Supplementary File S2 Study Level Selection Coding and Evidence Assessment

This file documents the evidence assessed for the 20-source analytical core, the classification of the 54-study focused corpus, the selection of six of the 11 Important papers, the coding framework, the treatment of difficult boundary cases and the evidential basis of the appraisal relationships.

Table S2 Material Assessed for the Analytical Core

Source	Analytical category	Material assessed	Use in the synthesis
Williams et al. [10], From WOM to aWOM	Essential	Full text examined	Definition of aWOM and the role of automated creation and distribution in tourism communication.
Li, Zheng and Guo [39], Detecting multi-modal GAI-manipulated tourism review	Essential	Full text examined	Boundary between algorithmic detection or verification and consumer-facing communication.
Cai, Shang and Cheng [41], Do AI summaries tell the whole story?	Essential	Full text examined	Human review evidence, omissions in generated summaries and consumer evaluation of summary completeness.
Kim and Jang [40], Information presentation strategies for recommender-chatbots	Essential	Full text examined	Review-grounded conversational recommendation and the presentation of supporting review information.
Wang, Tong and Dong [38], When generative artificial intelligence meets human reviews	Essential	Complete proceedings abstract and bibliographic record	Trip.com context, AI review-summary function, field-experiment design and the reported browsing, purchasing and hotel-sales outcomes. Sample characteristics, assignment procedures, measures, statistical analyses and effect sizes were recorded as unreported.
Cosentino et al. [42], From reviews to results	Essential	Full text examined	Generation of review-driven product and service comparisons from human review evidence.
Yhee and Koo [43], Seeing AI as human or machine?	Essential	Full text examined	Transparency, valence, readability and helpfulness in AI-generated review summaries.
Gu and Spann [44], The impact of generative artificial intelligence on consumer reviews	Essential	Full text examined	AI-assisted consumer review writing and the separation of human experience from message formulation.
Tuomi [45], Deepfake consumer reviews in tourism	Essential	Full text examined	AI-generated tourism reviews and the boundary of synthetic evaluative communication.
Tuomi et al. [46], Convincingness of AI-generated restaurant reviews	Essential	Full text examined	Consumer evaluation of AI-generated restaurant reviews and their perceived convincingness.
Amos and Zhang [47], Consumer reactions to perceived undisclosed ChatGPT usage	Essential	Full text examined	Perceived undisclosed AI authorship, authenticity and consumer reactions in an online review context.
Sâsâeac et al. [48], eWOM vs. aWOM	Essential	Full text examined	Comparison of eWOM and AI-powered WOM in tourism decision making.
Chan et al. [32], ChatGPT-empowered product recommendation and online word-of-mouth	Mechanism	Full text examined	Review contribution, reciprocity and changes in review quantity and language.
Remountakis et al. [33], ChatGPT and persuasive technology in hotel upselling	Mechanism	Full text examined	Organisational use of review-informed AI messages for personalisation and persuasion.
Cheng et al. [34], The effect of review summary	Mechanism	Full text examined	Review-summary effects on subsequent user-generated content, substitution and learning.
Li and Bang [35], How does artificial intelligence-generated content reshape user-generated content?	Mechanism	Full text examined	Changes in review contribution, specificity and rating composition after AIGC summaries.
Li et al. [36], When AI takes the wheel	Mechanism	Full text examined	Responses to disclosed AI-generated tourism content, originality and travel intention.

Source	Analytical category	Material assessed	Use in the synthesis
Singh and Mittal [37], Online review authenticity and helpfulness	Mechanism	Full text examined	Authenticity, helpfulness and purchase intention in hospitality review research.
Tassiello et al. [11], aiWOM	Conceptual anchor	Full text examined	Positioning of consumer-to-AI communication and aiWOM.
Mladenović et al. [12], Synthetic WOM?	Conceptual anchor	Full text examined	Positioning of Synthetic WOM and Generative AI-induced recommendations in tourism and hospitality.

Note: *The analytical core comprises 12 Essential studies, six selected Important mechanism studies and two conceptual anchors. Nineteen sources were assessed in full text.*

Table S3 Study Level Classification of the 54 Paper Focused Corpus

ID	Study	Screening layer	Priority category	Analytical-core status	Decision rationale
1	Biased by Design? Evaluating Bias and Behavioral Diversity in LLM Annotation of Real-World and Synthetic Hotel Reviews (2025)	CORE	Context-only	Context only	LLM annotation-bias and synthetic-dataset study; synthetic text is analytical material, not demonstrated consumer-facing WOM or persuasion.
2	The influence of eWOM. Analyzing its characteristics and consequences, and future research linesLa influencia de eWOM. Analizando sus caracteristicas, consecuencas y futuras lineas de investigación (2021)	BRIDGE / CONTEXT	Important mechanism	Retained in wider evidence base	Provides the human-eWOM baseline—source, message and receiver characteristics—needed to compare credibility, usefulness and behavioral effects across later AI-mediated forms.
3	Generative AI vs. humans in online hotel review management: A Task-Technology Fit perspective (2025)	CORE	Context-only	Context only	GPT outputs are comparison references for existing human managerial responses; no direct AI-authored WOM exposure, and the response domain is covered by ID 17.
4	New online personalized recommendation approach based on the perceived value of consumer characteristics (2017)	CORE	Context-only	Context only	Older technical personalized recommender; redundant with newer, user-facing mediation papers ID 28 and ID 34.
5	Artificial intelligence in service industries: customers' assessment of service production and resilient service operations (2024)	BRIDGE / CONTEXT	Context-only	Context only	AI is the service object/antecedent and human reviews are outcome data; AI does not create or mediate the WOM message.
6	A TOKENIZED FRAMEWORK FOR ENHANCING THE INTEGRITY AND AUTHENTICITY OF TOURISM REVIEWS (2026)	BRIDGE / CONTEXT	Context-only	Context only	Blockchain/loyalty-token integrity framework with an underspecified AI component; use only if the final framework needs platform governance.
7	Human employees versus robotic employees: Customers and hotel managers' perceived experience at unmanned smart hotels (2023)	BRIDGE / CONTEXT	Context-only	Context only	Smart-hotel/robot experience is assessed through human reviews; contextual antecedent, not AI-mediated WOM.
8	Deepfake consumer reviews in tourism: Preliminary findings (2021)	CORE	Essential	Selected as Essential	Direct early treatment of deepfake consumer reviews, but the Scopus record has no abstract; no defensible construct claim can be made without the full paper.
9	From WOM to aWOM – the evolution of unpaid influence: a perspective article (2020)	CORE	Essential	Selected as Essential	Primary conceptual anchor for the WOM → eWOM → aWOM transition and for locating Synthetic WOM relative to an existing construct.
10	ChatGPT-empowered Product Recommendation and Online Word-of-Mouth: Evidence from Online Travel Agency (2024)	CORE	Important mechanism	Selected as mechanism study	Shows that ChatGPT recommendations can alter subsequent human review production, creating a feedback loop between algorithmic advice and eWOM contribution.
11	INVESTIGATING THE IMPACT OF ONLINE REVIEWS, VIRTUAL REALITY, AND AI CHATBOTS ON FIRST-TIME HOTEL BOOKINGS IN RURAL DESTINATIONS: THE ROLE OF SENSE OF PRESENCE AND TRUST (2025)	BRIDGE / CONTEXT	Context-only	Context only	Reviews, VR and chatbots are separate booking stimuli; no transformation or mediation of review content by AI.
12	TOURIS: Tourism Optimization using Unified Reasoning and Integrated Semantics (2026)	CORE	Context-only	Context only	Technical itinerary system extracts preferences from reviews, but consumer-facing WOM mediation and persuasion are not evaluated; architecture is covered more directly elsewhere.
13	Seeing AI as human or machine? Effects of transparency, valence, and readability on review summary helpfulness (2026)	CORE	Essential	Selected as Essential	Connects AI-generated summaries to source perception, transparency, helpfulness and behavioral intentions; central to the mechanism by which mediated eWOM becomes persuasive.
14	Echoes of Innovation: Exploring the Use of Voice Assistants to Boost Hotel Reputation (2025)	BRIDGE / CONTEXT	Context-only	Context only	Voice-assistant attributes cause later human eWOM; AI is a service agent, not the WOM source or mediator.
15	Asymmetry of AI-generated review summaries on review contribution: Evidence from TripAdvisor (2026)	CORE	Important mechanism	Retained in wider evidence base	Adds regulatory fit and helpfulness-valence asymmetry as complementary evidence within a review-contribution mechanism also represented by other summary studies.
16	Travel Recommendations of Tomorrow: Generative Artificial Intelligence and Travel Planning (2026)	CORE	Important mechanism	Retained in wider evidence base	Useful for trust, information overload, recommendation quality and decision outcomes, while also testing whether GenAI travel advice actually qualifies as WOM-derived mediation.
17	ChatGPT and online service recovery: How potential customers react to managerial responses of negative reviews (2025)	CORE	Important mechanism	Retained in wider evidence base	Strong evidence on authenticity, uncanniness and algorithm aversion when AI authorship is disclosed in review-response environments.
18	The Effect of Review Summary: Evidence from a Natural Experiment (2025)	CORE	Important mechanism	Selected as mechanism study	Identifies substitution and learning mechanisms through which AI review summaries change later UGC, useful for consumer/platform outcomes and recursive WOM dynamics.

ID	Study	Screening layer	Priority category	Analytical-core status	Decision rationale
19	Tourists' Willingness to Adopt AI in Hospitality—Assumption of Sustainability in Developing Countries (2024)	BRIDGE / CONTEXT	Context-only	Context only	General AI quality/adoption model with eWOM as behavioral outcome; no WOM-message transformation.
20	Festivals in Age of AI: Smarter Crowds, Happier Fans (2025)	BRIDGE / CONTEXT	Context-only	Context only	Festival AI adoption/trust model with eWOM as an outcome; not construct-defining and outside review-message architecture.
21	The impact of generative artificial intelligence on consumer reviews: Insights from a quasi-experiment (2026)	CORE	Essential	Selected as Essential	Strongest evidence for human–AI co-produced consumer reviews and therefore central to separating AI-assisted eWOM from autonomous Synthetic WOM.
22	Generative AI in digital engagement: a quasi-experimental study of tourist sentiment (2026)	CORE	Context-only	Context only	AI-generated organizational responses affect sentiment, but this is adjacent service engagement and is redundant with the stronger source-disclosure mechanism in ID 17.
23	How do tourists perceive green customer-love service in restaurants? A qualitative exploration of ai and human collaboration (2025)	BRIDGE / CONTEXT	Context-only	Context only	Broad qualitative AI–human feedback-management framework; construct architecture is underspecified in the abstract and redundant with stronger response studies.
24	Detecting multi-modal GAI-manipulated tourism review (2025)	CORE	Essential	Selected as Essential	Defines a high-risk multimodal form of AI-produced/manipulated tourism reviews and helps separate synthetic, manipulated, fake and deepfake WOM.
25	Customer Care Meets Technology: Investigating the Role of AI in Managerial Responses to Online Reviews (2025)	CORE	Context-only	Context only	ChatGPT release is used as a time shock for manager response rates, without direct verification that responses were AI-authored.
26	Supporting Online Customer Feedback Management with Automatic Review Response Generation (2022)	CORE	Context-only	Context only	Early automatic-response prototype; technical/organizational adjacency and redundant once ID 17 is verified.
27	When Generative Artificial Intelligence Meets Human Reviews: Effects on Consumer Behavior and Hotel Sales (2025)	CORE	Essential	Selected as Essential	Field evidence that GenAI summaries transform human reviews into a new platform artifact with measurable browsing, purchasing and hotel-sales effects.
28	Information Presentation Strategies for Recommender-Chatbots (2026)	CORE	Essential	Selected as Essential	Tests how an LLM recommender-chatbot presents online reviews to users, making it essential for distinguishing selection/presentation from synthesis or autonomous generation.
29	How does artificial intelligence-generated content reshape user-generated content? An empirical study from TripAdvisor (2026)	CORE	Important mechanism	Selected as mechanism study	Adds review-writing motivations, authenticity/diversity concerns and topic shifts to the AI-summary feedback loop.
30	From intelligence to emotion: Investigating the influence of AI trust and user motivation on emotional value with the moderating effects of service experience and eWOM (2026)	BRIDGE / CONTEXT	Context-only	Context only	eWOM moderates AI-assisted restaurant selection; the contribution concerns the surrounding service context and the moderating role of eWOM.
31	eWOM vs. aWOM: AI Powered Word of Mouth and its Impact on Consumer Decision Making in Tourism (2025)	CORE	Essential	Selected as Essential	Only empirical paper in the corpus explicitly contrasting eWOM and aWOM; necessary to test whether aWOM is treated as AI-authored WOM or merely personalized recommendation.
32	Combining Content-Based Filtering Methods for Building a Powerful Hybrid Recommender System to Improve Tourism in Drâa-Tafilalet Area (2026)	CORE	Context-only	Context only	Generic technical review-driven recommender; redundant with the selected mediation and GenAI-transformation papers.
33	Online–offline combined adaptive hotel recommendation system considering attribute importance and group consensus (2025)	CORE	Context-only	Context only	Group-consensus hotel recommender; useful technical precedent but redundant for construct boundaries.
34	From Reviews to Results: Generative AI for Review-Driven Product and Service Comparisons (2025)	CORE	Essential	Selected as Essential	Shows the transition from algorithmic processing of human reviews to GenAI-generated comparisons and explanations; critical for the processed-versus-mediated boundary.
35	When AI takes the wheel: The effectiveness of AI versus human-generated content in tourism marketing (2025)	BRIDGE / CONTEXT	Important mechanism	Selected as mechanism study	Provides an adjacent synthetic-content boundary and a clean disclosure → originality → savoring → travel-intention mechanism relevant to AI-source persuasion.
36	Old roots, new faces: virtual influencers in legacy restaurants (2026)	BRIDGE / CONTEXT	Context-only	Context only	Virtual-influencer branding study using review sentiment as outcome data; not WOM-source research and covered by selected adjacent-content ID 35.
37	Animating arousal and engagement: empirical insights into AI-enhanced robotic performances and consumer reactions (2024)	BRIDGE / CONTEXT	Context-only	Context only	Robotic performance triggers human eWOM through emotion; AI is an experiential antecedent.

ID	Study	Screening layer	Priority category	Analytical-core status	Decision rationale
38	Exploring the role of trust and satisfaction in shaping AI-driven tourist behaviour (2026)	BRIDGE / CONTEXT	Context-only	Context only	AI adoption/trust/satisfaction model with eWOM as outcome; mechanism is too general for the WOM-message framework.
39	The Affective Iceberg Model for Review Manipulation Detection: A GPT-Based Design Artifact (2025)	BRIDGE / CONTEXT	Context-only	Context only	GPT detects review manipulation, but the manipulated target is not specifically AI-generated; ID 24 is the cleaner integrity boundary paper.
40	Consumer reactions to perceived undisclosed ChatGPT usage in an online review context (2024)	CORE	Essential	Selected as Essential	Directly tests whether perceived undisclosed ChatGPT authorship changes the status and reception of a review as trustworthy, authentic and useful.
41	An eye for an eye: Exploring how human-robot service attributes affect customers' negative electronic word-of-mouth (2025)	BRIDGE / CONTEXT	Context-only	Context only	Robot service failure causes negative human eWOM; relevant service antecedent but not AI-mediated WOM.
42	Rapport with a chatbot? The underlying role of anthropomorphism in socio-cognitive perceptions of rapport and e-word of mouth (2024)	BRIDGE / CONTEXT	Context-only	Context only	Chatbot rapport causes eWOM engagement; AI is the interaction partner, not the WOM message source/mediator.
43	Integrating ChatGPT in halal tourism: impact on tourist satisfaction, e-WoM and revisit intention (2025)	BRIDGE / CONTEXT	Context-only	Context only	ChatGPT moderates satisfaction/revisit relationships; eWOM remains a human behavioral outcome.
44	Charting Guest Experiences: A Graph-Powered Recommendation System Driven by Customer Reviews (2025)	CORE	Context-only	Context only	Technical graph/NLP review recommender; redundant with selected user-facing mediation papers.
45	Artificial Intelligence Research in Tourism and Hospitality Journals: Trends, Emerging Themes, and the Rise of Generative AI (2025)	BRIDGE / CONTEXT	Context-only	Context only	Broad bibliometric review of AI in tourism; intellectual context only and not a construct/mechanism source for this stage.
46	Using ChatGPT and Persuasive Technology for Personalized Recommendation Messages in Hotel Upselling (2023)	CORE	Important mechanism	Selected as mechanism study	Directly combines review extraction, ChatGPT-generated recommendation messages and persuasive techniques; important for deciding when AI advice becomes WOM-like persuasion versus advertising.
47	Convincingness of AI-Generated Restaurant Reviews (2025)	CORE	Essential	Selected as Essential	Direct human-versus-AI review comparison with source-detection and authenticity outcomes; essential for the claim that synthetic reviews can perform a human WOM-like persuasive function.
48	A Time-Aware Sliding Window-Based Hotel Recommendation Framework Using Multi-Stage BERT-MRC (2025)	CORE	Context-only	Context only	Technical sentiment-weighted recommender; redundant processing precedent without direct persuasion evidence.
49	When AI Meets Festivals: How eWOM Mediates the Route to Memorable Experiences and Well-Being (2026)	BRIDGE / CONTEXT	Context-only	Context only	Festival AI features stimulate human eWOM and well-being; antecedent/outcome context only.
50	Beyond the hype: Evaluating the impact of generative AI on brand authenticity, image, and consumer behavior in the restaurant industry (2025)	BRIDGE / CONTEXT	Context-only	Context only	AI social-media marketing content affects brand authenticity and eWOM, but the adjacent disclosure mechanism is already covered more cleanly by ID 35.
51	Online review authenticity and helpfulness: an integrative literature review and research agenda for consumer purchase intention in hospitality (2026)	BRIDGE / CONTEXT	Important mechanism	Selected as mechanism study	Potential source for consolidated definitions of authenticity, helpfulness and purchase intention, plus an S–O–R framework that explicitly incorporates AI-generated reviews.
52	Do AI summaries tell the whole story? A qualitative study of AI-generated hotel review summaries (2026)	CORE	Essential	Selected as Essential	The abstract explicitly calls AI summaries 'algorithmic mediators'; this is the cleanest qualitative anchor for the mediated-eWOM stage.
53	Dark side of generative AI in tourism: a stressor-strain-outcome perspective; using a mixed-methods approach (2026)	BRIDGE / CONTEXT	Important mechanism	Retained in wider evidence base	Covers the dark-side mechanism from hallucination, poor information quality and lack of empathy to distrust and negative eWOM.
54	Improving trust in online reviews: a machine learning approach to detecting artificial intelligence-generated reviews (2025)	CORE	Context-only	Context only	AI-generated-review detector is relevant but redundant with the multimodal boundary in ID 24 and provides no direct consumer mechanism; hold as backup for an integrity gap.

Note: *ID refers to the row identifier in the 54-study coding matrix. Screening layer and priority category are separate classifications. The two citation-traced conceptual anchors are outside this corpus.*

Table S4 Selection Decisions for the 11 Important Papers

Study	Thematic contribution	Decision	Rationale
The influence of eWOM. Analyzing its characteristics and consequences, and future research linesLa influencia de eWOM. Analizando sus caracteristicas, consecuencas y futuras lineas de investigación (2021)	Theoretical background — eWOM communication and emerging AI	Retained in wider evidence base	Human-eWOM background used in the wider evidence base. It did not add a distinct AI mechanism beyond the established eWOM literature used in Section 2.
ChatGPT-empowered Product Recommendation and Online Word-of-Mouth: Evidence from Online Travel Agency (2024)	ChatGPT recommendation → eWOM effects	Selected for analytical core	Selected for reciprocity and the effect of ChatGPT recommendations on subsequent review contribution and language.
Travel Recommendations of Tomorrow: Generative Artificial Intelligence and Travel Planning (2026)	Generative-AI travel recommendations / decision-making	Retained in wider evidence base	Broad GenAI travel-planning evidence. The study did not provide a sufficiently direct review-communication contribution for the close comparison.
Using ChatGPT and Persuasive Technology for Personalized Recommendation Messages in Hotel Upselling (2023)	ChatGPT-generated persuasive hotel recommendation messages	Selected for analytical core	Selected for the boundary between review-informed evidence and organisation-controlled personalised persuasion.
ChatGPT and online service recovery: How potential customers react to managerial responses of negative reviews (2025)	AI-generated managerial responses to online reviews	Retained in wider evidence base	AI-generated managerial responses constitute organisation-controlled communication around reviews. This adjacent mechanism was represented by the selected persuasion boundary study.
The Effect of Review Summary: Evidence from a Natural Experiment (2025)	Generative-AI review summaries — UGC effects	Selected for analytical core	Selected for substitution and learning mechanisms linking generated summaries with subsequent user-generated content.
How does artificial intelligence-generated content reshape user-generated content? An empirical study from TripAdvisor (2026)	AI-generated summaries reshape UGC/review behaviour	Selected for analytical core	Selected for review-writing motives and changes in review volume, specificity and rating composition.
Asymmetry of AI-generated review summaries on review contribution: Evidence from TripAdvisor (2026)	AI-generated review summaries — review contribution	Retained in wider evidence base	The review-contribution asymmetry mechanism overlapped with the selected natural-experiment and TripAdvisor studies on subsequent user-generated content.
When AI takes the wheel: The effectiveness of AI versus human-generated content in tourism marketing (2025)	AI-generated tourism marketing content → persuasion/behaviour	Selected for analytical core	Selected as an adjacent source-disclosure comparison connecting originality, anticipated savour and travel intention.
Online review authenticity and helpfulness: an integrative literature review and research agenda for consumer purchase intention in hospitality (2026)	Hospitality online-review review incorporating AI-generated reviews	Selected for analytical core	Selected for its integrative connection among authenticity, helpfulness and purchase intention in hospitality review research.
Dark side of generative AI in tourism: a stressor-strain-outcome perspective; using a mixed-methods approach (2026)	GenAI tourism stressors → distrust/negative eWOM	Retained in wider evidence base	GenAI stressors explain distrust and negative eWOM as outcomes. AI does not formulate or mediate the WOM message examined by the framework.

Note: *All 11 papers retained their Important classification. The decision reported here concerns inclusion in the six-paper mechanism component of the analytical core.*

The targeted robustness check in Table S15 records the conflicting findings and additional qualifications contributed by the five papers retained outside the analytical core.

Table S5 Coding Framework

Coding element	Recorded categories or indicators	Analytical use
Screening position	Core; Bridge/Context	Records whether AI enters review or recommendation communication directly or contributes adjacent explanatory context.
Priority category	Essential; Important; Context-only	Determines the depth of examination according to construct-definition value, mechanism evidence and contextual contribution.
Experiential source	Identifiable human experience; collective human review evidence; hybrid source; no identifiable human review evidence	Locates the evidence supporting the evaluation.
Message formulation	Human formulation; AI-assisted human formulation; AI generation from human review evidence; AI-originated evaluation	Identifies who produces the consumer-facing wording and evaluation.
Presentation control	Consumer; platform; organisation; model or interface	Records who selects, orders and presents the communication.
Role performed by AI	Processing; mediation; generative reformulation; assistance; origination	Places AI within the review-communication process.
Provenance cues	Disclosure; source identification; traceability to supporting human reviews	Records observable message or interface features and access to the human review evidence supporting a generated statement.
Provenance appraisal	Perceived authenticity; source certainty	Records the user's judgement that an evaluation is grounded in genuine consumer experience and has an identifiable source.
Information appraisal	Credibility; helpfulness; usefulness	Records perceived believability and decision value of the presented information.
Trust and reliance	Trust in the message, reviewer, platform or AI system; willingness to rely	Records a response to appraisal and requires the object of trust to be specified.
Outcomes	Search; attitude; choice; purchase; reuse; sales; service uptake; review contribution; corpus composition	Records consumer, business and platform outcomes separately from the appraisal constructs.
Unit of classification	Bounded AI function and resulting output at one stage of the review workflow	Assigns roles to specific outputs or interaction episodes instead of the application as a whole.
Multiple role applications	Primary role from the function immediately responsible for the output; upstream functions as secondary codes; later outputs as separate units	Allows processing, mediation, generation and writing assistance to coexist within one application without merging their communicative roles.
Communicative purpose	Consumer review communication; platform information service; promotional communication controlled by a firm	Separates WOM from promotional messages that use reviews as an input to organisational persuasion.
Experiential content and provenance	Explicit or sparse experiential language; human experience holder; identifiable review corpus; no identifiable human review evidence; indeterminate provenance	Separates what the text says from the experience and evidence supporting the evaluation.

Table S6 Difficult Coding Cases

Study	Boundary issue	Coding decision	Reasoning
Li, Zheng and Guo (2025)	AI detects or verifies generated tourism reviews but does not itself present review evidence to the consumer.	Algorithmically processed eWOM; Essential boundary case	Retained because it defines the point at which analysis or verification remains distinct from consumer-facing mediation.
Kim and Jang (2026)	A recommender chatbot retrieves and presents online-review information in response to a user request.	Algorithmically mediated eWOM; Essential	The system controls retrieval and presentation of human review evidence within a consumer-facing interface.
Gu and Spann (2026)	The consumer supplies the experience and evaluation while GenAI supports formulation of the review.	AI-assisted consumer eWOM; Essential	Human experiential provenance remains identifiable even though AI affects the wording of the message.
Cai, Shang and Cheng (2026)	AI-generated summaries are produced from multiple human hotel reviews.	Generative AI-mediated eWOM; Essential	The generated artefact reformulates collective human review evidence and enters consumer appraisal.
Remountakis et al. (2023)	Consumer reviews inform ChatGPT-generated hotel upselling messages controlled by the firm.	Promotional communication controlled by the firm and informed by eWOM; Important boundary case	The firm controls the objective, target, offer and publication. Consumer reviews inform the message, while the communicative act remains organisational persuasion.
Tan, Liu and Litvin (2025)	ChatGPT produces managerial responses to negative consumer reviews.	Important paper retained in the wider evidence base	The response is organisational communication around eWOM and adds adjacent authenticity evidence.
Hao et al. (2026)	AI-generated summaries affect subsequent review contribution through valence-related mechanisms.	Important paper retained in the wider evidence base	The mechanism is relevant but overlaps with the selected studies on review-summary effects and subsequent user-generated content.
Kumar and Malhotra (2026)	General GenAI stressors lead to distrust and negative eWOM.	Important paper retained in the wider evidence base	eWOM is an outcome of the tourism experience; the AI system does not produce or mediate the WOM message.
Operational case: composite application	One platform analyses and retrieves reviews, generates a summary and later helps a traveller formulate a new review.	Summary: generative AI-mediated eWOM, with processing and retrieval as supporting roles. Later review: AI-assisted consumer eWOM.	Each bounded output forms a separate unit. The application receives several stage-level codes because the outputs differ in experiential basis and communicative agency.
Operational case: experiential language and provenance	A human review contains little description of experience, while a generated first-person review imitates experiential detail.	Code experiential content and experiential provenance separately; retain indeterminate provenance when the evidential basis is unreported.	Surface language and experiential provenance can diverge. Classification follows the production conditions and traceability reported by the study.

Note: These examples show the operational separation of processing, mediation, generative mediation, AI-assisted consumer expression, promotional communication controlled by a firm, AI-originated evaluation, experiential content and experiential provenance.

Table S7 Evidence Profile of the 20 Sources in the Analytical Core

Source	Research context	Study type	Sample or dataset	AI application	Related constructs	Main findings or propositions	Limitations	Evidential status
Williams et al. [10]	Tourism WOM, eWOM and destination decision support	Conceptual perspective	Conceptual examination; no empirical sample	Automated creation, summarisation and distribution of WOM content	aWOM; autonomy; source; distribution; personalisation	Defines aWOM as communication created and shared by nonhuman AI tools and sets out possible roles for AI in creating and distributing communication.	The propositions were not empirically tested and precede current Generative AI platforms.	Conceptual proposition used for construct definition
Li, Zheng and Guo [39]	Tourism review integrity and detection	Technical system development and comparative evaluation	80,000 items: 40,000 human and 40,000 generated text and image reviews across 50 destinations	Multimodal detection of generated tourism reviews	Authenticity; manipulation detection; verification	The proposed multimodal system outperformed comparison models in detecting generated review text and images.	The dataset covers selected destinations and generation tools; consumer interpretation and behaviour were outside the study.	Application evidence supporting the processing boundary
Cai, Shang and Cheng [41]	Hotel review summaries in Changchun, China	Qualitative interviews and thematic analysis	22 hotel guests; thematic saturation reported after 19 interviews	AI generated summaries of hotel reviews	Information efficiency; aggregation; cognitive load; diagnosticity; trust; decision control	Participants used summaries for orientation and efficiency while checking individual reviews for omitted, conflicting or uncommon experiences.	A small sample in one Chinese city limits transferability across markets and platforms.	Focused qualitative evidence for mediation and appraisal mechanisms
Kim and Jang [40]	Hotel recommender chatbot for Jeju, South Korea	Two by two experiment with interaction with a working system	160 participants; chatbot database of 114 hotels and 100,360 Agoda reviews	Review grounded chatbot using Text to SQL and retrieval augmented generation	Perceived chatbot quality; satisfaction; reuse intention; price framing	Review provision and downward price framing improved perceived chatbot quality; quality and satisfaction carried indirect effects to reuse intention.	One destination, one service category and a single interaction limit generalization to repeated use and realized booking behaviour.	Direct experimental evidence for chatbot evaluation
Wang, Tong and Dong [38]	Trip.com hotel booking	Field experiment reported in a complete proceedings abstract	Sample, duration and assignment procedure unreported in the available material	Generative AI summaries of human hotel reviews	Subjectivity; sentiment; content quality; readability; browsing; purchase; hotel sales	The summaries increased purchasing and hotel exploration, reduced reading of individual reviews and performed better when objective, concise, readable and nonredundant.	The available material omits the sample, measures, statistical analyses, effect sizes and implementation details.	Limited abstract-based empirical evidence
Cosentino et al. [42]	Amazon products and TripAdvisor hotels	System framework and comparative technical evaluation	About 10,000 Amazon reviews; 150 hotels with several hundred reviews each; selected comparison pairs and repeated evaluations	Topic and sentiment extraction combined with a language model for review driven comparisons	Grounding; comparative explanation; decision support; weakness identification	Review informed prompting improved the specificity and usefulness of product and hotel comparisons, especially for weaknesses and differentiating attributes.	Evaluation used curated comparison pairs and model-based judging; consumer choice and behaviour were not observed.	Application evidence for generative mediation capability
Yhee and Koo [43]	Hotel review summaries presented to United States consumers	Five between subjects experiments with random assignment	Total N = 1,124 across five studies; United States online panels, August 2024–July 2025	AI generated hotel review summaries with source, transparency, valence and readability cues	AI perception; transparency; helpfulness; hotel attitude; visit intention	Source perception and presentation affected helpfulness; helpfulness and hotel attitude transmitted effects to visit intention under specified conditions.	Scenario-based tasks and online panels measure stated evaluations and intentions in place of actual booking behaviour. Random assignment supports inference for manipulated cues; measured AI perceptions and mediation estimates do not establish every causal link.	Evidence from five experiments on appraisal mechanisms
Gu and Spann [44]	TripAdvisor hotel reviews during the temporary ChatGPT ban in Italy	Quasi experiment using difference in differences; event-study and regression pre-trend checks, placebo timing, alternative periods, hotel fixed effects and propensity-score matching; supporting survey samples	1,930 Italian hotels and 2,979 comparison hotels in Germany, France, Spain and Greece; 117,816 hotel week device observations, 3 March–26 May 2023; four weeks before, during and after the ban; survey samples: United States N = 95, Italy N = 88	Generative AI assistance with consumer review writing	Writing effort; review volume; length; linguistic style; subjectivity; sentiment	ChatGPT availability was associated with higher review volume and length on desktop devices and changes in subjectivity and negative sentiment. The overall volume effect without device interactions was not significant. Survey responses were consistent with reduced writing effort.	Causal interpretation requires parallel trends and an exogenous policy interruption; reported pre-trend and robustness checks support these inferences but do not establish individual AI use. Circumvention, travel and reviewer-composition changes remain possible; device-specific findings limit generalization.	Direct quasi-experimental evidence for review contribution

Source	Research context	Study type	Sample or dataset	AI application	Related constructs	Main findings or propositions	Limitations	Evidential status
Tuomi [45]	Restaurant reviews evaluated by tourism employees	Two preliminary studies: randomized classification and purposive evaluation	Study 1: 100 employees and 1,000 evaluations; Study 2: 32 employees evaluating 15 generated reviews	GPT 2 generated restaurant reviews	Source detection; human likeness; valence; linguistic cues; convincingness	Participants frequently misclassified review source, while mixed and negative generated reviews received stronger human likeness assessments.	The studies were preliminary, used small occupational samples and relied on supervised GPT 2 generation and descriptive evidence.	Exploratory empirical evidence from two preliminary studies
Tuomi et al. [46]	Restaurant review evaluation	Randomized between subject choice experiment	80 participants and 800 evaluations; review sets pretested with 11 participants	Undisclosed GPT 4 Turbo restaurant reviews compared with human TripAdvisor reviews	Source detection; trustworthiness; realism; authenticity; behavioural intention; valence	Source detection was close to chance, while negative reviews were judged more trustworthy and authentic across source conditions.	The convenience sample and language context constrain generalization; the human and generated review sets also differed in content beyond authorship.	Direct experimental evidence for review evaluation
Amos and Zhang [47]	Hotel and restaurant review judgements	Three between subject experiments; replication with an expert badge and extension to restaurant reviews and uncertain attribution	Usable N = 194, 184 and 326; United States Prolific samples	Perceived undisclosed use of ChatGPT in an online review	Usefulness; trust; authenticity; valence; source attribution; reviewer attitude	Perceived ChatGPT authorship reduced usefulness, trust and authenticity; authenticity mediated consumer response across the experimental programme.	The studies manipulate perceived attribution and use judgement outcomes; realized market behaviour and verified hidden AI use were outside the design.	Replicated experimental evidence for perceived source attribution effects
Sâsâeac et al. [48]	Booking and TripAdvisor information used in tourism decisions	Sequential qualitative study using interviews and a focus group	12 frequent travellers interviewed; seven joined the subsequent focus group	ChatGPT generated reviews presented with platform and disclosure cues	Trust; credibility; authenticity; transparency; purchase intention; complementarity	Participants generally preferred human eWOM and treated AI communication as a complementary source shaped by detail, balance and transparency.	The small qualitative sample, repeated participation and limited platform setting constrain transferability.	Focused qualitative evidence for source appraisal
Chan et al. [32]	Online travel agencies, comparing Expedia and Booking.com	Cross platform natural experiment using difference in differences	Matched hotel review panel across Expedia and Booking.com. Hotel and observation counts and exact observation period are not reported in the source material available for this revision.	ChatGPT product recommendations	Reciprocity; review quantity; readability; analytical language; ratings	The introduction of ChatGPT recommendations was associated with lower review contribution and changes in review language, with a stronger decline among highly rated reviews.	Causal interpretation depends on comparable platform trends and absence of concurrent differential changes. Parallel-trends diagnostics and robustness-check details are not reported in the source material available for this revision.	Direct natural-experiment evidence for platform feedback
Remountakis et al. [33]	Hotel upselling through the eXclusivi platform	Application case and pilot system evaluation	Hotel marketing application with generated messages and ranked offers; no consumer outcome sample	Personalized multilingual persuasive messages generated from customer and review information	Social proof; scarcity; personalisation; recommendation; upselling	The study demonstrates the integration of review information, persuasive techniques and generated messages in hotel upselling.	Behavioural, conversion and revenue effects were not evaluated with a consumer sample.	Application evidence for organization controlled persuasion
Cheng et al. [34]	TripAdvisor and Expedia hotel reviews	Cross platform natural experiment using difference in differences; matched-pair (hotel) and year-month fixed effects; hotel-clustered standard errors	619 matched hotels in Texas, California and New York on TripAdvisor (treated) and Expedia (comparison); hotel-platform-month data for three months before and three months after GAIRS introduction in November 2023. Final dataset: 8,666 observations; main-model Ns: volume 8,666, rating 8,281 and length 8,208.	Generative AI review summaries	Substitution; learning; review quantity; length; rating; hotel status; user experience	Review summaries were associated with lower subsequent review quantity and length and higher ratings, with variation by hotel status, review valence and user experience.	Causal interpretation requires parallel trends and no concurrent differential platform changes. Relative-time analysis uses the month before introduction as baseline. Reported checks add city-by-year-month fixed effects, exclude hotels averaging fewer than one monthly review on either platform over seven months, and restrict analysis to English reviews. These checks support the design but do not remove its platform and regional scope limits.	Direct natural-experiment evidence for review ecosystem effects

Source	Research context	Study type	Sample or dataset	AI application	Related constructs	Main findings or propositions	Limitations	Evidential status
Li and Bang [35]	TripAdvisor hotel reviews in Singapore	Natural experiment using year-to-year difference in differences and structural topic modelling	Singapore hotel reviews around TripAdvisor's introduction of generated summaries on 23 October 2023. Hotel and review counts and exact observation period are not reported in the source material available for this revision.	TripAdvisor generated review summaries	Review motives; contribution volume; rating; length; specificity; hotel tier	Review volume fell after introduction, while remaining reviews became longer and more specific and their rating composition changed.	Evidence comes from one destination and platform. Year-to-year inference depends on comparable trends and absence of confounding temporal changes; the source discusses possible spillovers. Detailed robustness checks and comparison windows are not reported in the source material available for this revision.	Direct natural-experiment evidence for review ecosystem effects
Li et al. [36]	Tourism influencer and destination marketing content	Study 1: observational review analysis. Studies 2–4: between-subjects experiments with random assignment; two content-label conditions in Studies 2–3 and three creator/adaptivity conditions in Study 4	Study 1: 3,416 online reviews/comments in the final analysis from 10 tourism promotion posts on Rednote and Douyin. Credamo experimental samples: Study 2 N = 100; Study 3 N = 200; Study 4 N = 300.	Disclosed AI generated tourism content with differing algorithm adaptivity	Originality; anticipated savouring; disclosure; travel intention	AI disclosure reduced travel intention through perceived originality and anticipated savouring, while greater algorithm adaptivity reduced the penalty.	The stimuli concern organization controlled tourism marketing content adjacent to consumer WOM and measure intention in experimental settings.	Experimental evidence for an adjacent persuasion mechanism
Singh and Mittal [37]	Hospitality online review research	Integrative literature review	More than 190 peer reviewed articles published from 2000 to 2024 across more than 50 journals	AI generated and multimodal reviews within the broader review literature	Authenticity; helpfulness; purchase intention; stimulus organism response	The review integrates recurring review cues and proposes a framework linking authenticity and helpfulness with purchase intention.	The evidence is inherited from the reviewed literature; the proposed relationships require direct empirical testing.	Review synthesis used for mechanism integration
Tassiello et al. [11]	Consumer communication with socially enabled AI	Conceptual article	Conceptual development; no empirical sample	Social and conversational AI as a communication participant	aiWOM; social interaction; psychological response; behavioural response	The article defines aiWOM around communication between consumers and AI technologies with social features.	The construct awaits empirical validation and gives limited attention to the provenance of review evidence.	Conceptual proposition used for construct positioning
Mladenović et al. [12]	Generative AI recommendations in tourism and hospitality	Conceptual framework development	Structured conceptual development from literature on Generative AI, WOM, eWOM, reviews and tourism	Creation, curation, retrieval and dissemination of generated recommendations	Synthetic WOM; interactivity; personalisation; immediacy; information seeking and provision	The article introduces Synthetic WOM and develops functions and propositions for generated recommendation communication in tourism and hospitality.	The conceptual framework requires empirical validation and offers a broad account of AI participation across the communication process.	Conceptual proposition used for construct positioning

Note: *Evidential status describes the type and scope of support for the analytical use assigned to each source. Appraisal considers design, reporting transparency, alignment between design and inference, identification assumptions and reported robustness checks where applicable, and scope limitations. A design label alone does not establish evidential strength. Experimental evidence is bounded by the manipulation, measures and setting; qualitative evidence supports contextual interpretation; application evidence supports system capability; review synthesis draws on existing studies; conceptual propositions support definitions and construct positioning; abstract-based evidence is confined to the reported abstract and bibliographic record. The appraisal is qualitative and claim-specific, without numerical scores or a standardized risk-of-bias instrument.*

Table S8 Evidential Basis of the Appraisal Relationships

Relationship	Status in the synthesis	Supporting studies	Foundation and limit of inference
Disclosure or perceived AI authorship → perceived authenticity	Direct empirical evidence	Amos and Zhang [47]	Perceived undisclosed ChatGPT use reduced authenticity in experimental review settings. The evidence concerns perceived attribution.
Source and transparency cues → helpfulness or usefulness	Direct empirical evidence with qualitative support	Yhee and Koo [43]; Amos and Zhang [47]; Sâsâeac et al. [48]	Experiments connect source presentation or attributed AI use with helpfulness or usefulness. Qualitative evidence links transparency with consumer assessment. Effects depend on presentation and context.
Access to supporting human reviews → checking and decision control	Focused qualitative evidence	Cai, Shang and Cheng [41]	Participants used summaries for orientation and returned to individual reviews to inspect omitted, conflicting or uncommon experiences. The study provides interpretive evidence about review checking and decision control; causal effects of traceability remain for testing.
Review provision, readability and content quality → information appraisal	Experimental evidence with an abstract-based field component	Kim and Jang [40]; Wang, Tong and Dong [38]; Yhee and Koo [43]	Review evidence and presentation characteristics were associated with chatbot quality, summary helpfulness and consumer response. Evidence from Wang, Tong and Dong is limited to the complete proceedings abstract.
Provenance appraisal → information appraisal	Conceptual integration informed by empirical associations	Amos and Zhang [47]; Sâsâeac et al. [48]	The studies relate source assessment and authenticity to usefulness, credibility or trust. The directional effect from provenance appraisal to information appraisal remains for empirical testing.
Information appraisal → reuse or visit intention	Direct empirical evidence	Kim and Jang [40]; Yhee and Koo [43]	Perceived chatbot quality and satisfaction carried effects to reuse intention. Helpfulness and hotel attitude transmitted effects to visit intention under specified conditions.
Provenance appraisal → trust or reliance	Conceptual integration informed by empirical associations	Amos and Zhang [47]; Sâsâeac et al. [48]	Authenticity, trust and source assessment are related in the studies. Their directional ordering remains for empirical testing.
AI generated summaries → purchase, browsing and hotel sales	Limited direct field evidence	Wang, Tong and Dong [38]	The complete proceedings abstract reports increased purchasing, hotel exploration and order volume. Sample, model details and effect sizes are unavailable.
AI interfaces → subsequent review contribution and corpus composition	Direct platform evidence from natural and quasi-experimental studies	Chan et al. [32]; Cheng et al. [34]; Li and Bang [35]; Gu and Spann [44]	Natural and quasi experiments report changes in review volume, length, language, specificity or rating composition. Causal interpretation depends on each comparison, identification assumptions and reported checks; the findings are bounded by platform, period and, for Gu and Spann [44], device type. Table S7 records these limits.
Complete sequence from provenance cues to appraisal, reliance and behaviour	Conceptual integration	Integrated from the relationships above	Evidence is distributed across component relationships examined in separate designs. The complete sequence is proposed for empirical testing.
Boundary conditions on particular relationships	Relationship specific empirical evidence and conceptual extension	Cheng et al. [34]; Li and Bang [35]; Li et al. [36]; Yhee and Koo [43]; Amos and Zhang [47]	Valence, readability, user experience, hotel status and perceived algorithm adaptivity were reported in particular settings. Decision stage remains a proposed boundary condition.

Note: Direct empirical evidence identifies a tested relationship in an original study. Qualitative evidence reports a bounded participant account. Conceptual integration connects partial relationships across studies and remains a proposition for empirical testing.

Table S9. Bibliometric settings and threshold sensitivity

All networks used association-strength normalization and VOS clustering with resolution 1.00, minimum cluster size one, merging of small clusters, 10 random starts, 10 iterations, randomness 0.01 and fixed seed 0. Default VOS layout settings were used: attraction 2 for all networks; repulsion 0 for keyword co-occurrence and 1 for bibliographic coupling and co-citation; one random start; and a maximum of 1,000 iterations. Each sensitivity check changed only the inclusion threshold shown below.

Analysis	Main specification	Adjacent threshold check	Cluster result	Interpretation
Author keyword co-occurrence	Occurrences ≥ 3: 29 items; 122 links; TLS 202; 7 clusters	Occurrences ≥ 4: 20 items; 79 links; TLS 152; 4 clusters	7 → 4 clusters	The dominant terms remained and the same broad areas of computational review analysis, eWOM and consumer evaluation, and Generative AI language systems were visible. Smaller clusters consolidated at the higher threshold.
Bibliographic coupling of documents	Citations ≥ 0: 131 connected documents; 1,224 links; TLS 1,950; 8 clusters	Citations ≥ 1: 95 connected documents; 724 links; TLS 1,263; 9 clusters	8 → 9 clusters	The broad research fronts concerning review analytics and recommendation, AI enabled tourism services, consumer evaluation and trust, and Generative AI remained. Exact membership shifted among overlapping areas.
Co-citation of cited references	Citations ≥ 4: 41 connected references; 336 links; TLS 477; 4 clusters	Citations ≥ 5: 20 connected references; 87 links; TLS 132; 4 clusters	4 → 4 clusters	The main foundations in eWOM and review effects, computational review analysis, and AI enabled service research remained visible. Several references moved between clusters in the smaller network.

Note: Sensitivity checks used the final 142-publication Scopus corpus and the same thesaurus, counting method, normalization and clustering parameters as the main analyses. TLS denotes total link strength. The checks support interpretation of broad thematic domains and show that exact partitions remain threshold-sensitive.

Table S10. Complete membership of the bibliographic-coupling clusters

The table links each document displayed in Figures 4 and 5 to its cluster, bibliographic record and network metrics.

Cluster	Publication	Title	Source	Bibliographic link and network metrics
1	Chai C.; Song Y.; Qin Z. (2021)	A thousand words express a common idea? Understanding international tourists' reviews of mt. huangshan, china, through a deep learning approach	Land	DOI: 10.3390/land10060549 Citations: 10; TLS: 17
1	Chen H.; Dai Z.; Tang J.; Li M. (2018)	Web evaluation analysis of tourism destinations based on data mining	2018 IEEE 4th International Conference on Computer and Communications, ICCC 2018	DOI: 10.1109/CompComm.2018.8781024 Citations: 2; TLS: 3
1	Cheng X.; Chen Y.; Wang P.; Zhou Y.; Wei X.; Luo W.; Duan Q. (2024)	A novel ChatGPT-based multimodel framework for tourism review mining: a case study on China's five sacred mountains	Journal of Hospitality and Tourism Technology	DOI: 10.1108/JHTT-06-2023-0170 Citations: 17; TLS: 6
1	Choi B.; Kang S.-H. (2023)	Measuring Hotel Service Quality Using Social Media Analytics: The Moderating Effects of Brand of Origin	Asia Pacific Journal of Information Systems	DOI: 10.14329/apjis.2023.33.3.677 Citations: 1; TLS: 20
1	Christodoulou E.; Gregoriades A.; Pampaka M.; Herodotou H. (2021)	Evaluating the Effect of Weather on Tourist Revisit Intention using Natural Language Processing and Classification Techniques	Conference Proceedings - IEEE International Conference on Systems, Man and Cybernetics	DOI: 10.1109/SMC52423.2021.9658820 Citations: 2; TLS: 4
1	De Vink A.J.W.; Amat-Lefort N.; Han L. (2025)	ReviewGraph: A Knowledge Graph Embedding Based Framework for Review Rating Prediction with Sentiment Features	Proceedings - IEEE International Conference on Knowledge Graph, ICKG 2025	DOI: 10.1109/ICKG66886.2025.00013 Citations: 0; TLS: 9

Cluster	Publication	Title	Source	Bibliographic link and network metrics
1	Ferreira E.S.; Loureiro S.; Bilro R.G.; Ferro T. (2022)	Analyzing Madeira and Bermuda as Two Different Destinations: A Text Mining Approach	Journal of Promotion Management	DOI: 10.1080/10496491.2021.2015516 Citations: 6; TLS: 20
1	Félix L.G.S.; Cunha W.; de Andrade C.M.V.; Gonçalves M.A.; Almeida J.M. (2025)	Why are you traveling? Inferring trip profiles from online reviews and domain-knowledge	Online Social Networks and Media	DOI: 10.1016/j.osnem.2024.100296 Citations: 2; TLS: 7
1	Gai T.; Wu J.; Xing Y.; Liu Y.; Cao M. (2026)	Cruise service quality improvement: a quality function deployment approach with online reviews by large language models	Humanities and Social Sciences Communications	DOI: 10.1057/s41599-026-06941-6 Citations: 0; TLS: 5
1	Kim K.; Park O.-J.; Yun S.; Yun H. (2017)	What makes tourists feel negatively about tourism destinations? Application of hybrid text mining methodology to smart destination management	Technological Forecasting and Social Change	DOI: 10.1016/j.techfore.2017.01.001 Citations: 179; TLS: 11
1	Kirmizigul D.; Yildiz B.; Gercek B.; Kosar H.; Bilge A.; Ulusar U.D. (2025)	Charting Guest Experiences: A Graph-Powered Recommendation System Driven by Customer Reviews	Lecture Notes in Networks and Systems	DOI: 10.1007/978-3-031-98565-2_65 Citations: 0; TLS: 1
1	Kurniawan S.; Pramayoga A.S.; Ashari Y.F. (2025)	Sentiment Analysis in Coastal Tourism: A Systematic Literature Review	Engineering, Technology and Applied Science Research	DOI: 10.48084/etasr.14644 Citations: 3; TLS: 2
1	Lee C.; Kim H.; Hwang Y.; Sim H.; Kim W.; Lee D. (2026)	TOURIS: Tourism Optimization using Unified Reasoning and Integrated Semantics	Proceedings of the ACM Symposium on Applied Computing	DOI: 10.1145/3748522.3780000 Citations: 0; TLS: 8
1	Liu C.-H. (2026)	From intelligence to emotion: Investigating the influence of AI trust and user motivation on emotional value with the moderating effects of service experience and eWOM	International Journal of Hospitality Management	DOI: 10.1016/j.ijhm.2026.104691 Citations: 0; TLS: 9
1	Mohammadi S.; Fatoorchi A.A.; Babagoli M. (2026)	A TOKENIZED FRAMEWORK FOR ENHANCING THE INTEGRITY AND AUTHENTICITY OF TOURISM REVIEWS	Tourism and Hospitality Management	DOI: 10.20867/thm.32.1.5 Citations: 0; TLS: 5
1	Nawawi I.; Ilmawan K.F.; Maarif M.R.; Syafrudin M. (2024)	Exploring Tourist Experience through Online Reviews Using Aspect-Based Sentiment Analysis with Zero-Shot Learning for Hospitality Service Enhancement	Information (Switzerland)	DOI: 10.3390/info15080499 Citations: 38; TLS: 17
1	Ozturk A.C. (2026)	Discovering Aspect-Sentiment Drivers of Hotel Review Ratings With Interpretable High-Utility Rules	IEEE Access	DOI: 10.1109/ACCESS.2026.3672490 Citations: 0; TLS: 8
1	Remountakis M.; Kotis K.; Kourtzis B.; Tsekouras G.E. (2023)	Using ChatGPT and Persuasive Technology for Personalized Recommendation Messages in Hotel Upselling	Information (Switzerland)	DOI: 10.3390/info14090504 Citations: 39; TLS: 8
1	Rui J.; Xu Y.; Cai C.; Li X. (2025)	Leveraging large language models for tourism research based on 5D framework: A collaborative analysis of tourist sentiments and spatial features	Tourism Management	DOI: 10.1016/j.tourman.2024.105115 Citations: 20; TLS: 14
1	Santos A.M.; Antonio N. (2025)	Improving trust in online reviews: a machine learning approach to detecting artificial intelligence-generated reviews	Information Technology and Tourism	DOI: 10.1007/s40558-025-00329-z Citations: 9; TLS: 12
1	Takaew S.; Romsaiyud W. (2026)	An Explainable Approach to Sentiment Analysis of Thai Hotel Reviews Using a Fine-Tuned Language Model and SHAP	Journal of Current Science and Technology	DOI: 10.59796/jcst.V15N4.2025.149 Citations: 0; TLS: 2
1	Wang B.; Ge J.; Lu F. (2025)	From review filtering to topic modeling: a deep learning-based approach for analyzing negative online reviews of five-star hotels	Journal of Hospitality and Tourism Technology	DOI: 10.1108/JHTT-04-2025-0328 Citations: 1; TLS: 7

Cluster	Publication	Title	Source	Bibliographic link and network metrics
1	Wong I.A.; Zhang D.; Li Y.M.; Huang G.I.; Sun D. (2026)	Understanding Guests' Multisentiment Responses to Hotel Innovation	Cornell Hospitality Quarterly	DOI: 10.1177/19389655251379457 Citations: 1; TLS: 10
1	Yang T.; Hsu C.H.C. (2025)	An AI-driven framework for continuous tourist sentiment scoring using longitudinal and group-level insights with pre-trained language models (RoBERTa-CSS)	Tourism Review	DOI: 10.1108/TR-05-2025-0550 Citations: 1; TLS: 16
1	Ye Q.; Zhang Z.; Law R. (2009)	Sentiment classification of online reviews to travel destinations by supervised machine learning approaches	Expert Systems with Applications	DOI: 10.1016/j.eswa.2008.07.035 Citations: 569; TLS: 7
1	Zhang H.; Xiang Z.; Zach F.J. (2025)	Generative AI vs. humans in online hotel review management: A Task-Technology Fit perspective	Tourism Management	DOI: 10.1016/j.tourman.2025.105187 Citations: 34; TLS: 35
2	Alawadh H.M.; Alabrah A.; Meraj T.; Rauf H.T. (2023)	Discourse analysis based credibility checks to online reviews using deep learning based discourse markers	Computer Speech and Language	DOI: 10.1016/j.csl.2022.101450 Citations: 6; TLS: 7
2	Arulsivakumar T.; Veerasamy S. (2026)	Cognitive Analysis of eWOM Sentiments from Tripadvisor Perspectives Using ChatGPT	Smart Innovation, Systems and Technologies	DOI: 10.1007/978-981-95-1357-4_1 Citations: 0; TLS: 44
2	Carrasco P.; Dias S. (2024)	Enhancing Restaurant Management through Aspect-Based Sentiment Analysis and NLP Techniques	Procedia Computer Science	DOI: 10.1016/j.procs.2024.05.088 Citations: 13; TLS: 13
2	Chatterjee R.; Pandey M.; Thakur H.K.; Gupta A. (2025)	Facets of Fakes in Cyberspace: Machine and Ensemble Learning-Based Decisions and Detections	Acta Physica Polonica B	DOI: 10.31449/INF.V49I13.7050 Citations: 0; TLS: 3
2	Gholamnia M.; Eslamirad N.; Sajadi P.; Zarin Z.; Pilla F. (2025)	Leveraging large language models for citizen-centric urban accessibility analysis: a case study using Airbnb reviews in Dublin	Spatial Information Research	DOI: 10.1007/s41324-025-00646-9 Citations: 2; TLS: 5
2	Hajek P., Prof.; Sahut J.-M., Prof. (2022)	Mining behavioural and sentiment-dependent linguistic patterns from restaurant reviews for fake review detection	Technological Forecasting and Social Change	DOI: 10.1016/j.techfore.2022.121532 Citations: 41; TLS: 36
2	He C.; Liu Y.; Song H.; Qiu R.T.R.; Zhang X. (2026)	A large language model-based tourist satisfaction index	Annals of Tourism Research	DOI: 10.1016/j.annals.2026.104174 Citations: 0; TLS: 38
2	Lee M.; Kwon W.; Back K.-J. (2021)	Artificial intelligence for hospitality big data analytics: developing a prediction model of restaurant review helpfulness for customer decision-making	International Journal of Contemporary Hospitality Management	DOI: 10.1108/IJCHM-06-2020-0587 Citations: 123; TLS: 98
2	Lee M.; Song Y.H.; Li L.; Lee K.Y.; Yang S.-B. (2022)	Detecting fake reviews with supervised machine learning algorithms	Service Industries Journal	DOI: 10.1080/02642069.2022.2054996 Citations: 37; TLS: 82
2	Li J.; Zheng W.; Guo X. (2025)	Detecting multi-modal GAI-manipulated tourism review	Tourism Management	DOI: 10.1016/j.tourman.2025.105220 Citations: 8; TLS: 18
2	Liao Z.; Gou X.; Wei Q.; Xing Z. (2024)	Forecasting tourism demand with helpful online reviews	Nankai Business Review International	DOI: 10.1108/NBRI-10-2023-0097 Citations: 4; TLS: 44
2	Lin C.H.; Hsu P.Y.; Cheng M.S.; Lei H.T.; Hsu M.C. (2017)	Identifying deceptive review comments with rumor and lie theories	Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)	DOI: 10.1007/978-3-319-61833-3_44 Citations: 5; TLS: 2

Cluster	Publication	Title	Source	Bibliographic link and network metrics
2	Liu P.; Dang R.; Wang P.; Xu Y.; Zhang Y. (2025)	Online–offline combined adaptive hotel recommendation system considering attribute importance and group consensus	Decision Support Systems	DOI: 10.1016/j.dss.2025.114503 Citations: 14; TLS: 19
2	Liu S.; Wei Y.; Wang S. (2025)	The Affective Iceberg Model for Review Manipulation Detection: A GPT-Based Design Artifact	Journal of Travel Research	DOI: 10.1177/00472875251383550 Citations: 1; TLS: 35
2	Morini-Marrero S.; Ramos-Henriquez J.M.; Bilgihan A. (2025)	Analyzing the concordance and consistency of AI and human ratings in hospitality reviews	Journal of Hospitality and Tourism Technology	DOI: 10.1108/JHTT-04-2024-0251 Citations: 5; TLS: 66
2	Ruan W.; Shen Z. (2025)	A Hybrid Zero-Shot Profiling Framework with Generative ABSA for Tourism Marketing: Case of Gulangyu	Proceedings of 2025 5th International Symposium on Artificial Intelligence and Big Data, AIBDF 2025	DOI: 10.1109/AIBDF67964.2025.11440818 Citations: 0; TLS: 2
2	Sacristán-Díaz M.; Perdomo-Verdecia V.; Garrido-Vega P. (2025)	Improving Service Quality in Hotels: Development of an AI Algorithm for Classification and Analysis of Online Reviews	Springer Proceedings in Business and Economics	DOI: 10.1007/978-3-031-87019-4_32 Citations: 1; TLS: 14
2	Tuomi A. (2021)	Deepfake consumer reviews in tourism: Preliminary findings	Annals of Tourism Research Empirical Insights	DOI: 10.1016/j.annale.2021.100027 Citations: 28; TLS: 25
2	Wang A.; Tang M.; Cui G.; Peng L. (2027)	Singing praises vs. venting frustration: Multi-dimensional satisfaction gaps as drivers of high-quality hotel reviews	International Journal of Hospitality Management	DOI: 10.1016/j.ijhm.2026.104881 Citations: 0; TLS: 67
2	Yannacopoulou A.; Kallinikos K. (2025)	Measuring Destination Image Using AI and Big Data: Kastoria's Image on TripAdvisor	Societies	DOI: 10.3390/soc15010005 Citations: 5; TLS: 8
2	Zhang T.; Nguyen V.T.; Shimizu T. (2026)	Identifying tourist preferences from online reviews: An Integrated BERTopic-LLM approach with bidirectional validation	Journal of Open Innovation: Technology, Market, and Complexity	DOI: 10.1016/j.joitmc.2026.100757 Citations: 0; TLS: 22
3	Borghi M.; Mariani M.M.; Vega R.P.; Wirtz J. (2023)	The impact of service robots on customer satisfaction online ratings: The moderating effects of rapport and contextual review factors	Psychology and Marketing	DOI: 10.1002/mar.21903 Citations: 45; TLS: 109
3	Cheong F.; Law R. (2023)	Human employees versus robotic employees: Customers and hotel managers' perceived experience at unmanned smart hotels	Cogent Social Sciences	DOI: 10.1080/23311886.2023.2202937 Citations: 35; TLS: 56
3	Choi Y.; Oh M.; Choi M.; Kim S. (2021)	Exploring the influence of culture on tourist experiences with robots in service delivery environment	Current Issues in Tourism	DOI: 10.1080/13683500.2020.1735318 Citations: 145; TLS: 34
3	Gajić T.; Ranjbaran A.; Vukolić D.; Bugarčić J.; Spasojević A.; Đorđević Boljanović J.; Vujačić D.; Mandarić M.; Kostić M.; Sekulić D.; Bugarčić M.; Drašković B.D.; Rakić S.R. (2024)	Tourists' Willingness to Adopt AI in Hospitality—Assumption of Sustainability in Developing Countries	Sustainability (Switzerland)	DOI: 10.3390/su16093663 Citations: 41; TLS: 60
3	Guan X.; Zhang L.; Liu X.; Liu Q. (2025)	An eye for an eye: Exploring how human-robot service attributes affect customers' negative electronic word-of-mouth	International Journal of Hospitality Management	DOI: 10.1016/j.ijhm.2025.104104 Citations: 7; TLS: 61
3	Huang D.; Chen Q.; Huang J.; Kong S.; Li Z. (2021)	Customer-robot interactions: Understanding customer experience with service robot	International Journal of Hospitality Management	DOI: 10.1016/j.ijhm.2021.103078 Citations: 233; TLS: 127

Cluster	Publication	Title	Source	Bibliographic link and network metrics
3	Kallmuenzer A.; Mahasuar K. (2026)	Old roots, new faces: virtual influencers in legacy restaurants	International Journal of Contemporary Hospitality Management	DOI: 10.1108/IJCHM-06-2025-0893 Citations: 0; TLS: 4
3	Kaur N.; Mahajan N.; Singh V.; Gupta A. (2023)	Artificial Intelligence Revolutionizing The Restaurant Industry - Analyzing Customer Experience Through Data Mining and Thematic Content Analysis	Proceedings of 2023 3rd International Conference on Innovative Practices in Technology and Management, ICIPTM 2023	DOI: 10.1109/ICIPTM57143.2023.10117897 Citations: 9; TLS: 13
3	Kayeser Fatima J.; Khan M.I.; Bahmannia S.; Chatrath S.K.; Dale N.F.; Johns R. (2024)	Rapport with a chatbot? The underlying role of anthropomorphism in socio-cognitive perceptions of rapport and e-word of mouth	Journal of Retailing and Consumer Services	DOI: 10.1016/j.jretconser.2023.103666 Citations: 104; TLS: 29
3	Kim J.; Jang J. (2026)	Information Presentation Strategies for Recommender-Chatbots	Asia Pacific Journal of Information Systems	DOI: 10.14329/apjis.2026.36.2.266 Citations: 0; TLS: 21
3	Li Y.; Wang S.; Li Z. (2024)	Animating arousal and engagement: empirical insights into AI-enhanced robotic performances and consumer reactions	Journal of Hospitality and Tourism Technology	DOI: 10.1108/JHTT-01-2024-0053 Citations: 21; TLS: 50
3	Luo J.M.; Vu H.Q.; Li G.; Law R. (2021)	Understanding service attributes of robot hotels: A sentiment analysis of customer online reviews	International Journal of Hospitality Management	DOI: 10.1016/j.ijhm.2021.103032 Citations: 147; TLS: 97
3	Ma T.B.; Nguyen V.K.; Natoli R. (2026)	Exploring the role of trust and satisfaction in shaping AI-driven tourist behaviour	Journal of Hospitality and Tourism Insights	DOI: 10.1108/JHTI-04-2025-0507 Citations: 0; TLS: 65
3	Mariani M.; Borghi M. (2021)	Customers' evaluation of mechanical artificial intelligence in hospitality services: a study using online reviews analytics	International Journal of Contemporary Hospitality Management	DOI: 10.1108/IJCHM-06-2020-0622 Citations: 157; TLS: 130
3	Mariani M.M.; Borghi M. (2024)	Artificial intelligence in service industries: customers' assessment of service production and resilient service operations	International Journal of Production Research	DOI: 10.1080/00207543.2022.2160027 Citations: 86; TLS: 104
3	Park H.; Jiang S.; Lee O.-K.D.; Chang Y. (2024)	Exploring the Attractiveness of Service Robots in the Hospitality Industry: Analysis of Online Reviews	Information Systems Frontiers	DOI: 10.1007/s10796-021-10207-8 Citations: 54; TLS: 64
3	Pham T.N. (2025)	INVESTIGATING THE IMPACT OF ONLINE REVIEWS, VIRTUAL REALITY, AND AI CHATBOTS ON FIRST-TIME HOTEL BOOKINGS IN RURAL DESTINATIONS: THE ROLE OF SENSE OF PRESENCE AND TRUST	Geojournal of Tourism and Geosites	DOI: 10.30892/gtg.61343-1553 Citations: 4; TLS: 13
3	Wong I.A.; Huang J.; Lin Z.C.J.; Jiao H. (2022)	Smart dining, smart restaurant, and smart service quality (SSQ)	International Journal of Contemporary Hospitality Management	DOI: 10.1108/IJCHM-10-2021-1207 Citations: 78; TLS: 58
3	Yang F.; Ying T.; Liu X. (2025)	Echoes of Innovation: Exploring the Use of Voice Assistants to Boost Hotel Reputation	Journal of Theoretical and Applied Electronic Commerce Research	DOI: 10.3390/jtaer20010046 Citations: 6; TLS: 45
4	Chan F.Y.; Fang Y.; Gao C.; Ye Q.; Leung A.C.M. (2024)	ChatGPT-empowered Product Recommendation and Online Word-of-Mouth: Evidence from Online Travel Agency	45th International Conference on Information Systems, ICIS 2024	Scopus EID: 2-s2.0-105010817781 Citations: 0; TLS: 7
4	Cheng Y.; Gao B.; Zhang R.A.; Li X. (2025)	The Effect of Review Summary: Evidence from a Natural Experiment	Proceedings of the Annual Hawaii International Conference on System Sciences	DOI: 10.24251/hicss.2025.463 Citations: 0; TLS: 18

Cluster	Publication	Title	Source	Bibliographic link and network metrics
4	Cosentino C.; Gündüz Cüre M.; Marozzo F.; Öztürk Birim Ş. (2025)	From Reviews to Results: Generative AI for Review-Driven Product and Service Comparisons	Lecture Notes in Computer Science	DOI: 10.1007/978-3-032-05461-6_6 Citations: 2; TLS: 8
4	Gu W.K.M.; Spann M. (2026)	The impact of generative artificial intelligence on consumer reviews: Insights from a quasi-experiment	International Journal of Research in Marketing	DOI: 10.1016/j.ijresmar.2026.06.002 Citations: 1; TLS: 46
4	Guerrero-Rodríguez R.; Álvarez-Carmona M.A.; Aranda R.; Díaz-Pacheco Á. (2026)	AI-driven analysis of hotel digital reputation: insights from a Mexican destination	International Journal of Tourism Cities	DOI: 10.1080/20565607.2025.2600691 Citations: 1; TLS: 15
4	Helal M.; Nag K. (2025)	Sentiment and Emotion Analysis of Airline Customer Reviews from a Travel Review Platform	2025 IEEE International Conference on Emerging Trends in Engineering and Computing, ETECOM 2025	DOI: 10.1109/ETECOM66111.2025.11319037 Citations: 0; TLS: 6
4	Huang Y.; Lyu S. (2026)	Embodied Experiences Reshape Tourist Perceptions: A Computational Analysis of VR, AR, and AI in Heritage Tourism	Proceedings of 2025 International Conference on Embodied Intelligence and Large Models, EILM 2025	DOI: 10.1145/3788731.3788737 Citations: 0; TLS: 5
4	Huang H.; Zhu C.; Xie L.; La L. (2026)	LEVERAGING LARGE LANGUAGE MODELS FOR A CROSS-CULTURAL ANALYSIS OF THEME PARK VISITOR SATISFACTION	Journal of Nonlinear and Convex Analysis	Scopus EID: 2-s2.0-105035710661 Citations: 0; TLS: 29
4	Kovács G.; Bogdanova D.; Yussupova N.; Boyko M. (2015)	Informatics tools, AI models and methods used for automatic analysis of customer satisfaction	Studies in Informatics and Control	DOI: 10.24846/v24i3y201503 Citations: 10; TLS: 4
4	Li Z.; Bang Y. (2026)	How does artificial intelligence-generated content reshape user-generated content? An empirical study from TripAdvisor	Decision Support Systems	DOI: 10.1016/j.dss.2026.114623 Citations: 3; TLS: 10
4	Lin B.; Fan Y.; Yang R. (2025)	The future of urban travel and tourism: a text mining analysis of robotaxi sentiment and adoption	Journal of Travel and Tourism Marketing	DOI: 10.1080/10548408.2025.2469118 Citations: 16; TLS: 21
4	Shin J.; Joung J.; Lim C. (2024)	Determining directions of service quality management using online review mining with interpretable machine learning	International Journal of Hospitality Management	DOI: 10.1016/j.ijhm.2023.103684 Citations: 38; TLS: 21
4	Song B.; Xia H.; Law R.; Muskat B.; Li G. (2024)	Discovery of smart hotels' competitiveness based on online reviews	International Journal of Hospitality Management	DOI: 10.1016/j.ijhm.2024.103926 Citations: 16; TLS: 23
4	Wang S.; Tong J.S.; Dong J.Q.; Huang X. (2025)	When Generative Artificial Intelligence Meets Human Reviews: Effects on Consumer Behavior and Hotel Sales	Pacific Asia Conference on Information Systems	Scopus EID: 2-s2.0-105029279611 Citations: 1; TLS: 20
4	Widiantoro A.D.; Ependi U.; Sanjaya R.; Chamid A.A.; Harnadi B. (2025)	An Analytical Model for Interpreting and Classifying TripAdvisor Hotel Reviews Using Topic Modeling and Deep Learning	Proceeding - 2025 IEEE 9th International Conference on Software Engineering and Computer Systems: Advancements in Next-Generation Intelligent Solution, ICSECS 2025	DOI: 10.1109/ICSECS65227.2025.11279203 Citations: 0; TLS: 12
4	Yu T.; Rita P.; Moro S.; Oliveira C. (2022)	Insights from sentiment analysis to leverage local tourism business in restaurants	International Journal of Culture, Tourism, and Hospitality Research	DOI: 10.1108/IJCTHR-02-2021-0037 Citations: 17; TLS: 11

Cluster	Publication	Title	Source	Bibliographic link and network metrics
5	Ali L.; Ali F.; Abdalla M.J.; Alotaibi S. (2025)	Beyond the hype: Evaluating the impact of generative AI on brand authenticity, image, and consumer behavior in the restaurant industry	International Journal of Hospitality Management	DOI: 10.1016/j.ijhm.2025.104318 Citations: 30; TLS: 22
5	Amos C.; Zhang L. (2024)	Consumer reactions to perceived undisclosed ChatGPT usage in an online review context	Telematics and Informatics	DOI: 10.1016/j.tele.2024.102163 Citations: 34; TLS: 27
5	Battour M.; Salaheldeen M.; Anwar I.; Ratnasari R.T.; A. Hamid A.; Mady K. (2025)	Integrating ChatGPT in halal tourism: impact on tourist satisfaction, e-WoM and revisit intention	Journal of Islamic Marketing	DOI: 10.1108/JIMA-10-2024-0470 Citations: 15; TLS: 50
5	Cai Y.; Shang Y.; Cheng M. (2026)	Do AI summaries tell the whole story? A qualitative study of AI-generated hotel review summaries	Current Issues in Tourism	DOI: 10.1080/13683500.2026.2713761 Citations: 0; TLS: 6
5	Dai X.; Zhou X.; Dong Q.; Zhou K. (2026)	AI-Driven Exploration of Public Perception in Historic Districts Through Deep Learning and Large Language Models	Buildings	DOI: 10.3390/buildings16020437 Citations: 3; TLS: 3
5	Hajra V. (2023)	Unveiling the aesthetics of sacred elephant interactions: a ChatGPT-driven analysis of Tripadvisor reviews	Journal of Qualitative Research in Tourism	DOI: 10.4337/jqrt.2023.02.05 Citations: 1; TLS: 7
5	Hao J.-X.; Meng L.; Kong M.; Hao Z.; Law R. (2026)	Asymmetry of AI-generated review summaries on review contribution: Evidence from TripAdvisor	Journal of Hospitality and Tourism Management	DOI: 10.1016/j.jhtm.2026.101522 Citations: 0; TLS: 41
5	Kumar S.; Malhotra D. (2026)	Dark side of generative AI in tourism: a stressor-strain-outcome perspective; using a mixed-methods approach	Tourism Recreation Research	DOI: 10.1080/02508281.2025.2503997 Citations: 10; TLS: 37
5	Li C.; Cao Q.; Hua S.; Tao C. (2025)	When AI takes the wheel: The effectiveness of AI versus human-generated content in tourism marketing	Journal of Vacation Marketing	DOI: 10.1177/13567667251393512 Citations: 6; TLS: 10
5	Ming Y.; Shen Z.; Chang X.; Yang S. (2025)	The effect of anger on online review helpfulness: role of credibility	Current Issues in Tourism	DOI: 10.1080/13683500.2025.2482900 Citations: 3; TLS: 95
5	Mladenović D.; Ismagilova E.; Mogaji E.; Dwivedi Y.K. (2026)	Travel Recommendations of Tomorrow: Generative Artificial Intelligence and Travel Planning	Journal of Consumer Behaviour	DOI: 10.1002/cb.70126 Citations: 5; TLS: 53
5	Nella A.; Stergiou D.P. (2025)	ChatGPT as a Sentiment Analysis Tool: An Assessment Based on Negative Reviews of High-End UK Restaurants	Springer Proceedings in Business and Economics	DOI: 10.1007/978-3-031-87019-4_5 Citations: 0; TLS: 62
5	Orea-Giner A.; Fusté-Forné F.; Soliman M. (2025)	How do tourists perceive green customer-love service in restaurants? A qualitative exploration of ai and human collaboration	International Journal of Hospitality Management	DOI: 10.1016/j.ijhm.2025.104300 Citations: 8; TLS: 39
5	Singh S.; Mittal A. (2026)	Online review authenticity and helpfulness: an integrative literature review and research agenda for consumer purchase intention in hospitality	Journal of Hospitality and Tourism Insights	DOI: 10.1108/JHTI-09-2025-1048 Citations: 1; TLS: 41
5	Tan K.P.-S.; Liu Y.V.; Litvin S.W. (2025)	ChatGPT and online service recovery: How potential customers react to managerial responses of negative reviews	Tourism Management	DOI: 10.1016/j.tourman.2024.105057 Citations: 46; TLS: 37
5	Yhee Y.; Koo C. (2026)	Seeing AI as human or machine? Effects of transparency, valence, and readability on review summary helpfulness	Tourism Management	DOI: 10.1016/j.tourman.2025.105305 Citations: 18; TLS: 27

Cluster	Publication	Title	Source	Bibliographic link and network metrics
6	Akdim K. (2021)	The influence of eWOM. Analyzing its characteristics and consequences, and future research linesLa influencia de eWOM. Analizando sus caracteristicas, consecuencas y futuras lineas de investigación	Spanish Journal of Marketing - ESIC	DOI: 10.1108/SJME-10-2020-0186 Citations: 37; TLS: 90
6	Ali W.; Kasturiratne D.; Ameer I.; Bhaskar S. (2026)	Generative AI in digital engagement: a quasi-experimental study of tourist sentiment	Service Industries Journal	DOI: 10.1080/02642069.2026.2638226 Citations: 2; TLS: 92
6	Almeida A.; Toro Sanchez F. (2025)	Personality-based interpretation of online reviews: an AI-driven reader-centered framework	Tourism Review	DOI: 10.1108/TR-08-2025-0939 Citations: 0; TLS: 46
6	De Nicolò F.; Bellantuono L.; Borzì D.; Bregonzio M.; Cilli R.; De Marco L.; Lombardi A.; Pantaleo E.; Petruzzellis L.; Shashaj A.; Tangaro S.; Monaco A.; Amoroso N.; Bellotti R. (2023)	The verbalization of numbers: An explainable framework for tourism online reviews	International Journal of Engineering Business Management	DOI: 10.1177/18479790231151913 Citations: 8; TLS: 106
6	Katsiuba D.; Kew T.; Dolata M.; Schwabe G. (2022)	Supporting Online Customer Feedback Management with Automatic Review Response Generation	Proceedings of the Annual Hawaii International Conference on System Sciences	Scopus EID: 2-s2.0-85150803599 Citations: 8; TLS: 30
6	Ku C.-H.; Chang Y.-C.; Wang Y.; Chen C.-H.; Hsiao S.-H. (2019)	Artificial intelligence and visual analytics: A deep-learning approach to analyze hotel reviews & responses	Proceedings of the Annual Hawaii International Conference on System Sciences	Scopus EID: 2-s2.0-85108262844 Citations: 19; TLS: 64
6	Nnanna P.; Amujo O.; Ezenkwu C.P.; Ibeke E. (2025)	Leveraging LLMs for User Rating Prediction from Textual Reviews: A Hospitality Data Annotation Case Study	Information (Switzerland)	DOI: 10.3390/info16121059 Citations: 0; TLS: 13
6	Shawon M.N.H.; Hasan K.M.A. (2025)	A Time-Aware Sliding Window-Based Hotel Recommendation Framework Using Multi-Stage BERT-MRC	2025 IEEE High Performance Extreme Computing Conference, HPEC 2025	DOI: 10.1109/HPEC67600.2025.11196258 Citations: 0; TLS: 15
6	Sâsâeac Ș.-M.; Bertea P.E.; Jelea A.R.; Manolică A.; Roman C.T. (2025)	eWOM vs. aWOM: AI Powered Word of Mouth and its Impact on Consumer Decision Making in Tourism	Scientific Annals of Economics and Business	DOI: 10.47743/saeb-2025-0026 Citations: 1; TLS: 33
6	Tuomi A.; Zainal Abidin H.; Tuominen P.; Ascenção M.P. (2025)	Convincingness of AI-Generated Restaurant Reviews	Springer Proceedings in Business and Economics	DOI: 10.1007/978-3-031-83705-0_36 Citations: 0; TLS: 51
6	Voutsa M.C.; Tsapatsoulis N.; Djouvas C. (2025)	Biased by Design? Evaluating Bias and Behavioral Diversity in LLM Annotation of Real-World and Synthetic Hotel Reviews	AI (Switzerland)	DOI: 10.3390/ai6080178 Citations: 11; TLS: 16
6	Wang M.-X.; Wang J.-Q.; Li L. (2017)	New online personalized recommendation approach based on the perceived value of consumer characteristics	Journal of Intelligent and Fuzzy Systems	DOI: 10.3233/JIFS-17034 Citations: 21; TLS: 21
6	Williams N.L.; Ferdinand N.; Bustard J. (2020)	From WOM to aWOM – the evolution of unpaid influence: a perspective article	Tourism Review	DOI: 10.1108/TR-05-2019-0171 Citations: 45; TLS: 19
6	Yang K.; Wu T.; Zhang W. (2025)	Customer Care Meets Technology: Investigating the Role of AI in Managerial Responses to Online Reviews	Proceedings of 2024 5th International Conference on Computer Science and Management Technology, ICCSMT 2024	DOI: 10.1145/3708036.3708076 Citations: 0; TLS: 50

Cluster	Publication	Title	Source	Bibliographic link and network metrics
6	Zhu J.J.; Chang Y.-C.; Ku C.-H.; Li S.Y.; Chen C.-J. (2021)	Online critical review classification in response strategy and service provider rating: Algorithms from heuristic processing, sentiment analysis to deep learning	Journal of Business Research	DOI: 10.1016/j.jbusres.2020.11.007 Citations: 53; TLS: 52
7	Ansari D. (2016)	Sentiment Polarity Classification Using Structural Features	Proceedings - 15th IEEE International Conference on Data Mining Workshop, ICDMW 2015	DOI: 10.1109/ICDMW.2015.57 Citations: 9; TLS: 3
7	Fazzolari M.; Cozza V.; Petrocchi M.; Spognardi A. (2017)	A Study on Text-Score Disagreement in Online Reviews	Cognitive Computation	DOI: 10.1007/s12559-017-9496-y Citations: 20; TLS: 30
7	Gunathilaka D.; Pathirana S.; Senarathne S.; Weerasekara J.; Silva T. (2019)	Feature Based Opinion Mining for Hotel Profiling	Communications in Computer and Information Science	DOI: 10.1007/978-981-13-9129-3_16 Citations: 1; TLS: 2
7	Iswari N.M.S.; Afriliana N. (2025)	Enhancing Aspect-Based Sentiment Analysis in Tourism Reviews Through Hybrid Data Augmentation	Journal of Applied Data Sciences	DOI: 10.47738/jads.v6i3.842 Citations: 2; TLS: 2
7	Li Z.; Chan F.Y.; Gao C.; Ye Q. (2024)	Will Sentiment Extraction based on ChatGPT yield Better Predictive Outcomes? Evidence from an Online Travel Agency	Proceedings of the International Conference on Electronic Business (ICEB)	Scopus EID: 2-s2.0-85213400034 Citations: 0; TLS: 44
7	Tang T.; Huang L.; Chen Y. (2020)	Evaluation of Chinese Sentiment Analysis APIs Based on Online Reviews	IEEE International Conference on Industrial Engineering and Engineering Management	DOI: 10.1109/IEEM45057.2020.9309968 Citations: 21; TLS: 2
7	To W.M.; Yu B.T.W. (2025)	Artificial Intelligence Research in Tourism and Hospitality Journals: Trends, Emerging Themes, and the Rise of Generative AI	Tourism and Hospitality	DOI: 10.3390/tourhosp6020063 Citations: 36; TLS: 67
7	Valdivia A.; Luzón M.V.; Herrera F. (2017)	Sentiment Analysis in TripAdvisor	IEEE Intelligent Systems	DOI: 10.1109/MIS.2017.3121555 Citations: 163; TLS: 17
7	Yussupova N.; Kovács G.; Boyko M.; Bogdanova D. (2016)	Models and methods for quality management based on artificial intelligence applications	Acta Polytechnica Hungarica	Scopus EID: 2-s2.0-84962449173 Citations: 20; TLS: 1
7	Zhao Y.; Dong S.; Yang J. (2015)	Effect research of aspects extraction for Chinese hotel reviews based on machine learning method	International Journal of Smart Home	DOI: 10.14257/ijsh.2015.9.3.03 Citations: 10; TLS: 4
8	Budiharja J.R.; Juarsa M.A.; Karmagatri M. (2025)	NaïVe Bayes-Based Data Analysis on Online Travel Agency's Guest Review of Sheraton Bandung Hotel & Towers	Proceedings - 3rd International Conference on Artificial Intelligence and Machine Learning Applications: Healthcare and Internet of Things, AIMLA 2025	DOI: 10.1109/AIMLA63829.2025.11041674 Citations: 1; TLS: 1
8	Calero-Sanz J.; Orea-Giner A.; Villacé-Molinero T.; Muñoz-Mazón A.; Fuentes-Moraleda L. (2022)	Predicting A New Hotel Rating System by Analysing UGC Content from Tripadvisor: Machine Learning Application to Analyse Service Robots Influence	Procedia Computer Science	DOI: 10.1016/j.procs.2022.01.307 Citations: 23; TLS: 50
8	Fararni K.A.; Maada L.; Aghoutane B.; Sabri A.; Yahyaouy A.; Riffi J. (2026)	Combining Content-Based Filtering Methods for Building a Powerful Hybrid Recommender System to Improve Tourism in Drâa-Tafilalet Area	Technologies	DOI: 10.3390/technologies14070421 Citations: 0; TLS: 2

Cluster	Publication	Title	Source	Bibliographic link and network metrics
8	Hou X.; Paidi Z.B. (2025)	AI-based tourist behavior analysis and cultural communication optimization strategies for Shanxi great wall heritage site	Future Technology	DOI: 10.55670/fpll.futech.4.4.5 Citations: 1; TLS: 3
8	Ko J.; Kim J.; Byun Y.-C. (2025)	Tourist Attraction Recommendation Using a Word2Vec-Based Approach Enhanced by XGBoost Classifier	Lecture Notes in Electrical Engineering	DOI: 10.1007/978-981-96-2395-2_6 Citations: 0; TLS: 2
8	Kumar A.; Jain N.; H. M. A.I. (2026)	AI-Powered Mobile Feedback Systems for Real-Time Service Quality Improvement in Hotels	International Journal of Interactive Mobile Technologies	DOI: 10.3991/ijim.v20i07.61083 Citations: 0; TLS: 24
8	Lopes J.M.; Massano-Cardoso I.; Granadeiro C. (2025)	Festivals in Age of AI: Smarter Crowds, Happier Fans	Tourism and Hospitality	DOI: 10.3390/tourhosp6010035 Citations: 13; TLS: 50
8	Lopes J.M.; Silva F.; Massano-Cardoso I. (2026)	When AI Meets Festivals: How eWOM Mediates the Route to Memorable Experiences and Well-Being	International Journal of Tourism Research	DOI: 10.1002/jtr.70262 Citations: 0; TLS: 34

Note: Cluster membership corresponds to the final bibliographic-coupling network of 131 connected publications. TLS denotes total link strength. DOI and Scopus EID values link each cluster entry to the underlying bibliographic record.

Table S11. Complete membership of the co-citation clusters

The table links each cited reference displayed in Figure 6 to its cluster, full VOSviewer bibliographic label and network metrics.

Cluster	Full bibliographic label	Citations	TLS
1	Bradley G.L., Responding to negative online reviews: The effects of hotel responses on customer inferences of trust and concern, Tourism Management, 53, pp. 74-85, (2016)	8	30
1	Fan W., A comparative analysis of major online review platforms: Implications for social media analytics in hospitality and tourism, Tourism Management, 58, pp. 51-65, (2017)	7	21
1	Grootendorst M., BERTopic: Neural topic modeling with a class-based TF-IDF procedure, (2022)	6	4
1	Gursoy D., Developing and validating a service robot integration willingness scale, International Journal of Hospitality Management, 80, pp. 36-51, (2019)	5	20
1	Ivanov S., ChatGPT for tourism: Applications, benefits and risks, Tourism Review, 79, 2, pp. 290-303, (2024)	7	24
1	Jia Q., Mining meaning from online ratings and reviews: Tourist satisfaction analysis using latent Dirichlet allocation, Tourism Management, 59, pp. 467-483, (2017)	6	19
1	Kim S., Do you trust ChatGPTs? Effects of the ethical and quality issues of generative AI on travel decisions, Journal of Travel & Tourism Marketing, 40, 9, pp. 779-801, (2023)	4	13
1	Larcker D.F., Evaluating structural equation models with unobservable variables and measurement error, Journal of Marketing Research, 18, 1, pp. 39-50, (1981)	5	11
1	Law R., Hospitality and tourism online reviews: Recent trends and future directions, Journal of Travel & Tourism Marketing, 32, 5, pp. 608-621, (2015)	6	23
1	Magnini V.P., Factors affecting customer satisfaction in responses to negative online hotel reviews: The impact of empathy, paraphrasing, and speed, Cornell Hospitality Quarterly, 56, 2, pp. 223-231, (2015)	4	14
1	Micu A., Leveraging ChatGPT and other generative artificial intelligence (AI)-based applications in the hospitality and tourism industry: Practices, challenges and research agenda, International Journal of Contemporary Hospitality Management, 36, 1, pp. 1-12, (2024)	4	21
1	Sivathanu B., Adoption of AI-based chatbots for hospitality and tourism, International Journal of Contemporary Hospitality Management, 32, 10, pp. 3199-3226, (2020)	4	13

Cluster	Full bibliographic label	Citations	TLS
1	Song H., ChatGPT and the hospitality and tourism industry: An overview of current trends and future research directions, Journal of Hospitality Marketing & Management, 32, 5, pp. 579-592, (2023)	4	16
2	Au N., Exploring customer experiences with robotics in hospitality, International Journal of Contemporary Hospitality Management, 30, 7, pp. 2680-2697, (2018)	5	35
2	Lew A.A., From high-touch to high-tech: COVID-19 drives robotics adoption, Tourism Geographies, 22, 3, pp. 724-734, (2020)	5	28
2	Martins A., Brave new world: Service robots in the frontline, Journal of Service Management, 29, 5, pp. 907-931, (2018)	7	38
2	Mayzlin D., The effect of word of mouth on sales: Online book reviews, Journal of Marketing Research, 43, 3, pp. 345-354, (2006)	5	27
2	Oliver R.L., A cognitive model of the antecedents and consequences of satisfaction decisions, Journal of Marketing Research, 17, 4, pp. 460-469, (1980)	5	24
2	Patterson P.G., Service robots, customers and service employees: What can we learn from the academic literature and where are the gaps?, Journal of Service Theory and Practice, 30, 3, pp. 361-391, (2020)	4	34
2	Rust R.T., Artificial intelligence in service, Journal of Service Research, 21, 2, pp. 155-172, (2018)	6	43
2	Rust R.T., Engaged to a robot? The role of AI in service, Journal of Service Research, 24, 1, pp. 30-41, (2021)	4	30
2	Tussyadiah I., A review of research into automation in tourism: Launching the Annals of Tourism Research curated collection on artificial intelligence and robotics in tourism, Annals of Tourism Research, 81, (2020)	4	28
2	Wang M., Predicting overall customer satisfaction: Big data evidence from hotel online textual reviews, International Journal of Hospitality Management, 76, pp. 111-121, (2019)	4	26
2	Zeithaml V., Cost-effective service excellence, Journal of the Academy of Marketing Science, 46, 1, pp. 59-80, (2018)	4	34
3	Chatterjee S., Drivers of helpfulness of online hotel reviews: A sentiment and emotion mining approach, International Journal of Hospitality Management, 85, (2020)	4	17
3	Fan W., Understanding the determinants of online review helpfulness: A meta-analytic investigation, Decision Support Systems, 102, pp. 1-11, (2017)	4	18
3	Li L., Big data in tourism research: A literature review, Tourism Management, 68, pp. 301-323, (2018)	5	29
3	Mathayomchan B., Analysing TripAdvisor reviews of tourist attractions in Phuket, Thailand, Tourism Management, 75, pp. 550-568, (2019)	4	7
3	Park S., What makes a useful online review? Implication for travel product websites, Tourism Management, 47, pp. 140-151, (2015)	7	43
3	Pennebaker J.W., The psychological meaning of words: LIWC and computerized text analysis methods, Journal of Language and Social Psychology, 29, 1, pp. 24-54, (2010)	4	24
3	Toral S., Post-visit and pre-visit tourist destination image through eWOM sentiment analysis and perceived helpfulness, International Journal of Contemporary Hospitality Management, 28, 11, pp. 2609-2627, (2016)	4	21
3	Toral S.L., A machine learning approach for the identification of the deceptive reviews in the hospitality sector using unique attributes and sentiment orientation, Tourism Management, 75, pp. 393-403, (2019)	4	15
3	Uysal M., What can big data and text analytics tell us about hotel guest experience and satisfaction?, International Journal of Hospitality Management, 44, pp. 120-130, (2015)	5	26
3	Vitari C., Extremely negative ratings and online consumer review helpfulness: The moderating role of product quality signals, Journal of Travel Research, 60, 4, pp. 699-717, (2021)	5	19
4	Browning V., The impact of online reviews on hotel booking intentions and perception of trust, Tourism Management, 32, 6, pp. 1310-1323, (2011)	12	33
4	Gu B., The impact of online user reviews on hotel room sales, International Journal of Hospitality Management, 28, 1, pp. 180-182, (2009)	4	19

Cluster	Full bibliographic label	Citations	TLS
4	Pan B., Electronic word-of-mouth in hospitality and tourism management, Tourism Management, 29, 3, pp. 458-468, (2008)	5	22
4	Salvi F., New consumer behavior: A review of research on eWOM and hotels, International Journal of Hospitality Management, 36, pp. 41-51, (2014)	4	22
4	Seegers D., Tried and tested: The impact of online hotel reviews on consumer consideration, Tourism Management, 30, 1, pp. 123-127, (2009)	4	22
4	Wu C., Fake online reviews: Literature review, synthesis, and directions for future research, Decision Support Systems, 132, (2020)	4	17
4	Zhang Z., The business value of online consumer reviews and management response to hotel performance, International Journal of Hospitality Management, 43, pp. 1-12, (2014)	4	24

Note: Cluster membership corresponds to the final co-citation network of 41 connected cited references. Citation counts and TLS are the values used in the final VOSviewer map.

Table S12. Empirical and conceptual foundations of the five AI roles

The table consolidates the thematic findings reported in Section 5.1 and identifies the evidential and communicative basis of each role.

AI role	Experiential source	Message producer	Presentation control	Representative sources and evidence	Analytical boundary
Algorithmically processed eWOM	Existing human reviews or review material submitted for verification	Human reviewers produce the review message; AI produces analytical labels or detection output	Platform or analytical system controls processing and verification	Li, Zheng and Guo [39]: technical system development and comparative evaluation	AI analyses, classifies or verifies reviews without producing the consumer facing review message
Algorithmically mediated eWOM	Human review corpus	Human reviewers produce the evaluations communicated to consumers	AI and the platform select, retrieve, order or present review evidence	Kim and Jang [40]: experimental evidence	AI controls exposure and presentation while the underlying evaluations remain human generated
Generative AI-mediated eWOM	Human review corpus provides the experiential basis	AI formulates a new summary, comparison, explanation or recommendation from review evidence	Platform or application controls generation and delivery of the consumer facing output	Cai, Shang and Cheng [41]: qualitative evidence; Wang, Tong and Dong [38]: abstract based field experiment; Cosentino et al. [42]: application evidence; Yhee and Koo [43]: five experiments	AI changes the communicative form while identifiable human review evidence supports the message
AI-assisted consumer eWOM	Individual consumer experience and evaluation	The consumer supplies the evaluation; AI assists its formulation	The consumer retains publication agency within the platform interface	Gu and Spann [44]: quasi experiment with supporting surveys	Human experiential provenance and evaluative agency remain with the consumer
AI-originated evaluative communication	No identifiable human review evidence supports each evaluation	AI produces the evaluative review message	The application, researcher or platform controls generation and presentation	Tuomi [45]: exploratory empirical evidence; Tuomi et al. [46]: controlled experimental evidence	The model originates the evaluation presented in review form

Note: The table reports the analytical roles identified in the focused synthesis. Evidence descriptions follow the design and evidential status reported in Supplementary Table S7.

Table S13. Records from the supplementary terminology-sensitivity search of 14 October 2026

Source: the 11-record Scopus export of 14 October 2026. The four original-corpus matches are identified by their IDs in Table S3. Dispositions total 4 original-corpus records + 1 existing conceptual anchor + 1 additional supplementary study + 5 exclusions = 11. Publication years and document types follow the export; the ICCCN 2025 proceedings record has publication year 2026.

Scopus record	Relationship and disposition	Analytical use or exclusion rationale
Sâsâeac Ș.-M.; Bertea P.E.; Jelea A.R.; Manolică A.; Roman C.T. (2025). eWOM vs. aWOM: AI Powered Word of Mouth and its Impact on Consumer Decision Making in Tourism. Scientific Annals of Economics and Business. Article. DOI: 10.47743/saeb-2025-0026	Original corpus; retained.	Focused-corpus ID 31; Essential analytical-core source [48]. Comparison of eWOM and aWOM in tourism; no additional record added.
Chan F.Y.; Fang Y.; Gao C.; Ye Q.; Leung A.C.M. (2024). ChatGPT-empowered Product Recommendation and Online Word-of-Mouth: Evidence from Online Travel Agency. 45th International Conference on Information Systems, ICIS 2024. Conference paper. Scopus EID: 2-s2.0-105010817781	Original corpus; retained.	Focused-corpus ID 10; selected Important mechanism source [32]. ChatGPT recommendations and subsequent eWOM contribution; no additional record added.
Tam N.D.; Hiep P.M.; Lan L.T.M. (2025). A Bibliometric Analysis of Electronic Word-of-Mouth in Tourism: A Review and Identification of Future Research Themes. Asian Journal of Business and Accounting. Article. DOI: 10.22452/ajba.vol18no1.9	Supplementary retrieval; excluded.	Tourism eWOM bibliometric review. aWOM is proposed as a future research direction, rather than examined as a substantive AI review-communication mechanism.
Mladenović D.; Beheshti M.; Kolar T.; Ismagilova E.; Dwivedi Y.K. (2024). Synthetic WOM? The Emergence of Generative Artificial Intelligence-Induced Recommendations. Journal of Computer Information Systems. Article. DOI: 10.1080/08874417.2024.2409252	Existing conceptual anchor; retained.	Synthetic WOM construct positioning [12]. Retained as one of the two anchors in the analytical core.
Gu W.K.M.; Spann M. (2026). The impact of generative artificial intelligence on consumer reviews: Insights from a quasi-experiment. International Journal of Research in Marketing. Article. DOI: 10.1016/j.ijresmar.2026.06.002	Original corpus; retained.	Focused-corpus ID 21; Essential analytical-core source [44]. AI-assisted review contribution; no additional record added.

Scopus record	Relationship and disposition	Analytical use or exclusion rationale
(2013). 2013 International Conference on Management Science and Engineering, ICMSE 2013 - 20th Annual Conference Proceedings. International Conference on Management Science and Engineering - Annual Conference Proceedings. Conference review. Scopus EID: 2-s2.0-84884316752	Supplementary retrieval; excluded.	Scopus conference-review record describing a proceedings collection of 329 papers, rather than an individual study eligible for focused synthesis.
Furner C.P.; Yoon T.E.; Zinko R.; Goh S.H. (2021). The influence of reviewer and consumer congruence in online word-of-mouth transactions. Journal of Electronic Commerce in Organizations. Article. DOI: 10.4018/JECO.2021070101	Supplementary retrieval; excluded.	The focal mechanism is reviewer–consumer congruence and purchase intention. Algorithmic review ordering provides platform context; an AI communication mechanism is not examined.
Williams N.L.; Ferdinand N.; Bustard J. (2020). From WOM to aWOM – the evolution of unpaid influence: a perspective article. Tourism Review. Article. DOI: 10.1108/TR-05-2019-0171	Original corpus; retained.	Focused-corpus ID 9; Essential analytical-core source [10]. Definition and positioning of aWOM; no additional record added.
Zheng W.; Ye Q. (2009). Sentiment classification of Chinese traveler reviews by support vector machine algorithm. 3rd International Symposium on Intelligent Information Technology Application, IITA 2009. Conference paper. DOI: 10.1109/IITA.2009.457	Supplementary retrieval; excluded.	Backend sentiment-classification study: SVM classification of Chinese hotel reviews from Ctrip. The abstract reports classification performance, not generation, mediation or presentation of review communication to consumers.
(2026). 5th International Conference on Computing and Communication Networks, ICCCN 2025. Lecture Notes in Networks and Systems. Conference review. Scopus EID: 2-s2.0-105040586799	Supplementary retrieval; excluded.	Scopus conference-review record describing a proceedings collection of 42 papers, rather than an individual study eligible for focused synthesis.
Le H.T.P.M.; Phan M.T.N.; Le T.D.M.; Ha T.M. (2026). Harnessing AI-driven word of mouth: construction, validation, and impact on AI distinctiveness and visit intention in rural tourism. Journal of Travel and Tourism Marketing. Article. DOI: 10.1080/10548408.2026.2679970	Additional supplementary evidence; included separately.	Three-component AIWOM measure used only for construct-boundary comparison [25]. Outside the 142 / 54 / 20 sets; material assessed and evidential role are reported in Table S14.

Table S14. Supplementary evidence and material assessed for Le et al. [25]

Field	Supplementary-evidence entry
Source	Le H.T.P.M.; Phan M.T.N.; Le T.D.M.; Ha T.M. (2026). Harnessing AI-driven word of mouth: construction, validation, and impact on AI distinctiveness and visit intention in rural tourism. Journal of Travel and Tourism Marketing. DOI: 10.1080/10548408.2026.2679970.
Material assessed	Scopus bibliographic record, abstract and available indexed metadata.
Evidential role	Abstract-based description of the AIWOM measure. The abstract identifies three components: AI-mediated, AI-generated and AI-personalized WOM.
Use in construct-boundary analysis	Comparison of those three components with the five AI roles in Section 5.4. The entry supports construct differentiation only; detailed methods, effect estimates and causal relationships are not inferred from this material.
Corpus status	Supplementary evidence identified by the 14 October 2026 terminology-sensitivity search. Outside the 142-publication bibliometric corpus, 54-paper focused corpus and 20-source analytical core.

Table S15. Targeted robustness check of the five non-selected Important studies

The check compared the reported findings of the five studies with the framework for conflicting outcome directions, additional moderators and construct-boundary implications. IDs match Table S3. The material assessed for this check is specified below; the comparison is limited to findings stated in those abstracts. All five studies remain outside the 20-source analytical core.

Study and material assessed	Relevant finding or qualification	Relationship to selected evidence	Effect on synthesis	Final decision
ID 2. The influence of eWOM. Analyzing its characteristics and consequences, and future research lines (2021) DOI: 10.1108/SJME-10-2020-0186 Material: Published abstract in the University of Zaragoza repository; screening record.	The review links message valence, relevance, understandability and visual cues to usefulness and intentions. It also identifies source credibility and receiver susceptibility to interpersonal influence as relevant to responses.	Overlaps the appraisal constructs in [37,43,47,48] and extends their interpretation to receiver susceptibility.	Retain receiver susceptibility when interpreting appraisal and persuasion. No change to the five AI roles follows from the abstract-level comparison.	Remain outside the core: background synthesis; retain receiver susceptibility as a qualification.

Study and material assessed	Relevant finding or qualification	Relationship to selected evidence	Effect on synthesis	Final decision
ID 16. Travel Recommendations of Tomorrow: Generative Artificial Intelligence and Travel Planning (2026) DOI: 10.1002/cb.70126 Material: Published abstract on Wiley and in the Scopus export; screening record.	GenAI recommendations reduce information overload but do not necessarily simplify decision-making. The abstract identifies trust and information retrieval skills as relevant to the recommendation–overload relationship.	Qualifies the translation of information benefits into decision outcomes in [40,41,43]; broader travel advice is adjacent to review communication.	Reduced information overload need not simplify decisions. Retain trust and information retrieval skills as reported contextual factors, without assigning an unreported direction to their effects.	Remain outside the core: review provenance is unspecified in the abstract; retain the decision-making qualification.
ID 17. ChatGPT and online service recovery: How potential customers react to managerial responses of negative reviews (2025) DOI: 10.1016/j.tourman.2024.105057 Material: Published abstract on ScienceDirect; screening record.	Participants did not clearly distinguish human from ChatGPT managerial responses or prefer one on content alone. Identifying the source produced less favourable reactions to ChatGPT responses, with authenticity and uncanniness reported as parallel mediators.	Converges with source-attribution findings in [36,47] and extends them to managerial service recovery and uncanniness.	Disclosure need not improve evaluations. Retain authenticity and uncanniness as reported mediators in managerial responses, without treating those responses as consumer WOM.	Remain outside the core: managerial responses are organizational communication; retain the contextual mechanisms.
ID 15. Asymmetry of AI-generated review summaries on review contribution: Evidence from TripAdvisor (2026) DOI: 10.1016/j.jhtm.2026.101522 Material: Published abstract on ScienceDirect; screening record.	AI-generated summaries increase review volume overall. Negative-review helpfulness attenuates this increase; positive-review helpfulness amplifies it only for non-luxury hotels. The asymmetry concerns helpfulness signals on positive versus negative reviews, not summary valence.	Conflicts with the direction of review-volume change in [34,35]; adds helpfulness-by-valence and hotel-segment qualifications.	Qualifies a general reduction claim; the feedback connection allows either direction. Regulatory fit supplies the source's interpretive lens. Abstract evidence does not establish it as a separately tested psychological mechanism.	Remain outside the core: qualifies outcome conditions rather than defining another AI role. Retain the conflict and moderators in Section 5.3.
ID 53. Dark side of generative AI in tourism: a stressor-strain-outcome perspective; using a mixed-methods approach (2026) DOI: 10.1080/02508281.2025.2503997 Material: Published abstract on Taylor & Francis; screening record.	Hallucinations, poor information quality and lack of empathy are associated with distrust and indirectly with negative eWOM. The abstract reports a moderating role for cognitive destination image in the distrust–negative-eWOM relationship.	Extends the treatment of trust and consumer outcomes with distrust, negative eWOM and destination image in a broader GenAI-use setting.	Retain cognitive destination image as a reported moderator of distrust and negative eWOM, without inferring its direction. This is not evidence that AI formulates the resulting consumer WOM.	Remain outside the core: eWOM is an outcome of GenAI use; retain the destination-image qualification.

Outcome: the abstract-level check identifies a conflicting direction of review contribution and additional contextual qualifications, now retained in Section 5.3. None of the reported findings requires a sixth AI role or reassignment of an existing role. The five studies remain outside the analytical core; this conclusion is limited to the findings reported in the assessed abstracts and does not constitute full-text verification. The 142 / 54 / 20 corpus structure is unchanged.