Siber Nusantara Publisher
Jurnal Manajemen dan Pemasaran Digital (JMPD)
E-ISSN : 2963-0185
P-ISSN : 2963-0142
+62 811 7404 445 https://siberpublisher.org/ siberpublisher.info@gmail.com

DOI: https://doi.org/10.38035/jmpd.v4i3

Electronic Word of Mouth (eWOM) as Digital Decision Architecture: A Systematic Literature Review of Helping, Hindering, and Backfiring Effects Across Consumer Purchase Journeys

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Abstract: *Electronic word of mouth (eWOM) is increasingly embedded in ranked, filtered, sponsored, cross-device, and algorithmically assisted interfaces. Existing studies explain credibility, information adoption, and purchase effects, but remain fragmented in explaining why similar review environments can facilitate, complicate, or reverse consumer responses. This study develops a digital decision architecture perspective and synthesizes 148 Scopus-indexed studies published between 2016 and 2026, including 103 core studies and 45 supporting or adjacent studies. A theory building systematic literature review was conducted through transparent identification, screening, eligibility assessment, structured coding, and context mechanism outcome synthesis. The review identifies six interacting layers: cues, sources, platforms, processing mechanisms, outcomes, and boundary conditions. Helping effects were identified in 106 studies, hindering effects in 20, and backfiring effects in 8; these categories are non-mutually exclusive. The novelty lies in distinguishing decision friction from persuasive reversal and proposing three paradoxes, diagnosticity overload, credibility commercialization, and social proof autonomy, to explain contingent eWOM effects. The framework positions review ecosystems as decision-support and governance infrastructure rather than merely promotional communication.*

Keyword: *Electronic Word of Mouth, Digital Decision Architecture, Consumer Decision Making, Information Overload, Platform Governance*

Abstrak: Komunikasi mulut ke mulut elektronik (eWOM) semakin terintegrasi dalam antarmuka digital yang diperingkat, difilter, disponsori, digunakan lintas perangkat, dan dibantu algoritma. Penelitian terdahulu telah menjelaskan kredibilitas, adopsi informasi, dan keputusan pembelian, tetapi masih terfragmentasi dalam menerangkan mengapa lingkungan ulasan yang serupa dapat membantu, mempersulit, atau membalik respons konsumen. Penelitian ini mengembangkan perspektif arsitektur keputusan digital melalui sintesis 148 studi terindeks Scopus yang diterbitkan pada 2016–2026, terdiri atas 103 studi inti dan 45 studi pendukung atau berdekatan. Tinjauan literatur sistematis berbasis pengembangan teori dilakukan melalui identifikasi, penyaringan, penilaian kelayakan, pengodean terstruktur, dan sintesis konteks mekanisme hasil. Hasilnya mengidentifikasi enam lapisan yang saling berinteraksi: isyarat, sumber, platform, mekanisme pemrosesan, hasil, dan kondisi batas. Efek membantu ditemukan pada 106 studi, efek menghambat pada 20 studi, dan efek berbalik pada 8 studi; kategori tersebut tidak saling eksklusif. Kebaruan penelitian terletak pada pembedaan antara gesekan keputusan dan pembalikan persuasi serta pengembangan tiga paradoks, yaitu kelebihan diagnostik, komersialisasi kredibilitas, dan otonomi bukti sosial, untuk menjelaskan variasi dampak eWOM.

Kata Kunci: Komunikasi Mulut ke Mulut Elektronik, Arsitektur Keputusan Digital, Pengambilan Keputusan Konsumen, Kelebihan Informasi, Tata Kelola Platform

INTRODUCTION

Electronic word of mouth (eWOM) has become a central information mechanism in digital markets because consumers increasingly evaluate products, sellers, services, and brands through online reviews, ratings, social recommendations, user generated content, and platform mediated information. Recent reviews show that the field has expanded beyond conventional review valence and purchase intention toward credibility, review classification, cross cultural interpretation, and platform conditions (Donthu et al., 2021; Zheng, 2021; Pooja & Upadhyaya, 2024; Kusawat & Teerakapibal, 2024). This expansion matters because consumers no longer encounter eWOM as a single message; they encounter configurations of cues that are ordered, filtered, summarized, and displayed within digital interfaces. Foundational integrative and process models, information-adoption research, and meta-analytic evidence further show that eWOM characteristics shape information adoption, brand attitude, purchase intention, and intention to buy (Cheung & Thadani, 2012; Erkan & Evans, 2016; Kudeshia & Kumar, 2017; Ismagilova et al., 2020; Albayrak & Ceylan, 2021; Babić Rosario et al., 2020).

The research gap lies in the fragmentation of these configurations. Much of the literature still explains eWOM through linear pathways in which message or source characteristics influence trust, usefulness, perceived risk, and purchase-related outcomes. Such models remain useful, but they are less capable of explaining why similar information environments produce mixed or reversing responses. Recent studies show that excessive disclosure can weaken trust, contradictory reviews can increase perceived risk, incentivized programs can activate skepticism, and resistance to incentivized eWOM can generate boomerang effects (AlRabiah et al., 2022; Bo et al., 2023; Chen et al., 2023; Gvili & Levy, 2025). These findings indicate that adverse effects are not merely weaker versions of positive persuasion; they involve different mechanisms.

A second gap concerns platform mediation. Cross device search, ranking logic, reviewer status, incentives, and emerging artificial intelligence assisted decision support can alter visibility, sequence, cognitive load, and source interpretation. These mechanisms imply that the relevant unit of explanation is broader than the review message itself. The theoretical problem becomes configurational: which combinations of cues, sources, platform conditions, processing mechanisms, and consumer boundaries create decision support, decision friction, or persuasive reversal? (Han et al., 2022; Hoa, 2025; Zheng et al., 2024). Evidence also shows that rankings, platform type, consumer archetypes, and information-presentation complexity can change search and purchase processes, while sentiment-based computational decision methods illustrate the growing role of algorithmic support in online choice (Karimi et al., 2018; Ursu, 2018; Xu & Lee, 2020; Yang et al., 2019; Yu et al., 2020).

This study therefore reconceptualizes eWOM as digital decision architecture: a structured configuration of cues, sources, platform conditions, consumer processing mechanisms, outcomes, and boundary conditions through which online information becomes behaviorally consequential. The study has four objectives: to map the dominant architecture of the literature; to identify the mechanisms associated with helping, hindering, and backfiring effects; to integrate these findings into a theory building framework; and to formulate a research agenda for technology aware digital marketing and platform governance. The state of the art lies in moving from isolated stimulus response relationships toward a configuration-based explanation of how eWOM can facilitate, complicate, or reverse consumer responses across purchase journeys.

The novelty is developed in three steps. First, the study distinguishes helping, hindering, and backfiring as different effect orientations, with hindering defined as decision friction and backfiring defined as persuasive reversal. Second, it integrates the literature into a six-layer decision architecture. Third, it derives three paradoxes, diagnosticity overload, credibility commercialization, and social proof autonomy, that explain why information abundance, commercial amplification, and social endorsement may generate benefits and costs simultaneously. These contributions reposition eWOM as decision-support and information governance infrastructure, not merely as a promotional communication mechanism.

METHOD

This study employed a theory building systematic literature review because the included studies differed substantially in constructs, contexts, methods, platforms, and outcome measures. The review used Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020 for reporting transparency and the Scientific Procedures and Rationales for Systematic Literature Reviews framework for assembling, arranging, and assessing the evidence (Page et al., 2021; Paul et al., 2021). Theory, context, characteristics, and methodology mapping was adapted to organize the literature, while context-mechanism-outcome logic was used to explain how specific configurations produced helping, hindering, or backfiring effects (Paul & Rosado-Serrano, 2019). The theory-building choice is consistent with systematic-review guidance that heterogeneous evidence can be organized to develop evidence-informed and conceptual knowledge rather than being reduced to pooled effects alone (Tranfield et al., 2003; Snyder, 2019).

Scopus was used as the database because the review focused on peer reviewed work in marketing, consumer behavior, information systems, tourism, hospitality, e-commerce, and digital business. The analytical period was 2016–2026. Eligible records were English-language journal articles that contributed evidence on eWOM cues, sources, platforms, processing mechanisms, outcomes, boundary conditions, or closely related digital decision mechanisms. Offline word of mouth, general advertising without eWOM relevance, purely technical recommender-system studies without consumer-decision implications, and studies with insufficient methodological transparency were excluded.

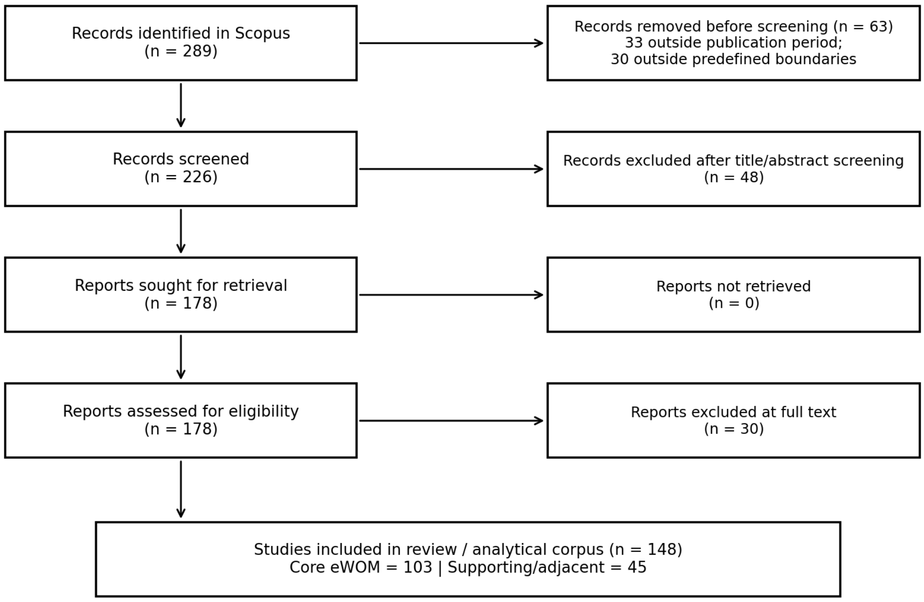
Table 1. Review Protocol and Eligibility Criteria

Protocol Element	Specification
Review Type	Systematic literature review with theory-building synthesis
Reporting and Review Logic	Preferred Reporting Items for Systematic Reviews and Meta-Analyses 2020; Scientific Procedures and Rationales for Systematic Literature Reviews
Synthesis Logic	Adapted theory-context-characteristics-methodology mapping plus context-mechanism-outcome coding
Database and Period	Scopus; 2016–2026
Document and Language	Peer-reviewed journal articles; English
Core Inclusion Focus	eWOM, online reviews, ratings, user generated content, influencer/social eWOM, credibility, purchase and decision outcomes

Protocol Element	Specification
Exclusion Focus	Offline word of mouth, generic advertising, purely technical recommender systems, inaccessible or methodologically insufficient studies
Screening Flow	289 identified; 226 screened; 178 full texts assessed; 148 included
Final Corpus	103 core eWOM studies and 45 supporting/adjacent studies

Source: Author's compilation and the review protocol (2026).

The screening process started with 289 records. Sixty-three records were removed before title and abstract screening, leaving 226 records. Forty-eight were excluded during screening, producing 178 reports for full text assessment. All were retrieved; 30 were excluded at eligibility, yielding 148 studies. The corpus was divided into 103 core eWOM studies and 45 supporting or adjacent studies. The distinction protects conceptual validity: direct eWOM claims are grounded primarily in core evidence, while adjacent studies are used to interpret platform and decision-architecture conditions.



Source: Author's compilation based on PRISMA 2020 and the final screening records (2026).

Figure 1. PRISMA 2020 Flow of Study Identification, Screening, Eligibility, and Inclusion.

A structured extraction matrix captured bibliographic information, context, platform, method, eWOM type, cue characteristics, source characteristics, mechanisms, outcomes, boundary conditions, variable roles, and effect orientation. Coding proceeded in two cycles: descriptive coding followed by reorganization into six decision architecture layers. Helping was coded when the evidence indicated lower uncertainty or risk, higher trust, usefulness, diagnosticity, comparison quality, or decision confidence. Hindering was coded when eWOM increased cognitive effort, ambiguity, risk, conflict, or decision difficulty without necessarily reversing the final decision. Backfiring required an adverse inference or behavioral reversal such as distrust, perceived manipulation, resistance, reduced credibility, or negative behavior. Categories were non-mutually exclusive.

The extraction matrix captured bibliographic information, context, platform, method, cue and source characteristics, mechanisms, outcomes, boundary conditions, variable roles, and effect orientation. Coding proceeded in two cycles: descriptive coding followed by reorganization into six layers: cue, source, platform, mechanism, outcome, and boundary condition. The synthesis then moved from descriptive mapping to thematic organization and theory building comparison of countervailing mechanisms. Because the preserved review record does not document independent duplicate coding or the final copy and paste Scopus Boolean string, no inter coder reliability statistic or reconstructed query is reported; these items are treated transparently as limitations rather than retroactively fabricated.

RESULTS AND DISCUSSION

Corpus Profile and Publication Trend

The final analytical corpus consists of 148 studies: 103 core and 45 supporting or adjacent studies. Publication activity is concentrated after 2018, with the largest totals in 2020 (21 studies) and 2022 (23 studies). The period 2020–2022 accounts for 57 studies, while 2023–2026 contributes 47. The 2026 count represents an incomplete publication year and should not be interpreted as a decline in scholarly interest.

Table 3. Publication-Year Distribution of The Analytical Corpus

Year	Core	Supporting	Total	%
2016	3	2	5	3.4
2017	8	1	9	6.1
2018	10	7	17	11.5
2019	9	4	13	8.8
2020	17	4	21	14.2
2021	9	4	13	8.8
2022	15	8	23	15.5
2023	11	4	15	10.1
2024	9	5	14	9.5
2025	8	3	11	7.4
2026	4	3	7	4.7
Total	103	45	148	100.0

Source: Author's analysis of the final analytical corpus (2026).

Descriptive Structure of The Decision Architecture

The descriptive results support the view that eWOM research is distributed across multiple decision environments. Online marketplaces and e-commerce are the most prominent contexts (61 studies), followed by social media and social commerce (53) and travel, tourism, hospitality, and online travel agencies (38). Mobile, cross-device, and interface contexts appear in 25 studies, while algorithmic ranking or decision-support contexts appear in 10. This distribution indicates that platform conditions are part of the exposure environment rather than a neutral background. Cross device behavior and emerging artificial intelligence assisted decision support further reinforce the need to treat visibility, sequence, and processing constraints as part of the explanatory structure (Han et al., 2022; Hoa, 2025).

At the cue level, valence and sentiment are most frequent (48 studies), followed by review length, readability, or quality (36), rating or star rating (34), credibility or trustworthiness cues (25), visual or multimedia cues (24), volume (17), and incentive, disclosure, or sponsorship cues (6). These counts show both continuity and expansion. Traditional cues remain central, yet contemporary studies increasingly examine richer, source dependent, and interface dependent signals. Experimental work on negative online reviews illustrates how amount, quality, and presentation order can change perceived risk, attitude, and purchase intention, while more recent research identifies diminishing marginal value from additional review information (Liao et al., 2021; Zheng et al., 2024). More specifically, review number, valence, and star ratings interact in credibility judgments, while the persuasiveness of emotional online reviews varies with reviewer status and valence (Hong & Pittman, 2020; Vendemia et al., 2019).

The mechanism layer reveals a pronounced asymmetry. Trust and credibility appear in 51 studies, affective responses in 39, risk or uncertainty reduction in 32, diagnosticity, usefulness, or information adoption in 26, and social influence, social proof, or tie strength in 25. By contrast, skepticism, manipulation, or resistance appear in only six studies, and information overload or cognitive effort in three. The literature therefore contains a stronger architecture of acceptance than of failure. Source related studies similarly show that expertise, tie strength, and credibility remain important, but the meaning of source signals depends on context and commercialization (Nofal et al., 2022; Pooja & Upadhyaya, 2024). Source-specific evidence also shows that online-celebrity credibility, brand feedback to negative eWOM, source trust, and bandwagon effects can shape trust, attitudes, and purchase-related responses (Djafarova & Rushworth, 2017; Bhandari & Rodgers, 2018; Wu & Lin, 2017).

Outcome coverage is broad but still intention-heavy. Purchase decision, choice, booking, or visit outcomes appear in 70 studies; risk, trust, or attitude as outcomes or intermediate responses in 60; and purchase intention in 47. Thirty-one studies examine helpfulness, adoption, or credibility, while 22 use sales, conversion, revenue, or other market outcomes. Evidence linking eWOM to observed sales and market response confirms the feasibility of moving beyond self-reported intention, although such designs remain less common than attitudinal models (Liu et al., 2022; Singh et al., 2022). Comparable market-facing evidence links eWOM valence to online retail sales and eWOM to used-video-game trading behavior under product-feature contingencies (Roy et al., 2017; Zhang et al., 2019).

Table 4. Descriptive Synthesis of The eWOM Decision Architecture

Dimension	Leading Categories and Counts	Interpretation
Platform/Context	Marketplace/e-commerce 61; social media/social commerce 53; travel/hospitality/online travel agencies 38; mobile/interface 25	eWOM is embedded in heterogeneous visibility and processing environments.
Cue	Valence/sentiment 48; length/readability/quality 36; rating 34; credibility cues 25; visual cues 24; volume 17; incentives/disclosure 6	Cue effects are conditional and increasingly multi-cue rather than isolated.
Mechanism	Trust/credibility 51; affect 39; risk reduction 32; diagnosticity/usefulness 26; social influence 25; skepticism/resistance 6; overload 3	Acceptance mechanisms dominate; failure mechanisms remain underdeveloped.
Outcome	Decision/choice/booking/visit 70; risk/trust/attitude 60; purchase intention 47; helpfulness/adoption 31; market outcomes 22	The field remains decision-oriented but still relies heavily on intention.
Effect Orientation	Helping 106; hindering 20; backfiring 8	Positive pathways dominate the evidence base; categories are non-mutually exclusive and are not prevalence estimates.

Source: Author's coding and synthesis of the final analytical corpus (2026).

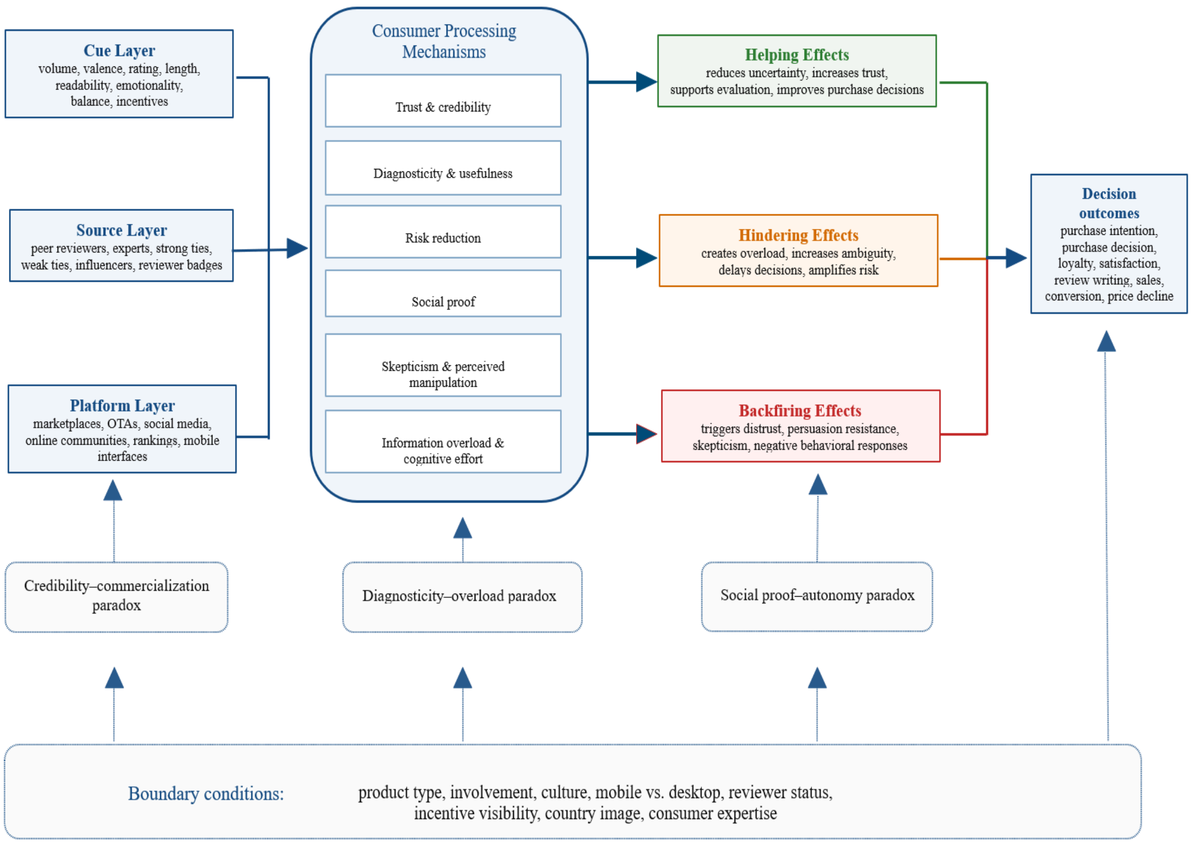
Helping, Hindering, and Backfiring Effects

Helping effects are coded in 106 studies and generally involve uncertainty reduction, higher trust or credibility, greater usefulness, better product evaluation, or stronger decision confidence. Hindering effects appear in 20 studies and include overload, ambiguity, conflicting cues, perceived risk, cognitive effort, and delayed or complicated decisions. Backfiring effects appear in 8 studies and involve distrust, perceived manipulation, skepticism, persuasion resistance, misinformation related concern, or adverse behavioral responses. Because a study could contain more than one pathway, these categories are non-mutually exclusive and should not be interpreted as estimates of real-market prevalence.

The distinction is theoretically important. Hindering means that the consumer faces higher decision cost, but the ultimate direction of persuasion may remain unchanged. Backfiring requires a stricter reversal mechanism in which an attempt to influence becomes evidence against the message, source, platform, or brand. Recent evidence on excessive disclosure, incentivized programs, misinformation related processing, and resistance to incentivized eWOM illustrates why these adverse pathways should not be collapsed into one generic category of negative effects (AlRabiah et al., 2022; Chen et al., 2023; Dai et al., 2022; Gvili & Levy, 2025). Contradictory reviews further show how information conflict can increase perceived risk and complicate purchase decisions without necessarily producing the same mechanism as distrust or resistance (Bo et al., 2023).

eWOM Decision Architecture Framework

The descriptive findings are integrated into a six-layer digital decision architecture. Cue, source, and platform layers define the information environment; processing mechanisms explain how consumers interpret that environment; outcomes capture consumer and market consequences; and boundary conditions modify effect strength or direction. The unit of explanation therefore shifts from isolated review variables to configured decision environments. This perspective extends recent systematic reviews by integrating message characteristics, review classification, cross-cultural variation, platform mediation, and adverse processing mechanisms within one theory-building structure (Donthu et al., 2021; Zheng, 2021; Kusawat & Teerakapibal, 2024; Pooja & Upadhyaya, 2024).



Source: Author's synthesis of the reviewed literature and development of the eWOM Decision Architecture Framework (2026).
Figure 2. eWOM as Digital Decision Architecture.

Table 5. Six Layers of The eWOM Decision Architecture Framework

Layer	Main Elements	Decision Role
Cue	Valence, rating, volume, length, readability, emotion, visuals, balance, disclosure	Provides observable information signals
Source	Peers, experts, influencers, ties, verified users, brand responses, badges	Shapes expertise, independence, authenticity, and trust
Platform	Marketplaces, online travel agencies, social media, communities, rankings, mobile interfaces	Structures visibility, order, salience, and comparison
Mechanism	Trust, credibility, usefulness, diagnosticity, risk, social proof, affect, skepticism, overload	Transforms exposure into judgment
Outcome	Intention, decision, sales, conversion, loyalty, satisfaction, review writing, price	Captures consumer and market consequences
Boundary	Product type, risk, involvement, culture, expertise, device, incentive visibility, platform	Conditions effect strength and direction

Source: Author's synthesis of the reviewed literature and the eWOM Decision Architecture Framework (2026).

Paradox-Based Synthesis and Novelty

The first paradox, diagnosticity overload, captures the tension between information richness and processing burden. Additional reviews, details, and cues can improve evaluation, yet their marginal value can diminish as redundancy, conflict, and limited attention increase. The proposition is therefore nonlinear: information organization, consumer expertise, and interface constraints should determine the point at which additional eWOM shifts from diagnostic value to decision friction (Zheng et al., 2024).

The second paradox, credibility commercialization, captures the tension between amplification and authenticity. Incentives and commercially amplified content can increase participation or visibility, but they can also activate skepticism and reduce trust when persuasive intent becomes more salient than informational value. Evidence on incentivized eWOM shows that warmth and skepticism can coexist, while resistance to incentivized requests can generate a boomerang effect on trust (Chen et al., 2023; Gvili & Levy, 2025).

The third paradox, social proof autonomy, is the most explicitly theory building. The corpus supports the importance of social influence and popularity cues, but it does not yet establish autonomy loss as a mature empirical effect. The novelty is therefore a testable inference rather than a settled finding: social proof may reduce uncertainty and search effort, yet its benefits should weaken when consumers interpret popularity cues as pressure, manipulation, or a substitute for independent judgment. This proposition creates a clear boundary between what the corpus demonstrates and what future empirical work must test.

Table 6. eWOM Paradoxes and Theory-Building Propositions

Paradox	Tension	Proposition
Diagnosticity Overload	More information can improve diagnosis but increase processing burden	P1: The relationship between information richness and decision quality is nonlinear and depends on organization, expertise, and interface constraints.
Credibility Commercialization	Amplification increases visibility but may reduce authenticity	P2: Positive effects weaken or reverse when perceived commercial intent exceeds perceived informational value.

Paradox	Tension	Proposition
Social Proof Autonomy	Collective validation reduces uncertainty but may create pressure	P3: Confidence benefits weaken or may reverse when popularity cues are interpreted as pressure or manipulation.

Source: Author's theoretical synthesis of the reviewed literature (2026).

Technological, Managerial, and Platform Implications

The decision-architecture perspective makes technological challenges analytically visible. Ranking and interface design affect what consumers encounter first, while cross-device search changes the sequence of information acquisition. Artificial intelligence assisted decision support introduces an additional layer because summarization and recommendation can reduce search cost while raising questions about provenance, information compression, review dispersion, and minority viewpoints. The current corpus supports the emergence of artificial-intelligence-assisted purchase decision support, but it does not justify treating specific risks of machine-generated review summaries as established findings; these remain design questions for future testing (Han et al., 2022; Hoa, 2025).

For managers, the main implication is to optimize decision value rather than review volume or positivity. Review environments should improve relevance, credibility, comparability, readability, and manageable cognitive load. Commercialization should be treated simultaneously as a reach mechanism and credibility risk. Transparent disclosure is necessary, but it should be accompanied by substantively useful information rather than scripted positivity. For platforms, ranking, verification, disclosure, and summarization are governance decisions because they shape visibility, sequence, and inference. Performance monitoring should therefore extend beyond engagement and conversion toward review quality, credibility complaints, perceived manipulation, and trust.

The broader significance is that trustworthy eWOM contributes to the informational integrity of digital markets. When consumer generated information is credible, relevant, transparent, and cognitively manageable, it can reduce uncertainty and improve comparison. When it is excessive, commercially opaque, or manipulatively organized, it can increase decision friction and weaken platform confidence. The theoretical contribution is thus not another estimate of whether eWOM works, but an explanation of why similar configurations can create different net effects under different platform and boundary conditions.

Future Research Agenda

Future research should test configurations rather than isolated main effects. Multi-cue experiments, fuzzy-set qualitative comparative analysis, longitudinal platform data, and theory-driven computational methods can examine how review valence, source credibility, incentive disclosure, ranking, and consumer expertise operate jointly. A stronger failure theory is also required to identify thresholds at which volume becomes overload, sponsorship becomes manipulation, and social proof becomes pressure. Behavioral validation should link trust, diagnosticity, skepticism, and overload to actual purchase, browsing, conversion, review writing, complaint behavior, loyalty, and revenue.

Table 7. Future Research Agenda for eWOM as Digital Decision Architecture

Research Direction	Current Gap	Priority for Future Work
Configurational Models	Isolated variables dominate	Test cue-source-platform-mechanism combinations with multi-cue experiments, fsQCA, and platform data
Hindering and Backfiring	Positive pathways dominate	Model overload, skepticism, manipulation, resistance, and reversal thresholds

Research Direction	Current Gap	Priority for Future Work
Behavioral Outcomes	Heavy use of purchase intention	Link mechanisms to actual purchase, conversion, sales, review writing, loyalty, and complaints
AI Mediated eWOM	Emerging and under-specified	Compare artificial intelligence as processing aid versus content source; test provenance, explanation, bias, and autonomy
Cross Platform Journeys	Single-platform snapshots dominate	Track information across discovery, evaluation, purchase, and post-purchase stages
Boundary Conditions	Often treated as controls	Theorize culture, risk, product type, involvement, expertise, and device
Methodological Rigor	Reproducibility and longitudinal evidence remain limited	Use transparent coding, exact search reporting, experiments, longitudinal designs, and behavioral traces
Platform Governance	Platforms often treated as neutral	Study ranking transparency, review integrity, disclosure, verification, and trustworthy summarization

Source: Author's synthesis and proposed future research agenda based on the reviewed literature (2026).

CONCLUSION AND SUGGESTIONS

Conclusion

This systematic literature review synthesizes 148 Scopus-indexed studies published between 2016 and 2026 and shows that eWOM is better explained as a platform-mediated decision architecture than as a single persuasion variable. The six-layer framework integrates cues, sources, platforms, processing mechanisms, outcomes, and boundary conditions. It also distinguishes helping, hindering, and backfiring effects, thereby separating decision friction from persuasive reversal.

The main novelty is the paradox-based explanation of contingent effects. Diagnosticity-overload and credibility-commercialization are grounded in observed countervailing mechanisms, while social proof-autonomy is advanced as a theory building proposition requiring direct empirical testing. Together, these paradoxes show why maximizing information volume, promotional visibility, or social endorsement does not necessarily maximize decision quality. The framework therefore contributes to digital marketing by connecting consumer behavior, platform design, information integrity, and governance within one explanatory structure.

Limitations

This review is limited to Scopus-indexed, English-language journal articles and therefore does not represent an exhaustive census of all eWOM research. The inclusion of both core and supporting/adjacent studies strengthens platform interpretation but makes corpus boundaries consequential. Effect-orientation counts are interpretive, non-mutually exclusive coding indicators rather than pooled effect sizes. Heterogeneity in research designs and measures also limits direct causal comparison. Future studies may strengthen reproducibility through complete reporting of database search strategies, transparent coding procedures, and independent coding verification.

Suggestions

Future studies should empirically test the three paradoxes through nonlinear models, multi-cue experiments, field experiments, cross-platform designs, and behavioral trace data. Particular attention should be given to artificial intelligence assisted review processing, source provenance, ranking transparency, commercialization disclosure, and the conditions under which social proof shifts from helpful validation to perceived pressure. For managers and platforms, the practical priority is to treat eWOM as decision support infrastructure by jointly managing credibility, relevance, transparency, interface usability, and cognitive load rather than optimizing review volume or positivity in isolation.

Author Contribution

The author was solely responsible for conceptualization, review design, literature screening and coding, evidence synthesis, framework development, interpretation, manuscript preparation and revision, and final approval of the article.

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