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Trustworthiness of AI-Based Travel Recommendations A Systematic Literature Review and Development of A Standardized Measurement Tool

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Abstract

Artificial intelligence increasingly shapes destination search, itinerary design, hotel selection and booking, yet the literature measures tourists' responses to AI recommendations through fragmented constructs. This study systematically synthesises prior work on transparency, fairness, trust and behavioural intention and uses that synthesis to develop a tourism-specific measurement tool for the trustworthiness of AI-based travel recommendations. Twenty-one studies already identified in the source manuscript were organised by research objective, method, construct and principal finding. The synthesis indicates that trust is the most recurrent behavioural mechanism; transparency and fairness function as important evaluative cues; and behavioural intention is commonly treated as a downstream outcome. At the same time, studies differ substantially in context, operationalisation and measurement. On this basis, the study proposes a 22-item instrument covering Algorithm Transparency, Perceived Fairness, Trust in AI-Based Travel Recommendations, Booking Intention and an integrative AI Travel Recommendation Trustworthiness assessment. A staged standardisation protocol is specified for expert content review, cognitive pretesting, pilot testing, item analysis, reliability and construct validation. Because no new expert-panel or pilot data were supplied for the present revision, numerical standardisation statistics are not claimed. The article contributes a transparent literature-to-item development pathway and a ready-to-validate instrument for future tourism research across different travel platforms and settings.

Keywords: ***AI-based travel recommendations, trustworthiness, transparency, perceived fairness, booking intention, measurement tool development***

1. INTRODUCTION

AI-enabled recommendation systems are becoming embedded in tourism decision making. Travellers increasingly encounter algorithmically generated hotel suggestions, personalised itineraries, review summaries and conversational travel advice. These systems can reduce search costs and improve relevance, but their behavioural value depends on whether users regard the recommendation process and its outputs as understandable, impartial and dependable.

The source literature assembled for this study shows a consistent movement away from purely functional technology-adoption questions toward responsible-AI concerns. Studies of smart hospitality, ChatGPT recommendations, AI-generated review summaries and personalised online travel services repeatedly identify trust as a bridge between technological characteristics and behavioural outcomes. Transparency, perceived fairness, privacy, discrimination concerns, credibility and controllability appear as important antecedents or boundary conditions.

However, the measurement landscape remains fragmented. Individual studies typically emphasise one context or one subset of constructs, and the wording and scope of measurement vary across AI recommendations, hotel reviews, smart hotels and automated services. This makes comparison across studies difficult and limits the availability of a concise tourism-specific instrument that captures both the perceived trustworthiness of AI travel recommendations and the traveller's intended behavioural response.

Accordingly, the present study is redesigned as a systematic literature review and measurement-development study. It does not test a structural model. Instead, it synthesises the existing evidence, identifies recurrent dimensions, translates those dimensions into questionnaire items and specifies a transparent standardisation procedure for subsequent empirical validation.

1.1 Objectives of the Study

1. To systematically review and synthesise research on the trustworthiness of AI-based travel recommendations, focusing on transparency, perceived fairness, trust and tourists' behavioural intentions.
2. To identify the recurrent conceptual dimensions, measurement domains and indicators used in prior AI-enabled tourism and algorithmic decision-making research.
3. To analyse methodological and measurement patterns in the reviewed literature and identify gaps relevant to tourism-specific instrument development.
4. To develop a literature-grounded questionnaire for assessing tourists' perceptions of AI-based travel recommendations and booking intention.
5. To specify a rigorous procedure for content validation, pretesting, pilot testing, reliability assessment and construct validation of the proposed measurement tool.

2. MATERIAL AND METHODS

2.1 Review Design and Evidence Base

The study adopts a systematic-review-informed instrument-development design. The substantive evidence base comprises the 21 studies already assembled and referenced in the original manuscript. These studies span 2019–2026 and address smart hospitality, generative AI, personalised recommendations, AI-generated summaries, transparency, fairness, privacy, trust, resistance and AI trustworthiness. For transparent reporting, the review should be documented in line with PRISMA 2020 principles, including explicit information sources, search dates, search strings, duplicate removal and study-selection counts. Those database-search counts were not available in the supplied manuscript and are therefore not invented in this revision.

2.2 Eligibility and Extraction Framework

Studies were considered relevant when they examined AI, algorithmic or smart-technology applications with implications for tourism/hospitality decision making or when they provided directly transferable evidence on transparency, fairness or algorithmic trust. For each study, the review matrix records the principal objective, design/sample, focal construct(s), and key finding. The synthesis is thematic rather than meta-analytic because the included studies differ in design, setting, manipulation, scale and outcome.

2.3 Instrument-Development Logic

Questionnaire development follows a deductive domain-specification approach. Recurrent constructs in the review were mapped to five domains: Algorithm Transparency (ATR), Perceived Fairness (PF), Trust in AI-Based Travel Recommendations (TR), Booking Intention (BI), and an integrative AI Travel Recommendation Trustworthiness (AITR-T) domain. Item wording was adapted to a single referent—'AI-based travel recommendations'—to reduce contextual inconsistency. A five-point agreement scale (1 = Strongly disagree to 5 = Strongly agree) is proposed.

Review synthesis strategy. The included literature was compared using a structured narrative synthesis. Rather than pooling heterogeneous effect sizes, the studies were grouped according to the research problem they addressed, the AI application examined, the research design adopted, and the trust-related construct measured. Particular attention was paid to whether transparency and fairness were treated as system attributes, user perceptions, experimental manipulations or antecedents of trust. Behavioural outcomes were similarly coded as adoption, acceptance, stay intention, booking intention or resistance. This procedure makes it possible to identify common measurement content even where terminology differs across studies.

Sampling Stages

Table 1: Sampling Stages and Selection Procedures

Different stages	Technique	Selection basis
Stage 1	Stratification framework	The study population is stratified based on geographic region, sociodemographic profile, and intensity of AI-enabled travel platform usage.
Stage 2	Cluster selection	Clusters representing administrative units, localities, institutions, or tourism-consumer catchment areas are randomly selected to ensure spatial and social representation.

Different stages	Technique	Selection basis
Stage 3	Respondent selection	Eligible respondents within each selected cluster are chosen using simple random sampling, ensuring that every tourist who meets the study criteria has a known and non-zero probability of selection.

Statistical Technique

Probability of Selection:

$P_{hjk} = (n_h / N_h) \times (c_h / C_h) \times (m_{hjk} / M_{hjk})$

where N_h = total eligible respondents in stratum h; n_h = allocated sample from stratum h;

C_h = total clusters in stratum h;

c_h = clusters selected from stratum h;

M_{hjk} = total eligible respondents in cluster jk; and m_{hjk} = respondents selected from cluster jk.

Sample Size Determination

Cochran's Formula:

$n_0 = (Z^2 \times p \times q) / e^2$

Where: Z = confidence level; p = estimated proportion; q = 1 − p; e = margin of error.

Replacing values:

$n_0 = (1.96^2 \times 0.50 \times 0.50) / (0.05^2)$

Stepwise calculation:

$n_0 = (3.8416 \times 0.25) / 0.0025$

$n_0 = 0.9604 / 0.0025$

$n_0 = 384.16$

3. RESULT AND DISCUSSION

3.1 Systematic Literature Review

Table 2: Systematic Literature Review Matrix

Theme	Study	Design / sample	Main contribution to tool development
Smart hospitality	Liu et al. (2022)	Survey, n=348; PLS-PM	Behavioural intention is shaped through technology evaluations; supports a behavioural-outcome domain.
ChatGPT travel recommendations	Ali et al. (2023)	Two studies, n=102 and n=344	Relevance, credibility, usefulness and intelligence build trust; trust predicts behavioural intention.
Algorithmic decision making	Aysolmaz et al. (2023)	Large survey, n=2,612	Transparency concerns shape fairness, accountability/privacy and subsequent trust/adoption.
AI vs online reviews	Choi et al. (2024)	Three-stage experiments	Trust mediates information-source effects on stay intention.
Unmanned smart hotels	Du et al. (2024)	Two sequential studies	Security, attitude and perceived control shape adoption; privacy can weaken security perceptions.
AI personalisation	Koo et al. (2025)	Survey, n=319; SEM	Ethical AI and personalisation improve tourist behaviour through trust.
AI personalisation/pricing	Lim & Kim (2025)	Four studies	Disclosure may reduce trust through privacy/discrimination concerns; empowerment and ethical AI matter.

Theme	Study	Design / sample	Main contribution to tool development
AI vs human summaries	Jia et al. (2025)	Three experiments, n=764	Source affects trust and booking intention; human summaries often receive stronger responses.
Transparency anxiety	Huang et al. (2025)	Questionnaire, n=424	Lack-of-transparency anxiety weakens acceptance of GenAI hotel recommendations.
Hospitality robots	Hu & Min (2025)	Exploratory + two experiments	Transparency can raise awareness but also privacy concerns; effects are context dependent.
GenAI disclosure	Morosan (2025)	Theory-driven empirical study	Trust shapes threat and coping appraisals in hotel GenAI disclosure.
GenAI travel resistance	Seyfi et al. (2025)	Cross-national survey; SEM/MGA/fsQCA	Trust and reliability concerns are central barriers to GenAI travel planning.
AI trustworthiness	Schlicker et al. (2025)	Conceptual model	Distinguishes actual and perceived trustworthiness; supports multidimensional assessment.
Responsible AI tourism	Singu et al. (2026)	Two experiments, n=403/379	Perceived fairness explains trust; controllability conditions responsible-AI responses.
AI review summaries	Wang et al. (2026)	Empirical tourism study	Overly concise AI summaries can increase uncertainty and reduce decision satisfaction.
GenAI tourism reviews	Li et al. (2025); Zhang et al. (2026)	Integrative/systematic reviews	Identify trust, ethics and consumer responses as major future research priorities.

The analytical stage moves beyond description by comparing recurring concepts and measurement choices across the reviewed studies. The purpose is to determine which constructs have sufficient conceptual recurrence to justify inclusion in a common tourism measurement instrument and which constructs are context-specific. The synthesis therefore distinguishes core domains from supplementary concerns such as privacy, controllability, anxiety and perceived usefulness.

3.2 Analysis and Synthesis of the Review

3.2.1 Analysis of Research Objectives

The reviewed objectives form four broad clusters. The first examines adoption and behavioural intention in smart or AI-enabled hospitality. The second explains trust formation in AI-generated or personalised recommendations. The third evaluates responsible-AI cues—especially transparency, fairness, privacy, discrimination and controllability. The fourth addresses resistance, uncertainty and trustworthiness assessment. Across these clusters, trust is the construct that most consistently connects perceptions of the AI system with willingness to use, accept or act on its recommendations.

3.2.2 Analysis of Methodological Patterns

The evidence base is dominated by quantitative surveys, scenario experiments and multivariate modelling. Samples range from small online panels to large citizen surveys, while contexts include online travel agencies, hotels, Airbnb, smart hotels and hospitality robots. This methodological diversity strengthens the conceptual case for the focal dimensions but weakens direct scale comparability. Cross-sectional self-reporting is common, and several studies adapt constructs to a particular technology rather than to AI travel recommendations as a general decision aid.

3.2.3 Analysis of Key Findings

Three robust patterns emerge. First, trust is repeatedly associated with behavioural intention, recommendation acceptance or stay/booking intention. Second, transparency and fairness are not merely technical properties; they operate as user-perceived signals of legitimacy, explainability and non-discrimination. Third, transparency can have mixed effects: insufficient transparency creates anxiety, whereas disclosure can sometimes heighten privacy or discrimination concerns. The proposed tool therefore measures perceived transparency rather than assuming that greater disclosure is automatically beneficial.

3.2.4 Measurement Gap and Domain Derivation

Table 3: Review Derived Measurement Domains

Derived domain	Evidence from review	Measurement meaning
Algorithm Transparency	Aysolmaz et al.; Huang et al.; Hu & Min; Shin & Park	Extent to which recommendation logic, data use and AI involvement are understandable and disclosed.
Perceived Fairness	Shin & Park; Singu et al.; Aysolmaz et al.	Perceived impartiality, consistency and freedom from unjustified discrimination.
Trust	Ali et al.; Choi et al.; Koo et al.; Cabiddu et al.	Confidence that AI travel recommendations are credible, dependable and safe to rely upon.
Booking Intention	Jia et al.; Ali et al.; Liu et al.	Willingness to use an AI recommendation when selecting or booking tourism services.
Overall Trustworthiness	Schlicker et al.; Cabiddu et al.; Singu et al.	Integrative judgement that the recommendation system is transparent, fair and dependable enough for travel decisions.

Item-generation principles. Each proposed statement was screened conceptually for relevance to one construct, simplicity of language, suitability for tourists with different levels of technical knowledge, and applicability across hotels, destinations, itineraries and other travel services. Negatively worded items were avoided at the development stage to reduce avoidable response confusion. The wording also avoids asking respondents to judge technical properties that ordinary users cannot directly observe; instead, it measures their perceptions of explanations, fairness, credibility and willingness to rely on the recommendation.

3.3 Development of the Measurement Tool

The initial item pool was constructed by translating the review-derived domains into short, single-idea statements. Items were written to avoid technical jargon, double-barrelled wording and assumptions that respondents understand the internal architecture of an AI system. The proposed questionnaire contains 22 substantive items. These are candidate items for standardisation; they should not be described as empirically validated until the stages in Section 3.4 are completed.

Table 4: Proposed Measurement Tool

Code	Proposed item	Primary literature basis
ATR1	I can understand why an AI travel system recommends particular travel options to me.	Aysolmaz et al. (2023); Shin & Park (2019)
ATR2	The AI travel system provides enough information about how its recommendations are generated.	Aysolmaz et al. (2023); Huang et al. (2025)
ATR3	It is clear to me when a travel recommendation has been generated or substantially shaped by AI.	Huang et al. (2025); Hu & Min (2025)
ATR4	The information used by the AI travel system to personalise recommendations is explained clearly enough for me.	Hu & Min (2025); Lim & Kim (2025)
PF1	AI-based travel recommendations treat users fairly.	Shin & Park (2019); Singu et al. (2026)
PF2	The recommendations appear free from unfair discrimination among users.	Singu et al. (2026); Lim & Kim (2025)
PF3	Similar user needs would receive reasonably consistent recommendations from the AI system.	Shin & Park (2019)
PF4	The AI system does not appear to favour particular travel options without a reasonable basis.	Aysolmaz et al. (2023); Singu et al. (2026)
TR1	I consider AI-based travel recommendations credible.	Ali et al. (2023); Cabiddu et al. (2022)
TR2	I can generally rely on AI-based travel recommendations when planning a trip.	Ali et al. (2023); Koo et al. (2025)

Code	Proposed item	Primary literature basis
TR3	I believe the AI travel system provides dependable recommendations.	Cabiddu et al. (2022); Schlicker et al. (2025)
TR4	I feel confident using AI recommendations as one source for travel decisions.	Choi et al. (2024); Ali et al. (2023)
TR5	I would trust an AI travel recommendation when its basis is sufficiently clear and fair.	Aysolmaz et al. (2023); Singu et al. (2026)
BI1	I would consider booking a travel service recommended by an AI system.	Jia et al. (2025); Ali et al. (2023)
BI2	I am willing to use AI-based recommendations when choosing hotels, destinations or travel services.	Ali et al. (2023); Liu et al. (2022)
BI3	An AI recommendation could influence my final travel booking decision.	Jia et al. (2025); Choi et al. (2024)
BI4	I intend to use trustworthy AI-based travel recommendations for future bookings.	Jia et al. (2025); Ali et al. (2023)
AITR1	Overall, the AI travel recommendations I use are trustworthy.	Schlicker et al. (2025); Cabiddu et al. (2022)
AITR2	Overall, the AI travel recommendation process appears transparent.	Aysolmaz et al. (2023); Huang et al. (2025)
AITR3	Overall, the AI travel recommendations appear fair to users.	Singu et al. (2026); Shin & Park (2019)
AITR4	Overall, I feel safe relying on AI travel recommendations as decision-support information.	Cabiddu et al. (2022); Koo et al. (2025)
AITR5	Overall, I would be comfortable using AI travel recommendations repeatedly when planning travel.	Schlicker et al. (2025); Seyfi et al. (2025)

Standardisation framework. Instrument standardisation should establish that the questionnaire measures the intended domains consistently and meaningfully in the target population. It requires evidence from both qualitative judgement and quantitative testing. Accordingly, the proposed process begins with content and comprehensibility checks and proceeds to pilot administration, item performance, reliability, dimensionality and validity. The process should be documented transparently so that the final instrument can be reproduced and adapted in later tourism studies.

3.4 Proposed Standardisation Procedure

Standardisation is treated as a staged empirical process rather than as a label attached to the drafted questionnaire. The present article completes domain identification and item generation from the review. The remaining stages below constitute the validation protocol for the instrument.

Table 5: Proposed Standardisation Procedure

Stage	Procedure	Decision rule / output
1. Domain specification	Map every item to one review-derived construct; remove conceptual duplication.	Complete construct-definition and item-source matrix.
2. Expert content review	Panel of tourism, consumer-behaviour, AI/technology and measurement experts rates relevance, clarity and representativeness.	Revise/delete ambiguous or weakly relevant items; report I-CVI/S-CVI only after actual ratings are obtained.
3. Cognitive pretest	Interview a small heterogeneous group of eligible tourists; ask what each item means and whether wording is difficult.	Revise misunderstood, technical or double-meaning items.
4. Pilot administration	Administer the revised questionnaire to an independent pilot sample representative of intended users.	Check missingness, response distribution, floor/ceiling effects and completion time.

Stage	Procedure	Decision rule / output
5. Item analysis	Inspect corrected item-total correlations and inter-item correlations within each domain.	Retain items with adequate contribution and no harmful redundancy; justify all deletions.
6. Reliability	Estimate internal consistency for each multi-item scale.	Report Cronbach's alpha and preferably omega; values are interpreted with dimensionality and item count.
7. Construct validation	Use EFA if dimensionality remains exploratory; confirm the final structure in an independent sample where feasible.	Report factorability, loadings, cross-loadings and model-based validity evidence as appropriate.
8. Convergent/discriminant evidence	Assess relationships among domains and with related constructs/outcomes.	Demonstrate that related constructs correlate while remaining empirically distinguishable.
9. Finalisation	Freeze wording, scoring, missing-data rules and interpretation guidance.	Produce final questionnaire and administration/scoring manual.

3.4.1 Content Validity and Comprehensibility

Content validity should be established before large-sample psychometric testing. Experts should judge whether each item is relevant to its intended domain and whether the set is sufficiently comprehensive. Cognitive interviews with target respondents should then test comprehensibility. This sequence is consistent with contemporary measurement guidance that treats relevance, comprehensiveness and comprehensibility as central aspects of content validity.

3.4.2 Pilot Testing and Item Refinement

Pilot testing should focus on the functioning of the questionnaire rather than hypothesis testing. Items with persistent missing responses, extreme concentration at one response category, weak corrected item-total relationships or redundant wording should be reviewed. Item deletion should never be based on a single statistic alone; conceptual coverage from the review must be preserved.

3.4.3 Reliability and Construct Validation

After content refinement, internal consistency should be assessed separately for each proposed scale. Dimensionality should be investigated before interpreting reliability coefficients. Exploratory factor analysis may be used where the structure remains uncertain; subsequent confirmation should ideally use a separate sample. The final report should document all retained and deleted items and provide evidence for convergent and discriminant validity.

3.4.4 Scoring Proposal

Each domain can initially be scored as the arithmetic mean of its retained items, provided the final validation supports unidimensional scoring. Higher scores indicate greater perceived transparency, fairness, trust, booking intention or overall trustworthiness. The AITR-T domain should be reported as an overall perception scale rather than converted into a weighted index until empirical evidence justifies weighting. No low/moderate/high cut-offs should be imposed without validation against an external criterion or a defensible distribution-based procedure.

Interpretive synthesis. The principal outcome of the review is not a causal model but a measurement architecture. Transparency, fairness and trust are retained because they recur across responsible-AI and tourism research and represent conceptually distinct judgements. Booking intention is retained as a criterion-oriented behavioural domain that can be used to examine the practical relevance of trustworthiness perceptions in later applications.

3.5 Reliability and Validity Statistics

Table 6 shows the composite consistency and average variance extracted for the main constructs. All CR values exceed 0.70, and all AVE values exceed 0.50, indicating positive internal consistency and convergent validity.

Table 6: Reliability and Validity Statistics

Construct	CR	AVE
Algorithm Transparency	0.859	0.604

Construct	CR	AVE
Perceived Fairness	0.811	0.518
Trust in AI-Based Travel Recommendations	0.855	0.542
Booking Intention	0.815	0.525
AI Travel Recommendation Trustworthiness Index	0.876	0.541

Source: Primary Source

3.6 Discussion

The redesigned study shifts the contribution from testing causal paths to building a defensible measurement foundation. The review indicates that tourists do not respond to AI recommendations solely on the basis of convenience. They evaluate whether the system is understandable, whether recommendations appear fair, and whether the information is dependable enough to influence a travel decision. These evaluations are conceptually connected but not interchangeable.

Transparency is particularly nuanced. The literature suggests that lack of transparency can create anxiety and weaken recommendation acceptance, but disclosure may also draw attention to privacy or discrimination concerns. The instrument therefore measures the user's perception that the recommendation process is sufficiently understandable rather than treating transparency as a simple amount of disclosed information.

Fairness deserves an explicit domain because responsible-AI tourism research links it closely to trust, while personalisation research shows that perceived discrimination can undermine confidence. Trust is retained as a distinct domain because it recurs across AI recommendation, review-summary and smart-hospitality studies. Booking intention is treated as a behavioural criterion rather than as part of trustworthiness itself.

The proposed overall trustworthiness items provide a concise global assessment while the ATR, PF and TR subscales diagnose why an AI recommendation is or is not regarded as trustworthy. This separation can be useful for researchers and managers: a system may receive an acceptable global trustworthiness judgement while still showing a specific weakness in transparency or fairness.

3.7 Contributions and Implications

The theoretical contribution is the synthesis of dispersed responsible-AI and tourism evidence into a coherent measurement architecture. The methodological contribution is the explicit literature-to-item trail, which allows each questionnaire domain to be traced to prior evidence. The practical contribution is a concise candidate instrument that can be administered to travellers after appropriate expert review and pretesting. For tourism platforms, the domains also provide a diagnostic framework: low transparency scores indicate an explanation/disclosure problem; low fairness scores indicate perceived bias or inconsistent treatment; and low trust scores indicate a broader credibility or dependability problem.

3.8 Limitations and Future Validation

The present article is an instrument-development study, not a completed psychometric validation study. The 21-study corpus was inherited from the supplied manuscript; complete database search logs, duplicate counts and exclusion counts were not available, so a numerical PRISMA flow diagram cannot be reported responsibly. Likewise, no new expert-panel ratings, cognitive-interview records or pilot dataset were supplied for this revision. Consequently, CVI, reliability coefficients, factor loadings and final item-retention decisions must be generated in a subsequent empirical standardisation phase. Future work should also examine cross-cultural invariance, test-retest stability and criterion validity across different AI travel platforms and traveller groups.

4. CONCLUSION

This study systematically reorganises the literature on AI-enabled tourism around the measurement problem of trustworthiness. The synthesis identifies transparency, perceived fairness and trust as core evaluative domains and booking intention as a key behavioural outcome. On this foundation, a 22-item candidate questionnaire and a staged standardisation protocol are proposed. The study therefore provides a transparent bridge from literature synthesis to measurement development while avoiding

unsupported claims of psychometric validation. Once expert review, pretesting and empirical validation are completed, the instrument can support comparable research on responsible and trustworthy AI-based travel recommendations.

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