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ChatGPT as a Real-Time Travel Companion: During-Trip Support and Tourist Satisfaction

Adi Prasetyo Tedjakusuma [1,2] and Waiphot Kulachai [3,*]

1 Department of Management, Faculty of Business and Economics, University of Surabaya, Surabaya 60293, Indonesia; atedjakusuma@staff.ubaya.ac.id
2 Department of Business Administration, College of Management, Chaoyang University of Technology, Taichung 413310, Taiwan
3 College of Politics and Government, Suan Sunandha Rajabhat University, Bangkok 10300, Thailand
* Correspondence: waiphot.ku@ssru.ac.th

Abstract

Grounded in the Stimulus–Organism–Response (SOR) framework, this study examines how tourists' in-trip use of ChatGPT shapes satisfaction during leisure travel. Survey data from 502 Indonesian travellers were analysed using PLS-SEM. Information diagnosticity, task efficiency, and perceived social support significantly strengthen travellers' confidence in on-site choices, with social support emerging as the strongest predictor. Greater confidence elevates positive destination emotion, which in turn enhances tourist satisfaction, supporting a sequential cognition–affect mechanism. The study extends SOR to the during-trip stage by conceptualising ChatGPT as a real-time, dialogic stimulus that influences experience formation. Practically, destination and tourism firms can deploy ChatGPT at key on-site touchpoints and prioritise reassuring, effort-reducing guidance, supported by reliable local information and clear escalation to human assistance for higher-stakes needs.

Keywords: information diagnosticity; task efficiency; social support; decision confidence; destination emotion; tourist satisfaction

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1. Introduction

Tourism is at a new level of human–AI interaction. Generative AI is no longer primarily used to brainstorm ideas before leaving or to write itineraries at home; increasingly, travellers turn to it when they are already on the move, as a fast, natural conversational guide for what they should do next. During a trip, they make a series of small yet significant decisions, such as choosing the best amusement park, selecting the most recommended place to visit, or changing plans as weather conditions or energy levels change. At that point, ChatGPT 5.1 will not be evaluated by whether tourists use it, but by whether it helps right away: does it clarify the choice, simplify the work, and allow a traveller to continue without hesitation?

This matters because satisfaction is formed during the course of the trip and not necessarily at the end. Tourists' overall evaluations reflect their sense of value and performance, but they are also strongly coloured by the emotional tone that builds across moments and episodes (Westbrook & Oliver, 1991). A mobile, conversational assistant can have a pragmatic impact on experience creation in a place such as Indonesia, where the quality of available information and service conditions may vary by location, helping travellers manage uncertainty, feel less stress during decision-making, and foster affective experiences that can later be encoded into overall satisfaction.

The literature on ChatGPT in tourism has expanded rapidly, yet much of it still centres on outcomes such as acceptance, continuance, and engagement, typically explained through mechanisms such as trust, attitudes, and parasocial interaction (Pham et al., 2024; Xu et al., 2024; Magano et al., 2025). Related work also indicates that travellers value AI advice most when it feels directly useful for the decision at hand and fits the immediate context (Stergiou & Nella, 2024), and that chatbots can simplify travel by cutting through information overload—reducing the number of options to consider and making planning feel easier (Shin et al., 2025). What remains missing, however, is a clear account of what happens during the trip itself: how tourists' real-time perceptions of ChatGPT's qualities are converted into satisfaction through the psychological states that shape how the experience is judged as it unfolds. At the same time, available consumer evidence suggests that generative AI use in travel is increasing but remains segment-specific; for example, ABTA (2025) reports that the share of UK adults using AI for holiday inspiration doubled year-on-year to 8%, and is higher among 25–34-year-olds (18%) (ABTA, 2025). Importantly, this study does not assume that ChatGPT is used (or desired) by all tourists. Rather, it examines the experience-formation mechanism among travellers who choose to use ChatGPT in-trip as a real-time decision aid. Tourists who intentionally avoid digital technologies as part of relaxation (e.g., "digital detox" travellers) fall outside the present sampling frame, and their experience formation may follow different mechanisms.

In light of this, the study tackles three clear gaps. Most existing research has not yet conceptualised during-trip (in situ) ChatGPT use as a distinct phase of travel, even though the trip itself is marked by disruptions and time–resource constraints that heighten uncertainty and make immediate decision support particularly consequential (Moore et al., 2012; Sigala et al., 2024). Prior work also tends to summarise tourists' evaluations with umbrella constructs such as usefulness or trust, which can understate the specific interaction qualities travellers need when circumstances shift—namely guidance that is clearly decision-relevant and actionable, exchanges that economise time and mental effort, and reassurance that helps dampen uncertainty-related concern (Feldman & Lynch, 1988; Herr et al., 1991; Stergiou & Nella, 2024). Finally, many models stop short of articulating the process through which these situational perceptions ultimately become satisfaction, notwithstanding strong evidence that satisfaction is jointly shaped by cognitive appraisal and affect, and that these momentary evaluations are subsequently carried into remembered travel experiences (Lazarus, 1991; Ellsworth & Scherer, 2003; Westbrook & Oliver, 1991; Hosany & Gilbert, 2010; Prayag et al., 2017). Accordingly, we shift away from adoption-focused outcomes and instead examine how experiences are formed during the trip, using the Indonesian tourism context as the empirical setting. To our knowledge, empirical work rarely models how during-trip (in situ) perceptions of ChatGPT translate into tourist satisfaction through sequential cognitive (decision confidence) and affective (destination emotion) processes.

Research questions. Based on these gaps, this study addresses two research questions. RQ1: How do tourists' during-trip perceptions of ChatGPT's interaction qualities—information diagnosticity, task efficiency, and social support—influence decision confidence, positive destination emotion, and tourist satisfaction? RQ2: To what extent do decision confidence and positive destination emotion operate as sequential mechanisms through which these perceived interaction qualities translate into tourist satisfaction (i.e., ID/TE/SS $\rightarrow$ DC $\rightarrow$ DE $\rightarrow$ TS)?

To structure our argument, we employ the Stimulus–Organism–Response (SOR) framework, which is particularly appropriate for modelling in situ experience formation

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(rather than adoption/continuance) because it explains how perceived interaction cues translate into cognitive and affective states that shape satisfaction (Mehrabian & Russell, 1974; Donovan & Rossiter, 1982). In the context of during-trip ChatGPT use, we conceptualise information diagnosticity, task efficiency, and social support as stimuli that strengthen decision confidence and subsequently positive destination emotion, culminating in tourist satisfaction (ID/TE/SS → DC → DE → TS).

This study contributes in three ways. First, it extends generative-AI tourism research into the during-trip decision arena, where choices are iterative and constraint-driven rather than fully predetermined (Moore et al., 2012; Sigala et al., 2024). Second, it specifies a mechanism-based explanation of how ChatGPT shapes experience by modelling a sequential cognitive–affective pathway (DC → DE) leading to TS (Lazarus, 1991; Hosany & Gilbert, 2010). Third, it bridges classic work on dynamic in-destination adjustment with the emerging idea of ChatGPT as a real-time travel companion, showing how specific interaction qualities—ID, TE, and SS—operate as actionable stimuli that scaffold on-site choices and feelings in real time (Stergiou & Nella, 2024; Shin et al., 2025; Pham et al., 2024). Together, these contributions position ChatGPT not merely as an information source, but as a socio-technical stimulus that shapes tourists' judgements and emotions while the trip is unfolding.

2. Literature Review

2.1. Theoretical Framework: The Stimulus-Organism-Response Model

The SOR model originated in environmental psychology to explain behaviour as a mediated process in which external cues (stimuli) shape internal cognitive and affective states (organism), which then drive downstream evaluations and actions (responses) (Mehrabian & Russell, 1974). This logic was later adopted in consumer and service research to show how offline and technology-mediated environments influence satisfaction through intervening appraisals and emotions (Donovan & Rossiter, 1982). In ChatGPT-enabled tourism, SOR is especially relevant because tourists often consult AI under uncertainty, making it likely that perceived interaction cues first alter psychological states before shaping satisfaction outcomes (Pham et al., 2024; Xu et al., 2024; Magano et al., 2025).

Although this study adopts SOR as the primary lens, alternative technology frameworks offer useful but different explanatory emphases. TAM and UTAUT are well-suited to explaining technology acceptance and usage intentions by highlighting beliefs such as perceived usefulness, perceived ease of use, performance expectancy, effort expectancy, and facilitating conditions (Davis, 1989; Venkatesh et al., 2003). Expectation-Confirmation Theory (ECT), in turn, is widely applied to post-adoption evaluation and continuance, proposing that satisfaction and continued use arise when experienced performance confirms prior expectations (Bhattacherjee, 2001). These perspectives are valuable for understanding whether travellers adopt or continue using ChatGPT; however, they are less directly focused on the in situ psychological process through which interaction cues during a trip shape experience evaluations. Our study therefore employs SOR because it is explicitly designed to model how perceived stimuli in an environment (here, information diagnosticity, task efficiency, and social support) shape internal cognitive and affective states (decision confidence and destination emotion) that culminate in an evaluative response (tourist satisfaction). In this sense, SOR is theoretically better aligned with our focus on during-trip experience formation and the sequential cognition–affect pathway underlying satisfaction, while TAM/UTAUT and ECT remain complementary lenses for future research on adoption, continuance, and expectation calibration in AI-assisted travel contexts.

Beyond the emergent ChatGPT-focused stream, a broader tourism literature conceptualises AI and automation as a structural shift in how value is produced and consumed across the travel journey, including destination-level "smart tourism" ecosystems and tourism service automation. Within this view, AI-enabled services reconfigure information search, real-time decision support, and on-site experience delivery under conditions of uncertainty and time pressure, making tourists' perceptions of AI interaction cues theoretically consequential well beyond adoption intentions. Positioning ChatGPT within this wider AI-in-tourism trajectory strengthens the external validity of our model by treating conversational AI as a specific instantiation of AI-enabled decision support in tourism settings (Gretzel et al., 2015; Tussyadiah, 2020).

From an HCI perspective, the focal stimuli in this study also map onto general design principles for human–AI systems. Human–AI interaction research emphasises that users' judgments and downstream outcomes depend on whether AI systems (i) provide decision-relevant support that helps users act, (ii) reduce interaction and cognitive effort, and (iii) communicate in ways that calibrate user confidence and reduce uncertainty during use (Amershi et al., 2019). These principles align closely with information diagnosticity (decision usefulness), task efficiency (effort/time reduction), and social support (reassurance/warmth), which we model as salient cues shaping internal cognitive and affective states in an in-trip context.

Finally, theories of social response to technology explain why "support" can function as a psychologically meaningful cue even when the agent is non-human. Social presence theory argues that communication media differ in the extent to which they convey a sense of interpersonal connection, shaping affective experience and evaluative judgments (Short et al., 1976). Relatedly, the "media equation" perspective and subsequent evidence on social responses to computing suggest that people often apply social heuristics to computers and conversational interfaces, responding to them as social actors in ways that can influence comfort, perceived support, and satisfaction (Reeves & Nass, 1996; Nass & Moon, 2000). This provides a generalisable theoretical foundation for modelling social support as a stimulus in AI-mediated tourism interactions, particularly under in-trip uncertainty.

Building on this foundation, the present study treats ID, TE, and SS as key stimuli during in-trip ChatGPT use because they capture decision usefulness, effort reduction, and reassurance within the interaction. These perceptions are expected to strengthen DC and subsequently DE, such that more defensible choices generate more favourable feelings toward the destination. TS is modelled as the response emerging from this cognitive-to-affective pathway, aligning with recent ChatGPT tourism studies that emphasise mediated effects from perceived chatbot qualities to downstream evaluations (Xu et al., 2024; Magano et al., 2025).

As noted in the Introduction, existing research has largely prioritised adoption- and engagement-oriented outcomes, leaving the in situ pathway to satisfaction comparatively under-specified. Accessibility–diagnosticity work likewise suggests that tourists value AI advice when it is relevant and decision-useful (Stergiou & Nella, 2024). However, the during-trip setting—where decisions are iterative and constrained—has received limited empirical attention, and prior work has not clearly specified how diagnosticity, efficiency, and social support translate into satisfaction through sequential cognitive (DC) and affective (DE) states. Addressing this gap, this study models ID, TE, and SS as in-trip stimuli that influence TS via DC and then DE.

2.2. Hypothesis Development

2.2.1. Information Diagnosticity, Task Efficiency, and Social Support on Decision Confidence

ID concerns whether the information a traveller receives can genuinely do work in a decision—helping them distinguish between alternatives and justify a choice (Feldman & Lynch, 1988; Herr et al., 1991). In the middle of a trip, tourists rarely make a single "big" decision; instead, they make a stream of micro-decisions under shifting constraints (time, location, queues, weather, fatigue). Under these conditions, ChatGPT becomes more consequential when its suggestions feel situationally fitted rather than generic, consistent with the accessibility–diagnosticity view applied to ChatGPT in tourism (Stergiou & Nella, 2024). When travellers perceive the advice as credible and immediately usable, it supplies justification cues ("this option makes sense for me now"), reducing doubt and increasing willingness to commit—thereby strengthening decision confidence (DC) (Ali et al., 2023; J. H. Kim et al., 2023).

DC is also shaped by how efficiently tourists can arrive at an option they can accept. If ChatGPT reduces search, comparison, and synthesis effort—by structuring trade-offs or translating constraints into clear next steps—it should increase perceived control over the decision process, which is a proximal driver of confidence in technology-assisted choices (Davis, 1989; Venkatesh et al., 2003). This argument is consistent with human–computer interaction research on human–AI interaction, which stresses that AI systems are evaluated more favourably when they reduce user effort and support timely, actionable decisions—especially in situationally constrained contexts where users must move quickly from information to action (Amershi et al., 2019).

SS adds a different pathway. Rather than re-specifying DC, we emphasise that supportive interaction functions as a reassurance cue under uncertainty, helping travellers feel safer relying on recommendations. When ChatGPT's interaction feels supportive (e.g., warm, responsive, competent), it can lower uncertainty-related stress and make acting on the recommendation feel safer, reinforcing confidence to proceed (Pham et al., 2024). Relatedly, parasocial and social-influence processes can create perceived closeness and expertise, further stabilising confidence in travel decisions (Xu et al., 2024). More broadly, social presence and "computers as social actors" research suggests that conversational systems can elicit interpersonal responses (e.g., reassurance and perceived companionship), making supportive communication a psychologically credible pathway through which AI interactions stabilise confidence under uncertainty (Short et al., 1976; Reeves & Nass, 1996; Nass & Moon, 2000). Collectively, tourists should feel most confident when ChatGPT is experienced as decision-helpful, effort-saving, and reassuring.

H1a. *ChatGPT's information diagnosticity positively influences tourists' decision confidence.*

H1b. *ChatGPT's task efficiency positively influences tourists' decision confidence.*

H1c. *ChatGPT's social support positively influences tourists' decision confidence.*

2.2.2. Decision Confidence on Positive Destination Emotion

Decision confidence (DC) captures a tourist's sense that an on-site choice is appropriate and defensible. Once established, it should reduce second-guessing and uncertainty-related concern that can undermine enjoyment, thereby shaping emotional responses during the trip. Emotions are shaped less by events themselves than by how travellers appraise those events—especially in terms of predictability, controllability, and goal congruence (Lazarus, 1991; Ellsworth & Scherer, 2003). In ChatGPT-supported travel, confidence that AI-guided choices are well-justified (e.g., fit current constraints and preferences) should therefore shift appraisals toward "this will work out," making the destination feel more promising and increasing DE. Recent evidence in ChatGPT tourism further suggests that cognition-led evaluations (e.g., trustworthiness/expertise) precede and support affect-laden outcomes: parasocial interaction strengthens emotional connection, while anxiety-related mechanisms can dampen favourable responses (Xu et al., 2024; Pham et al., 2024). Accordingly, higher decision confidence should elevate positive destination emotion.

H2. *Tourists' decision confidence positively influences positive destination emotion.*

2.2.3. Positive Destination Emotion on Tourist Satisfaction

DE refers to the pleasant feelings tourists experience toward a place (e.g., joy, delight, positive surprise) and these emotions matter because satisfaction is shaped not only by what tourists think about the trip, but also by how the trip feels (Westbrook & Oliver, 1991). Tourism research shows that when travellers feel excited and emotionally connected to a destination, they are more likely to remember the experience as rewarding, which increases overall satisfaction (Hosany & Gilbert, 2010). In ChatGPT-assisted trips, the link should be stronger because ChatGPT can make the trip feel smoother and less stressful—by giving timely guidance, reassurance, and personalised suggestions—helping tourists maintain positive feelings that later translate into higher satisfaction (Pham et al., 2024; Xu et al., 2024).

H3. *Positive destination emotion positively influences tourist satisfaction.*

2.2.4. Mediating Effects

When tourists use ChatGPT during a trip, its perceived benefits are expected to enhance TS primarily through proximal cognitive and affective states, rather than through a purely direct effect. ID—whether ChatGPT's advice helps travellers distinguish among options and justify a choice—should increase DC by reducing ambiguity and strengthening justification at the point of action (Feldman & Lynch, 1988; Herr et al., 1991; Stergiou & Nella, 2024). TE should likewise strengthen DC because time and effort savings increase perceived control and reduce decision friction (Davis, 1989; Venkatesh et al., 2003). SS provides an additional pathway: reassuring and responsive interaction can dampen uncertainty and make tourists feel safer relying on the recommendations (Pham et al., 2024; Xu et al., 2024). As DC increases, appraisal theory suggests that tourists are more likely to perceive the situation as controllable and goal-congruent, which should intensify DE (Lazarus, 1991; Ellsworth & Scherer, 2003). Such DE then fosters satisfaction as the tourists compare and retain trips based on the emotions they had (Westbrook & Oliver, 1991; Hosany & Gilbert, 2010).

Accordingly, ID, TE, and SS should improve satisfaction indirectly via DC and then DE.

H4a. *Information diagnosticity has a positive indirect effect on tourist satisfaction via decision confidence and then positive destination emotion.*

H4b. *Task efficiency has a positive indirect effect on tourist satisfaction via decision confidence and then positive destination emotion.*

H4c. *Social support has a positive indirect effect on tourist satisfaction via decision confidence and then positive destination emotion. Figure 1 exhibits all the hypotheses posited in this study.*

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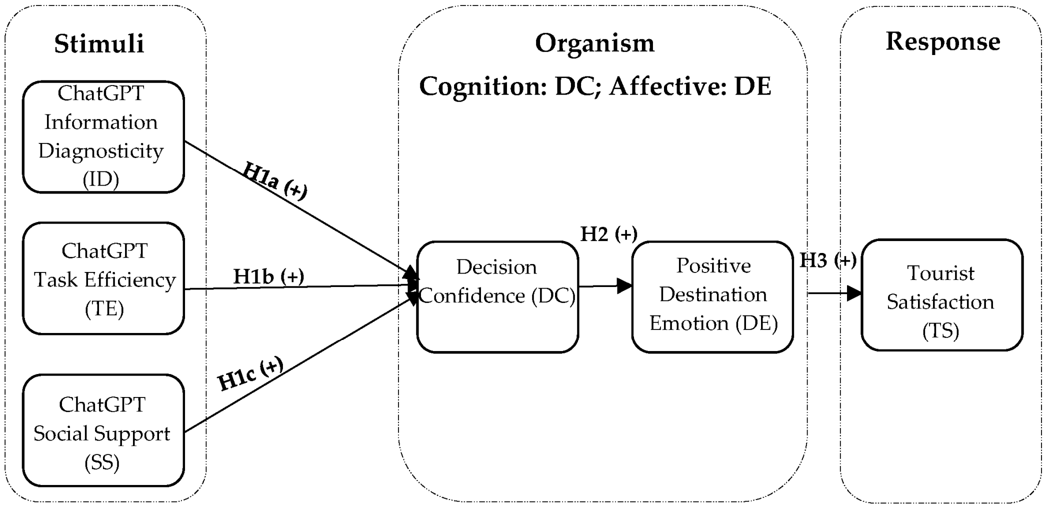

Figure 1. Research Framework.

3. Methodology

3.1. Research Design and Context

The current study employs a cross-sectional survey design to test the hypothesis of how the use of ChatGPT during a trip affects the cognitive and affective aspects of the tourists and, ultimately, their satisfaction with the trip. The data setting is Indonesia as an emerging tourist destination and the adoption of smartphones and AI-based applications is growing at a high pace. The respondents were Indonesian residents who had recently completed a domestic or international trip and used ChatGPT to aid their travel-related choices. Focusing on this group allows us to capture tourists' lived experience of interacting with a generative-AI "companion" in situ rather than in hypothetical scenarios.

3.2. Sampling Technique and Data Collection

Data were collected through an online survey that was distributed via widely used social media and messaging platforms like Facebook, Line, Instagram, and WhatsApp communities and other travel-themed groups in Indonesia. Respondents were eligible if they had used ChatGPT during their most recent leisure trip—i.e., at the destination/on the move rather than only for pre-trip planning—within the past 12 months, and they were instructed to answer all items with that trip in mind. Additional inclusion criteria required participants to (1) be at least 20 years old and (2) hold at least a high-school qualification (or equivalent). Accordingly, the study is designed to explain experience-formation mechanisms among in-trip ChatGPT users rather than to estimate the population prevalence of ChatGPT use among all tourists. Data collection took place from June to September 2025. After filtering out incomplete questionnaires and the ones with poor-quality patterns (straight-lining, or high-fraction missing data, etc.), 502 valid observations were left. The sample size is aligned to the recommended PLS-SEM parameters to obtain sufficient statistical power due to the count of constructs and structural paths in the model (J. F. Hair et al., 2019). Respondents were informed of the academic purpose of the research and participation was entirely voluntary and anonymous.

3.3. Measures

All constructs were modelled reflectively and measured using multi-item scales adapted from validated instruments in tourism, marketing and information systems research. Items were reworded to adjust the during-trip ChatGPT context and rated on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). All items were translated into the Indonesian language following a translation–back-translation procedure to ensure semantic equivalence. The refinement of the wording and confirmation of the clarity and face validity were carried out with a small pilot study of 30 Indonesian travellers. Table 1 presents complete operationalisation and measurement items.

Table 1. Operationalization and Measurement Items.

Variable	Operationalization	Measurement Items	Source
ChatGPT information diagnosticity	The extent to which information from ChatGPT helps tourists distinguish among and evaluate in-destination alternatives (e.g., activities, restaurants, routes) during the trip.	1. During my trip, information from ChatGPT helps me evaluate and compare different travel options 2. During my trip, ChatGPT's responses give me a clear sense of what to expect from different places or activities at this destination 3. During my trip, ChatGPT's information helps me choose the option (e.g., route, attraction, restaurant) that best fits my needs 4. Overall, during my trip, ChatGPT provides information that is useful for evaluating in-destination travel choices	Z. Jiang and Benbasat (2004); Filieri (2015); Filieri et al. (2018)
ChatGPT Task Efficiency	The extent to which using ChatGPT during the trip helps tourists complete travel-related tasks faster, with less effort, and with better decision outcomes.	1. Using ChatGPT during my trip saves me time when completing travel-related tasks (e.g., finding routes, places to eat, etc) 2. Using ChatGPT during my trip makes travel-related tasks easier to complete 3. Using ChatGPT during my trip improves the quality of my travel decisions 4. Using ChatGPT during my trip helps me manage multiple travel-related tasks at the same time	Baek and Kim (2023)
ChatGPT social support	Tourists' perceived emotional and informational reassurance provided by ChatGPT during the trip, particularly the extent to which ChatGPT makes them feel supported, comforted, accompanied, and less alone when facing travel-related problems or uncertainties	1. When I feel unsure during my trip, interacting with ChatGPT makes me feel supported 2. During my trip, ChatGPT provides reassurance when I worry about travel-related decisions 3. During my trip, I feel that ChatGPT is available when I need advice 4. During my trip, using ChatGPT makes me feel less alone when dealing with travel-related problems	Nick et al. (2018); Lin and Bhattacherjee (2009); L. Zhang et al. (2025)
Decision Confidence	The extent to which travellers feel certain and assured about the on-site choices they make during the trip, particularly when those choices are informed by ChatGPT's suggestions	1. I feel sure that the decisions I make during this trip are right for me. 2. I am confident that the activities and services I choose based on ChatGPT's suggestions suit my trip well. 3. I am unlikely to regret the travel decisions I have made on this trip. 4. Overall, I have a high level of confidence in the decisions I make while travelling on this trip.	Heitmann et al. (2007); Zhong et al. (2025); Krishnan and Smith (1998)
Positive Destination Emotion	Tourists' positive affective responses (e.g., joy, excitement, pleasant surprise) experienced at the destination during the trip, shaped in part by on-site experiences and activities discovered or supported through ChatGPT	1. During this trip, being at this destination makes me feel joyful and delighted. 2. During this trip, I feel emotionally connected to this destination. 3. During this trip, I often feel pleasantly surprised by the experiences I am having here. 4. Overall, during this trip, this destination makes me feel excited and uplifted.	Hosany and Gilbert (2010); Hosany et al. (2015); Prayag et al. (2017)

Table 1. *Cont.*

Variable	Operationalization	Measurement Items	Source
Tourist Satisfaction	The extent to which the ongoing trip to this destination, including experiences discovered via ChatGPT, meets or exceeds the traveller's expectations	1. Overall, I am satisfied with this trip to this destination. 2. Given how this trip has gone so far, visiting this destination was a wise decision. 3. So far, I have really enjoyed my experience at this destination. 4. Overall, my experience at this destination on this trip has been a good one.	del Bosque and San Martín (2008); Gajić et al. (2025)

3.4. Analysis Technique

To test the proposed model, PLS-SEM was employed using SmartPLS 4. This technique is appropriate given the study's theory-extending objective and the presence of several latent constructs measured with reflective indicators. Following J. F. Hair et al.'s (2019) recommendation, the analysis proceeded in two stages. First, the measurement model was evaluated by examining indicator loadings, internal consistency reliability (Cronbach's alpha and composite reliability), convergent validity (average variance extracted) and discriminant validity using the Fornell–Larcker criterion, HTMT ratios and inspection of cross-loadings. Potential common method variance was assessed through full collinearity variance inflation factors (VIFs) for all latent variables, with values below the commonly accepted threshold suggesting that CMV was unlikely to pose a serious threat. Second, the structural model was assessed by checking collinearity (VIF), interpreting path coefficients and coefficients of determination (R^2), and determining the significance of the hypothesised relationships via a bootstrapping procedure with 5000 resamples.

4. Results

4.1. Common Method Variance (CMV)

Because all variables were measured using a single self-report survey, we assessed the potential impact of common method variance (CMV). Following Kock's (2015) full collinearity procedure, we computed variance inflation factors (VIFs) for each latent construct in SmartPLS 4s by regressing it on all other constructs simultaneously. The resulting full collinearity VIFs ranged from 1.141 to 2.039, which is well below the conservative cut-off value of 3.3 suggested by Kock (2015) and recent PLS-SEM guidelines (J. F. Hair et al., 2019). These values indicate that multicollinearity is not problematic and that CMV is unlikely to meaningfully distort the relationships estimated in the structural model.

4.2. Sample Demographics

Data from 502 usable questionnaires formed the basis of the analysis. As summarised in Table 2, the sample was dominated by males, who account for 59.16% of respondents, while females represent 40.84%. In terms of age, participation is concentrated in the economically active cohorts: 46.41% of respondents are between 21 and 35 years, and a further 39.24% fall within the 36–50 years bracket. The educational profile is skewed toward higher education. A bachelor's degree is the most frequently reported qualification (41.04%), followed by a master's degree (34.46%). Occupationally, the sample is dominated by individuals in stable employment: 28.09% work in the private sector, followed by entrepreneurs with 20.32%. Use of ChatGPT is not limited to recent adopters. Most respondents were classified as long-term users with 30.68% have used ChatGPT for 9–12 months, and 36.25% for more than 12 months. Collectively, the respondents constitute a relatively young, well-educated, professionally active group with substantial exposure to ChatGPT, providing an appropriate context for the subsequent analyses.

Table 2. Sample Demographics.

Measure	Items	Frequency	Percentage
Gender	Female	205	40.84%
	Male	297	59.16%
Age Group	≤20 years old	31	6.18%
	21–35 years old	233	46.41%
	36–50 years old	197	39.24%
	≥50 years old	41	8.17%
Educational Background	High school and equivalent	84	16.73%
	Bachelor's degree	206	41.04%
	Master's degree	173	34.46%
	Doctoral degree	39	7.77%
Occupation	Student	44	8.76%
	Doctor	33	6.57%
	Entrepreneur	102	20.32%
	Private Sector	141	28.09%
	Civil servant	95	18.92%
	Others	87	17.33%
Experience in using ChatGPT	<1 month	19	3.78%
	1–4 month (s)	67	13.35%
	5–8 month (s)	80	15.94%
	9–12 month (s)	154	30.68%
	>12 months	182	36.25%

4.3. Validity and Reliability Assessment

The measurement model was assessed with respect to reliability as well as convergent and discriminant validity. To evaluate item reliability and convergence, we examined standardised factor loadings, average variance extracted (AVE) and internal consistency statistics. All indicators showed strong loadings on their respective constructs, with values were predominantly ≥0.70, suggesting that each item meaningfully represents its underlying latent variable (J. Hair et al., 2017). As summarised in Table 3, all constructs exhibit AVE values exceeding 0.50, indicating that the latent variables account for more than half of the variance in their associated indicators. We also inspected composite reliability (CR) and Cronbach's alpha (CA), and for every construct both coefficients surpass the commonly accepted 0.70 benchmark (J. Hair et al., 2017), providing evidence of satisfactory internal consistency.

Table 3. Convergent Validity and Reliability.

Construct	Items	FL	CA	CR	AVE
ChatGPT Information Diagnosticity (ID)	ID2	0.703	0.758	0.815	0.596
	ID3	0.800			
	ID4	0.808			
ChatGPT Task Efficiency (TE)	TE1	0.734	0.791	0.865	0.617
	TE2	0.865			
	TE3	0.805			
	TE4	0.729			

Table 3. *Cont.*

Construct	Items	FL	CA	CR	AVE
ChatGPT Social Support (SS)	SS1	0.749	0.772	0.854	0.594
	SS2	0.813			
	SS3	0.741			
	SS4	0.779			
Decision Confidence (DC)	DC1	0.765	0.760	0.847	0.580
	DC2	0.798			
	DC3	0.726			
	DC4	0.757			
Positive Destination Emotion (DE)	DE1	0.743	0.749	0.841	0.570
	DE2	0.791			
	DE3	0.735			
	DE4	0.748			
Tourist Satisfaction (TS)	TS1	0.742	0.755	0.845	0.576
	TS2	0.797			
	TS3	0.761			
	TS4	0.734			

Note: FL: Factor Loading ≥ 0.7; CA: Cronbach Alpha ≥ 0.7; CR: Composite Reliability ≥ 0.7; AVE: Average Variance Extracted ≥ 0.5.

Discriminant validity was evaluated using multiple, mutually reinforcing criteria. First, we applied the Fornell–Larcker test by comparing the square root of each construct's AVE with its correlations with other constructs. As shown in Table 4, for each construct the square root of its AVE is larger than any of its inter-construct correlations, offering initial support for discriminant validity (Fornell & Larcker, 1981). Second, we assessed discriminant validity using the HTMT criterion. As shown in Table 5, all HTMT values were below 0.90, indicating adequate discriminant validity (Henseler et al., 2015). Third, the cross-loading matrix (Table 6) shows that each item loads more strongly on its intended construct than on any alternative latent variable. Taken together, these results indicate satisfactory convergent validity and adequate discriminant validity for the measurement model.

Table 4. Fornell-Larcker Criterion.

	DC	DE	ID	SS	TE
DC	**0.762**				
DE	0.671	**0.755**			
ID	0.540	0.479	**0.772**		
SS	0.779	0.629	0.531	**0.771**	
TE	0.720	0.599	0.552	0.744	**0.785**

Notes: The diagonal and bold values are the square roots of AVE.

Table 5. Heterotrait-Monotrait Ratio (HTMT).

	DC	DE	ID	SS	TE
DC					
DE	0.878				
ID	0.758	0.672			
SS	0.808	0.820	0.735		
TE	0.822	0.762	0.753	0.845	
TS	0.870	0.780	0.856	0.827	0.817

Table 6. Cross-Loading Matrix.

	DC	DE	ID	SS	TE	TS
DC1	**0.765**	0.49	0.453	0.648	0.541	0.525
DC2	**0.798**	0.607	0.386	0.651	0.586	0.59
DC3	**0.726**	0.458	0.435	0.521	0.505	0.458
DC4	**0.757**	0.474	0.378	0.54	0.56	0.446
DE1	0.492	**0.743**	0.4	0.435	0.472	0.458
DE2	0.57	**0.791**	0.342	0.55	0.537	0.527
DE3	0.457	**0.735**	0.314	0.476	0.376	0.406
DE4	0.495	**0.748**	0.394	0.427	0.404	0.396
ID2	0.426	0.437	**0.703**	0.438	0.461	0.45
ID3	0.359	0.274	**0.8**	0.359	0.35	0.441
ID4	0.45	0.379	**0.808**	0.422	0.451	0.508
SS1	0.593	0.484	0.453	**0.749**	0.642	0.605
SS2	0.647	0.556	0.437	**0.813**	0.656	0.599
SS3	0.539	0.439	0.342	**0.741**	0.489	0.513
SS4	0.616	0.454	0.401	**0.779**	0.501	0.472
TE1	0.574	0.432	0.456	0.571	**0.734**	0.554
TE2	0.649	0.579	0.463	0.657	**0.865**	0.647
TE3	0.522	0.452	0.433	0.542	**0.805**	0.558
TE4	0.5	0.397	0.377	0.557	**0.729**	0.478
TS1	0.515	0.399	0.447	0.582	0.522	**0.742**
TS2	0.576	0.516	0.466	0.59	0.59	**0.797**
TS3	0.443	0.418	0.45	0.455	0.475	**0.761**
TS4	0.483	0.465	0.484	0.524	0.578	**0.734**

4.4. Model Robustness Testing

The robustness of the structural model was assessed by considering its explanatory capacity for the endogenous variables. The coefficients of determination (R^2) indicate that the predictors account for a substantial share of variance in decision confidence ($R^2 = 0.660$), a moderate share in positive destination emotion ($R^2 = 0.450$) and a reasonable proportion in tourist satisfaction ($R^2 = 0.357$). All three values clearly exceed the 0.10 benchmark proposed by Falk and Miller (1992) and fall within the range typically viewed as moderate to strong explanatory power in PLS-SEM research (J. Hair et al., 2017; J. F. Hair et al., 2019). These results suggest that the model performs well in explaining the key outcome constructs. Substantively, these R^2 values suggest that the model explains a large portion of travellers' on-site decision confidence and a meaningful share of downstream emotional and satisfaction outcomes, providing an adequate basis for interpreting the hypothesised mechanism.

Global model fit was further evaluated using the standardised root mean square residual (SRMR) together with additional approximate-fit statistics. The SRMR value of 0.083 is marginally above the strict 0.08 guideline but remains below the more lenient 0.10 threshold often applied in PLS-SEM, indicating an acceptable level of discrepancy between observed and model-implied correlations (Henseler et al., 2015). The d_ULS (1.883) and d_G (0.612) indices fall within ranges commonly reported for well-specified PLS models, while the NFI (0.681) is lower than the conventional 0.90 cut-off typically used in covariance-based SEM. In line with recent recommendations that place greater emphasis on SRMR and explanatory power in PLS-SEM, we interpret the combination of acceptable SRMR and moderate-to-strong R^2 values as evidence that the structural model is empirically adequate, supporting the subsequent hypothesis testing results, while acknowledging that incremental fit indices such as NFI point to some scope for further optimisation in future model refinements. Accordingly, given the model's acceptable explanatory power and fit,

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we next evaluate the hypothesised direct and indirect relationships in the structural model (Section 4.5).

4.5. Hypothesis Testing

To provide a narrative interpretation of the structural results, we report both statistical significance (β, T-values, and confidence intervals) and substantive magnitude (f^2), and we compare coefficients to identify which relationships are most influential in the proposed pathway (J. Hair et al., 2017; J. F. Hair et al., 2019). For transparency, each hypothesis test yields a single *p*-value; significance is reported using conventional star notation (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$), such that lower *p*-value thresholds indicate stronger statistical support.

The findings for H1a–c indicate that all three perceived affordances of ChatGPT significantly contribute to DC. H1a exposes that the ID has small and significant impact with β = 0.116 and T = 2.755; H1b TE has more impact with β = 0.275 and T = 4.829; and H1c SS has the most impact with β = 0.512 and T = 9.439. Comparatively, the β values indicate that social support is the dominant driver of decision confidence, followed by task efficiency, whereas information diagnosticity plays a smaller—yet still meaningful—role in strengthening travellers' confidence during on-site decision-making. To complement these significance tests, we examined effect sizes (f^2) to assess the magnitude of each predictor's contribution to explained variance, using the commonly applied benchmarks of 0.02 (small), 0.15 (medium), and 0.35 (large) (J. Hair et al., 2017; J. F. Hair et al., 2019). The results show that ID → DC has a small effect ($f^2 = 0.026$), TE → DC has a small effect ($f^2 = 0.092$), whereas SS → DC exhibits a medium-to-large effect ($f^2 = 0.328$), indicating that socio-emotional support is the most substantively influential driver of decision confidence. Therefore, at the point where ChatGPT is perceived to generate precise information, energy-saving and socio-emotional encouragement, travellers report increased confidence in decisions that they make on-site.

The downstream relationships are equally clear. H2 asserts that DC has a substantial positive impact on DE with β = 0.671 and T = 19.148, and these DE, in turn, significantly enhance TS (H3) with β = 0.597 and T = 18.327. The corresponding effect sizes are large (DC → DE: $f^2 = 0.817$; DE → TS: $f^2 = 0.554$), indicating that the proposed cognitive-to-affective pathway contributes strongly to explaining tourists' emotional responses and overall satisfaction. In substantive terms, decision confidence emerges as a pivotal psychological lever: once travellers feel confident about their on-site choices, this strongly elevates positive destination emotion, which subsequently translates into higher tourist satisfaction. In other words, decisions made with the aid of ChatGPT foster more favourable affect toward the destination and, ultimately, a more satisfying trip experience.

The serial mediation tests (H4a–c) further corroborate the proposed mechanism in which ChatGPT's perceived qualities enhance TS through sequential changes in cognition and affect. Specifically, the indirect effect of ID on satisfaction via DC and DE is significant (β = 0.046, T = 2.560). The corresponding indirect effects are also significant for task efficiency (β = 0.110, T = 4.236) and social support (β = 0.205, T = 7.469). Comparing the indirect effects, social support shows the strongest total mediated influence on satisfaction, followed by task efficiency and information diagnosticity, indicating that supportive and effort-reducing interactions are especially consequential for improving satisfaction through the DC → DE sequence. Collectively, these results indicate that the informational, instrumental, and social facets of ChatGPT increase satisfaction primarily by strengthening travellers' confidence and subsequently intensifying positive emotions toward the destination. Table 7 and Figure 2 depict all hypothesis testing results.

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Table 7. The Results of Hypothesis Testing.

Hypothesis	β	f^2	T-Value	Bootstrapping CI 97.5% (N = 5000)		Decision
				Min	Max	
H1a(+) ID → DC	0.116 **	0.026	2.755	0.031	0.197	Supported
H1b(+) TE → DC	0.275 ***	0.092	4.829	0.168	0.390	Supported
H1c(+) SS → DC	0.512 ***	0.328	9.439	0.399	0.612	Supported
H2(+) DC → DE	0.671 ***	0.817	19.148	0.598	0.735	Supported
H3(+) DE → TS	0.597 ***	0.554	18.327	0.534	0.661	Supported
H4a(+) ID → DC → DE→ TS	0.046 *	-	2.560	0.011	0.083	Supported
H4b(+) TE → DC → DE → TS	0.110 ***	-	4.236	0.063	0.165	Supported
H4c(+) SS → DC → DE → TS	0.205 ***	-	7.469	0.152	0.260	Supported

Notes: Each hypothesis test produces one *p*-value; the star notation reports which conventional threshold that *p*-value meets (*** $p < 0.001$, ** $p < 0.01$, and * $p < 0.05$). T-values and confidence intervals are based on bootstrapping (N = 5000, two-tailed). Effect size f^2 benchmarks: 0.02 (small), 0.15 (medium), and 0.35 (large) (J. Hair et al., 2017; J. F. Hair et al., 2019).

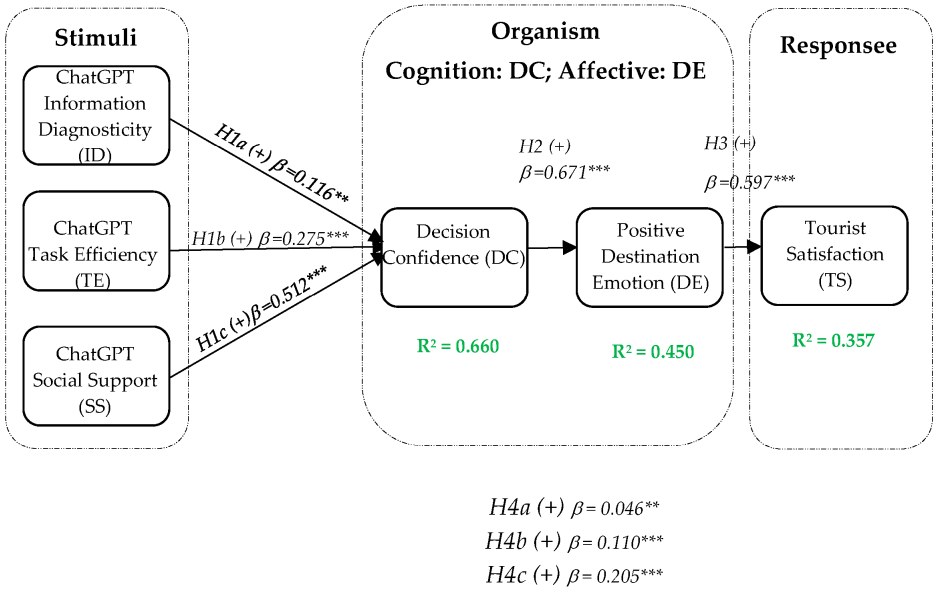

Figure 2. Hypothesis Summary. Notes: Significance level with *** $p < 0.001$; ** $p < 0.01$.

Table 7 summarises the direct and indirect hypothesis tests. Overall, the most influential relationships in the model are DC → DE and DE → TS (both large f^2), highlighting that the experience-formation mechanism is driven primarily by the cognitive-to-affective pathway, while SS is the strongest upstream stimulus shaping decision confidence among the three ChatGPT interaction qualities. The next section discusses the theoretical and practical implications of these findings for understanding in-trip human–AI interactions and tourist experience formation.

5. Discussion

Against a wider backdrop of increasing consumer exposure to generative AI in travel information search, our results provide mechanism-level evidence for how perceived interaction qualities translate into confidence, emotion, and satisfaction among in-trip users. This study set out to explain, through the lens of the SOR framework, how tourists' during-trip use of ChatGPT shapes their evaluation of the travel experience. The empirical evidence is drawn from Indonesian tourists, providing insight into AI-mediated travel experiences in an emerging-market, mobile-first context. The proposed model is most applicable when conversational AI is actively used to support in-trip decisions; it is not intended to characterise tourists who deliberately minimise technology use as part of relaxation. Consistent with SOR logic, the findings suggest that ChatGPT does not enhance satisfaction simply by adding another information channel. Rather, perceptions of its informational, functional and social affordances (stimuli) strengthen decision confidence and foster positive destination emotions (organismic states), which then translate into higher tourist satisfaction (response). This pattern aligns with recent SOR applications in tourism and technology-mediated experiences, which emphasise the role of internal cognitive–affective states in transmitting the influence of smart technologies on behavioural outcomes (M. J. Kim et al., 2020; Xiong et al., 2023; S. Jiang et al., 2024).

The first mechanism is predominantly cognitive. All three ChatGPT affordances contribute to DC, but SS emerges as the most influential driver, TE occupies a middle position, and ID has only a modest impact. This hierarchy is consistent with evidence that, in technology-mediated services, social presence and socio-emotional indicators tend to exert a stronger influence on users' assessments and intentions than purely informational characteristics (K. Zhang et al., 2025; Yun & Park, 2022). In a travel environment saturated with information, what builds confidence is less the incremental accuracy of content and more the feeling of being accompanied, reassured and guided by the AI. Social support and efficiency minimise cognitive load and anxiety, enabling tourists to perceive their choices as competent and under control. Information quality remains a necessary baseline, but its incremental leverage appears limited once a reasonable reliability threshold is reached—consistent with work showing diminishing returns of additional diagnostic content in complex decision environments (del Bosque & San Martín, 2008; Prayag et al., 2017).

The second mechanism is affective and links organismic states to the evaluative response. DC feeds into more DE toward the destination, and these emotions play a central role in how tourists judge their trip. This pattern reinforces cognitive–affective models of tourist satisfaction, where emotions are a proximal determinant of evaluations and behavioural intentions (del Bosque & San Martín, 2008; Prayag et al., 2017). In our context, ChatGPT functions as a facilitator of emotional engagement: by helping tourists feel that their choices are sound, it frees them from continuous second-guessing and creates psychological room for immersion, enjoyment and curiosity. This is consistent with recent calls to treat emotions as a core construct in tourism research rather than a residual outcome, and to recognise that technology can shape the emotional tone of experiences as much as their efficiency or convenience (Hosany et al., 2021; Volo, 2021).

Integrating these mechanisms, the serial mediation results portray ChatGPT as an "emotionalised decision-support" system rather than a neutral information tool. The strongest downstream effects on satisfaction originate from SS, followed by TE, while ID plays a subtler background role. This pattern demonstrates that emotion-oriented and socially competent chatbots are more likely to generate satisfaction, trust and loyalty than purely transactional agents (J. Zhang et al., 2024; Yun & Park, 2022; K. Zhang et al., 2025). In tourism, AI-based and destination-specific chatbots are increasingly framed as experience co-producers that shape users' feelings and intentions, not just their information sets (Orden-Mejía et al., 2025; Wüst & Bremser, 2025). From an SOR perspective, the most potent stimuli in our model are thus those that carry socio-emotional meaning and reduce cognitive effort rather than those that merely upgrade information quality.

Overall, these findings extend current debates on AI in tourism in three ways. First, they move beyond pre-trip planning to highlight the during-trip phase, showing that ChatGPT's value in situ lies in modulating on-site cognitive and affective states rather than simply providing destination knowledge (Xiong et al., 2023; S. Jiang et al., 2024; Xu et al., 2024). Second, they reposition decision confidence as a central organismic state that bridges AI affordances and experiential outcomes, complementing prior research that treats confidence as a secondary by-product of information use. Third, they contribute to human–AI interaction and online social support studies by demonstrating that travellers implicitly treat ChatGPT as a socio-emotional partner whose reassurance and encouragement are integral to their overall journey evaluation (J. Zhang et al., 2024; K. Zhang et al., 2025; Orden-Mejía et al., 2025). Although these mechanisms are evidenced among Indonesian tourists, they provide a theoretically grounded baseline against which future studies can test cultural and contextual contingencies in other destinations and traveller segments. Taken together, the results support a view of AI in tourism as a socio-technical actor that co-produces cognitive assurance and emotional engagement—two intertwined foundations of tourist satisfaction in contemporary travel.

6. Implications

6.1. Theoretical Implications

Building on the above findings, this study offers several theoretical implications for four strands of research: AI and smart tourism, SOR–based experience models, cognitive–affective explanations of tourist satisfaction, and work on social support and human–AI interaction (del Bosque & San Martín, 2008; Prayag et al., 2017; Orden-Mejía & Huertas, 2022; Stergiou & Nella, 2024; Sigala et al., 2024). These implications are derived from an empirical study conducted with Indonesian tourists, an emerging-market context where rapid adoption of mobile and AI-based services provides an important Global South perspective on AI-mediated travel experiences.

Theoretically, the study makes three core contributions. First, it advances a stage-based account of generative-AI effects by isolating the during-trip phase—responding directly to calls to examine ChatGPT's psychological impacts across pre-, during-, and post-trip stages (Sigala et al., 2024). Second, it offers a process contribution by specifying a cognitive–affective pathway through which AI-enabled stimuli shape satisfaction (DC $\rightarrow$ DE $\rightarrow$ TS), extending integrative emotion–satisfaction models in tourism (del Bosque & San Martín, 2008; Prayag et al., 2017). Third, it provides a bridge contribution that connects classic work on dynamic, on-site adjustment in tourist decision-making with the emerging idea of AI as a real-time travel companion (Moore et al., 2012; Stergiou & Nella, 2024). Where much of the current ChatGPT–tourism literature concentrates on pre-trip planning or broad adoption/continuance intentions, this study shifts attention to the during-trip setting and explains how real-time interaction shapes tourists' cognitive and affective states and, ultimately, satisfaction.

Consistent with the stage-based contribution, the study extends the SOR framework to the context of during-trip interaction with a generative-AI companion. Prior tourism applications of SOR have largely examined physical servicescapes or smart technologies as stimuli, with emotions and satisfaction as broad organismic and response states (Goo et al., 2022; Xiong et al., 2023). By modelling ChatGPT's ID, TE, and SS as distinct stimuli and specifying a dual organismic layer—cognitive (DC) and affective (DE)—this research refines SOR for AI-mediated tourism experiences. The results suggest that SOR is not limited to ambient environments or platforms but is also suitable for theorising dialogic AI "companions" that continuously shape on-site judgements and feelings. Conceptually, this matters because in situ travel decisions are iterative and constraint-driven; by embedding ChatGPT within SOR as a real-time stimulus, the model captures how tourists re-evaluate options on-site, rather than treating AI use as a generic, trip-level intention or adoption outcome (Moore et al., 2012; Sigala et al., 2024).

Aligned with the process contribution (cognition $\rightarrow$ affect $\rightarrow$ satisfaction), the findings reposition decision confidence as a central organismic mechanism rather than a secondary by-product of information use. Cognitive-affective models of tourist satisfaction typically emphasise perceived performance, value, or image as the main cognitive antecedents of emotion and satisfaction (del Bosque & San Martín, 2008; Prayag et al., 2017). In contrast, this study shows that confidence in one's decisions is the key conduit through which ChatGPT affordances are translated into positive destination emotion and, ultimately, tourist satisfaction. This suggests that technology-enabled experience models should treat decision confidence as a core psychological state linking technological stimuli to affective and evaluative outcomes, alongside more traditional constructs such as perceived quality or usefulness. More broadly, by foregrounding confidence as the pivotal "cognitive assurance" state, the study aligns tourism AI research with decision-making evidence showing that confidence is a consequential psychological output of advisory interactions under uncertainty (Sniezek & Buckley, 1995), thereby elevating confidence from a peripheral outcome to a theoretically central organismic mechanism in AI-supported travel.

Extending the bridge contribution (dynamic in-destination adjustment × AI companionship), the study advances human–AI and online social support research by foregrounding the socio-emotional role of generative AI in tourism. Much of the emerging chatbot literature in destinations and travel services emphasises informativeness, usefulness, or efficiency as dominant drivers of satisfaction and intentions (Orden-Mejía & Huertas, 2022; Wüst & Bremser, 2025). Our results show that perceived social support from ChatGPT is the most powerful driver of decision confidence and, through the cognitive–affective chain, of satisfaction, whereas information diagnosticity plays more of a baseline role. This pattern aligns with evidence that social support and positive emotions are critical in shaping satisfaction in digitally mediated tourism experiences (Chung et al., 2017), and extends it to a generative-AI setting. Conceptually, the findings challenge the implicit assumption that AI in tourism is primarily an information system and instead position ChatGPT as a socio-emotional interaction partner whose reassurance and companionship materially shape experience evaluations. Importantly, this socio-emotional function appears especially consequential during the trip—where decisions are frequent, constraint-driven, and susceptible to uncertainty—thus directly speaking to calls for stage-specific understanding of ChatGPT's psychological impacts across the tourist journey (Sigala et al., 2024).

Synthesising the stage-based and process contributions, the study introduces the notion of ChatGPT as an "emotionalised decision-support" system in tourism. Existing frameworks increasingly recognise that tourists value both functional and relational/experiential facets of AI (Scarpi, 2024), yet they rarely integrate these into a single mechanism-based process model. By demonstrating a coherent pathway from functional and social affordances → decision confidence → destination emotions → satisfaction, our model shows how AI simultaneously performs advisory and affect-regulation roles. This integrated perspective complements emerging evidence that AI chatbots can shape destination-related judgements and decisions (Orden-Mejía et al., 2025) and provides a process-based account of how functional and socio-emotional values are co-produced. In doing so, it offers a more explicit characterisation of AI as a socio-technical agent that jointly generates cognitive assurance and affective involvement in real time, rather than as a purely informational or hedonic add-on. By tying these functions explicitly to the during-trip phase, the model also complements dynamic in-destination adjustment theory by clarifying how on-site adjustments are psychologically scaffolded through AI-enabled cognitive assurance and socio-emotional support (Moore et al., 2012; Stergiou & Nella, 2024).

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6.2. Practical Implications

These findings give practical direction for organisations that want to use generative AI during the trip, not just before people travel. In our data, ChatGPT improves TS mainly because it helps travellers feel more confident about their choices and more positive about the destination. Since SS and TE matter more than pure ID, the main takeaway is simple: ChatGPT should be treated less like a digital information desk and more like a supportive travel companion. Even though the sample is Indonesian tourists, the same logic should apply in places where travellers rely heavily on phones and make many quick, on-the-go decisions. In other words, the goal is not only to support itinerary planning before travel, but to help tourists feel confident and emotionally settled while they make moment-to-moment decisions on-site.

First, DMOs and tourism businesses should put ChatGPT exactly where travellers face problems in real life, rather than offering it as a “nice extra” that sits unused. During a trip, plans change all the time—because of queues, closures, weather, fatigue, or disruptions—so ChatGPT adds the most value when it helps people adjust in the moment (Moore et al., 2012; Sigala et al., 2024). For DMOs, this means integrating ChatGPT into the destination’s main visitor touchpoints (official apps, QR codes at attractions and transit spots, and visitor centres) and making sure it can access reliable, frequently updated local information, such as opening times, closures, transport changes, crowd levels, and safety messages. This matches what smart tourism research has argued for years: these tools work best when they are connected to the destination’s information system, not when they are deployed in isolation (Pai et al., 2020; Sustacha et al., 2023). A practical way to start is to build a small “core dataset” that stays up to date for high-change items, use consistent place IDs so recommendations stay location-accurate, and add clear escalation routes for health, safety, and legal questions so tourists are directed to official channels. Over time, the questions tourists ask repeatedly can also help destinations improve operations: if lots of people are confused about transport, congestion, or safety in certain areas, that can guide better signage, timed-entry nudges, or targeted information to reduce bottlenecks (Czyz & Javed, 2025; Sustacha et al., 2023).

Second, organisations should judge success by whether ChatGPT helps travellers feel sure about what to do and emotionally comfortable, not only by whether the information is correct. This is because the pathway in the model is psychological: confidence shapes emotion, and emotion feeds into satisfaction. So, the interaction should be designed to make decisions easier. For example, ChatGPT can ask a few quick questions (time available, walking tolerance, budget, and risk preference), offer two or three realistic options, explain the trade-offs clearly, and then ask a simple follow-up like “Do you prefer fastest, cheapest, or least walking?” For tourism businesses (hotels, attractions, OTAs, tour operators), the best role is an AI concierge that reduces effort and choice overload by filtering options and giving step-by-step guidance. This fits prior evidence showing that chatbots can influence tourism decisions, but also that poor design can reduce satisfaction and future intentions (Orden-Mejía et al., 2025; Wüst & Bremser, 2025). To strengthen the “social support” effect, firms can also build in reassuring responses for stressful situations (missed trains, sold-out attractions, late arrivals), default to safer alternatives, and treat time-sensitive advice carefully by encouraging travellers to verify details rather than presenting uncertain information as fact.

Third, destinations should not rely on AI alone. The best approach is to combine ChatGPT support with human oversight and clear rules. A practical operating model is “two-layer” service: ChatGPT handles first-pass recommendations and information filtering, while staff step in to add local nuance, empathy, and accountability—especially for safety issues, accessibility needs, medical concerns, complaints, or sensitive incidents

(Bulchand-Gidumal et al., 2024; Knani et al., 2022). At the policy level, AI travel support needs to be managed as both innovation and consumer protection, because there are real concerns about misinformation, bias, and uneven capability across destinations (OECD, 2024; European Travel Commission, 2025). Minimum safeguards can be simple but effective: clear disclosure that advice is AI-generated, a documented list of trusted sources for high-stakes topics, logs for safety-related interactions, and an obvious "talk to a human" route when something goes wrong. Finally, national tourism strategies can use AI to reduce decision stress and support sustainability by encouraging destinations to publish machine-readable datasets (hours, mobility, accessibility, capacity indicators), which can help ChatGPT recommend less crowded options and more sustainable transport without undermining travellers' confidence or wellbeing (Siddik et al., 2025; Wang et al., 2025).

7. Conclusions

Using a during-trip S–O–R lens, the findings indicate that ChatGPT's perceived information diagnosticity, task efficiency, and—most strongly—social support significantly build decision confidence (ID→DC: $\beta = 0.116$, T = 2.755, $f^2 = 0.026$; TE→DC: $\beta = 0.275$, T = 4.829, $f^2 = 0.092$; SS→DC: $\beta = 0.512$, T = 9.439, $f^2 = 0.328$). Higher decision confidence then increases positive destination emotion (DC→DE: $\beta = 0.671$, T = 19.148, $f^2 = 0.817$), which subsequently enhances tourist satisfaction (DE→TS: $\beta = 0.597$, T = 18.327, $f^2 = 0.554$). All hypothesised direct paths and the serial indirect effects are supported (ID→DC→DE→TS: $\beta = 0.046$, T = 2.560; TE→DC→DE→TS: $\beta = 0.110$, T = 4.236; SS→DC→DE→TS: $\beta = 0.205$, T = 7.469), confirming a clear cognitive-to-affective route through which ChatGPT is associated with more favourable in situ travel evaluations ($R^2 = 0.660$ for DC; $R^2 = 0.450$ for DE; $R^2 = 0.357$ for TS). Because these results are based on self-reported survey perceptions, they reflect tourists' subjective evaluations rather than objective behavioural usage or experimentally identified causal effects; future research should triangulate the mechanism using behavioural data (e.g., interaction logs, experience sampling during trips, or field experiments).

Limitations and Future Research

This study has several limitations that should be acknowledged when interpreting the results. First, respondents were recruited online, which may create self-selection bias: travellers who are more digitally active, more experienced with ChatGPT, or more inclined to share technology-related experiences may be disproportionately represented. Although this profile is suitable for examining the proposed relationships among active users, future research could mitigate selection effects by adopting broader recruitment approaches (e.g., on-site intercept sampling at destinations, collaboration with tourism operators, or stratified sampling across traveller groups) and by testing whether findings differ across recruitment methods.

In addition, the findings should be interpreted as conditional on a user segment. Because respondents were recruited from travellers with experience using ChatGPT, the study is designed to test the proposed in-trip mechanism rather than to estimate the population prevalence of ChatGPT acceptance versus non-acceptance among tourists. Future research should directly compare user and non-user segments (including technology-avoidant travellers) and test whether the structural relationships differ across technology acceptance profiles, for example, using segmentation or multi-group analysis.

Second, the study relies on single-source, self-reported perceptions, which may be affected by recall limitations, social desirability, and method-related covariance, and may not fully reflect travellers' real-time behaviours during trip decisions. While our diagnostics suggest common method variance is unlikely to materially bias the structural estimates, subsequent work should enhance measurement validity by integrating behavioural or objective data, such as interaction logs (e.g., prompt categories, frequency, and timing), task completion metrics, digital traces of itinerary adjustments, or triangulation with companion reports and service-provider records.

Third, the design is cross-sectional, which constrains causal inference. Although the proposed sequence (ID/TE/SS $\rightarrow$ DC $\rightarrow$ DE $\rightarrow$ TS) is theoretically motivated, the temporal ordering cannot be conclusively established using single-wave data. Future studies employing longitudinal panels, experience-sampling during travel, or field/experimental designs (e.g., manipulating diagnosticity or supportive cues in AI responses) would provide stronger evidence on causality and clarify how confidence, emotion, and satisfaction evolve across travel episodes.

Fourth, the model specifies a primarily linear mechanism and does not test potential boundary conditions or heterogeneity across traveller or trip contexts. Future research should examine moderators such as trip complexity, time pressure, destination familiarity, travel-party characteristics, perceived risk, and AI literacy to identify when information diagnosticity, efficiency, and social support are most consequential for decision confidence, emotion, and satisfaction.

Finally, the empirical setting is Indonesia, and the extent to which the findings generalise may depend on contextual factors such as information environments, service variability, language practices, and infrastructural conditions. Replications across countries and destination types—spanning mature versus emerging destinations and differing cultural and technological settings—would strengthen external validity and help distinguish context-specific patterns from more generalisable mechanisms. Relatedly, while the study explains psychological pathways linking in-trip ChatGPT use to satisfaction among users, it does not assess the economic "price–result" ratio of implementation (e.g., development, data integration, staffing, and maintenance costs relative to operational gains). Future research should pair experience measures with behavioural and operational indicators (e.g., resolution rates, time saved, staff workload reduction, conversion/booking uplift, and incremental spending) to evaluate cost-effectiveness and ROI under real deployment conditions.

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