Journal of Business and Management Studies (JBMS)
ISSN: 2709-0876
DOI: 10.32996/jbms
Journal Homepage: www.al-kindipublisher.com/index.php/jbms

JBMS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| REVIEW ARTICLE

Artificial Intelligence in eWOM: Roles, Mechanisms, and an Integrative Framework

Aaron Joyal
Assistant Professor, Alfiero School of Business, Daemen University, Amherst, NY, United States
Corresponding Author: Aaron Joyal, **E-mail**: ajoyal@daemen.edu

| ABSTRACT
Artificial intelligence (AI) is changing electronic word-of-mouth by participating directly in the production, revision, circulation, evaluation, and governance of consumer information. This systematic literature review synthesizes 71 peer-reviewed studies on how AI functions within electronic word-of-mouth (eWOM), how consumers respond to those roles, and when those effects vary. Using SPAR-4-SLR and PRISMA 2020 procedures, the review draws on database, supplemental, and citation-based searches. It identifies five recurring AI roles -- Creator, Co-Creator, Curator, Intermediary, and Regulator -- and shows that their effects depend largely on perceptions of authenticity, credibility, usefulness, humanness, transparency, and manipulation risk. These effects are context dependent, varying across products, tasks, message formats, consumer orientations toward AI, levels of AI involvement, and platform environments. The review also argues that AI reshapes not only how eWOM is presented, but also what consumers are likely to contribute afterward. Building on these findings, the review proposes an AI-enabled lifecycle of Creation, Transformation, Transmission, Evaluation, and Governance and develops an AI-eWOM fit perspective. A TCCM-organized research agenda identifies priorities for future research.

| KEYWORDS

electronic word-of-mouth; eWOM; artificial intelligence; generative AI; online reviews; systematic literature review; AI-eWOM fit

| ARTICLE INFORMATION
ACCEPTED: 18 July 2026 **PUBLISHED:** 22 August 2026 **DOI:** 10.32996/jbms.2026.8.9.10

1. Introduction
Electronic word-of-mouth (eWOM) has become integral to consumer decision making because digital platforms allow marketplace experiences and evaluations to be created, distributed, and accessed at unprecedented scale. Babić Rosario et al. (2016) demonstrated the importance of eWOM for marketplace outcomes and research by Cheung et al. (2012) and Filieri (2015) emphasized the roles of credibility, usefulness, and information adoption. More broadly, Babić Rosario et al. (2020) conceptualize eWOM as a communication process involving the creation, exposure, and evaluation of consumer-generated information.

Artificial intelligence changes that conceptualization because consumer experience, message expression, transmission, and evaluation no longer need to be performed exclusively by people. Instead, AI can independently generate review-like content, assist consumers in expressing genuine experiences, summarize collections of existing reviews, conversationally communicate recommendations, and identify synthetic or manipulated content. Thus, emerging concepts such as algorithmic word-of-mouth (WOM), word-of-machine, synthetic WOM, and AI-WOM reflect this expanding participation of automated systems in marketplace communication (Williams et al., 2020; Longoni & Cian, 2022; Mladenović et al., 2024; Tassiello et al., 2025).

In addition, a simple human-versus-AI distinction does not fully capture the effects: For example, Amos and Zhang (2024) documented authenticity and trust penalties for AI-generated reviews and Drozd and Söllen (2026) demonstrated that consumers distinguish AI assistance from full AI generation. Conversely, Bian and Che (2025) found that AI-generated review overviews can increase usefulness through diagnosticity, and Feng et al. (2025) showed that machine communication becomes more effective when its informational strengths fit the decision task. AI involvement varies not only in degree but also in function.

Existing reviews, such as Donthu et al. (2021) -- who mapped the broader development of eWOM research -- and Ben Jabeur et al. (2023) -- who examined AI applications in fake-review detection address parts of this shift -- do not yet integrate all of the functions. More recent reviews address ChatGPT and consumer reviews, generative AI and eWOM, and AI developments in hospitality-review research (Ishak et al., 2026; Tao et al., 2026; Singh & Mittal, 2026). Therefore, the remaining gap is an integrative framework that explains the distinct roles AI performs across the eWOM process, the mechanisms through which those roles affect consumers, and the conditions under which their effects change.

To address that, this review proposes three research questions:

RQ1: What distinct functional roles does AI perform within the eWOM process?

RQ2: Through which cross-cutting mechanisms and boundary conditions does AI involvement influence consumer responses and eWOM outcomes?

RQ3: How can these roles, mechanisms, and boundary conditions be integrated into a framework explaining the evolving structure of AI-enabled eWOM?

Synthesizing 71 peer-reviewed studies, this review makes four contributions. First, it identifies five functional AI roles: Creator, Co-Creator, Curator, Intermediary, and Regulator. Second, it develops an AI-eWOM fit perspective in which outcomes depend on alignment among AI role, task requirements, message characteristics, consumer orientations, and the surrounding information environment. Third, it extends the traditional Creation -> Exposure -> Evaluation architecture into an AI-enabled lifecycle of Creation -> Transformation -> Transmission -> Evaluation -> Governance. Finally, evidence from Gu and Spann (2026), Deng et al. (2026), Li and Bang (2026), and Li and Zhang (2026) is used to show that AI interventions can alter subsequent review production, making the lifecycle recursive. The result is a view of AI-enabled eWOM as a developing human-AI information ecosystem.

2. Conceptual Background

2.1 Traditional eWOM and the AI Disruption

eWOM extends interpersonal WOM into digital environments in which consumer opinions can be created, distributed, retained, and accessed beyond the temporal and geographic limits of face-to-face communication (Hennig-Thurau et al., 2004) and prior research has established the importance of credibility, helpfulness, diagnosticity, and other information characteristics in shaping consumer responses to eWOM (Cheung et al., 2012; Filieri, 2015; Mudambi & Schuff, 2010).

As the literature developed, eWOM came to be understood as a communication process, not simply a collection of online reviews. More specifically, Babić Rosario et al. (2020) conceptualized this process around creation, exposure, and evaluation: that is, consumers create marketplace information, other consumers encounter that information, and then recipients subsequently interpret and respond to it. This framework remains useful, but it implicitly assumes that the underlying marketplace expression originates with people.

The rise of artificial intelligence (AI) has weakened that assumption: Earlier research showed that consumers can display either algorithm aversion or algorithm appreciation depending on perceived capabilities and task requirements (Dietvorst et al., 2015; Logg et al., 2019; Castelo et al., 2019). However, generative AI creates a more fundamental disruption because it can now participate directly in activities traditionally performed by eWOM actors. AI can generate consumer-facing text, rewrite human reviews, summarize collections of evaluations, communicate recommendations, and detect synthetic content (Amos & Zhang, 2024; Bian & Che, 2025; Mladenović et al., 2024; Xylogiannopoulos et al., 2024).

Thus, there is a useful distinction between AI applied to eWOM and AI participating in eWOM. In the former, AI functions primarily as a back-end analytical tool, such as for sentiment classification or topic extraction. In the latter, AI becomes part of the communication process itself by producing, modifying, summarizing, transmitting, or governing consumer-facing information. This leads to the theoretical question of how AI changes the relationship among consumer experience, message expression, transmission, and reception.

2.2 From Human Authorship to Role-Based AI Participation

AI-enabled eWOM makes the boundary between human and machine authorship less clear. Existing terms, such as algorithmic WOM, word-of-machine, synthetic WOM, and AI-WOM, each reflect different forms of machine participation in marketplace communication (Williams et al., 2020; Longoni & Cian, 2022; Mladenović et al., 2024; Tassiello et al., 2025) but none fully captures the range of roles AI now plays.

Generative AI further separates experiential origin from expressive authorship. A consumer may supply the underlying experience, with AI correcting grammar, changing tone, restructuring the message, paraphrasing their text, or even generating the entire narrative from human-provided information. Drozd and Söllen (2026) and Kim and Lee (2026) documented different consumer responses to AI-assisted and fully AI-generated reviews, underscoring the theoretical importance of distinguishing augmentation from replacement. Additionally, Xylogiannopoulos et al. (2024) illustrated how AI paraphrasing can transform human-originated content and make its provenance more difficult to identify.

It also should be noted that authorship alone does not capture the full range of AI involvement: Bian and Che (2025) examined AI transforming collections of reviews through summarization, Ma, Huang, et al. (2026) looked at AI transmitting and personalizing WOM, and Santos and Antonio (2025) explored AI governing synthetic content. Each of those functions raise a different theoretical problem involving authorship, representational fidelity, adaptive transmission, and information integrity.

For that reason, this review classifies AI according to its primary functional contribution and identifies five roles: Creator, Co-Creator, Curator, Intermediary, and Regulator. These roles provide the foundation for the role-based synthesis and integrative framework developed below.

3. Methodology

3.1 Review Design and Search Strategy

This study uses a systematic literature review to synthesize research on how AI acts as a substantive participant in electronic word-of-mouth. The review follows the SPAR-4-SLR protocol developed by Paul et al. (2021) and the PRISMA 2020 reporting framework of Page et al. (2021). The goal is an integrative, role-based synthesis focused on what AI does, how those functions affect eWOM outcomes, and the conditions shaping those effects.

Four databases -- Business Source Premier, ABI/INFORM Complete, Academic Search Complete, and ProQuest Research Library -- were searched from inception through August 1, 2026 and results were limited to peer-reviewed, English-language records. The search strategy combined two concept blocks: one covering AI terms (generative AI, ChatGPT/GPT, large language models, AI-generated and AI-assisted content, and machine- or computer-generated text) and one covering eWOM terms (electronic word-of-mouth, online and consumer reviews, product and service reviews, fake reviews, and review summaries) and the syntax for each database was adjusted as needed without changing the underlying structure. The four searches returned 347 records before deduplication, which was performed using DOI matching followed by normalized-title and metadata comparison for records without matching DOIs.

Because terminology in AI-enabled eWOM remains fragmented, the formal search was supplemented with backward and forward citation searching and a second database search to capture older studies using terminology underrepresented in the initial search. Citation tracing focused on specific topics: AI-generated and AI-assisted reviews, AI-generated review summaries, AI-WOM, algorithmic WOM, synthetic WOM, word-of-machine, and AI-generated fake-review detection and this process contributed 43 eligible studies.

Finally, a supplemental search was run across the same four databases with expanded terminology, retrieving 207 raw records: 110 from Business Source Premier, 51 from ABI/INFORM Complete, 24 from Academic Search Complete, and 22 from ProQuest Research Library. Algorithmic deduplication left 147 unique records, and removing one metadata duplicate brought the count to 146. Of those, 19 were already accounted for -- eight from the original database search, 10 from citation searching, and one known background article -- leaving 127 genuinely new records for title and abstract screening. All but one were excluded at screening; the remaining study passed full-text assessment and was included in the review.

The exact Boolean search strings used for the original and supplemental database searches are provided in Appendix A1.

3.2 Eligibility and Study Selection

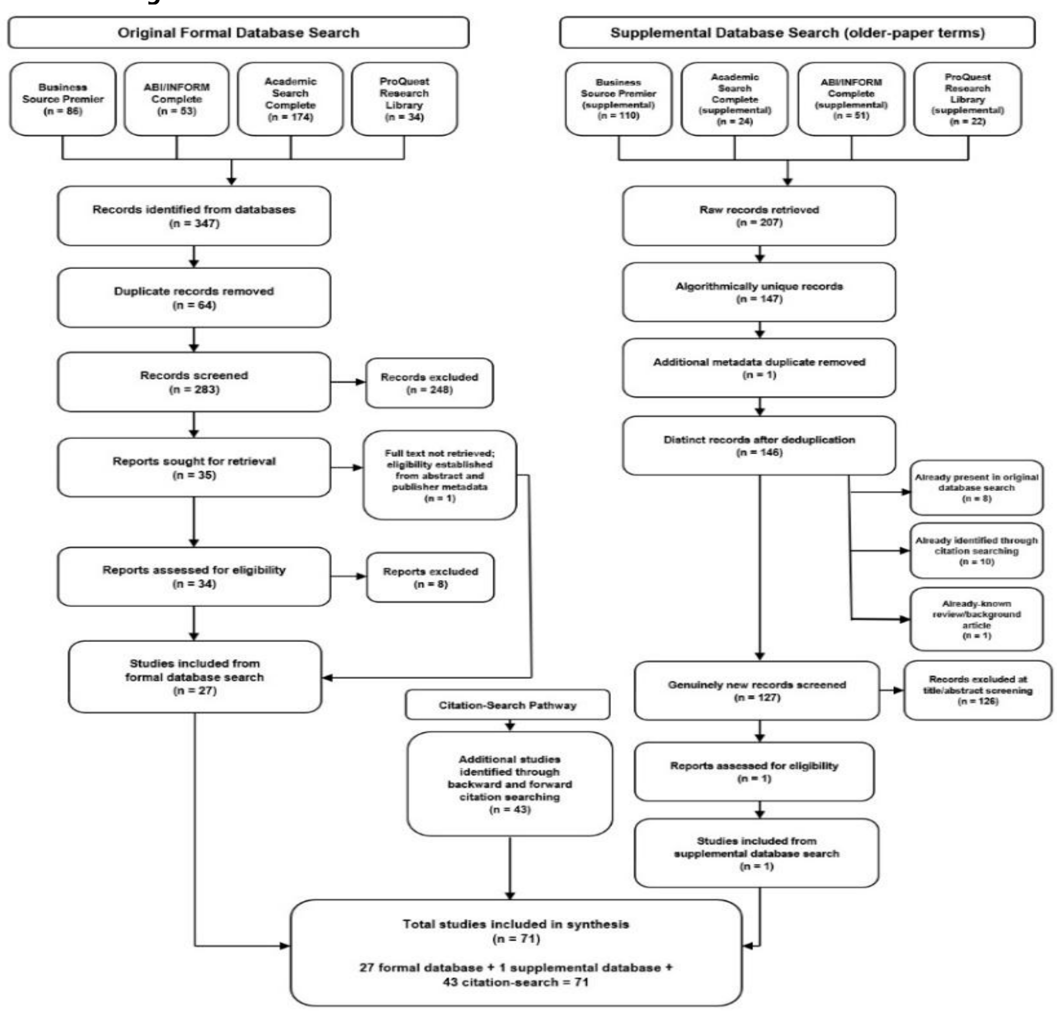
Studies were deemed to be eligible if they were peer-reviewed journal articles directly examining AI involvement in consumer eWOM, online reviews, or closely related AI-mediated WOM communication. Eligible studies included research in which AI generated review content; assisted with editing, paraphrasing, or structuring human-originated reviews; summarized or transformed existing reviews; transmitted or conversationally communicated WOM; or detected, labeled, authenticated, or otherwise governed AI-generated or manipulated content.

Studies were excluded when AI served only as a back-end analytical technique applied to existing reviews, when WOM appeared only as a downstream outcome of general chatbot or AI adoption, or when the focal communication involved advertising, customer service, firm-generated responses, or contexts outside consumer WOM. In addition, generic fake-review detection studies were included only if they specifically addressed AI-generated or AI-manipulated content.

After removal of 64 duplicates, 283 unique records from the original database search underwent title and abstract screening and 248 were excluded. Thirty-five reports were sought for retrieval; one could not be obtained, leaving 34 for full-text assessment. Eight were excluded, resulting in 26 eligible full-text studies. The unretrieved report was retained using abstract-level evidence because eligibility could be established unambiguously from the abstract and publisher metadata, yielding 27 studies from the original formal database pathway. In addition, the supplemental database search contributed an additional eligible study after 127 genuinely new records were screened, while backward and forward citation searching contributed 43 studies. Thus, the final synthesis included 71 studies: 27 from the original database search, one from the supplemental database search, and 43 from citation searching.

All screening and eligibility decisions were conducted by a single reviewer, who applied the prespecified inclusion and exclusion criteria consistently across the title-and-abstract and full-text screening stages. Records presenting ambiguous eligibility were re-examined against the stated criteria before a final inclusion decision was made. Because screening was conducted by one reviewer, interrater agreement statistics are not applicable. Figure 1 presents the complete study-identification and selection process.

Figure 1. PRISMA Flow Diagram for Identification and Selection of AI-Enabled eWOM Studies



Full articles or corresponding author manuscripts were available for 59 studies (83.1%). Twelve studies (16.9%) were retained using abstract-only evidence when eligibility could be established unambiguously from the abstract and publisher metadata. For these studies, coding was restricted to information explicitly reported; unreported theories, methodological characteristics, and findings were not inferred.

3.3 Data Extraction and Synthesis

A structured evidence matrix captured bibliographic information, publication year, eWOM form, research context, theoretical perspective, method, sample or data source, focal variables, mechanisms, moderators, outcomes, principal findings, and evidence basis. Data extraction, functional-role classification, and thematic coding were conducted by the same reviewer using the predefined evidence-matrix fields and role definitions described below.

Studies were then classified according to the primary functional role performed by AI. Specifically, the Creator role refers to AI-generated consumer-facing WOM; the Co-Creator role to AI assistance in shaping human-originated reviews; the Curator role to AI aggregation or summarization of existing reviews; the Intermediary role to AI systems that personalized, recommended, or communicated WOM; and the Regulator role to systems that detected, authenticated, labeled, filtered, or otherwise governed eWOM integrity. Secondary roles were recorded when studies crossed functional categories. If a study involved multiple AI functions, the primary role was assigned according to the AI function most directly aligned with the study's focal research question, manipulation, or principal outcome and additional functions were recorded as a secondary role(s).

The synthesis proceeded in two stages: First, the corpus was descriptively mapped by publication year, AI role, evidence basis, inclusion pathway, research context, and methodological approach. Second, the findings were compared within and across roles to identify recurring mechanisms and boundary conditions and the resulting analyses provided the basis for the subsequent integrative synthesis and Theory-Context-Characteristics-Methodology (TCCM)-organized future research agenda (Paul & Rosado-Serrano, 2019).

As a sensitivity analysis, the synthesis was re-examined after excluding the 12 studies for which only abstract-level evidence was available. The resulting 59-study full-text/manuscript corpus retained all five functional AI roles (Curator, n = 16; Creator, n = 15; Intermediary, n = 10; Regulator, n = 11; Co-Creator, n = 7) and all six cross-cutting mechanism categories identified in the full synthesis. Excluding abstract-only studies therefore did not alter the role taxonomy or the principal mechanism-level conclusions of the review; studies included in the final review corpus are identified with an asterisk in the reference list.

4. Results: Descriptive Mapping of the Literature

4.1 Characteristics of the Final Corpus

The final synthesis included 71 studies, of which 59 (83.1%) were assessed using full articles or corresponding manuscripts and 12 (16.9%) using abstract-only evidence. Notably, the vast majority of the literature is very recent: 20 studies (28.2%) were published in 2025 and 38 (53.5%) in 2026, meaning that 81.7% of the corpus appeared in 2025 or 2026. Complete descriptive characteristics of the review corpus are reported in Appendix Table A2.

4.2 Functional, Contextual, and Methodological Patterns

AI participation extended well beyond synthetic review generation. Specifically, Creator and Curator were the largest functional categories, with 18 studies each (25.4%), followed by Intermediary (n = 14, 19.7%), Regulator (n = 13, 18.3%), and Co-Creator (n = 8, 11.3%). In other words, 74.6% of the studies examined AI primarily in a role other than Creator, which reinforces the need for a broader functional perspective on AI-enabled eWOM.

Research was concentrated in general or cross-context online reviews (n = 30), e-commerce/retail (n = 19), and tourism/hospitality (n = 18). Methodologically, experimental consumer research (n = 18), computational/text analytics (n = 18), and mixed methods (n = 13) dominated the corpus. The methodological profile also varied by role: Regulator research was overwhelmingly computational; by contrast, Creator, Co-Creator, and Curator research each were more behaviorally oriented. These patterns set up the role-based thematic synthesis that follows.

5. Thematic Synthesis of AI Roles in eWOM

The thematic synthesis identifies five recurring functions through which artificial intelligence participates in eWOM: Creator, Co-Creator, Curator, Intermediary, and Regulator. These roles are classified by what AI does within the communication process, not by the specific technology employed. As previously noted, they are analytical categories that may overlap; a single system may perform several roles across the eWOM lifecycle. Table 1 summarizes the primary function and central theoretical issue associated with each role.

Table 1. Functional Roles of AI in the eWOM Lifecycle

Role / Lifecycle	Function and Central Issue	Representative Studies
Creator -- Creation	Generates consumer-facing WOM. Experiential provenance: AI can produce persuasive reviews without possessing the underlying consumption experience.	Amos & Zhang (2024); Kovács (2024); Mao et al. (2026)
Co-Creator -- Creation/Transformation	Assists human expression. Experiential vs. expressive authorship: improves expression while creating ambiguity about authorship and provenance.	Drozd & Söllen (2026); Gu & Spann (2026); Kim & Lee (2026)
Curator -- Transformation	Summarizes or reorganizes existing reviews. Efficiency-fidelity tradeoff: reduces overload but may omit or distort collective opinion.	Bian & Che (2025); Chai et al. (2026); Luo, Liu, et al. (2026)
Intermediary -- Transmission	Recommends or communicates WOM. Source-task fit: effectiveness depends on alignment between AI capabilities and decision requirements.	Feng et al. (2025); Longoni & Cian (2022); Ma, Zhang, et al. (2026)
Regulator -- Governance	Detects or governs synthetic/manipulated eWOM. Adaptive governance: detection must adapt across generators, domains, and manipulation strategies.	Narayan et al. (2026); Santos & Antonio (2025); Zhao et al. (2025)

5.1 AI as Creator

The Creator role refers to AI systems that generate substantive consumer-facing reviews or WOM content instead of merely assisting with human expression. Its central theoretical problem is experiential provenance: AI can produce fluent and persuasive review-like communication without having consumed the product or service being evaluated. Kovács (2024) documented frequent misidentification of GPT-4-generated reviews as human; Sands et al. (2026) similarly observed that contemporary AI-generated reviews can be difficult to distinguish from human-authored content. This can cause issues, because when readers discover that reviews were written with AI, Amos and Zhang (2024) showed that perceived authenticity, trustworthiness, and usefulness decrease. Further, Mao et al. (2026) linked even suspected AI authorship to reduced helpfulness through diminished authenticity.

That said, the penalties are not uniform across the literature. For example, Cheng et al. (2025) reported no significant human-AI differences in review credibility, richness, or usefulness but Lu et al. (2025) observed that negative AI-generated reviews could increase credibility and reduce perceived risk. Product characteristics matter as well: Yu et al. (2026) documented stronger effects of AI reviews for search than experience products. Overall, Creator studies suggest that AI performs better when consumers value analytical information more than experiential testimony. At the same time, synthetic content creates governance problems: Salminen et al. (2022) were able to generate convincing fake reviews and Zhao et al. (2025) showed that there were systematic differences among authentic, human-fake, and AI-generated fake reviews. Thus, this connects the production of synthetic eWOM directly to later questions of authentication and governance.

5.2 AI as Co-Creator

The Co-Creator role occurs when a genuine human experience or evaluation remains the informational foundation of eWOM and AI helps produce its final expression. In this role, AI might edit, paraphrase, structure, expand, or even rewrite a consumer's contribution, making authorship a continuum instead of a binary human-versus-machine condition. With respect to this role, Drozd and Söllen (2026) observed stronger authenticity and trust penalties for fully AI-generated than AI-assisted reviews and Kim and Lee (2026) found that human-centered collaboration preserved authenticity more effectively than AI-centered authorship. However, AI assistance instead of AI creation does not completely eliminate provenance concerns: Zhong and Ha (2026) demonstrated that AI-assisted labels are perceived to be lower in trustworthiness, resulting in lower purchase intention.

However, co-creation can help consumers express their experiences more fully. For instance, Pandey and Singh (2025) generated detailed review narratives from human-supplied aspect evaluations and reported strong readability, relevance, and informativeness. More importantly, Gu and Spann (2026) documented increases in review volume and length alongside changes in subjectivity and sentiment extremity when generative AI was available. AI assistance might therefore affect not only how consumers express experiences, but also whether they contribute and how much they say. That said, this capability can be misused: Xylogiannopoulos et al. (2024) demonstrated AI's ability to paraphrase human reviews at scale, and their further research on the topic documented how paraphrasing could be used to help disguise manipulated reviews (Xylogiannopoulos et al., 2025). The key distinction of this role is that co-creation separates experiential origin from expressive authorship, bringing both participation benefits and new provenance challenges.

5.3 AI as Curator

The Curator role involves summarizing, aggregating, organizing, or reframing collections of existing consumer reviews. Its principal advantage is a reduced information overload for the user, but curation creates an efficiency-fidelity tradeoff because summarization necessarily determines which consumer experiences are emphasized and which are omitted. This role can be highly useful, as Bian and Che (2025) linked AI-generated review overviews to greater usefulness through diagnosticity, particularly among consumers lower in need for cognition. Further, Jia et al. (2026) identified credibility and helpfulness as central to adoption of AI-generated summaries.

The effectiveness of AI curation depends on how accurately and appropriately collective opinion is represented. Demonstrating this, Jia et al. (2025) observed an initial trust advantage for human-generated hotel summaries and Chai et al. (2026) identified conditions under which AI-generated summaries produced greater perceived objectivity and trust. Additionally, representational inconsistency can be particularly damaging: Luo, Liu, et al. (2026) associated disagreement between an AI summary and aggregate ratings with lower trust; Cai et al. (2026) noted that consumers valued reduced search effort but worried about omitted information. Further, Y. Wang et al. (2026) documented that positively biased summaries could raise expectations and reduce later decision satisfaction. Interestingly, curation can also reshape future eWOM: Deng et al. (2026) identified increased contribution intentions under some conditions; Li and Bang (2026) observed reduced review volume after the introduction of AI summaries, and Li and Zhang (2026) documented reduced sentiment intensity in later reviews. Curation therefore affects not only the information consumers see now, but also the environment in which later eWOM is produced.

5.4 AI as Intermediary

The Intermediary role refers to AI systems that actively recommend, personalize, interpret, or conversationally communicate WOM to consumers. The dominant pattern in research in this area is source-task fit. For example, Longoni and Cian (2022) documented greater receptivity to machine recommendations for utilitarian attributes but stronger preferences for human recommendations when hedonic attributes were important across nine separate studies. Feng et al. (2025) similarly observed that virtual WOM senders are more effective with numerical than experiential information, particularly for search products. Thus, AI appears strongest in this role when its perceived analytical capabilities match the informational demands of the task.

It must be noted that interaction and personalization can complicate this relationship. Ma, Zhang, et al. (2026) identified a preference for unidirectional AI-WOM for utilitarian products but interactive AI-WOM for hedonic products, with functional trust explaining the former effect and human-like trust the latter. Sun et al. (2026) likewise found that informational persuasion could be particularly effective for AI travel recommenders and Pham Thi Phuong et al. (2026) showed that responsiveness, personalization, conversational tone, and anthropomorphism are related to stronger emotional resonance. However, these social capabilities have limits: Nguyen and Dang (2026) documented irritation, distrust, and perceived manipulation when AI communication was excessively polished or contextually inappropriate. This indicates that the pattern is more nuanced than "more human is better": AI communication appears to be most effective when it is responsive and personalized without becoming intrusive or implausibly human-like.

5.5 AI as Regulator

The Regulator role encompasses systems that detect, authenticate, classify, label, and/or filter AI-generated and manipulated eWOM and this role responds directly to the provenance problems created by more capable generative systems. Specific to this role, human judgment appears insufficient on its own. For example, Santos and Antonio (2025) showed that while humans were only about 60.5% accurate when distinguishing between AI-generated and genuine hotel reviews, machine-learning could be as much as 94.63% accurate. Further, Luo, Nan, et al. (2026) documented strong performance using interpretable linguistic and probabilistic features.

Even so, reliable AI detection remains difficult: Zhao et al. (2025) and Markowitz et al. (2024) both identified some linguistic differences between AI-generated and human reviews, but Narayan et al. (2026) reported that detection accuracy depended strongly on how the synthetic content was generated. AI-assisted paraphrasing weakens generalizability, as demonstrated by AlQadi et al. (2025) and Xylogiannopoulos et al. (2025); He and You (2026) extended the problem to multimodal synthetic eWOM. Finally, Nawara and Kashef (2025) illustrated the resulting generator-detector arms race, in which improvements in synthetic-content generation continually create new challenges for authentication. Because of this, governance should be viewed as an ongoing capability that must adapt to new generators, domains, manipulation techniques, and content forms rather than as a one-time classification solution.

6. Cross-Cutting Mechanisms and Boundary Conditions

Across the five AI roles, the same psychological and informational processes appear repeatedly. Although AI enters eWOM through different functions, consumer responses depend on authenticity and provenance, credibility and trust, diagnosticity and cognitive efficiency, perceived humanness and agency, transparency and disclosure, and risk or manipulation. The importance of these mechanisms can vary by role, but together they explain why similar AI interventions can produce favorable responses in one setting but unfavorable responses in another.

6.1 Cross-Cutting Mechanisms

Authenticity and provenance are especially important when AI involvement changes the perceived connection between consumer experience and message expression. This is shown in research by Amos and Zhang (2024), who observed lower authenticity and trust for AI-generated reviews. Further, Mao et al. (2026) linked suspected AI authorship to lower perceived levels of helpfulness. On the other hand, investigations by Drozd and Söllen (2026) and Kim and Lee (2026) both documented weaker penalties when AI assistance was used than for when it completely replaced a human author. Therefore, the central issue is not simply whether AI participated in creating the message, but whether consumers believe a genuine human experience remains the foundation of the communication.

In addition, credibility and trust recur across all five roles, although the object of trust differs. Consumers may trust the review, the AI system, the platform, or the human contributor underlying the output. Further, Jia et al. (2025) identified differences in trust between human- and AI-generated summaries while Ma, Zhang, et al. (2026) distinguished functional trust from human-like trust in AI-mediated WOM. In Regulator settings, the role of trust shifts: it instead concerns whether an automated system can reliably identify synthetic content. More specifically, what changes across roles is the object of trust, not its importance to reliance on AI-enabled eWOM.

AI also creates value through diagnosticity, helpfulness, and cognitive efficiency. This was shown both by Bian and Che (2025), who linked AI review overviews to increased usefulness through diagnosticity, and by Alkhofaily and Noureldin (2026), who demonstrated how transparent summaries result in higher trust and diagnosticity. It should be noted, however, that efficiency does not guarantee decision quality: Research by Y. Wang et al. (2026) indicated that communication that was more efficient due to AI usage required lower processing demands but had poorer outcomes as the AI summaries biased consumer expectations.

Interestingly, some evidence suggests that more human-like communication is not always better. Longoni and Cian (2022) and Feng et al. (2025) both reported advantages for machine-like, analytical communication in objective settings while Pham Thi Phuong et al. (2026) identified benefits from responsiveness and anthropomorphic cues in situations where social interaction mattered. Additionally, Nguyen and Dang (2026) demonstrated that readers have concerns about inauthenticity and manipulation when AI communications are excessively polished.

Transparency and risk also heavily depend on how AI involvement is presented. For example, Liu et al. (2026) observed that when AI-authorship was disclosed, credibility and perceived usefulness both decreased. In contrast, Alkhofaily and Noureldin (2026) showed that there are positive effects from explaining how AI produced a summary. More specifically, these studies point to a useful distinction between source transparency, which identifies AI participation, and process transparency, which explains how an AI output was produced. Ethical concerns, privacy, and perceived manipulation further influence responses to AI communication, as shown by Cheng et al. (2025) and Ma, Zhang, et al. (2026).

6.2 Boundary Conditions and AI-eWOM Fit

These mechanisms operate differently depending on the product and task type, the message characteristics, the level of transparency and disclosure, the consumer's AI orientation, the degree and form of their AI involvement, and the surrounding platform information environment. Product type is especially consequential: Longoni and Cian (2022) showed that there is a stronger receptivity to AI recommendations for utilitarian products while Yu et al. (2026) reported stronger AI-review effects for search products over experience products. Additionally, Mao et al. (2026) observed stronger penalties from suspected AI authorship for experiential information about products.

Further, message format, consumer orientation, and degree of AI participation all shape these relationships. For example, Feng et al. (2025) identified that numerical communication is particularly effective for virtual WOM senders while research by Bian and Che (2025) indicated that there are larger benefits from AI summaries with consumers lower in need for cognition. Investigations by both Drozd and Söllen (2026) and Kim and Lee (2026) showed that there are consumer distinctions between assistance and full generation; meanwhile, Ma, Huang, et al. (2026) indicated that greater personalization of AI messages does not necessarily produce higher levels of adoption by consumers. Platform context also matters, primarily because AI outputs must coexist with human reviews and ratings: Luo, Liu, et al. (2026) linked summary-rating inconsistency to lower trust while Li and Bang (2026) and Deng et al. (2026) both reported that AI summaries can alter subsequent review contributions.

In short, across all of these studies, AI effects appear to depend on how well the function performed by AI fits the broader eWOM context. Table 2 summarizes the cross-cutting mechanisms and boundary conditions identified across the reviewed literature and that pattern provides the basis for the AI-eWOM fit perspective developed below.

Table 2. Cross-Cutting Mechanisms and Boundary Conditions in AI-Enabled eWOM

Factor	General Pattern	Representative Studies
MECHANISMS		
Authenticity / provenance	AI authorship can reduce authenticity; assistance is generally penalized less than full generation.	Amos & Zhang (2024); Drozd & Söllen (2026); Mao et al. (2026)
Credibility / trust	Reliance on AI-enabled eWOM increases with perceived capability, consistency, diagnosticity, and fit.	Jia et al. (2025); Luo, Liu, et al. (2026); Ma, Zhang, et al. (2026)
Diagnosticity / efficiency	AI can reduce processing effort and increase usefulness, but information loss may offset these benefits.	Bian & Che (2025); Y. Wang et al. (2026)
Humanness / agency	Human-like cues can improve social fit but may become inauthentic, intrusive, or manipulative.	Ma, Zhang, et al. (2026); Nguyen & Dang (2026)
Transparency / disclosure	Authorship disclosure may reduce authenticity, whereas process explanations can improve trust and diagnosticity.	Alkhofaily & Noureldin (2026); Liu et al. (2026)
Risk / manipulation	Privacy, deception, manipulation, and ethical concerns generally reduce trust and adoption.	Cheng et al. (2025); Nguyen & Dang (2026)
BOUNDARY CONDITIONS		
Product / task type	AI tends to fit search/utilitarian tasks better than experience/hedonic decisions.	Longoni & Cian (2022); Yu et al. (2026)
Message characteristics	Valence, format, specificity, tone, and presentation can alter AI effects.	Feng et al. (2025); Jia et al. (2025); Lu et al. (2025)
Disclosure design	Effects depend on what is disclosed, how it is framed, and whether disclosure concerns source or process.	Liu et al. (2026); Zhong & Ha (2026)
Consumer AI orientation	AI attitudes, cognition, trust, innovativeness, and privacy concerns shape reliance on AI information.	Bian & Che (2025); Cheng et al. (2025)
Degree / form of AI involvement	Responses vary across assistance, generation, summarization, personalization, and interaction.	Drozd & Söllen (2026); Kim & Lee (2026); Ma, Zhang, et al. (2026); Ma, Huang, et al. (2026)
Platform environment	Reviews, ratings, volume, placement, and platform design can strengthen, weaken, or reverse AI effects.	Deng et al. (2026); Li & Bang (2026); Luo, Liu, et al. (2026)

Note: Mechanisms explain how AI influences consumer responses; boundary conditions identify when, where, or for whom those effects change.

7. Integrative Framework

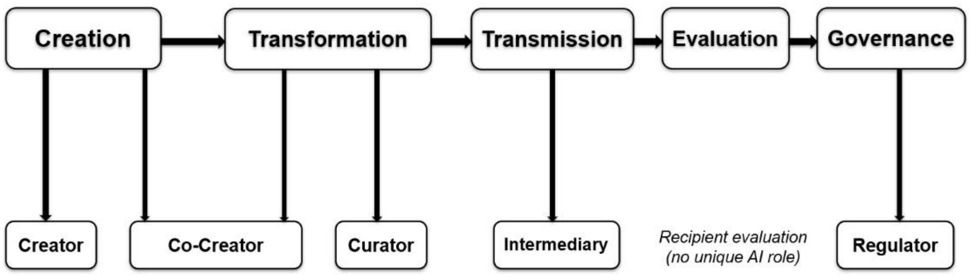
The synthesis shows that artificial intelligence can enter electronic word-of-mouth at several points and perform different functions. For example, AI can generate consumer-facing content, can reshape human expression, can summarize collective opinion, can communicate recommendations, and can govern the authenticity of the resulting information environment. Therefore, building on the traditional Creation -> Exposure -> Evaluation architecture identified by Babić Rosario et al. (2020), this review proposes an expanded AI-enabled lifecycle of Creation -> Transformation -> Transmission -> Evaluation -> Governance.

7.1 The AI-Enabled eWOM Lifecycle

Within this lifecycle, Creation concerns the origination of marketplace communication, whether by consumers, AI, or a combination of the two. Transformation captures changes made after initial creation, including AI-assisted rewriting and AI-generated summarization. Transmission reflects AI's active role in selecting, personalizing, and conversationally communicating WOM beyond just exposing consumers to static information. Evaluation encompasses the authenticity, credibility, trust, diagnosticity, and risk judgments that consumers must make when encountering AI-enabled eWOM; and finally Governance includes the detection, authentication, labeling, and filtering of synthetic or manipulated content. As shown below, unlike the other lifecycle stages, Evaluation represents a recipient-level interpretive process and therefore does not correspond to a unique AI functional role in the taxonomy.

The expanded lifecycle captures the fact that AI can alter consumer information after its initial creation, actively shape its transmission, and subsequently participate in governing its authenticity. Thus, these interventions make the information consumers encounter potentially different from the human communication from which it originated.
Figure 2 maps the five functional AI roles onto the expanded AI-enabled eWOM lifecycle.

Figure 2. Integrative Framework of AI Roles Across the eWOM Lifecycle



Note: Co-Creator spans both Creation and Transformation because AI can assist consumers in producing or refining their own eWOM, thereby participating in both the origination and modification of consumer-generated content.

7.2 AI-eWOM Fit and Recursive Feedback

A recurring tension runs through the lifecycle between human experiential legitimacy and machine informational capability. Human eWOM derives distinctive value from lived consumption experience while AI derives value from its capacity to aggregate, organize, compare, personalize, and communicate information efficiently. Research shows that neither advantage dominates universally: Longoni and Cian (2022) indicated that consumers had a stronger receptivity to AI recommendations when utilitarian product attributes were important, and Feng et al. (2025) found that virtual WOM senders are particularly effective with numerical communication. Conversely, Mao et al. (2026) observed that there are stronger penalties due to suspected AI authorship when experiential information is more important to the consumer.

The above findings support the principle of AI-eWOM fit: favorable outcomes are increasingly likely when the role performed by AI is congruent with the task requirements, the message form, the consumer's expectations, and the surrounding information environment. In practical terms, AI-eWOM fit reflects an alignment between the function performed by AI, the informational or experiential demands of the consumer's decision task, the form of the information, and the consumers' expectations regarding appropriate levels of human and machine participation. Fit should be higher when AI performs functions that capitalize on its strengths, such as aggregating data, providing comparisons, summarizing information, or making recommendations based on specific features. Further, fit should be lower when AI involvement conflicts with expectations, such as level of authenticity or desire for human feedback. When AI-eWOM fit is high, the consumer's trust, the perceived usefulness of the information, and the level of product adoption should be higher; when it is low, authenticity concerns, worries about manipulation, and consumer resistance should increase. Therefore, this perspective shifts the theoretical question from whether consumers generally prefer human or AI information to which allocation of human and machine capabilities best fits a particular eWOM context. Additionally, this makes hybrid arrangements especially relevant because they both preserve experiential legitimacy and can exploit AI's organizational and computational strengths. Along those lines, Li and Ha (2026) observed greater levels of consumer trust and decision confidence when human reviews were combined with AI-generated summaries.

It must be noted that the framework is recursive, not strictly linear. This is reflected in the research on this area, as Deng et al. (2026) found that AI summaries could increase later review intentions, Li and Bang (2026) observed a reduced level of reviews after AI summaries were introduced, and Li and Zhang (2026) identified lower sentiment intensity in subsequent reviews after encountering an AI review. In short, AI does not merely process a fixed supply of eWOM; instead, it reshapes the information environment from which future eWOM is created.

8. Future Research Agenda

The TCCM framework offers a practical way to organize priorities in AI-enabled eWOM research (Paul & Rosado-Serrano, 2019). Because the literature is both recent and fragmented across multiple AI roles, future research should move beyond asking whether consumers respond differently to human and AI information and instead explain which AI functions are effective, through which mechanisms, under what conditions, and with what longer-term consequences.

8.1 Theory
Theory should integrate findings across the five AI roles instead of treating AI-generated reviews, AI-assisted reviews, summaries, recommendations, and governance as separate domains. One research priority is a more precise theory of provenance: research conducted by Drozd and Söllen (2026) showed how consumers make distinctions between AI assistance and full AI generation while Xylogiannopoulos et al. (2024) demonstrated that AI can transform human-originated content without consumers necessarily perceiving the changes. Therefore, future research should distinguish between experiential, expressive, and representational provenance. A related priority is to test the proposed AI-eWOM fit perspective and model the recursive effects through which AI-generated outputs influence later human contributions. Evidence from Gu and Spann (2026) and Li and Zhang (2026) suggests that these feedback processes are already consequential, but further investigation is warranted.

8.2 Context
In addition, research should expand beyond the current concentration in general online reviews, e-commerce, retail, and tourism/hospitality. Exploring higher-risk and/or more personally consequential decisions may place greater weight on experiential provenance. Further, platform design may also alter how AI summaries, recommendations, and disclosures are interpreted by consumers. The contrasting contribution effects reported by Deng et al. (2026) and Li and Bang (2026) also illustrate the need for cross-platform research. Finally, cross-cultural and longitudinal studies are needed to determine whether authenticity penalties, privacy concerns, disclosure effects, and trust in AI change as generative AI becomes more familiar and socially normalized.

8.3 Characteristics
Future studies should treat AI involvement as a continuum, not a binary human-versus-AI condition. As discussed above, Kim and Lee (2026) and Drozd and Söllen (2026) document differences in consumer responses that depend on the degree and form of AI's involvement with the message. Transparency also deserves more precise treatment: Liu et al. (2026) report that AI authorship disclosure can reduce message credibility while Alkhofaily and Noureldin (2026) indicate that process transparency can actually increase trust and diagnosticity. Additional research should therefore examine disclosure content, timing, and framing separately. Personalization and anthropomorphism also warrant nonlinear tests because Ma, Huang, et al. (2026) and Nguyen and Dang (2026) suggest that greater AI sociality can eventually become intrusive or manipulative.

8.4 Methodology
More field, longitudinal, natural-experiment, and behavioral designs would strengthen the evidence base. Studies such as Gu and Spann (2026) and Li and Bang (2026) illustrate the value of observing actual consumer behavior instead of relying exclusively on their stated intentions. Combining methods would also make it easier to connect marketplace outcomes with the consumer processes behind them: For example, regulator research would require cross-model, cross-domain, and out-of-distribution validation because Narayan et al. (2026) report that AI detector performance can deteriorate when generation strategies change. Replication of this research will be especially important as AI models and consumer familiarity continue to change. Appendix Table A3 provides a consolidated summary of the principal research priorities and illustrative questions across the four TCCM dimensions.

9. Theoretical and Managerial Implications
9.1 Theoretical Implications
The clearest theoretical implication of this review is that AI participation in eWOM is better understood in terms of function rather than technology. Distinguishing the Creator, Co-Creator, Curator, Intermediary, and Regulator roles reveals that AI raises different theoretical problems depending on whether it originates, transforms, transmits, or governs consumer information. This distinction also separates experiential provenance from expressive authorship and representational fidelity, extending eWOM theory beyond the conventional source-based classifications.

The findings of this review also suggest that human and machine communication derive value from different sources: human-derived communication provides experiential legitimacy while AI-derived communication provides informational capability through aggregation, organization, personalization, and ability to scale. The resulting AI-eWOM fit perspective directs research away from generalized algorithm aversion or appreciation and toward various configurations of human and machine capabilities. Additionally, the evidence that AI interventions alter subsequent human contributions also suggests that the appropriate unit of analysis may be the human-AI information ecosystem, instead of the isolated review or consumer-message encounter.

9.2 Managerial Implications
For platforms and firms, the practical implication is straightforward: firms should deploy AI according to the function it performs, not as a generic technological feature. In addition, platforms should preserve visible human provenance anywhere eWOM derives value from a genuine consumption experience. As previously noted, Drozd and Söllen (2026) document consumer

distinctions between AI assistance and complete AI generation, suggesting that AI can support clarity, organization, translation, or accessibility without replacing the consumer as the perceived source of the evaluation.

Managers should also consider where human and AI contributions complement one another: Research shows this already occurs, with Li and Ha (2026) demonstrating that combining human reviews with AI-generated summaries can improve consumer trust and decision confidence. However, AI summaries should preserve access to underlying consumer information because Luo, Liu, et al. (2026) showed that summary-rating inconsistencies lower consumer trust. Transparency should also distinguish authorship disclosure from process explanation: Liu et al. (2026) identify potential costs of AI-authorship disclosure, but Alkhofaily and Noureldin (2026) find benefits from explaining how AI generated a summary.

Finally, AI interfaces should reflect task requirements rather than assume that more personalization or human-likeness is always better. This has been demonstrated in research by Ma, Zhang, et al. (2026), who reported that preferred interaction styles vary with product type. Further, Nguyen and Dang (2026) demonstrated that excessive human-likeness in AI can appear manipulative. Governance also needs to remain adaptive, as Narayan et al. (2026) reported that detection performance changes across generation strategies. Thus, platforms should evaluate AI not only through immediate usefulness or conversion but also through its longer-term effects on review volume, diversity, and information quality. The managerial objective is not to maximize AI participation, but to allocate human and machine functions where each provides the greatest value.

9.3 Limitations

The above findings should be interpreted with several limitations in mind. First, study screening, eligibility assessment, data extraction, and coding were conducted by a single reviewer. Although prespecified inclusion and exclusion criteria and structured evidence-matrix fields were used to promote consistency, the absence of independent coding means that reviewer judgment may have influenced study selection, functional-role classification, and thematic interpretation. Second, 12 of the 71 included studies were retained using abstract-only evidence because full articles or corresponding manuscripts were unavailable. Coding for these studies was restricted to information explicitly reported in abstracts and publisher metadata, but the absence of full-text evidence necessarily limited the depth with which their theoretical perspectives, methods, mechanisms, and findings could be assessed.

The search strategy that was employed also placed boundaries on the review’s conclusions: The database searches were restricted to peer-reviewed, English-language records and were conducted across Business Source Premier, ABI/INFORM Complete, Academic Search Complete, and ProQuest Research Library, supplemented by backward and forward citation searching and an additional search using alternative terminology. Thus, relevant studies published in other languages or indexed elsewhere may have been missed. A further limitation is the speed at which AI-enabled eWOM is developing: 58 of the 71 studies in the corpus were published in 2025 or 2026. The functional roles, mechanisms, and boundary conditions identified here therefore represent the literature at a rapidly evolving stage of development and should be revisited as new AI models, platform practices, consumer behaviors, and governance approaches emerge.

10. Conclusion

AI is moving eWOM away from a predominantly human-generated process and toward a human-AI information ecosystem. This review identifies five functional AI roles -- Creator, Co-Creator, Curator, Intermediary, and Regulator -- and situates them within an expanded lifecycle of Creation -> Transformation -> Transmission -> Evaluation -> Governance. Across these roles, consumer responses depend not on AI involvement alone but on AI-eWOM fit, or the alignment among the machine function, the task requirements, the message characteristics, the consumer’s expectations, and the surrounding information environment. As AI-generated and AI-transformed information begins to shape what consumers contribute next, future eWOM research will need to look beyond individual messages and responses to the broader interaction between human experiential legitimacy and machine informational capability.

Funding: This research received no external funding.
Conflicts of Interest: The author declares no conflict of interest.

References

Note: References marked with an asterisk indicate studies included in the systematic review corpus.

[1] *Alkhofaily, F., & Noureldin, A. (2026). How AI-Generated Review Summary Transparency Shapes Online Purchase Intention: The Dual Mediating Roles of Perceived Diagnosticity and Algorithm Trust. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2026.104911

[2] *AlQadi, R. A., Taie, S. A., Idrees, A. M., & Elhariri, E. (2025). Explainable Deep Learning Model for ChatGPT-Rephrased Fake Review Detection Using DistilBERT. *Big Data and Cognitive Computing*. https://doi.org/10.3390/bdcc9080205

[3] *Amos, C., & Zhang, L. (2024). Consumer Reactions to Perceived Undisclosed ChatGPT Usage in an Online Review Context. *Telematics and Informatics*. https://doi.org/10.1016/j.tele.2024.102163

[4] Babić Rosario, A., De Valck, K., & Sotgiu, F. (2020). Conceptualizing the Electronic Word-of-Mouth Process: What We Know and Need to Know About eWOM Creation, Exposure, and Evaluation. *Journal of the Academy of Marketing Science*. https://doi.org/10.1007/s11747-019-00706-1

[5] Babić Rosario, A., Sotgiu, F., De Valck, K., & Bijmolt, T. H. A. (2016). The Effect of Electronic Word of Mouth on Sales: A Meta-Analytic Review of Platform, Product, and Metric Factors. *Journal of Marketing Research*. https://doi.org/10.1509/jmr.14.0380

[6] *Balcı, M. A., Erdoğan, D. R., Akgüller, Ö., & Gaban, L. (2026). Detecting AI-Generated E-Commerce Reviews with Sheaf-Hypergraph Consensus Residuals: Interpretable Signals and Cross-Domain Asymmetry. *Applied Sciences*. https://doi.org/10.3390/app16147071

[7] *Barbu, A. M., Popa, I.-C., Florescu, M. S., Chivu (Popa), R.-G., Crețu, A. I., & Chenic, A. Ș. (2025). Generational Differences in Perceptions of AI-Generated Reviews in Online Textile Purchases: Implications for Sustainable Digital Consumption. *Industria Textila*. https://doi.org/10.35530/IT.076.04.202558

[8] Ben Jabeur, S., Ballouk, H., Ben Arfi, W., & Sahut, J.-M. (2023). Artificial Intelligence Applications in Fake Review Detection: Bibliometric Analysis and Future Avenues for Research. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2022.113631

[9] *Bhangale, S. P., & Roy, P. K. (2025). Is It Genuine or Fake? Analyzing E-Commerce Reviews Using Large Language Models. *Knowledge-Based Systems*. https://doi.org/10.1016/j.knosys.2025.114556

[10] *Bian, Z., & Che, C. (2025). How AI Overview of Customer Reviews Influences Consumer Perceptions in E-Commerce? *Journal of Theoretical and Applied Electronic Commerce Research*. https://doi.org/10.3390/jtaer20040315

[11] *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*. https://doi.org/10.1080/13683500.2026.2713761

[12] Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-Dependent Algorithm Aversion. *Journal of Marketing Research*. https://doi.org/10.1177/0022243719851788

[13] *Chai, S., Chang, Y., & Wang, H. (2026). How Consumers Respond to AI- versus Human-Generated Review Summaries: The Moderating Role of Verbal versus Numerical Probability Expressions. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2026.116245

[14] *Cheng, X., Zeng, A., Yang, B., Liu, Y., & Zhang, X. (2025). Online Reviews Generated by Generative Artificial Intelligence versus Human: A Study of Perceived Differences and User Adoption Behavior. *Electronic Commerce Research and Applications*. https://doi.org/10.1016/j.elerap.2025.101497

[15] *Chernyaeva, O., Lee, O.-K. D., & Hong, T. (2025). From Fake to AI-Generated: Leveraging Information Manipulation Theory and Explainable AI for Robust Detection of Manipulated Reviews. *Decision Support Systems*. https://doi.org/10.1016/j.dss.2025.114522

[16] Cheung, C. M. Y., Sia, C. L., & Kuan, K. K. Y. (2012). Is This Review Believable? A Study of Factors Affecting the Credibility of Online Consumer Reviews from an ELM Perspective. *Journal of the Association for Information Systems*. https://doi.org/10.17705/1jais.00305

[17] *Deng, L., Li, C., & Ye, Q. (2026). Cool or Poor: Assessing the Effectiveness of GenAI-Powered Review Summary Feature on the OTA Platform. *Tourism Management*. https://doi.org/10.1016/j.tourman.2025.105388

[18] Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm Aversion: People Erroneously Avoid Algorithms After Seeing Them Err. *Journal of Experimental Psychology: General*. https://doi.org/10.1037/xge0000033

[19] Donthu, N., Kumar, S., Pandey, N., Pandey, N., & Mishra, A. (2021). Mapping the Electronic Word-of-Mouth (eWOM) Research: A Systematic Review and Bibliometric Analysis. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2021.07.015

[20] *Drozd, D., & Söllen, K. S. (2026). AI Labels, Perceived Authenticity, and Consumer Trust in User-Generated Reviews. *Journal of Theoretical and Applied Electronic Commerce Research*. https://doi.org/10.3390/jtaer21050154

[21] *Eze, M. (2025). Investigating the Effect of AI-Generated Customer Reviews on Purchase Intent and Perceived Authenticity in E-Commerce Environments. *International Journal of Marketing Studies*. https://doi.org/10.5539/ijms.v17n2p62

[22] *Feng, W., Yang, L., Han, T., & Xu, J. (2025). Why AI Needs to "Speak with Data": The Impact Mechanism of Digitalized Descriptions by Virtual eWOM Senders on eWOM Effectiveness. *Journal of Theoretical and Applied Electronic Commerce Research*. https://doi.org/10.3390/jtaer20040303

[23] Filieri, R. (2015). What Makes Online Reviews Helpful? A Diagnosticity-Adoption Framework to Explain Informational and Normative Influences in e-WOM. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2014.11.006
[24] *Furner, C. P., & Zinko, R. (2026). When Trust Breaks: The Impact of AI-Generated Reviews on Consumer Trust and Purchase Intention in Entrepreneurial Marketing. *Journal of Enterprising Culture*. https://doi.org/10.1142/S0218495826500032
[25] *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*. https://doi.org/10.1016/j.ijresmar.2026.06.002
[26] *He, X., & You, W. (2026). Research on Chinese Multimodal Fake Review Detection for AIGC-Generated Content. *International Journal of Intelligent Computing and Cybernetics*. https://doi.org/10.1108/ijicc-10-2025-0655
[27] Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic Word-of-Mouth via Consumer-Opinion Platforms: What Motivates Consumers to Articulate Themselves on the Internet? *Journal of Interactive Marketing*. https://doi.org/10.1002/dir.10073
[28] *Huang, Y., Zhou, J., Dong, W., Li, W., Chi, M., Jiang, C., Wang, W., & Deng, S. (2026). Decoding LLMs' Verbal Deception in Online Reviews. *Decision Support Systems*. https://doi.org/10.1016/j.dss.2025.114529
[29] Ishak, M. I., Muslim, A. K., & Ahmad, N. (2026). Exploring Research on ChatGPT in Online Consumer Reviews: A Systematic Literature Review and Thematic Analysis. *Journal of Research, Innovation & Technologies (JoRIT)*. https://doi.org/10.56578/jorit050104
[30] *Jia, M., Zhao, Y. (Chris), & Zhang, X. (2026). Navigating the Perceived Credibility and Adoption of AI-Generated Review Summaries in Online Shopping: An Affordance Perspective. *Information Processing & Management*. https://doi.org/10.1016/j.ipm.2025.104404
[31] *Jia, S., Chi, O. H., & Chi, C. G. (2025). Unpacking the Impact of AI vs. Human-Generated Review Summary on Hotel Booking Intentions. *International Journal of Hospitality Management*. https://doi.org/10.1016/j.ijhm.2024.104030
[32] *Kim, H., & Lee, S.-W. (2026). How Users Interpret AI-Assisted Reviews: Disclosure Design and Authenticity Perceptions. *Computers in Human Behavior*. https://doi.org/10.1016/j.chb.2026.109148
[33] *Knoedler, S. A., Sofo, G., Kern, B., Frank, K., Cotofana, S., von Isenburg, S., Könneker, S., Mazzarone, F., Dorafshar, A., Knoedler, L., & Alfertshofer, M. (2024). Modern Machiavelli? The Illusion of ChatGPT-Generated Patient Reviews in Plastic and Aesthetic Surgery Based on 9000 Review Classifications. *Journal of Plastic, Reconstructive & Aesthetic Surgery*. https://doi.org/10.1016/j.bjps.2023.10.119
[34] *Kordzadeh, N. (2026). Empowerment over Automation in AI Summarization of Online Reviews. *Communications of the ACM*. https://doi.org/10.1145/3773101
[35] *Kovács, B. (2024). The Turing Test of Online Reviews: Can We Tell the Difference Between Human-Written and GPT-4-Written Online Reviews? *Marketing Letters*. https://doi.org/10.1007/s11002-024-09729-3
[36] *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 & Tourism Marketing*. https://doi.org/10.1080/10548408.2026.2679970
[37] *Lee, S.-C., Lee, D.-G., & Seo, Y.-S. (2024). Determining the Best Feature Combination Through Text and Probabilistic Feature Analysis for GPT-2-Based Mobile App Review Detection. *Applied Intelligence*. https://doi.org/10.1007/s10489-023-05201-3
[38] *Lei, K., & Liu, Y. (2025). When AI Becomes a Shopping Advisor: A Study on the Impact of Generative AI Review on Consumer Purchase Decision. *SAGE Open*. https://doi.org/10.1177/21582440251357671
[39] *Li, Y., & Ha, H. Y. (2026). Human and AI Reviews Coexist: How Hybrid Review Systems Enhance Trust and Decision Confidence in E-Commerce. *Journal of Theoretical and Applied Electronic Commerce Research*. https://doi.org/10.3390/jtaer21010014
[40] *Li, Y., & Zhang, Y. (2026). Calm Me Down: The Impact of AI-Generated Review Summarization on the Sentiment Intensity of Consumer Reviews. *Industrial Management & Data Systems*. https://doi.org/10.1108/IMDS-07-2025-0951
[41] *Li, Z., & Bang, Y. (2026). How Does Artificial Intelligence-Generated Content Reshape User-Generated Content? An Empirical Study from TripAdvisor. *Decision Support Systems*. https://doi.org/10.1016/j.dss.2026.114623
[42] *Li, Z., Li, Y., Zhou, J., Ye, F., & Zhan, Y. (2026). How AI-Generated Summaries of Reviews Are Reshaping E-Commerce With Competing Retailers? *IEEE Transactions on Engineering Management*. https://doi.org/10.1109/TEM.2025.3637769
[43] *Liu, C., Ding, L., & Um, G. (2026). Who Should Disclose AI-Generated Reviews? Evidence from Two Experiments. *The Journal of International Trade & Commerce*. https://doi.org/10.16980/jitc.22.2.202604.71
[44] Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm Appreciation: People Prefer Algorithmic to Human Judgment. *Organizational Behavior and Human Decision Processes*. https://doi.org/10.1016/j.obhdp.2018.12.005
[45] *Longoni, C., & Cian, L. (2022). Artificial Intelligence in Utilitarian vs. Hedonic Contexts: The "Word-of-Machine" Effect. *Journal of Marketing*. https://doi.org/10.1177/0022242920957347
[46] *Lu, H., Wang, Y., Ge, L., & Ma, S. (2025). Positive Effects of Negative Disclosure: The Persuasive Power of Negative AI-Generated Content in Shaping Consumer Product Attitude. *Journal of Electronic Commerce Research*.
[47] *Luo, J., Nan, G., & Li, D. (2026). AI-Generated Fake Review Detection. *Decision Support Systems*. https://doi.org/10.1016/j.dss.2026.114628

[48] *Luo, L., Liu, L., & Zheng, Y. (2026). When AI Summary Is Inconsistent with Aggregated Rating: The Role of Trust, Valence, and Algorithmic Explanation in Consumer Attitudes. *Telematics and Informatics*. https://doi.org/10.1016/j.tele.2025.102361
[49] *Ma, J., Huang, H., Zhang, D., & Li, Z. (2026). Interactive Personalization and Consumer Adoption of Generative AI Word-of-Mouth: An Emotional Arousal Perspective. *Journal of Research in Interactive Marketing*. https://doi.org/10.1108/JRIM-06-2025-0341
[50] *Ma, J., Zhang, D., Chen, C., & Du, H. S. (2026). Matching Generative AI Word-of-Mouth with Product Type: Impact on Consumer Adoption and Trust. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2025.104615
[51] *Mao, M., Guo, T., Zhang, F., & Chen, S.-H. (2026). Sounds Like AI? Consumer Suspicion of AI Authorship in Mixed-Source Online Reviews. *Internet Research*. https://doi.org/10.1108/INTR-07-2025-1039
[52] *Markowitz, D. M., Hancock, J. T., & Bailenson, J. N. (2024). Linguistic Markers of Inherently False AI Communication and Intentionally False Human Communication: Evidence from Hotel Reviews. *Journal of Language and Social Psychology*. https://doi.org/10.1177/0261927X231200201
[53] *Mesquita, E., Herrero, E., Lopes, E. L., Ribeiro, T. de L. S. A., & Scrivano, P. (2026). Artificial Influence: How AI and Influencers Shape Choices in Tourism and Hospitality. *International Journal of Contemporary Hospitality Management*. https://doi.org/10.1108/IJCHM-12-2024-1898
[54] *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*. https://doi.org/10.1080/08874417.2024.2409252
[55] *Mladenović, D., Ismagilova, E., Mogaji, E., & Dwivedi, Y. K. (2026). Travel Recommendations of Tomorrow: Generative Artificial Intelligence and Travel Planning. *Journal of Consumer Behaviour*. https://doi.org/10.1002/cb.70126
[56] Mudambi, S. M., & Schuff, D. (2010). What Makes a Helpful Online Review? A Study of Customer Reviews on Amazon.com. *MIS Quarterly*. https://doi.org/10.2307/20721420
[57] *Narayan, A., Kumar, S. D. M., & Chacko, A. M. (2026). Trust at Risk: Detecting Misinformation in LLM-Generated Product Reviews and Its Implications for Consumer Behavior and Platform Governance. *Telematics and Informatics Reports*. https://doi.org/10.1016/j.teler.2025.100285
[58] *Nawara, D., & Kashef, R. (2025). A Dual-Phase Framework for Detecting Authentic and Computer-Generated Customer Reviews Using Large Language Models. *Decision Analytics Journal*. https://doi.org/10.1016/j.dajour.2025.100581
[59] *Nguyen, T.-T., & Dang, T.-T. (2026). Beyond the “Rainbow Lollipop”: Uncanny Cues in AI-WOM and Its Impact on Trust Erosion and Negative Consumer Responses. *International Journal of Human-Computer Interaction*. https://doi.org/10.1080/10447318.2026.2674826
[60] Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., ... Moher, D. (2021). The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. *BMJ*. https://doi.org/10.1136/bmj.n71
[61] *Pandey, P., & Singh, J. P. (2025). Generating Product Reviews from Aspect-Based Ratings Using Large Language Models. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2025.104244
[62] Paul, J., & Rosado-Serrano, A. (2019). Gradual Internationalization vs Born-Global/International New Venture Models: A Review and Research Agenda. *International Marketing Review*. https://doi.org/10.1108/IMR-10-2018-0280
[63] Paul, J., Lim, W. M., O’Cass, A., Hao, A. W., & Bresciani, S. (2021). Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR). *International Journal of Consumer Studies*. https://doi.org/10.1111/ijcs.12695
[64] *Pérez-Castro, A., Martínez-Torres, M. R., & Toral, S. L. (2023). Efficiency of Automatic Text Generators for Online Review Content Generation. *Technological Forecasting and Social Change*. https://doi.org/10.1016/j.techfore.2023.122380
[65] *Pham Thi Phuong, D., Hoang Cuu, L., Ho Minh, A., & Nguyen Phuc, K. (2026). AI-WOM Echo Pathway Model: Unveiling the Role of Cognitive and Emotional Resonance in Shaping eWOM and Purchase Intention. *International Journal of Human-Computer Interaction*. https://doi.org/10.1080/10447318.2025.2596304
[66] *Radovanović, A., & Dimitrovski, D. (2026). Metadiscourse in AI-Generated Hotel Review Summaries. *Journal of Hospitality and Tourism Technology*. https://doi.org/10.1108/JHTT-06-2025-0492
[67] *Rajagukguk, S. A., & Sofyan, D. (2025). Detecting Sophisticated Fake Reviews on E-Commerce Platforms Using Adversarial Transformer Networks. *Engineering, Technology & Applied Science Research*. https://doi.org/10.48084/etasr.13369
[68] *Salminen, J., Kandpal, C., Kamel, A. M., Jung, S.-G., & Jansen, B. J. (2022). Creating and Detecting Fake Reviews of Online Products. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2021.102771
[69] *Sands, B., Wang, Y., Xu, C., Zhou, Y., Wei, L., & Chandra, R. (2026). An Evaluation of LLMs for Generating Movie Reviews: GPT-4o, Gemini-2.0 and DeepSeek-V3. *Neural Computing and Applications*. https://doi.org/10.1007/s00521-026-12247-0
[70] *Santos, A. M., & Antonio, N. (2025). Improving Trust in Online Reviews: A Machine Learning Approach to Detecting Artificial Intelligence-Generated Reviews. *Information Technology & Tourism*. https://doi.org/10.1007/s40558-025-00329-z

[71] *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*. https://doi.org/10.47743/saeb-2025-0026
[72] *Shi, S., Zhang, Y., Xu, X., Filieri, R., & Jia, R. (2026). Biased or Credible? Investigating Perceived Persuasiveness of AI-Generated Review Summaries in Online Travel Platforms. *Tourism Management*. https://doi.org/10.1016/j.tourman.2026.105446
[73] 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*. https://doi.org/10.1108/jhti-09-2025-1048
[74] *Su, Z., Yang, M., Zhai, Q., Guo, K., Huang, Y., & Cong, Y. (2025). A Multigrained Preference Analysis Method for Product Iterative Design Incorporating AI-Generated Review Detection. *Scientific Reports*. https://doi.org/10.1038/s41598-025-86551-5
[75] *Sun, D., Wong, I. A., Xiong, X., & Li, S. (2026). When Cutting Edge Meets Silver Tongue: Understanding the Word-of-Machine Effect on Travel Decisions. *Tourism Management*. https://doi.org/10.1016/j.tourman.2025.105271
[76] Tao, X., Zeng, J., Shahzad, M. F., Asif, M., & Butt, S. (2026). Exploring the Intersection of Generative AI and eWOM: A Bibliometric Perspective on Emerging Research Directions. *SAGE Open*. https://doi.org/10.1177/21582440261423988
[77] *Tassiello, V., Amatulli, C., Tillotson, J. S., & Laker, B. (2025). aiWOM: Artificial Intelligence Word-of-Mouth. Conceptualizing Consumer-to-AI Communication. *International Journal of Human-Computer Interaction*. https://doi.org/10.1080/10447318.2024.2349362
[78] *Wang, Q., Wang, Y., Wei, T., & Fu, S. (2026). Effects of AI-Assisted Review Presentation Formats on Consumer Decision-Making Efficiency from a Cognitive Load Perspective. *Scientific Reports*. https://doi.org/10.1038/s41598-026-45101-3
[79] *Wang, Y., Zhang, Z., Wang, C., Li, Z., Law, R., & Zhang, Z. (2026). Too Concise to Decide? The Impact of AI-Generated Review Summaries on Tourist Decision Satisfaction. *Tourism Management*. https://doi.org/10.1016/j.tourman.2026.105415
[80] *Wani, M. A., ElAffendi, M., & Shakil, K. A. (2024). AI-Generated Spam Review Detection Framework with Deep Learning Algorithms and Natural Language Processing. *Computers*. https://doi.org/10.3390/computers13100264
[81] *Williams, N. L., Ferdinand, N., & Bustard, J. (2020). From WOM to aWOM - the Evolution of Unpaid Influence: A Perspective Article. *Tourism Review*. https://doi.org/10.1108/TR-05-2019-0171
[82] *Xylogiannopoulos, K. F., Xanthopoulos, P., Karampelas, P., & Bakamitsos, G. A. (2024). ChatGPT Paraphrased Product Reviews Can Confuse Consumers and Undermine Their Trust in Genuine Reviews. Can You Tell the Difference? *Information Processing & Management*. https://doi.org/10.1016/j.ipm.2024.103842
[83] *Xylogiannopoulos, K. F., Xanthopoulos, P., Karampelas, P., & Bakamitsos, G. A. (2025). Is AI-Assisted Paraphrase the New Tool for Fake Review Creation? Challenges and Remedies. *Knowledge-Based Systems*. https://doi.org/10.1016/j.knosys.2025.114151
[84] *Yhee, Y., & Koo, C. (2026). Seeing AI as Human or Machine? Effects of Transparency, Valence, and Readability on Review Summary Helpfulness. *Tourism Management*. https://doi.org/10.1016/j.tourman.2025.105305
[85] *Yu, X., Xu, D. J., & Li, K. (2026). Effects of AI Reviews on Consumers' Purchase Intention: Influence of Product Category, Review Breadth, and Consumer Review Volume. *Decision Support Systems*. https://doi.org/10.1016/j.dss.2025.114590
[86] *Zhang, W., Sun, L., Wang, X., & Wu, A. (2022). The Influence of AI Word-of-Mouth System on Consumers' Purchase Behaviour: The Mediating Effect of Risk Perception. *Systems Research and Behavioral Science*. https://doi.org/10.1002/sres.2871
[87] *Zhao, Y., Tang, S., Zhang, H., & Lyu, L. (2025). AI vs. Human: A Large-Scale Analysis of AI-Generated Fake Reviews, Human-Generated Fake Reviews and Authentic Reviews. *Journal of Retailing and Consumer Services*. https://doi.org/10.1016/j.jretconser.2025.104400
[88] *Zhong, Z., & Ha, H.-Y. (2026). Human or Artificial? How AI Review Labeling Shapes Trust and Consumer Interaction in Food Delivery Platforms. *Journal of Research in Interactive Marketing*. https://doi.org/10.1108/JRIM-11-2025-0738

Appendix

Appendix A1. Exact Database Search Strategies

The original formal database search was conducted in Business Source Premier, ABI/INFORM Complete, Academic Search Complete, and ProQuest Research Library. The same two-block Boolean strategy was applied to the abstract field in each database, with syntax adjusted to the respective database interface where necessary.

Original Formal Database Search

AB: ("generative AI" OR "generative artificial intelligence" OR GenAI OR ChatGPT
OR "GPT-2" OR "GPT-3" OR "GPT-4" OR "large language model*" OR LLM*
OR "AI-generated" OR "AI-assisted" OR "AI-powered" OR "machine-generated"
OR "computer-generated")

AND

AB: (eWOM OR "electronic word of mouth" OR "electronic word-of-mouth"
OR "online review*" OR "consumer review*" OR "customer review*"
OR "product review*" OR "user review*" OR "hotel review*"
OR "restaurant review*" OR "fake review*" OR "spam review*"
OR "review summar*" OR "review overview*")

The search returned 86 records from Business Source Premier, 53 from ABI/INFORM Complete, 174 from Academic Search Complete, and 34 from ProQuest Research Library, for a total of 347 records before deduplication. These counts correspond to the search and screening process reported in Section 3.

Supplemental Database Search

The supplemental search was designed to capture older and alternative terminology that was underrepresented in the original generative-AI-focused search. The following Boolean strategy was applied to the abstract field in the same four databases:

AB: ("AI-WOM" OR "AI WOM" OR "AI word-of-mouth" OR "AI word of mouth"
OR "artificial intelligence word-of-mouth"
OR "artificial intelligence word of mouth" OR aWOM)

OR

AB: ("algorithmic word-of-mouth" OR "algorithmic word of mouth"
OR "word-of-machine" OR "word of machine" OR "synthetic WOM" OR syWOM)

OR

AB: ("artificial intelligence"
AND (eWOM OR "electronic word of mouth" OR "electronic word-of-mouth"
OR "word of mouth" OR "word-of-mouth"))

The supplemental search returned 110 records from Business Source Premier, 51 from ABI/INFORM Complete, 24 from Academic Search Complete, and 22 from ProQuest Research Library, for a total of 207 raw records. After deduplication and removal of records already identified through the original database search, citation searching, or the review/background set, 127 genuinely new records remained for screening.

Table A2. Descriptive Characteristics of the Final Corpus

Characteristic	Distribution
Publication year	2020: 1 (1.4%); 2022: 3 (4.2%); 2023: 1 (1.4%); 2024: 8 (11.3%); 2025: 20 (28.2%); 2026: 38 (53.5%)
Evidence basis	Full text/manuscript: 59 (83.1%); Abstract only: 12 (16.9%)
Inclusion pathway	Formal database search: 27 (38.0%); Citation search: 43 (60.6%); Supplemental database search: 1 (1.4%)
Primary AI role	Creator: 18 (25.4%); Co-Creator: 8 (11.3%); Curator: 18 (25.4%); Intermediary: 14 (19.7%); Regulator: 13 (18.3%)
Research context	General/cross-context: 30 (42.3%); E-commerce/retail: 19 (26.8%); Tourism/hospitality: 18 (25.4%); Restaurants/food delivery: 3 (4.2%); Social media/influencers: 1 (1.4%)
Methodological	Experimental: 18 (25.4%); Computational/text analytics: 18 (25.4%); Mixed methods: 13 (18.3%);

Characteristic	Distribution
approach	Conceptual/analytical: 5 (7.0%); Archival/field: 4 (5.6%); Qualitative: 4 (5.6%); Survey/SEM: 2 (2.8%); Multi-study empirical, method unspecified: 3 (4.2%); Empirical, method unspecified: 4 (5.6%)

Note: Online-first 2026 publications were coded as 2026. Percentages may not sum to 100.0 because of rounding.

Table A3. TCCM Future Research Agenda for AI-Enabled eWOM

TCCM Dimension	Priority Research Directions	Illustrative Research Questions
Theory	Develop theory that integrates findings across AI roles; distinguish experiential, expressive, and representational provenance; model recursive human-AI information ecosystems; formally develop and test AI-eWOM fit.	How do authenticity and trust operate differently across AI roles? When does AI-assisted expression preserve experiential authenticity? How do AI outputs reshape later human eWOM? When does machine informational capability outweigh human experiential legitimacy?
Context	Extend research to understudied and higher-consequence decisions; compare platforms and industries; conduct coordinated cross-cultural studies; examine longitudinal change as AI involvement becomes normalized.	Does provenance matter more in high-risk decisions? Why do AI summaries increase contribution on some platforms but suppress it on others? Do disclosure, privacy, and human-likeness effects vary across cultures? Do AI-authorship penalties decline over time?
Characteristics	Treat AI participation as a continuum rather than a binary condition; distinguish source disclosure from process transparency; identify appropriate levels of personalization and sociality; examine hybrid human-AI information configurations and ecosystem-level outcomes.	How do consumers respond across human-written, AI-assisted, AI-transformed, and fully synthetic content? When does transparency improve calibration without reducing authenticity? When does personalization become intrusive? When do hybrid systems outperform single-source systems?
Methodology	Increase field, natural-experiment, longitudinal, and behavioral research; triangulate experimental, qualitative, field, and computational evidence; conduct cross-model and out-of-distribution detector validation; develop cross-role measures; prioritize replication and technological documentation.	Do laboratory effects persist on real platforms? How do AI interventions change eWOM over time? Do detectors generalize to unseen models and prompting strategies? Can provenance, transparency, manipulation, and trust be measured consistently across AI roles? Do established effects replicate with newer AI models?

Note: The research directions synthesize gaps identified across the review and emphasize movement beyond binary human-versus-AI comparisons toward the study of AI roles, mechanisms, contingencies, and ecosystem-level effects.