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Beyond Engagement: How Perceived Reliability, Recommendation Neutrality, and Technology Readiness Shape the Generative AI-Supported Tourist Journey

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Abstract

Generative AI is becoming increasingly embedded in digital travel planning and decision-making, reshaping how tourists search for information, evaluate alternatives, and navigate the customer journey. Yet, less is known about how engagement with conversational AI is associated with customer journey enhancement and the evaluative mechanisms and user-level conditions that accompany this association. This study examines the relationship between ChatGPT engagement and customer journey enhancement, with perceived system reliability and recommendation neutrality modeled as parallel mediators and technology readiness as a moderator. Using a quantitative, cross-sectional design, data were collected from 1012 tourists with prior decision-oriented experience using ChatGPT for travel-related purposes and analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM). The findings show that ChatGPT engagement is positively associated with customer journey enhancement, perceived system reliability, and recommendation neutrality. Perceived system reliability and recommendation neutrality are also positively associated with customer journey enhancement, with significant indirect associations consistent with complementary partial mediation. Technology readiness positively moderates the associations between ChatGPT engagement and customer journey enhancement and between perceived system reliability and customer journey enhancement. Supplementary analysis further indicates that the indirect association through perceived system reliability becomes stronger at higher levels of technology readiness. By distinguishing AI engagement from tourists' evaluations of system reliability and recommendation neutrality while incorporating technology readiness as a user-level boundary condition, the study offers a more differentiated account of generative AI-supported travel decision-making and digital customer journeys. It also emphasizes that perceived reliability and recommendation neutrality represent user evaluations rather than verified properties of AI performance. Practically, the findings highlight the need to distinguish between general-purpose generative AI, which tourism organizations do not directly control, and organization-managed AI services, where data quality, transparency, verification, and user support can be more actively governed.

Keywords: ChatGPT engagement; customer journey enhancement; perceived system reliability; recommendation neutrality; technology readiness; generative AI; tourist decision-making

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1. Introduction

Artificial intelligence (AI) is becoming increasingly embedded in the digital infrastructure of tourism and hospitality, influencing how travelers obtain information, evaluate

alternatives, and organize travel-related decisions [1]. Among the most prominent manifestations of this transformation is ChatGPT, a conversational generative AI application that has attracted growing scholarly and managerial attention for its ability to support destination search, itinerary planning, comparison of travel options, and other decision-oriented activities [2]. Its relevance differs from that of many conventional digital tools because users can engage in iterative exchanges, refine requests, introduce new constraints, and receive context-sensitive responses as the conversation develops [3]. In tourism, where decisions frequently involve uncertainty, information overload, time pressure, and changing preferences, such interaction creates new possibilities for how travelers engage with destinations, platforms, and service providers [4].

These developments are particularly consequential for the tourist customer journey. Travel experiences increasingly unfold through an interconnected sequence of digital and physical touchpoints rather than through isolated service encounters [5]. Before travel, tourists may use AI to explore destinations and construct itineraries; during a trip, they may seek immediate assistance or revise plans; and AI-supported interaction may continue to influence evaluation and future choices after the journey. ChatGPT can participate in these stages through personalized travel advice, responsive information exchange, itinerary refinement, and real-time decision support [6,7]. Customer journey enhancement therefore provides a meaningful outcome for examining conversational AI because it shifts attention from whether travelers merely adopt an AI application toward how engagement with that application is associated with the broader quality of their travel experience [8].

The relationship between ChatGPT engagement and customer journey enhancement is unlikely to be explained by interaction intensity alone. Travelers also form judgments about the quality and character of the assistance they receive. Two perceptions are especially relevant in this process. Perceived system reliability reflects the degree to which users regard ChatGPT as dependable and consistent when providing tourism-related support, which becomes particularly important when decisions require timely and credible information [2,9]. Recommendation neutrality, in turn, concerns whether AI-generated suggestions are perceived as balanced and impartial rather than disproportionately favoring particular alternatives. This issue has become increasingly salient in digital tourism environments, where sponsored visibility, commercial incentives, and algorithmic bias may shape the recommendations encountered by travelers [10,11]. These perceptions offer two conceptually distinct routes through which engagement with conversational AI may correspond with evaluations of the overall customer journey.

Not all tourists, however, are equally positioned to translate AI-supported interaction into experiential benefits. Technology readiness introduces an important individual-level condition because travelers differ in their preparedness, confidence, and willingness to engage with emerging digital technologies. Natural-language interfaces can reduce some of the technical barriers associated with advanced systems, but the extent to which users exploit conversational AI may still depend on their underlying readiness to work with technology [12]. Accordingly, the present study does not treat technology readiness as an outcome generated by ChatGPT engagement. Instead, it is positioned as a moderating condition that may strengthen or weaken selected relationships within the model. This distinction allows the framework to separate the mechanisms through which ChatGPT engagement is associated with customer journey enhancement from the user characteristic that may determine when those relationships become more pronounced.

The theoretical logic of the study draws on the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2). TAM emphasizes perceived usefulness and perceived ease of use as central considerations underlying technology acceptance [13,14], whereas UTAUT2 broadens this perspective through per-

formance expectancy, effort expectancy, facilitating conditions, hedonic motivation, and habit [15]. These frameworks remain useful for situating ChatGPT engagement within a broader process of technology evaluation and use. The present study, however, does not claim to formally extend or empirically re-specify either theory, since their core constructs are not modeled directly. Rather, TAM and UTAUT2 provide complementary theoretical lenses for understanding engagement with conversational technology, while perceived reliability, recommendation neutrality, and technology readiness capture additional evaluative and individual differences that are especially pertinent to AI-supported tourism experiences.

Despite growing interest in AI within tourism research, important questions remain unresolved. Existing scholarship has extensively examined recommender systems, predictive applications, general AI adoption, and user attitudes toward emerging technologies, yet comparatively less attention has been directed toward conversational generative AI as an interactive decision-support environment that can accompany travelers throughout multiple stages of the journey [11,16,17]. This distinction is important because conversational interaction is inherently iterative: travelers can pose questions, assess responses, reformulate requests, reconsider alternatives, and alter subsequent decisions within the same interaction sequence [18]. Such characteristics make it necessary to examine not only whether tourists engage with generative AI but also how the perceptions formed during that engagement relate to subsequent journey evaluations.

A further gap concerns the simultaneous consideration of explanatory mechanisms and boundary conditions. Perceived reliability has received attention in technology-related research, while questions surrounding recommendation fairness and neutrality have increasingly entered discussions of responsible AI. Yet relatively little is known about whether these perceptions statistically account for part of the association between ChatGPT engagement and customer journey enhancement. At the same time, technology readiness is often discussed as an important source of individual variation in technology-related behavior, but its role in conditioning the experiential consequences of conversational AI remains less developed in tourism research. Bringing these elements together enables the study to distinguish between how ChatGPT engagement is associated with the customer journey and when or for whom those relationships may be stronger. Importantly, perceived reliability and recommendation neutrality are treated as user evaluations rather than objectively verified properties of ChatGPT outputs.

Against this background, the study develops and empirically tests a model in which ChatGPT engagement is associated with customer journey enhancement both directly and indirectly through perceived system reliability and recommendation neutrality. Technology readiness is introduced as a moderator of the relationship between ChatGPT engagement and customer journey enhancement and of the relationship between perceived system reliability and customer journey enhancement. This configuration allows the model to examine parallel mediating processes alongside individual differences that may condition the strength of selected relationships. Because the data are cross-sectional, the proposed indirect and moderating relationships are interpreted as statistical associations rather than definitive evidence of temporal or causal processes.

The study contributes to the emerging literature on generative AI in tourism by integrating these distinct explanatory roles within a single framework. It first places customer journey enhancement, rather than technology adoption alone, at the center of the analysis. It then distinguishes two perceptual pathways—reliability and recommendation neutrality—through which ChatGPT engagement may be associated with the tourist journey. Finally, by positioning technology readiness as a boundary condition rather than another intervening mechanism, the framework recognizes that the experiential relevance of conversational

AI may vary across users with different levels of technological preparedness. In doing so, the study retains the broader technology-evaluation insights of TAM and UTAUT2 while directing attention toward the mechanisms and contingencies associated with AI-supported tourism experiences.

2. Literature Review and Hypotheses Development

2.1. Theoretical Foundation

The present study is theoretically anchored in the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2), which together provide a useful basis for understanding how individuals evaluate and engage with emerging technologies. Their relevance to conversational generative AI lies less in reproducing their original structural specifications and more in the broader logic they offer for explaining technology-related evaluations and behavioral responses. ChatGPT differs from many conventional information systems because interaction is iterative rather than episodic: users can reformulate requests, respond to generated content, introduce new preferences, and continue the exchange as their travel needs evolve. Such interaction creates a setting in which the value of the technology may depend not only on whether travelers choose to use it, but also on the evaluations that emerge during use and on individual differences in their capacity to benefit from that interaction.

TAM provides the most immediate foundation for this reasoning. Its emphasis on perceived usefulness and perceived ease of use explains why individuals are more inclined to engage with technologies that appear capable of supporting their goals without imposing excessive interaction effort. In tourism, ChatGPT can perform functions that align closely with this logic by helping travelers obtain personalized information, compare alternatives, reduce uncertainty, and access assistance at different stages of the journey [19,20]. The natural-language interface further reduces some of the technical complexity traditionally associated with advanced digital systems, allowing travelers with different levels of technological experience to communicate through familiar forms of expression [21]. These principles establish the broader technology-evaluation context of the study. Perceived usefulness and perceived ease of use themselves, however, are not operationalized in the empirical model; TAM therefore serves as a theoretical lens rather than as a structural model being replicated or formally extended.

UTAUT2 complements this perspective by recognizing that consumer technology use involves performance-related, effort-related, contextual, and motivational considerations. In conversational AI settings, performance expectancy is relevant to the expectation that interaction should contribute meaningfully to travel-related tasks, whereas effort expectancy emphasizes the accessibility of the interaction itself [6,22]. Facilitating conditions also highlight the environment within which technology use takes place, including access to appropriate devices, platforms, and digital resources [11]. Together, these elements reinforce the idea that engagement with an emerging technology does not occur in isolation but is embedded within broader evaluations of what the system enables and how readily individuals can interact with it. As with TAM, the corresponding UTAUT2 constructs are not entered directly into the proposed structural model; instead, the framework provides a complementary behavioral perspective for interpreting tourists' engagement with conversational AI.

The characteristics of generative AI nevertheless introduce evaluations that are not explicitly represented in the core constructs of either framework. Perceived system reliability becomes salient because travelers may be reluctant to incorporate AI-generated assistance into consequential decisions unless the interaction appears sufficiently consistent and dependable [23]. Recommendation neutrality raises a different issue. ChatGPT gen-

erates rather than merely retrieves suggestions, and these outputs may influence choices concerning destinations, accommodation, transportation, and other tourism services. Users can therefore form judgments about whether the recommendations appear balanced, impartial, or influenced by commercial priorities [17,24]. These two constructs are positioned in the present model as perceptual mechanisms associated with ChatGPT engagement and customer journey enhancement. Importantly, they capture users' evaluations of the system; neither construct is intended to establish the objective accuracy or impartiality of the underlying AI outputs.

Technology readiness occupies a different theoretical position. Rather than treating readiness as another perception through which ChatGPT engagement is transmitted to the customer journey, the revised framework conceptualizes it as an individual boundary condition. Travelers vary in their preparedness, confidence, and inclination to engage with emerging technologies, and these differences may influence the extent to which a given level of AI engagement or perceived system reliability translates into a more favorable journey evaluation [25]. Technology readiness therefore enters the model as a moderator rather than a mediator. This distinction separates two theoretical questions: perceived system reliability and recommendation neutrality address how ChatGPT engagement may be associated with customer journey enhancement, whereas technology readiness addresses when, or for whom, selected relationships may become stronger. Accordingly, the theoretical role of TAM and UTAUT2 in this study is deliberately bounded. The research does not claim to re-specify their original constructs or to provide a formal empirical extension of either framework. Instead, their established technology-acceptance logic provides the conceptual foundation for examining a conversational AI context in which user evaluations and individual differences become increasingly important. Within that foundation, perceived system reliability and recommendation neutrality are treated as parallel mediating perceptions, while technology readiness functions as a moderating condition. This configuration allows the study to connect technology engagement with customer journey enhancement while distinguishing between the mechanisms associated with that relationship and the user characteristic that may condition its strength.

2.2. ChatGPT Engagement and Tourist Behavioral Outcomes

Generative artificial intelligence has altered the nature of digital travel assistance by allowing tourists to move beyond one-way information retrieval toward continuous, conversational interaction. ChatGPT is particularly relevant in this context because travelers can formulate requests in natural language, refine their preferences, revisit alternatives, and adjust subsequent questions as their travel needs evolve [2,3]. This iterative structure distinguishes ChatGPT engagement from more passive forms of digital technology use and embeds the system more directly within the process through which tourists evaluate options and organize travel decisions [7].

One important consequence of such engagement concerns the broader customer journey. Travel planning often requires tourists to process substantial amounts of information while dealing with uncertainty, unfamiliar alternatives, and changing situational requirements. Conversational AI can make this process more manageable by organizing information around individual requests, providing context-specific assistance, and enabling users to revisit or refine earlier decisions without restarting the search process [26,27]. Prior research further associates AI-supported interaction with stronger engagement, greater perceived control, and increased confidence in tourism-related decision-making [28,29]. Greater engagement with ChatGPT may therefore correspond with a more coherent and supportive customer journey because travelers can draw on the same conversational environment across multiple decision points.

Engagement with ChatGPT also provides users with opportunities to evaluate the quality of the system itself [30]. Perceived system reliability reflects the extent to which AI-generated assistance is regarded as consistent, coherent, and dependable across interactions. Such assessments are especially consequential in tourism because travel information may influence financially significant, time-sensitive, or unfamiliar decisions [23,31]. Through repeated interaction, users can compare responses across situations and determine whether ChatGPT appears sufficiently stable and dependable for travel-related support [18,32]. Accordingly, deeper engagement may be accompanied by stronger perceptions of system reliability, although these perceptions do not constitute independent verification of the factual accuracy of ChatGPT outputs.

A different evaluation emerges in relation to recommendation neutrality. Travelers increasingly encounter digital recommendations shaped by ranking algorithms, sponsored placement, commercial partnerships, and selective visibility. Against this background, conversational AI may be evaluated according to whether the suggestions it provides appear responsive to users' stated needs rather than visibly driven by external commercial priorities [11]. Research on AI-supported recommendations suggests that users tend to evaluate outputs more favorably when they appear balanced, transparent, and aligned with the information supplied during the interaction [33,34]. Such perceptions may increase tourists' willingness to consider AI-generated recommendations when making subsequent travel decisions [17]. Because these judgments develop through exposure to generated suggestions, greater ChatGPT engagement is expected to correspond with stronger perceptions of recommendation neutrality.

The proposed relationships are compatible with the broader technology-evaluation logic underlying TAM and UTAUT2. TAM emphasizes the importance of favorable assessments of technological usefulness and ease of interaction [13], whereas UTAUT2 highlights performance-, effort-, and context-related considerations in shaping responses to emerging technologies [15]. Rather than re-testing the core constructs of either framework, the present study draws on this logic to explain why engagement with conversational AI may be associated with both experiential outcomes and evaluations formed during use. Accordingly, the following hypotheses are proposed:

H1. *ChatGPT engagement is positively associated with customer journey enhancement.*

H2. *ChatGPT engagement is positively associated with perceived system reliability.*

H3. *ChatGPT engagement is positively associated with perceived recommendation neutrality.*

2.3. AI Perceptions and Customer Journey Enhancement

The experiential relevance of conversational AI depends partly on how tourists evaluate the assistance they receive during travel-related interactions. Perceived system reliability becomes particularly important when travelers face incomplete information, unfamiliar destinations, time constraints, or decisions that involve considerable financial or practical consequences. Under such conditions, a system that appears consistent and dependable can reduce uncertainty and provide users with greater confidence when incorporating AI-generated information into their decisions [35,36]. Reliable-seeming interaction may also lower the cognitive effort involved in repeatedly questioning the credibility of each response, allowing AI assistance to be incorporated more smoothly into planning, comparison, and evaluation activities [37]. This relationship is broadly consistent with the technology-evaluation logic of TAM and UTAUT2. The experiential benefits associated with a system that appears useful or capable of supporting performance are likely to be greater when its outputs are also perceived as dependable enough to support users'

goals [13,38,39]. Perceived system reliability therefore provides an important link between evaluations of AI-supported interaction and the broader tourist journey. The construct remains perceptual, however, and should not be interpreted as an objective assessment of the factual correctness of generated information [37].

Recommendation neutrality addresses a separate concern. Personalized travel suggestions may be useful while still generating skepticism when users believe that certain destinations, providers, or services are being favored for reasons unrelated to their stated preferences [11,22]. Recommendations that appear balanced and responsive to user requirements may consequently be easier to incorporate into decisions concerning destinations, accommodation, transportation, and other travel alternatives [40,41]. This consideration becomes particularly relevant with generative AI because users are generally unable to directly observe the information sources, ranking processes, or possible commercial influences underlying a generated response [17,42]. Perceived recommendation neutrality may therefore contribute to a more favorable customer journey by reducing skepticism surrounding the recommendation process and enabling travelers to engage with alternative choices more confidently. As with system reliability, the emphasis is on the user's evaluation: perceived impartiality does not demonstrate that the underlying recommendations are objectively free from algorithmic or informational bias. On this basis, the following hypotheses are advanced:

H4. *Perceived system reliability is positively associated with customer journey enhancement.*

H5. *Perceived recommendation neutrality is positively associated with customer journey enhancement.*

2.4. The Mediating Roles of Perceived System Reliability and Recommendation Neutrality

The direct association between ChatGPT engagement and customer journey enhancement does not imply that the relationship operates through interaction alone. Engagement also exposes tourists to repeated system responses and recommendations from which they form evaluations that may subsequently correspond with their assessment of the travel journey. Mediation provides a means of examining whether part of the association between conversational AI engagement and customer journey enhancement is statistically accounted for by such evaluations [7,10]. Within the proposed framework, perceived system reliability and recommendation neutrality represent two parallel but conceptually distinct pathways.

The first pathway centers on dependability. More extensive interaction with ChatGPT exposes travelers to a broader range of responses, giving them opportunities to assess whether the system appears coherent and reliable across different travel-related situations. Favorable reliability evaluations may reduce uncertainty surrounding AI-supported decisions and facilitate the integration of generated information into planning and other journey activities [11,12]. In this way, the association between engagement and journey enhancement may partly operate through users' perceptions that the system provides dependable support. This reasoning is consistent with previous work emphasizing the importance of system-performance evaluations in shaping users' broader experience outcomes [19,43].

Recommendation neutrality provides a second route. Continued exposure to AI-generated suggestions allows tourists to develop impressions regarding whether recommendations appear balanced, impartial, and aligned with their stated preferences. When suggestions are perceived as less commercially driven and more responsive to users' requirements, travelers may be more willing to incorporate them into destination comparisons, itinerary development, and related decisions [22,44,45]. Perceived recommendation neutrality may therefore statistically account for part of the association between ChatGPT engagement and customer journey enhancement by capturing users' evaluations of the

character of the recommendations they encounter. This interpretation neither equates neutrality with trust as a separately measured construct nor assumes that AI-generated suggestions are objectively unbiased [11,12].

The proposed indirect relationships are examined alongside the direct association between ChatGPT engagement and customer journey enhancement, consistent with established mediation principles. Because all constructs were measured within a cross-sectional design, the indirect effects are interpreted as statistical mediation rather than evidence of temporal or causal transmission. Accordingly:

H6. *Perceived system reliability statistically mediates the positive association between ChatGPT engagement and customer journey enhancement.*

H7. *Perceived recommendation neutrality statistically mediates the positive association between ChatGPT engagement and customer journey enhancement.*

2.5. The Moderating Role of Technology Readiness

Technology readiness occupies a different conceptual position from perceived system reliability and recommendation neutrality. Rather than representing an evaluation arising from a specific ChatGPT interaction, it reflects differences in users' preparedness, confidence, and willingness to engage with emerging technologies [46]. Travelers with comparable exposure to conversational AI may therefore derive different levels of benefit from that engagement depending on how ready they are to explore technological capabilities and incorporate them into travel-related activities [47]. The accessibility of conversational interfaces can reduce some of the barriers traditionally associated with advanced technologies because users can communicate through ordinary language rather than specialized commands. Nevertheless, tourists still vary in their willingness to experiment with different prompts, explore unfamiliar functions, reformulate requests, and integrate generated information into decision-making processes [29,32,48]. Individuals displaying stronger technology readiness may therefore be better positioned to convert ChatGPT engagement into improvements in the overall customer journey [49,50]. They may use the system more strategically across different journey stages, whereas less technology-ready travelers may derive more limited benefits even when their level of engagement appears similar. Evidence linking technological preparedness with more confident and extensive use of digital and AI-enabled services lends support to this conditional perspective [51].

Technology readiness may also alter the experiential relevance of perceived system reliability [52]. Considering ChatGPT dependable does not necessarily mean that all tourists will make equivalent use of that perception. Users with limited technological confidence may recognize the apparent reliability of the system yet remain reluctant to incorporate its assistance extensively into travel decisions [53]. By contrast, technology-ready tourists may be more willing to act on dependable-seeming information, experiment with the system's capabilities, and integrate AI assistance into a broader range of journey activities [54,55]. In this sense, readiness can determine how effectively a favorable evaluation of reliability is translated into a more positive journey experience.

This moderating logic is also consistent with research emphasizing the role of user preparedness in converting technological potential into meaningful use outcomes [13,56,57]. Technology readiness is therefore conceptualized as a boundary condition for two selected relationships in the model rather than as another mediator or direct consequence of ChatGPT engagement. The final two hypotheses are thus proposed:

H8. *Technology readiness positively moderates the association between ChatGPT engagement and customer journey enhancement.*

H9. *Technology readiness positively moderates the association between perceived system reliability and customer journey enhancement.*

Figure 1 illustrates the proposed research model.

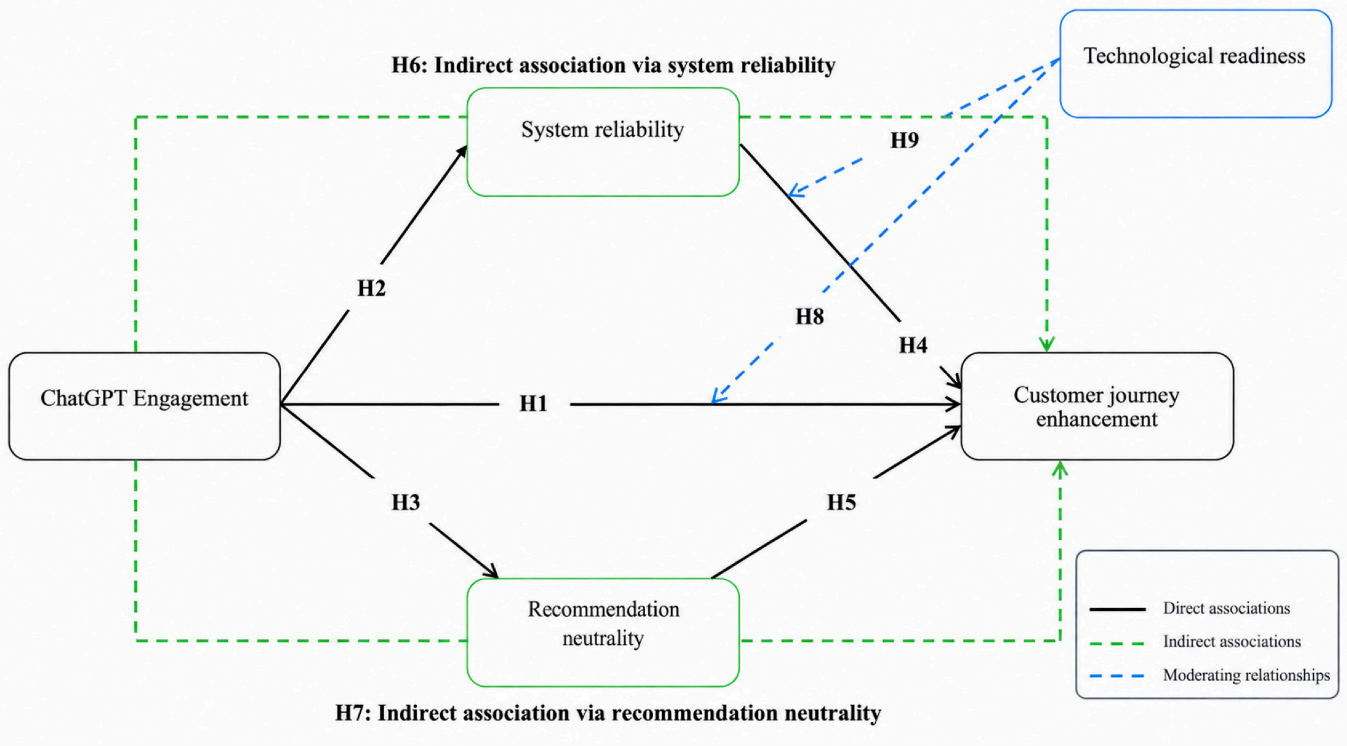


Figure 1. Proposed research model.

3. Methods

3.1. Sample and Data Collection

The target population consisted of tourists with recent and purposeful experience using ChatGPT for travel-related decision-making. As no identifiable sampling frame was available for individuals meeting this specific behavioral criterion, a non-probability purposive sampling approach was adopted. This approach enabled the study to focus on respondents with relevant firsthand experience rather than individuals whose exposure to ChatGPT was unrelated to tourism. Recruitment was conducted online through LinkedIn, TikTok, Facebook, and Instagram, where travel- and technology-related content and communities provided access to potentially eligible participants. Survey invitations were circulated through posts, story-based participation calls, and relevant online communities. Using several platforms also helped broaden recruitment beyond the audience of any single social-media channel. Recruitment was not restricted to a particular country or geographic region, and no country-specific quotas were applied. Country of residence was not collected as a separate demographic variable; instead, the questionnaire recorded the broader nationality grouping of Arab and non-Arab respondents. Accordingly, the available demographic data do not permit a country-level geographic distribution of the sample.

Data collection took place using a web-based questionnaire. The online format was appropriate because both ChatGPT use and the tourism-related behaviors examined in the study occur largely within digital environments. The questionnaire was available in both Arabic and English. Among the 1012 eligible completed questionnaires retained for analysis, 618 were completed using the English version and 394 using the Arabic version. Respondents selected their preferred language before beginning the questionnaire, and the

selected survey version was automatically recorded in the survey dataset. Before entering the questionnaire, prospective respondents received a brief description of the study, an explanation of the relevance of ChatGPT to tourism-related activities, and information concerning voluntary participation and privacy. Electronic informed consent was obtained before participation.

A two-stage screening procedure was applied to establish eligibility. The first question asked whether respondents had used ChatGPT during the preceding 12 months to obtain travel-related information. Individuals answering "no" did not proceed further. Those satisfying the first criterion were subsequently asked whether their use had involved a purposeful travel decision, such as choosing a destination, comparing accommodation options, developing an itinerary, or addressing another travel-planning requirement. This second question distinguished decision-oriented engagement from casual experimentation or ChatGPT use unrelated to a specific tourism activity. Only respondents satisfying both conditions were retained. The questionnaire then asked eligible participants to evaluate their recent travel-related use of ChatGPT over this period. The measurement content covered activities associated with both travel planning and the management or execution of travel, allowing the study to capture perceptions formed across these connected stages of the journey. Responses were therefore framed around participants' recent ChatGPT-supported tourism experience over the 12-month reference period rather than around a single travel episode.

Overall, 1897 individuals accessed the survey, of whom 1012 met both eligibility requirements and completed the questionnaire. The remaining 885 individuals were excluded because they failed one or both screening criteria, including having no relevant ChatGPT experience within the specified period or reporting use that was unrelated to purposeful tourism decision-making. The relatively high exclusion rate therefore resulted from the deliberately focused eligibility criteria rather than from post hoc removal based on respondents' answers to the study constructs. The individual tourist served as the unit of analysis. The resulting sample provided the empirical basis for examining the direct and indirect relationships linking ChatGPT engagement with customer journey enhancement and for assessing whether technology readiness conditions selected relationships within the proposed model.

Before analysis, the dataset was subjected to a series of response-quality checks. These included verification of questionnaire completion and screening eligibility, checks that recorded values fell within the permitted response ranges, inspection for missing values in the measurement items, and review for coding or data-entry errors. Potential duplicate submissions were assessed by jointly examining submission timestamps and response-pattern similarity across completed questionnaires. A submission was flagged as a potential duplicate when it showed an identical or near-identical response pattern across the screening, demographic, and substantive questionnaire items and was also supported by temporal proximity in the submission records. Similarity in substantive scale responses alone was not considered sufficient evidence of duplication.

Straight-lining was operationalized as selection of the same response category for at least 90% of the substantive Likert-scale items. Because highly consistent responses may occasionally reflect genuine respondent evaluations, cases meeting this threshold were flagged for additional examination rather than automatically excluded. A straight-lined questionnaire was considered problematic only when the pattern coincided with at least one additional indicator of poor response quality, such as an unusually short completion time or internally inconsistent responses.

The web-based survey platform automatically recorded questionnaire start and submission times; consequently, timing data were available for all 1012 eligible completed

questionnaires. Completion time was calculated as the interval between questionnaire initiation and final submission. An unusually short completion time was defined as less than one-third of the median completion time observed among the eligible completed questionnaires. Responses falling below this threshold were flagged for further inspection and evaluated jointly with evidence of straight-lining, duplication, missing data, and response inconsistency rather than being excluded solely on the basis of completion speed.

Application of these specified quality-control criteria identified no duplicate submissions or response-quality patterns that warranted further exclusion. Although a small number of questionnaires were initially flagged on the basis of straight-lining or unusually short completion times, none simultaneously exhibited sufficient evidence across the combined quality indicators to justify removal. Consequently, no additional observations were excluded following the response-quality assessment, and the final analytical sample remained 1012 respondents. These procedures ensured that cases were assessed according to explicit indicators of response validity rather than excluded on the basis of their substantive scores on the study constructs.

3.2. Measures

The questionnaire comprised previously established multi-item scales adapted to the context of ChatGPT-assisted tourism activities. All construct indicators were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Minor contextual rewording was applied where necessary to align the items with tourism-related use of ChatGPT while preserving the conceptual meaning of the original measures. The wording of the adapted items reflected the range of activities represented in respondents' recent use of ChatGPT, including information search, travel planning, travel management, and support during the journey. For bilingual administration, an Arabic version was developed using a back-translation procedure to maintain equivalence with the English questionnaire. The adapted and translated wording was reviewed by experts before field administration to assess clarity, contextual appropriateness, and consistency with the intended construct meanings. Appendix A reproduces the measurement items administered in the questionnaire, together with their corresponding sources. Construct reliability and validity were subsequently evaluated through the measurement-model assessment reported in Section 4.2.

ChatGPT engagement was measured using three items adapted from [58]. The scale captures respondents' recurring engagement with and reliance on ChatGPT when seeking hospitality- and tourism-related information.

Perceived system reliability was assessed using six items adapted from [17]. The scale captures respondents' perceptions of ChatGPT as dependable, responsive, accessible, and consistently functional across tourism-related activities and travel contexts.

Recommendation neutrality was measured using six items adapted from [51] and conceptually informed by [59]. The scale assesses the extent to which respondents perceive ChatGPT-generated travel suggestions as balanced, impartial, and not unduly influenced by the promotion of particular destinations, brands, companies, or service providers.

Technology readiness was measured using four items drawn from [16]. The scale reflects respondents' perceived capability, confidence, skills, and ability to understand and apply ChatGPT-generated information when planning or managing tourism-related activities.

Customer journey enhancement was assessed using four items adapted from [43], with the conceptualization of journey coherence and continuity informed by [60]. In the present study, the construct captures perceived improvements in the organization, smoothness, efficiency, and continuity of the journey as travelers move from planning into travel execution. Its operationalization therefore reflects the connected stages explicitly represented in the

scale items rather than an undifferentiated assessment of the entire tourism experience. One perceived system reliability item refers to ChatGPT's reliability in "enhancing my tourism experience," creating some potential conceptual overlap with customer journey enhancement. This wording overlap is acknowledged because both constructs refer to respondents' evaluations of their ChatGPT-supported tourism experience. Conceptually, however, the reliability item concerns the perceived dependability of ChatGPT, whereas customer journey enhancement captures perceived improvements in the organization, smoothness, efficiency, and continuity of the travel journey. The empirical distinctiveness of the two constructs is examined further through the discriminant-validity assessment reported in Section 4.2.

3.3. Common Method Bias

The reliance on a single self-administered survey raises the possibility that part of the covariance among the study constructs may reflect shared measurement conditions rather than substantive relationships alone. Common method bias was therefore assessed from more than one statistical perspective rather than inferred from a single diagnostic procedure [61,62]. An unrotated exploratory factor analysis showed that the first factor accounted for less than 50% of the total variance, which does not suggest dominance by a single common factor [63]. The PCA results were consistent with this pattern, as the indicators were distributed across several components rather than being concentrated in one overarching component [64,65]. In addition, the full-collinearity assessment produced VIF values ranging from 1.539 to 2.749. These values remained below the conservative 3.3 threshold proposed by [66], providing further indication that severe method-related collinearity is unlikely to characterize the data. In this vein, the three diagnostics point in the same direction and do not reveal evidence of substantial common method bias. Nevertheless, these procedures cannot rule out method variance entirely, particularly given the single-source and cross-sectional nature of the survey. The structural estimates are therefore interpreted cautiously as statistical relationships rather than as definitive evidence of temporal or causal processes.

3.4. Data Analysis

Data analysis was conducted using SmartPLS 4 following the partial least squares structural equation modeling (PLS-SEM) procedure. All constructs were specified as reflective and estimated using Mode A with the path-weighting scheme. The PLS algorithm was run on standardized data using a maximum of 3000 iterations and a convergence criterion of 10^{-7}. These settings were retained consistently across the measurement and structural model analyses.

The analysis proceeded in two stages. First, the measurement model was evaluated by examining indicator loadings, Cronbach's alpha, rho_A, composite reliability (rho_C), and average variance extracted (AVE). Discriminant validity was assessed using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). Second, the structural model was evaluated in terms of collinearity, explained variance, effect sizes, direct and indirect associations, interaction effects, and predictive performance. Statistical inference for the structural coefficients and indirect effects was based on nonparametric bootstrapping with 10,000 subsamples drawn with replacement, two-tailed significance testing at the 5% level, and 95% percentile bootstrap confidence intervals.

The complete structural specification included ChatGPT engagement as a predictor of perceived system reliability, perceived recommendation neutrality, and customer journey enhancement. Perceived system reliability and perceived recommendation neutrality were, in turn, specified as predictors of customer journey enhancement, allowing the two corre-

sponding indirect associations to be estimated simultaneously. Technology readiness was modeled as a moderator of both the ChatGPT engagement–customer journey enhancement association and the perceived system reliability–customer journey enhancement association. To preserve the hierarchical specification of the moderation model, the lower-order main effect of technology readiness on customer journey enhancement was also estimated together with the predictor main effects and the two interaction terms, although this path was not associated with a separate substantive hypothesis.

The two interaction terms—ChatGPT engagement × technology readiness and perceived system reliability × technology readiness—were constructed using the two-stage approach. In the first stage, latent variable scores were obtained from the main-effects model. In the second stage, the standardized latent scores of each predictor and technology readiness were used to construct the corresponding product term, which was then entered into the structural model together with its constituent lower-order effects. This approach separates estimation of the latent constructs from estimation of the interaction terms and is particularly suitable for testing latent-variable moderation in PLS-SEM.

Significant interaction terms were further examined using simple-slope analysis. Conditional associations were calculated at three levels of technology readiness: one standard deviation below its mean, at the mean, and one standard deviation above the mean. Accordingly, the conditional association between ChatGPT engagement and customer journey enhancement was calculated as the corresponding lower-order path coefficient plus the ChatGPT engagement × technology readiness interaction coefficient multiplied by the selected value of technology readiness. The same procedure was applied to the association between perceived system reliability and customer journey enhancement.

Because technology readiness moderated the second stage of the indirect pathway involving perceived system reliability, a supplementary conditional indirect-effect analysis was also performed. The indirect association through perceived system reliability was calculated at low, mean, and high levels of technology readiness by multiplying the ChatGPT engagement–perceived system reliability coefficient by the conditional perceived system reliability–customer journey enhancement coefficient at each moderator level. The statistical variation of this indirect association across technology readiness was additionally assessed through the index of moderated mediation, defined as the product of the ChatGPT engagement–perceived system reliability coefficient and the perceived system reliability × technology readiness interaction coefficient. Bootstrap confidence intervals were used for inference. The indirect association through perceived recommendation neutrality was estimated independently because technology readiness was not specified as moderating that pathway.

Out-of-sample predictive performance was assessed using PLSpredict with 10-fold cross-validation and 10 repetitions. Predictions were generated for the indicators of the endogenous constructs. Predictive relevance was evaluated using Q^2predict while predictive errors from PLS-SEM were compared with those obtained from a linear-model benchmark using both root mean squared error (RMSE) and mean absolute error (MAE). The use of repeated 10-fold cross-validation reduces dependence of the predictive assessment on a single random partition of the sample.

Finally, the structural specification can be expressed as three linked equations: perceived system reliability was modeled as a function of ChatGPT engagement; perceived recommendation neutrality was modeled as a function of ChatGPT engagement; and customer journey enhancement was modeled as a function of ChatGPT engagement, perceived system reliability, perceived recommendation neutrality, technology readiness, ChatGPT engagement × technology readiness, and perceived system reliability × technology readi-

ness. This specification enabled the direct, parallel indirect, moderation, and conditional indirect associations to be estimated within a single coherent analytical framework.

4. Results

4.1. Demographics Profile

Table 1 summarizes the demographic characteristics of the 1012 respondents. The gender distribution was nearly balanced, with males representing 50.7% of the sample and females 49.3%. In terms of age, respondents aged 25–34 years constituted the largest group (44.0%), followed by those aged 35–44 years (18.5%) and 45–54 years (16.9%), while respondents under 25 years accounted for 9.0% and those aged 55 years and above for 11.6%. Regarding educational attainment, most participants held a bachelor's degree (72.3%), whereas 20.1% reported less than a bachelor's degree and 7.6% held a postgraduate qualification. The sample also included both Arab (45.3%) and non-Arab (54.7%) respondents.

Table 1. Demographic characteristics of the respondents.

Measure	Category	Frequency	Percentage
Gender	Male	513	50.7%
	Female	499	49.3%
Age	Under 25 years	91	9.0%
	25–34 years	445	44.0%
	35–44 years	187	18.5%
	45–54 years	171	16.9%
	55 years and above	118	11.6%
Educational level	Less than bachelor's degree	203	20.1%
	Bachelor's degree	732	72.3%
	Postgraduate degree	77	7.6%
Nationality group	Arab nationality	458	45.3%
	Non-Arab nationality	554	54.7%

4.2. Measurement Model Assessment

The measurement model results indicate satisfactory reliability and convergent validity across all constructs. As shown in Table 2, all indicator loadings exceeded 0.80, while Cronbach's alpha, rho_A, and composite reliability (rho_C) values were above the recommended 0.70 threshold. The AVE values ranged from 0.722 to 0.777, exceeding the commonly applied 0.50 criterion and indicating that each construct explained more than half of the variance in its indicators. Discriminant validity was subsequently examined using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio. In Table 3, the square root of the AVE for each construct was greater than its correlations with the other constructs. Table 4 provides the more stringent HTMT assessment, with values ranging from 0.366 to 0.701. All values were below the conservative threshold of 0.85, providing support for discriminant validity among the constructs included in the measurement model [61]. Notably, the HTMT value between perceived system reliability and customer journey enhancement was 0.701, remaining well below the 0.85 threshold. This result supports the empirical distinctiveness of the two constructs despite both reflecting evaluations formed within the broader ChatGPT-supported tourism experience.

Table 2. Measurement model assessment.

Construct	Indicator	Loading	Cronbach's α	rho_A	Composite Reliability (rho_C)	AVE
ChatGPT engagement			0.856	0.864	0.913	0.777
	ChatGPT1	0.866				
	ChatGPT2	0.875				
	ChatGPT3	0.903				
Perceived system reliability			0.925	0.931	0.941	0.727
	SR1	0.871				
	SR2	0.843				
	SR3	0.851				
	SR4	0.836				
	SR5	0.849				
	SR6	0.866				
Perceived recommendation neutrality			0.922	0.926	0.940	0.722
	RN1	0.855				
	RN2	0.859				
	RN3	0.832				
	RN4	0.821				
	RN5	0.837				
	RN 6	0.893				
Technology readiness			0.875	0.882	0.914	0.727
	TR1	0.878				
	TR2	0.866				
	TR3	0.829				
	TR4	0.837				
Customer journey enhancement			0.888	0.895	0.922	0.748
	CJE1	0.883				
	CJE2	0.869				
	CJE3	0.866				
	CJE4	0.841				

Table 3. Fornell–Larcker criterion.

Construct	ChatGPT Engagement	SR	RN	TR	CJE
ChatGPT engagement	0.881				
Perceived system reliability (SR)	0.448	0.853			
Perceived recommendation neutrality (RN)	0.397	0.344	0.850		
Technology readiness (TR)	0.365	0.386	0.318	0.853	
Customer journey enhancement (CJE)	0.575	0.623	0.567	0.479	0.865

Table 4. Heterotrait–Monotrait ratio (HTMT).

Construct	ChatGPT Engagement	SR	RN	TR	CJE
ChatGPT engagement	—				
Perceived system reliability (SR)	0.512	—			
Perceived recommendation neutrality (RN)	0.448	0.392	—		
Technology readiness (TR)	0.417	0.441	0.366	—	
Customer journey enhancement (CJE)	0.657	0.701	0.641	0.544	—

4.3. Structural Model

The structural model was first assessed in terms of its explanatory power. As reported in Table 5, ChatGPT engagement accounted for 20.1% of the variance in perceived system reliability and 15.8% of the variance in perceived recommendation neutrality. For customer journey enhancement, the model explained 63.2% of the observed variance, with an adjusted R^2 of 0.630. The relatively small differences between the R^2 and adjusted R^2 values indicate that adjustment for the number of predictors produced little change in the reported explanatory levels.

Table 5. Explanatory power.

Endogenous Construct	R^2	Adjusted R^2
Perceived system reliability	0.201	0.200
Perceived recommendation neutrality	0.158	0.157
Customer journey enhancement	0.632	0.630

Predictive performance was further examined using PLSpredict. As shown in Table 6, all Q^2predict values were positive, ranging from 0.109 to 0.449, indicating that the PLS-SEM predictions outperformed the naïve benchmark for all endogenous indicators. Comparison with the linear-model benchmark produced a generally favorable but not uniform pattern. PLS-SEM yielded lower RMSE values for most indicators, although the LM benchmark performed slightly better for SR2, RN3, and CJE4. A similar pattern was observed for MAE, where PLS-SEM produced lower errors for most indicators, with small exceptions for RN3 and CJE3. Taken together, these results suggest that the model demonstrates out-of-sample predictive relevance, while the comparison with the LM benchmark indicates that its predictive advantage varies modestly across individual indicators.

Table 6. Out-of-sample predictive performance (PLSpredict).

Construct	Indicator	Q^2predict	PLS-SEM RMSE	LM RMSE	PLS-SEM MAE	LM MAE
Perceived system reliability	SR1	0.174	0.819	0.831	0.637	0.646
	SR2	0.158	0.846	0.842	0.653	0.658
	SR3	0.185	0.806	0.819	0.623	0.633
	SR4	0.142	0.871	0.881	0.678	0.687
	SR5	0.169	0.832	0.840	0.647	0.653
	SR6	0.191	0.798	0.812	0.616	0.628

Table 6. *Cont.*

Construct	Indicator	Q^2predict	PLS-SEM RMSE	LM RMSE	PLS-SEM MAE	LM MAE
Perceived recommendation neutrality	RN1	0.139	0.862	0.872	0.670	0.679
	RN2	0.151	0.844	0.856	0.655	0.665
	RN3	0.123	0.886	0.882	0.690	0.687
	RN4	0.109	0.909	0.921	0.707	0.716
	RN5	0.134	0.871	0.879	0.676	0.683
	RN6	0.162	0.834	0.848	0.646	0.657
Customer journey enhancement	CJE1	0.449	0.691	0.718	0.532	0.553
	CJE2	0.425	0.717	0.736	0.554	0.569
	CJE3	0.397	0.744	0.756	0.576	0.573
	CJE4	0.372	0.769	0.765	0.588	0.592

Table 7 reports supplementary approximate model-fit indices. The SRMR value was 0.031 and the NFI was 0.942. These values fall within commonly referenced approximate benchmarks of SRMR below 0.08 and NFI above 0.90. However, because global fit criteria have a more limited role in PLS-SEM than in covariance-based SEM, these indices are treated as supplementary evidence rather than as the primary basis for evaluating the structural model.

Table 7. Supplementary approximate model fit.

Fit Index	Value
SRMR	0.031
NFI	0.942

4.4. Hypothesis Testing

Table 8 summarizes the direct, indirect, and interaction effects examined in the structural model. All five hypothesized direct relationships were positive and statistically significant. ChatGPT engagement was positively associated with customer journey enhancement (β = 0.240, $p < 0.001$), perceived system reliability (β = 0.448, $p < 0.001$), and perceived recommendation neutrality (β = 0.397, $p < 0.001$), supporting H1–H3. Perceived system reliability (β = 0.350, $p < 0.001$) and perceived recommendation neutrality (β = 0.300, $p < 0.001$) were also positively associated with customer journey enhancement, supporting H4 and H5. The non-hypothesized lower-order main effect of technology readiness on customer journey enhancement, included as a constituent term in the moderation specification, was also positive and statistically significant (β = 0.161, SE = 0.042, t = 3.833, $p < 0.001$, 95% CI [0.079, 0.243]). Among the hypothesized direct relationships, the largest coefficient was observed for the association between ChatGPT engagement and perceived system reliability, followed by the association between ChatGPT engagement and perceived recommendation neutrality. The 95% confidence intervals for all reported direct and lower-order effects excluded zero.

The indirect relationships were also statistically supported. The indirect association between ChatGPT engagement and customer journey enhancement through perceived system reliability was positive and significant (β = 0.157, SE = 0.024, t = 6.542, $p < 0.001$, 95% CI [0.112, 0.206]), supporting H6. Similarly, the indirect association through perceived recommendation neutrality was positive and significant (β = 0.119, SE = 0.022, t = 5.409,

$p < 0.001$, 95% CI [0.078, 0.164]), supporting H7. The indirect association through perceived system reliability was somewhat larger than that through perceived recommendation neutrality. At the mean level of technology readiness, the direct association between ChatGPT engagement and customer journey enhancement remained positive and statistically significant (β = 0.240, $p < 0.001$). Accordingly, both perceived system reliability and perceived recommendation neutrality exhibited partial mediation. As the direct and indirect associations were significant and operated in the same positive direction, the mediation pattern can be characterized as complementary partial mediation.

Table 8. Hypothesis testing results.

H	Relationship	Effect Type	β	SE	t-Value	*p*-Value	95% CI	f^2	Inner VIF
H1	ChatGPT engagement → CJE	Direct	0.240	0.041	5.854	<0.001	[0.160, 0.320]	0.111	1.415
H2	ChatGPT engagement → SR	Direct	0.448	0.039	11.487	<0.001	[0.372, 0.524]	0.251	1.000
H3	ChatGPT engagement → RN	Direct	0.397	0.043	9.233	<0.001	[0.313, 0.481]	0.187	1.000
H4	SR → CJE	Direct	0.350	0.045	7.778	<0.001	[0.262, 0.438]	0.241	1.384
H5	RN → CJE	Direct	0.300	0.047	6.383	<0.001	[0.208, 0.392]	0.193	1.270
—	TR → CJE	Lower-order main effect	0.161	0.042	3.833	<0.001	[0.079, 0.243]	0.055	1.274
H6	ChatGPT engagement → SR → CJE	Indirect	0.157	0.024	6.542	<0.001	[0.112, 0.206]	—	—
H7	ChatGPT engagement → RN → CJE	Indirect	0.119	0.022	5.409	<0.001	[0.078, 0.164]	—	—
H8	ChatGPT engagement × TR → CJE	Interaction	0.105	0.032	3.281	0.001	[0.042, 0.168]	0.022	1.366
H9	SR × TR → CJE	Interaction	0.090	0.030	3.000	0.003	[0.031, 0.149]	0.016	1.366

Note: The TR → CJE path is a non-hypothesized lower-order main effect included as a constituent term in the moderation specification; therefore, it is reported without a hypothesis number.

Finally, both interaction terms were positive and statistically significant. Technology readiness moderated the association between ChatGPT engagement and customer journey enhancement (β = 0.105, $p = 0.001$, 95% CI [0.042, 0.168]), supporting H8. The interaction between perceived system reliability and technology readiness was also significant (β = 0.090, $p = 0.003$, 95% CI [0.031, 0.149]), supporting H9. The corresponding interaction-effect sizes were limited in magnitude ($f^2 = 0.022$ for H8 and 0.016 for H9), suggesting that the moderating relationships, although statistically detectable, were modest. Inner VIF values ranged from 1.000 to 1.415, indicating no apparent collinearity concern among the predictors included in the structural model.

4.5. Moderation Effects

Table 9 and Figures 2 and 3 report the simple-slope results for the two moderation hypotheses. For H8, the positive association between ChatGPT engagement and customer

journey enhancement was statistically significant at low, mean, and high levels of technology readiness. The conditional coefficient increased from β = 0.135 at low technology readiness (−1 SD) to β = 0.240 at the mean level and β = 0.345 at high technology readiness (+1 SD). Figure 2 reflects the same pattern, with the slope becoming progressively steeper as technology readiness increases. These results indicate that the association between ChatGPT engagement and customer journey enhancement is stronger at higher levels of technology readiness.

Table 9. Simple-slope analysis of the moderating role of Technology Readiness.

H	Conditional Relationship	Level of Technology Readiness	Conditional β	SE	t-Value	*p*-Value	95% CI
H8	ChatGPT engagement → CJE	Low TR (−1 SD)	0.135	0.050	2.700	0.007	[0.038, 0.233]
		Mean TR	0.240	0.041	5.854	<0.001	[0.160, 0.320]
		High TR (+1 SD)	0.345	0.052	6.635	<0.001	[0.244, 0.448]
H9	Perceived system reliability → CJE	Low TR (−1 SD)	0.260	0.052	5.000	<0.001	[0.159, 0.362]
		Mean TR	0.350	0.045	7.778	<0.001	[0.262, 0.438]
		High TR (+1 SD)	0.440	0.055	8.000	<0.001	[0.333, 0.548]

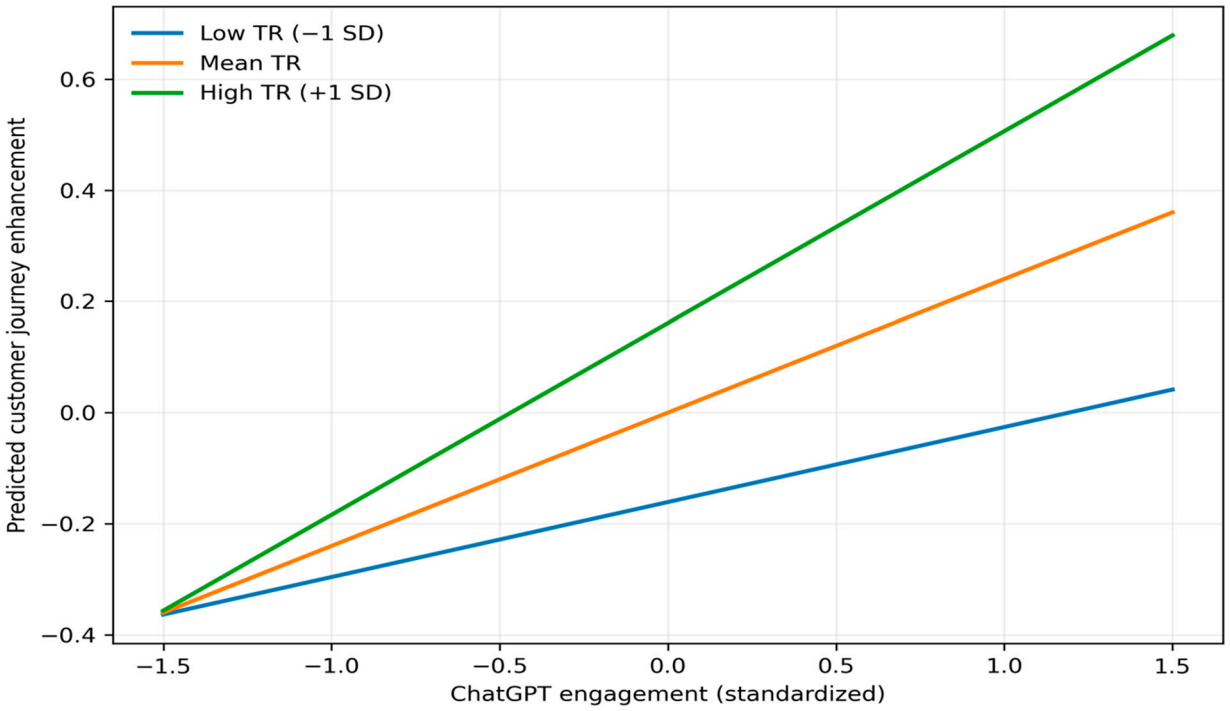


Figure 2. Moderating effect of technology readiness on the relationship between ChatGPT engagement and customer journey enhancement.

For H9, a similar pattern was observed for perceived system reliability. Its association with customer journey enhancement remained positive and statistically significant across all three levels of technology readiness, increasing from β = 0.260 at low technology readiness to β = 0.350 at the mean level and β = 0.440 at high technology readiness. Figure 3 visually illustrates this increase in slope. Taken together with the significant interaction terms reported in Table 8, the simple-slope results provide further support for H8 and H9 and show that technology readiness strengthens both examined relationships. The pattern is

consistent across the three moderator levels, although the interaction effects themselves remain modest in magnitude.

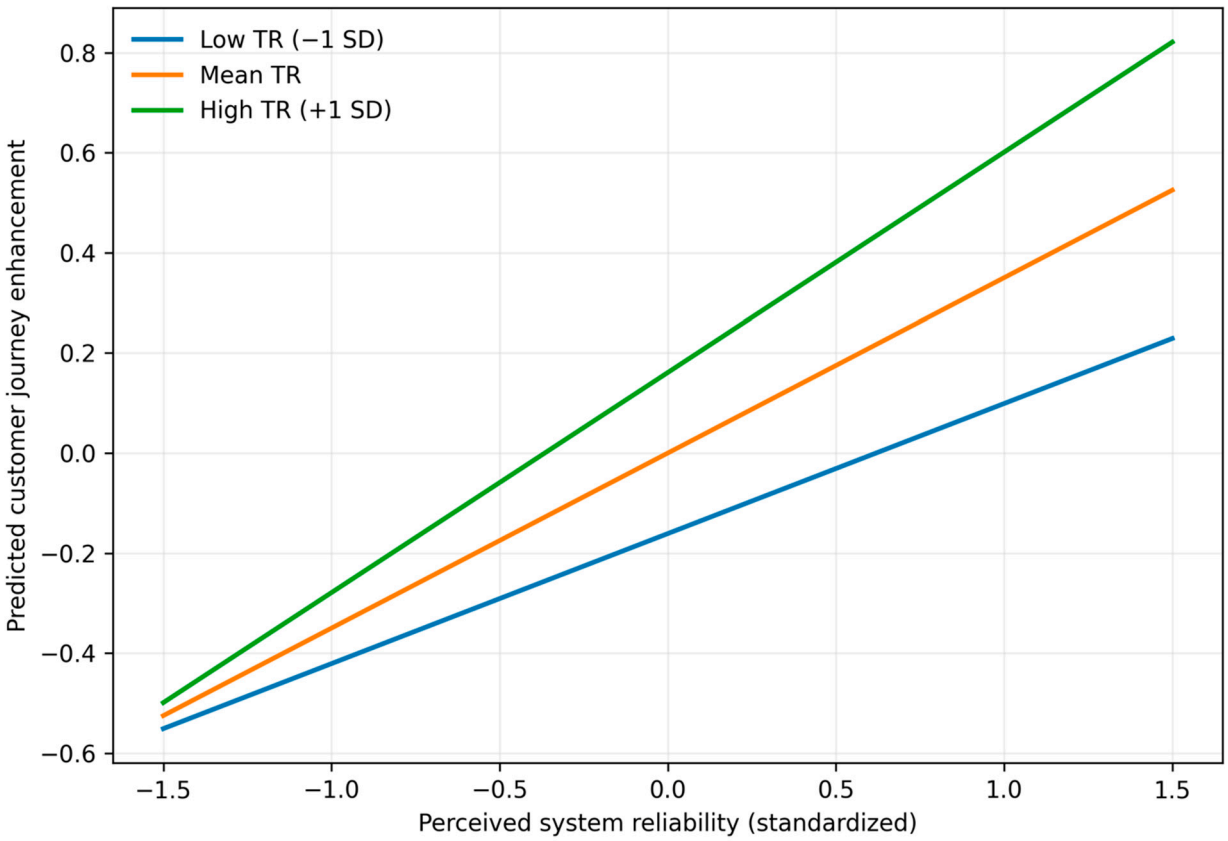


Figure 3. Moderating effect of technology readiness on the relationship between perceived system reliability and customer journey enhancement.

4.6. Supplementary Conditional Mediation Analysis

Table 10 reports the conditional indirect association between ChatGPT engagement and customer journey enhancement through perceived system reliability across three levels of technology readiness. The indirect association was positive and statistically significant at low technology readiness (β = 0.116, $p < 0.001$, 95% CI [0.074, 0.164]), at the mean level (β = 0.157, $p < 0.001$, 95% CI [0.112, 0.206]), and at high technology readiness (β = 0.197, $p < 0.001$, 95% CI [0.143, 0.255]). None of the confidence intervals included zero. The magnitude of the conditional indirect association increased progressively across the three levels of technology readiness, from 0.116 at the low level to 0.197 at the high level. Figure 4 provides a visual representation of this pattern.

Table 10. Conditional indirect effect through perceived system reliability.

Level of Technology Readiness	ChatGPT Engagement → SR → CJE	SE	t-Value	*p*-Value	95% CI
Low TR (−1 SD)	0.116	0.023	5.043	<0.001	[0.074, 0.164]
Mean TR	0.157	0.024	6.542	<0.001	[0.112, 0.206]
High TR (+1 SD)	0.197	0.029	6.793	<0.001	[0.143, 0.255]

Whether this variation in the indirect association was statistically meaningful was further assessed using the index of moderated mediation. As reported in Table 11, the index

was positive and statistically significant (β = 0.040, SE = 0.014, t = 2.879, p = 0.004), with a 95% confidence interval [0.014, 0.069] that excluded zero. This result provides statistical evidence that the indirect association through perceived system reliability varies according to technology readiness, with a stronger indirect association observed at higher levels of the moderator. Considered together, Tables 10 and 11 and Figure 4 indicate a conditional mediation pattern in which the indirect association between ChatGPT engagement and customer journey enhancement through perceived system reliability becomes stronger as technology readiness increases. As this analysis extends the hypothesized mediation and moderation relationships, it is treated as a supplementary finding rather than as a separate hypothesis test.

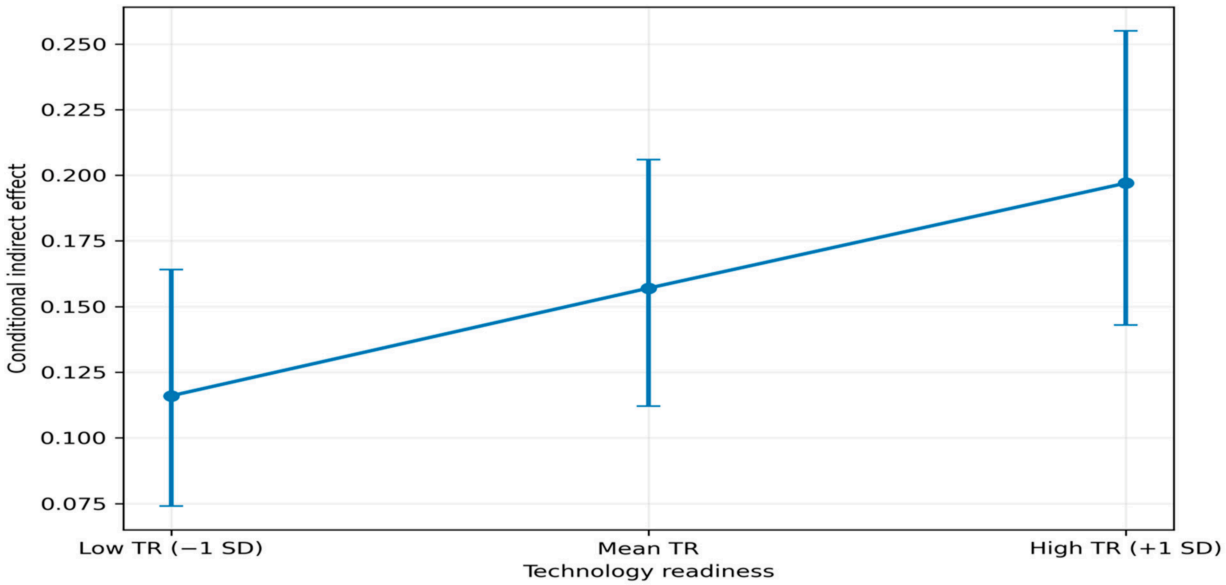


Figure 4. Conditional indirect association of ChatGPT engagement with customer journey enhancement through perceived system reliability across levels of technology readiness.

Table 11. Index of moderated mediation.

Effect	β	SE	t-Value	p-Value	95% CI
Index of moderated mediation via perceived system reliability	0.040	0.014	2.879	0.004	[0.014, 0.069]

4.7. Conditional Association Decomposition

Table 12 decomposes the conditional association between ChatGPT engagement and customer journey enhancement into its direct and indirect components across different levels of technology readiness. At low technology readiness, the direct association was 0.135, while the indirect associations through perceived system reliability and perceived recommendation neutrality were 0.116 and 0.119, respectively, producing a total indirect association of 0.235 and a conditional total association of 0.370. At the mean level of technology readiness, the direct association increased to 0.240 and the indirect association through perceived system reliability to 0.157, resulting in a total indirect association of 0.276 and a conditional total association of 0.516. At high technology readiness, the direct association reached 0.345 and the indirect association through perceived system reliability increased to 0.197, whereas the indirect association through perceived recommendation neutrality remained unchanged at 0.119. Consequently, the total indirect association rose to 0.316 and the conditional total association to 0.661. This pattern reflects the specification of the model, in which technology readiness moderates the ChatGPT engagement–customer

journey enhancement relationship and the perceived system reliability–customer journey enhancement relationship, but not the pathway involving perceived recommendation neutrality. Overall, the decomposition indicates that the combined direct and indirect association between ChatGPT engagement and customer journey enhancement becomes stronger as technology readiness increases.

Table 12. Conditional effect decomposition.

TR Level	Direct Effect	Via SR	Via RN	Total Indirect Effect	Conditional Total Effect
Low (−1 SD)	0.135	0.116	0.119	0.235	0.370
Mean	0.240	0.157	0.119	0.276	0.516
High (+1 SD)	0.345	0.197	0.119	0.316	0.661

5. Discussion

Conversational AI appears to enter the tourist customer journey through more than one route. Engagement with ChatGPT was associated with more favorable journey evaluations, yet the relationship was not confined to interaction intensity itself. Perceived system reliability and recommendation neutrality accounted for additional portions of that association, whereas technology readiness modestly conditioned the strength of selected relationships. The resulting picture is therefore not one of a single technology variable leading to a single experiential outcome. Instead, interaction, evaluation, and user preparedness operate at different levels of the same process. Examining these elements together adds to existing accounts of AI-assisted travel decisions by distinguishing three analytically different questions within the same framework: whether the system appears dependable, whether its recommendations appear impartial, and whether users are sufficiently prepared to derive value from those perceptions and interactions. Reliability and neutrality therefore capture distinct evaluations formed around AI-supported decision-making, whereas readiness represents a user-level condition under which selected associations vary. This reading is consistent with [7] view of conversational AI as an active component of travel decision-making and with [27], who position AI-supported tourism experiences as broader than simple information acquisition.

What may matter most about engagement is not merely frequency of use, but the continuity that conversational interaction introduces into travel planning. Tourism decisions often evolve rather than occur once: destinations are reconsidered, constraints emerge, budgets change, and earlier choices require revision. ChatGPT allows these adjustments to occur within an ongoing conversational context. That continuity may explain why engagement retains an association with customer journey enhancement even after perceived reliability and recommendation neutrality are considered. In addition, ref. [29] describes intelligent technologies as increasingly embedded across different stages of the travel process, while ref. [11] highlights the experiential relevance of AI-supported personalization. Seen together, these arguments suggest that conversational AI may derive value from its capacity to accompany an evolving decision process rather than from functioning as a more sophisticated search box.

The two mediating perceptions, however, are not equivalent. Reliability-related cues are comparatively more observable from the user's perspective. Travelers can repeatedly observe whether responses are available, coherent, stable, and apparently dependable across different requests. As well, ref. [31] emphasize the importance of performance-oriented assessments in digital tourism settings, and repeated interaction may provide the experiential basis from which such assessments become established. Recommendation neutrality is more difficult to infer. A user can inspect the recommendation that appears on screen but cannot normally see the informational hierarchy, training data, retrieval logic, or possible asymmetries underlying that recommendation. Moreover, ref. [10] identify this opacity as a central difficulty in AI-supported decision environments. The somewhat more pronounced role of perceived reliability can therefore be understood in terms of observability: apparent dependability is experienced through recurring interactional cues, whereas neutrality is inferred from outputs whose production process remains largely invisible.

That difference also changes how the mediation results should be interpreted. Both perceived system reliability and recommendation neutrality partially accounted for the association between ChatGPT engagement and customer journey enhancement, indicating that engagement was statistically associated with journey evaluations partly through these two perceptual pathways. Ref. [19] characterize technology-supported tourism experiences as multidimensional, which fits this pattern well. Reliability addresses whether the system appears dependable enough to use; neutrality addresses whether the recommendations appear sufficiently balanced to consider. These are complementary judgments, not alternative labels for the same favorable attitude. Nor should the apparently stronger reliability pathway be read as definitive evidence that reliability is more important than neutrality, because the study does not establish a statistical difference between the two indirect mechanisms. What can be said more cautiously is that dependability may occupy a more immediate role in deciding whether AI-generated assistance enters the travel decision process at all. These indirect associations should nevertheless remain explicitly associational. Because ChatGPT engagement, perceived reliability, recommendation neutrality, and customer journey enhancement were measured concurrently, the observed mediation pattern does not establish temporal ordering among them. The specified direction is theoretically consistent with the proposed model, but the reverse possibility cannot be excluded: travelers who retrospectively evaluate their journey more favorably may also remember ChatGPT as having been more dependable or its recommendations as having been more balanced. The present results therefore identify covariation consistent with the proposed mediating structure rather than demonstrating that reliability or neutrality necessarily preceded and produced the journey evaluation.

The fact that a direct association remained after accounting for both mediators is analytically important. If reliability and neutrality completely represented the experiential meaning of ChatGPT engagement, little would remain once they were introduced. That was not the pattern observed. Engagement therefore seems to carry an additional component that cannot be reduced to whether the system appears dependable or impartial. This residual dimension may reflect the adaptive nature of dialogue, the convenience of iterative questioning, the sense of conversational continuity, or other features embedded in the interaction itself. Ref. [67] likewise portray AI-supported tourism experiences as comprising multiple dimensions rather than a single evaluative route. The mediation structure thus narrows the explanation without exhausting it.

Technology readiness shifts the discussion from how engagement is associated with the journey to for whom those associations are more pronounced. Travelers differ in their ability to formulate requests, refine prompts, interpret generated responses, and integrate those responses into wider travel decisions. Ref. [18] show that technological dispositions matter for participation in emerging digital tourism environments, while ref. [68] draw attention to the role of user capability in working effectively with AI-enabled tools. The moderation pattern is compatible with that logic: greater engagement appears to correspond more strongly with customer journey enhancement among users who are better prepared to work with intelligent technologies. Importantly, this does not make readiness a substitute for engagement. Nor should readiness be interpreted as a dominant determinant of journey enhancement. The interaction effect was modest, indicating that technology readiness provides a limited but detectable qualification of the engagement–journey association rather than fundamentally changing it.

A similar, but likewise modest, conditional pattern emerges around perceived system reliability. A system may appear dependable to two travelers, yet that perception need not carry the same experiential significance for both. A technologically prepared user may be more capable of converting apparently reliable assistance into itinerary adjustments, comparison tasks, planning decisions, or problem solving. Someone less prepared may recognize the same apparent reliability without incorporating the system as extensively into the journey. Ref. [49] emphasize this broader role of preparedness in shaping how technology evaluations correspond with subsequent responses. The conditional mediation result is consistent with a stronger reliability-related association at higher levels of technology readiness, but the modest size of the underlying interaction warrants restraint in interpreting the extent of this difference. Readiness, in that sense, does not create reliability; it is associated with relatively small differences in how strongly perceived reliability corresponds with the broader journey evaluation.

Recommendation neutrality occupies a different position within the specified model because its relationship with customer journey enhancement was not modeled as contingent on technology readiness. This means that the resulting asymmetry between the reliability and neutrality pathways should be interpreted as a feature of the proposed model rather than as evidence that technology readiness is irrelevant to the neutrality pathway. Reliability is closely tied to the practical use of system performance, whereas neutrality concerns the interpretation of how alternatives are presented, suggesting that the two perceptions may enter the customer journey through different evaluative processes. As well, ref. [17] shows that system-related perceptions need not function identically within tourism technology experiences. The current pattern therefore reinforces the importance of avoiding the treatment of favorable AI perceptions as a single generalized assessment merely because each is positively associated with customer journey enhancement.

The most important caution arises from the word perceived. A response can appear reliable because it is fluent, coherent, detailed, and confidently expressed, even when parts of it are inaccurate, incomplete, outdated, or fabricated. Ref. [24] discuss the governance difficulties created by such characteristics of generative AI. Tourism makes this issue particularly consequential. Errors concerning transport schedules, destination requirements, accommodation conditions, opening hours, prices, or safety may influence real decisions rather than remain abstract informational inaccuracies. Perceived reliability can therefore improve the subjective smoothness of decision-making while simultaneously creating conditions for over-reliance. The same perception that reduces uncertainty may reduce scrutiny.

Recommendation neutrality carries an equivalent problem from another direction. Balanced wording does not guarantee balanced generation. A recommendation may appear impartial despite being shaped by unequal data representation, differential visibility of tourism providers, limitations in available information, prompt framing, or model-specific tendencies. Ref. [33] connect such concerns to fairness and transparency in responsible AI use. For travelers, however, these underlying processes are usually inaccessible. They judge the recommendation primarily from what is presented to them. That creates a meaningful gap between apparent neutrality and demonstrated neutrality, especially when fluent conversational presentation makes the recommendation appear naturally objective.

Here lies the central tension running through the results. Conversational AI can reduce search friction, maintain contextual continuity, and make travel planning feel more manageable, yet those same characteristics can increase dependence on outputs whose provenance is difficult to inspect. Ref. [10] highlight the challenge posed by opaque AI-mediated decisions; in the present context, that opacity sits alongside clearly favorable journey evaluations. Experiential value and informational assurance therefore need not move together. A traveler can experience a smoother journey because ChatGPT appears dependable and balanced even when the underlying accuracy or impartiality of specific outputs has not been independently established. This is not an anomaly in the results. It is a substantive feature of human interaction with generative AI.

Taken as a whole, the results describe an AI-supported customer journey built from distinct but interdependent components. Engagement captures the ongoing encounter with ChatGPT. Perceived system reliability and recommendation neutrality capture judgments formed around the quality and presentation of that encounter. Technology readiness provides a modest boundary condition for selected associations rather than a dominant explanation of journey enhancement. Considering the three together therefore adds a layered account of AI-assisted travel decision-making that separates judgments about system dependability from judgments about recommendation impartiality and, in turn, separates both from the user capability that conditions selected relationships. The value of maintaining these distinctions is that they prevent favorable use, favorable perception, and technological capability from being treated as interchangeable phenomena. More critically, they reveal the dual character of conversational AI in tourism: the system can be experienced as convenient, adaptive, and supportive while still requiring travelers to make consequential judgments under conditions of limited informational transparency. Given the concurrent measurement design, these relationships should ultimately be read as an interconnected pattern of associations rather than as a confirmed temporal sequence. The relationship between generative AI and the tourist journey is therefore best understood as one involving both experiential opportunity and vulnerability arising from judgments made about outputs that users cannot fully verify.

6. Theoretical Implications

This study contributes to research on conversational AI in tourism by shifting attention from technology acceptance toward post-engagement experiential outcomes. TAM and UTAUT2 remain useful as broad technology-evaluation lenses, but the present framework does not re-specify or formally extend either model because their core constructs are not directly measured. Instead, customer journey enhancement is positioned as the focal outcome. This repositioning is theoretically meaningful because it treats engagement with generative AI as a starting point for understanding post-engagement experience rather than as an endpoint of technology use.

A second contribution lies in separating evaluative mechanisms from user-level boundary conditions. Perceived system reliability and recommendation neutrality represent parallel perceptual pathways that statistically account for part of the association between engagement and customer journey enhancement, whereas technology readiness modestly conditions the strength of selected relationships. This distinction clarifies the different theoretical roles played by system-related evaluations and user preparedness, avoiding the treatment of all technology-related constructs as equivalent intervening variables. More specifically, examining reliability, neutrality, and readiness within the same framework separates three questions that are often conflated in accounts of AI-assisted travel decisions: whether the system appears dependable, whether its recommendations appear impartial, and whether users differ in their preparedness to benefit from AI-supported interaction. Their joint consideration therefore connects evaluations of the AI system and its generated content with a distinct user-level condition without collapsing them into a single favorable orientation toward technology.

The findings further support the conceptual differentiation of perceived system reliability and recommendation neutrality. Reliability concerns whether AI-supported assistance appears dependable, while neutrality concerns whether generated recommendations appear balanced and impartial. In generative AI settings, this distinction is particularly relevant because users evaluate not only system performance but also the character of generated content. Recommendation neutrality therefore adds a perceptual dimension that is especially salient in opaque AI-mediated decision environments. Importantly, neutrality is not treated as equivalent to trust, which was not directly measured in this study. A further theoretical implication concerns the gap between perceived AI quality and objective AI performance. Perceived reliability does not establish factual accuracy, and perceived neutrality does not demonstrate the absence of bias. This distinction is important because tourists form experience evaluations based on qualities they can perceive, while many aspects of AI performance remain difficult to verify directly. The framework therefore highlights how favorable customer journey evaluations may coexist with uncertainty regarding the actual accuracy, transparency, or impartiality of AI-generated outputs.

Hence, these contributions support a layered conceptualization of conversational AI in tourism in which engagement, evaluative perceptions, and technology readiness occupy distinct theoretical roles. The added value of the framework lies in showing that AI-assisted travel decisions cannot be reduced either to engagement with the technology or to a generalized favorable evaluation of it: system dependability, recommendation impartiality, and user preparedness represent theoretically distinct components that can be examined simultaneously while retaining their separate roles. The contribution lies not in formally extending TAM or UTAUT2, but in showing how their broader technology-evaluation logic can be connected to post-engagement customer journey outcomes while preserving a clear distinction between perceptual pathways, modest boundary conditions, and perceived versus objectively verified AI performance.

7. Practical Implications

The findings suggest that tourism organizations should treat conversational AI as part of the customer journey even when the AI system itself is outside their direct control. Because the study examined travelers using the general-purpose ChatGPT interface, tourism firms should not be assumed to control the content, ranking, or reliability of its outputs. Their practical role is therefore indirect: they can improve the information environment surrounding AI-assisted decisions by maintaining accurate, current, and easily accessible official information. This is particularly important for time-sensitive matters such as prices, schedules, operating hours, availability, destination requirements, and service

disruptions, where travelers may otherwise rely on plausible but outdated or incomplete AI-generated responses.

The prominence of perceived system reliability in the results makes verification especially important. Travelers who regard ChatGPT as dependable are more likely to report a more favorable journey, yet perceived reliability does not guarantee factual accuracy. Tourism providers should therefore create visible verification points within the wider customer journey rather than assuming that positive perceptions of AI reliability are sufficient. Official webpages, booking systems, service-status pages, and customer-support channels should present consistent and up-to-date information that can be checked against AI-generated advice. Where errors could have material consequences, organizations should make authoritative information easy to identify and avoid communicating in ways that encourage customers to treat third-party AI output as officially validated.

A different set of actions becomes possible when the organization controls the conversational system itself. For destination management organizations, hotels, airlines, attractions, or travel platforms deploying their own AI assistants, the reliability pathway identified in this study points toward the importance of grounding responses in verified organizational data rather than relying solely on unconstrained generation. Curated knowledge bases, retrieval from maintained operational systems, regular testing of common travel scenarios, and escalation to human support can help reduce discrepancies between perceived and actual reliability. In settings where information changes rapidly, AI responses should be linked to live or frequently updated data sources so that the convenience of conversational interaction does not come at the expense of information currency.

Recommendation neutrality requires a different managerial response. The results indicate that travelers' journey evaluations are also associated with whether AI-generated suggestions appear balanced and impartial. For public ChatGPT, firms have little control over how providers or destinations are selected or ranked, and they should therefore avoid presenting such recommendations as if they were organization-verified. In organization-managed recommendation systems, however, greater transparency is possible. Sponsored or commercially prioritized options should be clearly distinguishable from preference-based recommendations, users should be shown meaningful alternatives where appropriate, and the basis for prominent recommendations should be communicated in understandable terms. These practices do not guarantee objective neutrality, but they reduce the risk that commercially influenced recommendations are experienced as undisclosed or misleading.

Technology readiness adds an important segmentation implication. The moderation results show that the relationships involving ChatGPT engagement and perceived reliability are more pronounced among users with greater technological readiness. Tourism organizations should therefore avoid designing AI-supported journeys around the assumption that all customers can use conversational systems equally effectively. For users with lower readiness, suggested prompts, guided question formats, short explanations of how to refine a request, and easy access to non-AI alternatives can reduce interaction barriers. Human assistance, conventional search, and standard booking or information channels should remain available so that AI adoption does not unintentionally disadvantage travelers who are less confident with emerging technologies.

The conditional reliability pattern further suggests that improving AI performance alone may not produce equivalent customer value across user groups. A technically capable traveler may be better able to convert dependable AI assistance into planning, comparison, and journey-management decisions, whereas another user may need more structured support before the same information becomes useful. Organizations managing their own AI services can therefore combine system-quality improvements with interface support and user guidance rather than treating these as separate priorities. In practical terms, reliability

should be managed together with usability and user preparedness if organizations expect AI assistance to contribute meaningfully across a heterogeneous customer base.

Finally, organizations should evaluate AI-supported customer journeys using both perceptual and objective indicators. The mediation results show that perceived reliability and perceived neutrality are relevant to customer journey evaluations, but these perceptions should not replace operational quality assessment. Customer perceptions of reliability can be considered alongside factual accuracy checks, response consistency, and information freshness. Perceptions of neutrality can be reviewed alongside audits of recommendation sources, ranking practices, sponsored content, and provider representation. This combined approach is particularly important because a conversational system can be experienced as smooth, dependable, and balanced even when some of its outputs remain inaccurate or opaque.

8. Limitations and Future Research

Several limitations should be considered when interpreting the findings. First, the cross-sectional, single-source design limits conclusions about temporal ordering among ChatGPT engagement, perceived system reliability, recommendation neutrality, technology readiness, and customer journey enhancement. Although the analysis identified significant direct, indirect, interaction, and conditional indirect relationships, these estimates represent statistical associations rather than evidence of causal processes. This qualification is particularly important for the mediation results, because the predictor, mediators, and outcome were measured concurrently. Accordingly, the temporal direction implied by the proposed model cannot be established from the present data. Reverse relationships are also plausible: travelers who retrospectively evaluate their ChatGPT-supported journey more favorably may subsequently report higher perceived reliability or greater recommendation neutrality. The indirect effects should therefore be interpreted as statistical mediation consistent with the proposed model rather than as evidence that these perceptions necessarily preceded or caused customer journey enhancement. Longitudinal, multi-wave, or experimental designs could establish temporal sequencing more clearly and distinguish the proposed directional relationships from plausible reverse or reciprocal associations, while also assessing whether the observed relationships persist as travelers accumulate experience with generative AI.

A second limitation concerns the distinction between perceived and objective AI performance. The study measured whether users regarded ChatGPT as reliable and its recommendations as neutral; it did not independently verify factual accuracy, information recency, consistency, or recommendation bias. Favorable perceptions may therefore coexist with inaccurate, outdated, or systematically uneven outputs. Future studies could pair user evaluations with external assessments of response accuracy, source quality, recency, and recommendation composition. Such designs would make it possible to examine the degree of calibration between perceived reliability or neutrality and objectively evaluated system performance, an issue that is particularly important where fluent AI outputs may encourage confidence that exceeds their actual informational quality.

The conceptual boundaries surrounding recommendation neutrality also deserve closer examination. Trust was not included as a measured construct, so the present findings do not establish whether perceived neutrality is empirically distinct from trust, transparency, fairness, or related evaluations when these constructs are modeled simultaneously. Subsequent research could test these distinctions using validated measures and determine whether neutrality operates independently, contributes to trust formation, or interacts with other evaluations of AI-supported recommendations. The continuing direct association between ChatGPT engagement and customer journey enhancement also indicates that perceived reliability and recommendation neutrality provide only a partial account of the

relationship, leaving scope to examine additional mechanisms such as perceived usefulness, personalization, decision confidence, or perceived control.

A further limitation concerns respondents' experience across the stages of the tourist journey. The questionnaire did not separately establish whether the travel plans associated with respondents' ChatGPT use had subsequently been undertaken. Consequently, some participants may have evaluated their ChatGPT-supported experience primarily from the travel-planning stage rather than from experience spanning the full tourist journey. The findings regarding customer journey enhancement should therefore not be interpreted as demonstrating enhancement across all stages of a completed trip for every respondent. Future research should explicitly distinguish between planning-only users and travelers who have undertaken the associated trip and examine whether the observed relationships differ across pre-trip, during-trip, and post-trip stages.

The empirical context provides another boundary. Respondents evaluated their experience with the general-purpose ChatGPT interface, which differs from AI assistants deployed and governed directly by tourism organizations. Organization-managed systems may rely on curated knowledge bases, proprietary customer data, real-time operational information, or explicit commercial objectives, all of which could alter perceptions of reliability, neutrality, and the role of technology readiness. Comparative studies across public generative AI, hotel or airline assistants, online travel platforms, and destination-managed systems could therefore establish whether the relationships identified here remain consistent under different levels of organizational control and information governance.

Finally, the purposive online sampling strategy was appropriate for reaching travelers with recent, decision-oriented ChatGPT experience, but it does not provide a probability-based representation of the wider tourist population. In addition, because country of residence was not collected as a separate demographic variable, the study cannot characterize the sample at the country level or examine whether the observed relationships vary across specific national contexts. Replication across countries, cultural settings, demographic groups, travel contexts, and levels of AI experience would help assess the robustness of the model. Attention could be given to whether the modest moderating effects of technology readiness replicate across different user groups and tourism settings, and whether the conditional reliability pathway remains evident when travelers differ substantially in technological experience. Given the limited magnitude of the observed interaction effects, future studies should also assess whether these conditional relationships remain substantively meaningful across alternative samples, technologies, and travel contexts rather than relying on statistical significance alone. Such replication would provide a stronger basis for determining which relationships are broadly transferable and which depend on the characteristics of users or travel environments.

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Appendix A. Measurement Items

All items were measured on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree).

Items	Source
ChatGPT Engagement	[58]
I regularly use ChatGPT when searching for hospitality and tourism-related information.	
I prefer to rely on ChatGPT as a primary source for hospitality and tourism information.	
I usually turn to ChatGPT whenever I need information or clarification about hospitality or tourism topics.	
Perceived System Reliability	[17]
Overall, I am satisfied with ChatGPT's reliability in enhancing my tourism experience.	
ChatGPT is accessible and responsive across different platforms used during travel.	
ChatGPT is continuously updated to ensure consistent and reliable performance in tourism-related tasks.	
ChatGPT consistently delivers dependable performance during travel planning and support.	
I trust ChatGPT to function reliably even when switching between devices or networks.	
ChatGPT maintains stable functionality even during peak travel periods or time-sensitive situations.	
Recommendation Neutrality	[51,59]
ChatGPT provides travel suggestions based solely on my input, without promoting specific companies or providers.	
ChatGPT avoids biased recommendations and presents options objectively.	
I feel that ChatGPT's suggestions are balanced and not influenced by commercial interests.	
ChatGPT explains options clearly without favoring one destination, brand, or service over another.	
ChatGPT presents multiple travel alternatives without implying that one option is inherently superior to others.	
ChatGPT maintains a neutral tone when comparing travel options, focusing on factual differences rather than preferences.	
Technology Readiness	[16]
I am fully capable of using intelligent tools like ChatGPT for tourism purposes.	
I am confident in my ability to use ChatGPT to access travel-related information and support.	
I have the necessary skills to effectively interact with ChatGPT when planning or managing travel activities.	
I can easily understand and apply the travel-related information provided by ChatGPT.	
Customer Journey Enhancement	[43,60]
ChatGPT positively contributed to enhancing my travel journey, from planning to execution.	
Using ChatGPT helped make my travel journey more structured and organized.	
My overall travel experience felt smoother and more efficient thanks to the information provided by ChatGPT.	
Using ChatGPT improved the continuity and flow of my travel journey across different stages.	

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