior, underscoring the foundational role of information quality in digital tourism decision-making. Madaniah et al. (2024) further confirmed that user-generated content plays a central role in how tourists evaluate travel destinations, with online reviews, travel blogs, and social media posts serving as primary information sources during trip planning.

AI-Driven Analytics and Sentiment Analysis. George (2024) demonstrated that sentiment analysis and NLP techniques can effectively classify traveler opinions as positive, negative, or neutral, providing tourism businesses with actionable insights for service improvement. Lan et al. (2025) proposed

an LLM-driven framework for analyzing travel-related social media posts at scale, demonstrating AI's capacity to identify trends in tourist opinion. Ruan et al. (2024) confirmed that large language models can accurately measure travel sentiments from electronic feedback, while Tan et al. (2025) showed that AI-based frameworks can successfully identify traveler sentiments and destination preferences from digital data.

Theoretical Frameworks. The Technology Acceptance Model (Davis, 1989) posits that perceived usefulness and perceived ease of use are the primary determinants of technology adoption. The Theory of Planned Behavior (Ajzen, 1991) adds subjective norms and perceived behavioral control as drivers of intention. Gretzel et al. (2020) applied smart tourism frameworks to demonstrate that AI and big data technologies significantly influence traveler decision-making processes, while Kaplan and Haenlein (2020) confirmed that social media platforms play a crucial role in shaping consumer perceptions and purchasing behavior.

Research Gap. Despite this extensive body of work, limited empirical research has integrated AI-generated social media analysis with traveler behavioral intention in a single, unified framework. Most existing studies address either the impact of social media on travel decisions or the application of AI in tourism services independently. This study bridges this gap by empirically examining how AI-generated social media content influences travelers' perceptions, trust, and future trip-planning behavioral intentions within an integrated TAM-TPB framework.

METHODOLOGY

Research Design. This study adopted a quantitative, descriptive, and explanatory research design. The quantitative approach enabled statistical

testing of relationships between constructs, while the descriptive-explanatory design facilitated both the characterization of respondent profiles and the examination of causal associations between AI-generated content perceptions and behavioral intention.

Data Collection. Primary data were collected through a structured questionnaire administered online via Google Forms. The instrument comprised 25 items: 18 Likert-scale items (1 = Strongly Disagree to 5 = Strongly Agree) measuring five latent constructs, two binary (yes/no) items, and five demographic questions. The target population consisted of frequent travelers who actively use social media platforms for travel information. Convenience sampling was employed, yielding 150 valid responses.

Theoretical Constructs and Variables. The study measured five independent constructs — Perceived Credibility (Q7–Q11, 5 items), Perceived Usefulness (Q12–Q14, 3 items), Perceived Ease of Use (Q16–Q18, 3 items), Social Influence (Q18, 1 item), and Digital Literacy (Q21–Q23, 3 items) — and one dependent variable, Behavioral Intention (Q20, Q24, 2 items), all grounded in the TAM-TPB framework.

Research Hypotheses.

- **H1:** Perceived credibility of AI-generated travel content positively influences trip-planning behavioral intention.
- **H2:** Perceived usefulness of AI-generated travel content positively influences trip-planning behavioral intention.
- **H3:** Perceived ease of use of AI-generated content positively influences trip-planning behavioral intention.

- **H4:** Social influence positively influences trip-planning behavioral intention.
- **H5:** Digital literacy positively influences the adoption of AI-generated content for trip planning.

Analytical Approach. Data were analyzed using Python (Pandas, NumPy, Matplotlib, Seaborn). Analysis proceeded through five stages: (i) descriptive statistics; (ii) Cronbach's Alpha reliability analysis; (iii) Pearson correlation analysis; (iv) OLS multiple linear regression; and (v) group-comparison tests (one-way ANOVA, Kruskal-Wallis H-test, Mann-Whitney U test). All inferential tests were evaluated at $\alpha = 0.05$.

DATA ANALYSIS & IMPLICATIONS

Demographic Profile

The sample was broadly balanced across genders, with the 18–24 cohort forming the largest age group (30.7%). Notably, 50.7% of respondents had prior exposure to AI-generated travel content, and 68.6% held undergraduate or postgraduate qualifications.

Reliability Analysis

All constructs exceeded the 0.70 minimum threshold (Nunnally, 1978), confirming satisfactory internal consistency across all measurement scales.

Descriptive Statistics of Constructs

All construct means exceeded 3.90, reflecting uniformly favorable perceptions of AI-generated travel content. Digital Literacy ($M = 4.117$) and Perceived Usefulness ($M = 4.040$) achieved the highest means, while Perceived Credibility ($M = 3.921$) registered the lowest indicating residual hesitancy regarding AI content authenticity.

Pearson Correlation Analysis

All five independent constructs exhibited large, statistically significant positive correlations with Behavioral Intention ($r = 0.694$ to 0.804 , all $p < 0.001$), providing strong bivariate support for H1 through H5. Perceived Ease of Use demonstrated the strongest bivariate association with Behavioral Intention ($r = 0.804$), followed closely by Perceived Usefulness ($r = 0.791$).

Multiple Linear Regression Analysis

The model explains 76.5% of variance in Behavioral Intention an exceptional level of predictive validity. Perceived Usefulness was the dominant driver ($\beta = 0.530$), confirming the primacy of functional utility in AI content adoption. Perceived Ease of Use ($\beta = 0.382$) ranked second, emphasizing that content accessibility is a prerequisite for usefulness to translate into action.

Hypothesis Testing Summary

All five hypotheses were supported. The consistent direction and magnitude of these associations confirm that AI-generated social media content exerts a significant, positive, and multi-dimensional influence on travelers' trip-planning behavioral intentions.

Group-Comparison Analyses

Prior AI content exposure was a significant differentiator of behavioral intention. Counterintuitively, mid-career travelers (35–54 years) demonstrated the highest adoption intent, challenging assumptions that digital nativity among younger cohorts drives AI content engagement. Gender did not moderate behavioral intention. Binary items confirmed that 84.2% of respondents found AI content useful for destination identification, and 79.5% indicated willingness to recommend it to others.

DISCUSSION AND CONCLUSION

This study set out to investigate the influence of AI-generated social media content on the trip-planning behavioral intentions of frequent travelers, employing an integrated TAM-TPB framework. The empirical findings are robust, coherent, and theoretically significant.

Dominance of Usefulness and Ease of Use. The regression model's exceptional explanatory power (Adjusted $R^2 = 0.756$) confirms that the TAM-TPB framework is highly appropriate for studying AI content adoption in travel contexts. Perceived Usefulness emerged as the single strongest predictor ($\beta = 0.530$), reaffirming Davis's (1989) foundational proposition that functional utility is the primary driver of technology adoption. The prominence of Perceived Ease of Use ($\beta = 0.382$) as the second strongest predictor and the strongest bivariate correlate of Behavioral Intention ($r = 0.804$) extends TAM by suggesting that in AI-mediated content contexts, accessibility functions as a prerequisite condition: if travelers cannot readily interpret AI-generated recommendations, their utility value becomes effectively inaccessible. This finding is consistent with cognitive load theory (Sweller, 1988).

Social Influence and Digital Literacy. Social Influence ($\beta = 0.213$) retained independent predictive value, confirming that engagement cues embedded in AI travel content likes, comments, peer reviews function as credible social proof that elevates adoption intent. Digital Literacy ($\beta = 0.124$) contributed independent incremental value, suggesting that digitally competent travelers are better positioned to convert AI content into concrete planning actions. Future theoretical models should treat digital literacy as a first-order construct rather than a demographic covariate.

Age and Exposure as Moderators. The Kruskal-Wallis finding that travelers aged 35–54 exhibited the highest Behavioral Intention significantly higher than the 18–24 cohort challenges the digital nativity paradigm in technology adoption literature. This pattern aligns with a maturity-based decision-making hypothesis: experienced travelers engage more deliberately with AI recommendations as planning tools, while younger audiences may consume such content recreationally without converting it into action. The ANOVA result further confirms that prior exposure itself is a significant driver of intent a self-reinforcing mechanism with practical implications for platform growth strategies.

Credibility Gap. Perceived Credibility recorded the lowest composite mean ($M = 3.921$) and exhibited multicollinearity suppression in the regression model, though its strong bivariate correlation ($r = 0.694$, $p < 0.001$) confirms its theoretical relevance. This persistent credibility gap signals that travelers retain residual hesitancy about AI content authenticity a finding consistent with prior research on digital trust and represents a strategic priority for platform designers.

Conclusion. In sum, AI-generated social media content has transitioned from a novel technological curiosity to a substantive, trusted, and influential input in the trip-planning behavior of frequent travelers. The study confirms that usefulness, accessibility, social validation, and digital competence collectively drive travelers' willingness to adopt AI-generated recommendations. For practitioners, these findings provide a data-driven roadmap for designing, deploying, and scaling AI travel content strategies. For academics, they enrich TAM-TPB theory and open productive new directions for inquiry into AI-mediated tourism behavior.

FUTURE SCOPE FOR RESEARCH

The findings and limitations of this study identify several productive directions for future empirical inquiry.

Longitudinal and Behavioral Studies. The present cross-sectional design captures stated intention at a single point in time. Future research should employ longitudinal designs to track whether positive behavioral intention translates into actual trip bookings and sustained AI content adoption over time, providing evidence of genuine behavioral change rather than expressed intent.

Structural Equation Modeling (SEM). The high inter-construct multicollinearity observed in this study constrains the interpretability of individual regression coefficients. SEM would enable simultaneous testing of direct, indirect, and mediating pathways among TAM-TPB constructs particularly the credibility-usefulness-intention chain and would accommodate measurement error, providing a more precise decomposition of the adoption process.

Segment-Specific and Cross-Cultural Research. This study examined travel planning behavior in a general context. Comparative studies across travel typologies (leisure, business, adventure, cultural), geographic markets, and cultural contexts would reveal whether the adoption drivers identified here are universal or context-dependent, informing globally differentiated AI content strategies.

AI Content Format and Modality Effects. Future studies should investigate whether different AI content formats text-based recommendations, video itineraries, conversational AI chatbots, or augmented reality overlays produce differential effects on perceived usefulness, ease of use, and behavioral intention, guiding platform-specific content design decisions.

Trust Dynamics and Credibility Over Time. Research tracking how traveler trust in AI-generated content evolves with repeated exposure and examining how specific design interventions such as transparency disclosures, editorial verification badges, and algorithmic explanation features moderate credibility perceptions would generate directly actionable insights for platform designers seeking to close the credibility gap identified in this study.

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- You are out of free [messages](#) until 12:30 AM
- [Upgrade](#)
- humanise the entire contents and give me a final word document.
- Sonnet 4.6
- [Claude is AI and can make mistakes. Please double-check responses.](#)

Table 1: Demographic Profile of Respondents (N = 150)

Variable	Category	n	%
Age Group	18–24 years	46	30.7%
	25–34 years	28	18.7%
	35–44 years	27	18.0%
	45–54 years	25	16.7%
	55 and above	23	15.3%
Gender	Female	72	48.0%
	Male	63	42.0%
	Other/Prefer not to say	15	10.0%
Education	High School	40	26.7%
	Undergraduate	53	35.3%
	Postgraduate	50	33.3%
AI Content Exposure	Yes	76	50.7%
	No	50	33.3%
	Maybe/Unsure	20	13.3%
Top Social Media Platform	Instagram	36	24.0%
	Travel Blogs	35	23.3%
	Facebook	29	19.3%

Table 2: Cronbach's Alpha Reliability Statistics

Construct	Items	No. of Items	Cronbach's α	Interpretation
Perceived Credibility	Q7–Q11	5	0.854	Good
Perceived Usefulness	Q12–Q14	3	0.814	Good
Perceived Ease of Use	Q16–Q18	3	0.751	Acceptable
Behavioral Intention	Q20, Q24	2	0.846	Good
Digital Literacy	Q21–Q23	3	0.772	Acceptable

Table 3: Construct-Level Descriptive Statistics

Construct	n	Mean	Std. Dev.	Min	Max	Interpretation
Perceived Credibility	149	3.921	0.723	1.40	5.00	Moderately High
Perceived Usefulness	149	4.040	0.792	1.00	5.00	High
Perceived Ease of Use	149	3.954	0.793	1.00	5.00	Moderately High
Social Influence	148	3.966	0.986	1.00	5.00	Moderately High
Behavioral Intention	149	3.953	0.964	1.00	5.00	Moderately High
Digital Literacy	149	4.117	0.768	1.00	5.00	High

Table 4: Pearson Correlation Matrix (n = 148–149)

Construct	(1)	(2)	(3)	(4)	(5)	(6)
(1) Credibility	1.000					
(2) Usefulness	0.810***	1.000				
(3) Ease of Use	0.743***	0.720***	1.000			
(4) Social Influence	0.632***	0.618***	0.820***	1.000		
(5) Behavioral Intention	0.694***	0.791***	0.804***	0.747***	1.000	
(6) Digital Literacy	0.643***	0.708***	0.685***	0.622***	0.699***	1.000

Note: *** $p < 0.001$ (two-tailed)

Table 5: OLS Regression Results — Predictors of Behavioral Intention

Predictor	Beta (β)	Direction	Hypothesis Outcome
Perceived Usefulness	0.530	Positive (+)	H2 — Supported (strongest predictor)
Perceived Ease of Use	0.382	Positive (+)	H3 — Supported
Social Influence	0.213	Positive (+)	H4 — Supported
Digital Literacy	0.124	Positive (+)	H5 — Supported
Perceived Credibility	-0.122	Suppressed*	H1 — Supported (bivariate level)

$R^2 = 0.765$ | Adjusted $R^2 = 0.756$ | Model significant at $p < 0.001$ | $n = 149$

*Note: Credibility's negative beta reflects multicollinearity suppression (r with Usefulness = 0.810; r with Ease of Use = 0.743). H1 is accepted based on strong bivariate evidence ($r = 0.694$, $p < 0.001$).

Table 6: Summary of Hypothesis Testing Results

Hypothesis	Statement	r value	p-value	Outcome
H1	Credibility → Behavioral Intention	0.694	< 0.001	Supported
H2	Usefulness → Behavioral Intention	0.791	< 0.001	Supported
H3	Ease of Use → Behavioral Intention	0.804	< 0.001	Supported
H4	Social Influence → Behavioral Intention	0.747	< 0.001	Supported
H5	Digital Literacy → Behavioral Intention	0.699	< 0.001	Supported

Table 7: ANOVA, Kruskal-Wallis, and Mann-Whitney U Test Results

Test	Variable	Key Finding	Statistic	p-value
One-Way ANOVA	AI Exposure vs. BI	Exposed (M=4.178) > Maybe (M=4.000) > Not Exposed (M=3.600)	F = 5.789	0.004
Kruskal-Wallis	Age Group vs. BI	Ages 35–44 (M=4.444) and 45–54 (M=4.420) highest; 18–24 (M=3.359) lowest	H = 27.156	< 0.001
Mann-Whitney U	Gender vs. BI	Male (M=3.857) vs. Female (M=3.986) — no significant difference	U = 2192	0.732