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FROM ONLINE REVIEWS TO SERVICE GOVERNANCE: A REVIEW OF SERVICE QUALITY RESEARCH IN HOSPITALITY AND TOURISM

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Abstract:

Standard bibliometric summaries no longer capture what online review research in hospitality and tourism is actually doing — the corpus has grown too large and internally varied for that. Applied to a Scopus corpus of 243 articles, bibliometric mapping and latent Dirichlet allocation (K = 8) recover four functional domains: managerial response, experience evaluation, computational analytics, and contextual extension. These domains do not carry equal influence. T6 (Service failure and recovery) leads the taxonomy with 13.61% prevalence and a citation impact of 40.93; T4 (NLP/LLM-enabled review understanding) has expanded in recent visibility but carries the lowest impact score in the set (28.25). The field is not simply becoming more technological—it is becoming more stratified, with a durable managerial core sitting alongside an experimental analytics layer. A literature-derived governance framework links these thematic streams to monitoring signals, response priorities, and evaluation metrics. The framework is not a field-tested operational model, but it makes explicit a logic for service quality governance that the accumulated evidence already supports.

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Keyword:

Hospitality And Tourism; Online Reviews; Review Analytics; Service Governance; Service Quality; Service Recovery

Introduction

Online reviews now sit at the centre of how hospitality and tourism researchers study service quality. Managers read them to find out where guest expectations broke down, which attributes the guest singled out, what the hotel said in response, and how that pattern of complaint has shifted over time. Research has treated them as digital word-of-mouth (WoM) through which customer perceptions and service performance are made visible, framing established early and tested repeatedly (Litvin et al., 2008; Cantallops & Salvi, 2014; Chen & Law, 2016). Pattern in that record is manageable; aggregate satisfaction scores are harder to act on. Getting to that pattern requires analytical skills that practitioners rarely have ready access to, and research has not always provided it in a form managers can use. Managerial attention is also finite, which makes a workable routine for converting reviews into governance decisions urgent rather than optional (Palese et al., 2021).

Meanwhile the toolkit kept growing. Sentiment analysis came first, then text mining; AI-enabled interpretation arrived last and spread quickly, in journals and in hotels alike. Bibliometric and scientometric studies document the change: data-driven interpretation of service now sits at the centre of customer experience research and keeps expanding into questions of operational competitiveness and adaptability (Zheng et al., 2023). Methodological development has benefited tourism and hospitality researchers on two fronts, the analytical toolkit and the philosophy of interpretation behind it. Recent studies of topic modelling and AI-assisted text analytics in tourism argue that these methods make large bodies of review text interpretable rather than merely countable. Earlier reviews treated these methods as analytical add-ons; more recent workplaces them at the centre of how the field interprets service experience (Li, 2025). No tool displaced what came before it: sentiment analysis built on keyword mapping, LDA arrived alongside manual reading rather than in place of it. One approach settled on top of another, which is why the toolkit now looks heterogeneous — and why the accumulated output resists easy synthesis.

Publication counts and citation totals track activity; they do not flag what the accumulated work is still missing. The major themes have sat unsorted catalogued by frequency and mapped by co-occurrence, but not weighed against each other for scholarly influence or practical priority. Journals, countries, and keyword networks have been mapped many times, yet such maps say little about whether the underlying themes are integrated or fragmented, or how they compare when assessed for prevalence, scholarly impact, and momentum simultaneously. The harder

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gap to fill is practical. Prior syntheses describe what the field has studied, and generally do so well, but they stop short of a framework that puts accumulated knowledge to direct use.

The analysis draws on a Scopus corpus of 243 English-language journal articles published between 2005 and 2026. Bibliometric mapping and topic-based analysis are used here as supporting tools to organise the literature, not as ends in themselves. The review process is summarised in Figure 1. The design yields a more integrated picture than bibliography-scanning alone can provide how online review and service quality research in hospitality and tourism is structured and differentiated, why reviews are more usefully read as governance-relevant service signals than as feedback, and how the main thematic streams translate into something hospitality managers could actually work from.

Literature Review and Review Design

Online Reviews and Service Quality Research in Hospitality and Tourism

The earliest question in online review research was simple: do reviews affect demand? Early evidence said yes, quickly and consistently. Review information shapes booking evaluation, trust, and hotel market visibility in ways that put reviews at the centre of the digital service environment, not at its margins (Ye, Law, & Gu, 2009; Sparks & Browning, 2011). Service quality scholarship, for its part, had long held that customers assess service through multiple independent dimensions rather than a single summary judgement — a position that holds just as well when the evidence arrives in text rather than survey form (Parasuraman, Zeithaml, & Berry, 1988).

Volume and reach are both larger now. Reviews sit inside a digital tourism environment shaped by platform mediation, information abundance, and technology-enabled comparison — a shift earlier tourism scholarship had anticipated but not fully mapped (Buhalis & Law, 2008; Xiang et al., 2015). Hospitality work has followed. Shin, Kim, Choe, and Hwang (2024) apply interpretable machine learning to extract service feature importance from hotel reviews; Tran et al. (2025) trace how response satisfaction feeds back into perceived quality and return intention in an emerging destination. The question has shifted: those earlier studies asked whether reviews affected demand. These ask what to do with them once the answer is clearly yes.

No shared conceptual core has kept pace with the growth. One cluster stays close to complaint handling, recovery logic, and response design. A second has moved into topic modelling, interpretable machine learning, deep learning, and conversational AI. The two clusters share a corpus but not a governing idea, and recent reviews of hospitality service quality, AI in tourism, and topic modelling all confirm as much (Olawuyi & Kleynhans, 2025; Grljević, 2025; Wang et al., 2025). Publication counts and keyword maps no longer convey what the field is actually doing.

The field is no longer centred on Western platform data. Studies from China, Vietnam, and Indonesia now treat review systems as direct operational evidence of service inconsistency and platform-mediated expectations — not as post-stay opinion appended to a booking record (Bi et al., 2024; Tran et al., 2025; Permatasari et al., 2025). Cultural variation and smart hotel service priorities compound this: a framework built on one market's review behaviour does not automatically transfer (Wąsowicz-Zaborek, 2025). A field spread this far across settings, methods, and managerial concerns cannot be synthesised by reading a subset of its output.

Bibliometric mapping — journal counts, country tallies, keyword clusters — has done useful work in this field. What it cannot do is show whether the literature's strands connect, or how far the accumulated evidence bears on what hospitality managers actually face. A synthesis that stops at structural description misses both questions.

Research Gaps and Study Objectives

Existing reviews and bibliometric studies have done the structural work: publication growth, source concentration, keyword patterns. What they have not done — and what becomes harder to avoid as the field expands — is explain how those strands connect, or what the expansion means for service management in practice. Recent reviews of hospitality service quality, AI in tourism, and topic modelling share this limitation (Olawuyi & Kleynhans, 2025; Grljević, 2025; Wang et al., 2025).

The analytical gap runs deeper. Theme-based studies rarely separate prevalence from influence or momentum, and those are different things. A high-frequency theme may carry modest scholarly influence; a smaller theme may be disproportionately consequential for practice. That distinction is now harder to ignore as long-standing managerial themes sit alongside fast-growing AI-oriented fronts. Work on review response productivity, negative review dynamics, and AI-enabled service interpretation has made the unevenness visible (Xie, Zhang, & Zhang, 2014; Ku et al., 2024; Skovoroda et al., 2025; Alharbi et al., 2025).

Operationally, the most consequential gap concerns what reviews do inside service systems rather than what they record about them. Review research has mostly treated reviews as feedback, reputational content, or classification data — none of that is wrong, but it misses something hospitality-specific. Managers working under limited attention and uneven response capacity face recurring complaints, multilingual content, platform constraints, and guest expectations that shift week to week. Work on managerial response design, service improvement priorities, and review-based quality diagnosis has started reaching for this practical problem (Chen et al., 2019; Tran et al., 2025). The accumulated evidence has yet to be organised into a logic of monitoring, prioritisation, and response that those managers could use.

This study takes up all three. The 243-article corpus is used to map how the field developed and to separate the most influential thematic lines from high-volume but lower-impact work. That evidence is then translated into a framework for service monitoring and response.

Review Design, Data Source, Corpus Construction, and Analytical Approach

We combined a systematic literature review with bibliometric mapping and topic modelling. The aim was to use bibliometric mapping and topic modelling to support synthesis rather than to treat the techniques as ends in themselves. A corpus of 243 articles spread across 116 sources and built over two decades cannot be synthesised convincingly by hand alone. We follow the PRISMA 2020 guideline and report identification, screening, and inclusion step by step (Page et al., 2021). Recent calls in hospitality and tourism research support this more interpretive use

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of computational methods alongside standard review procedures (Grljević, 2025; Yu & Cheng, 2025).

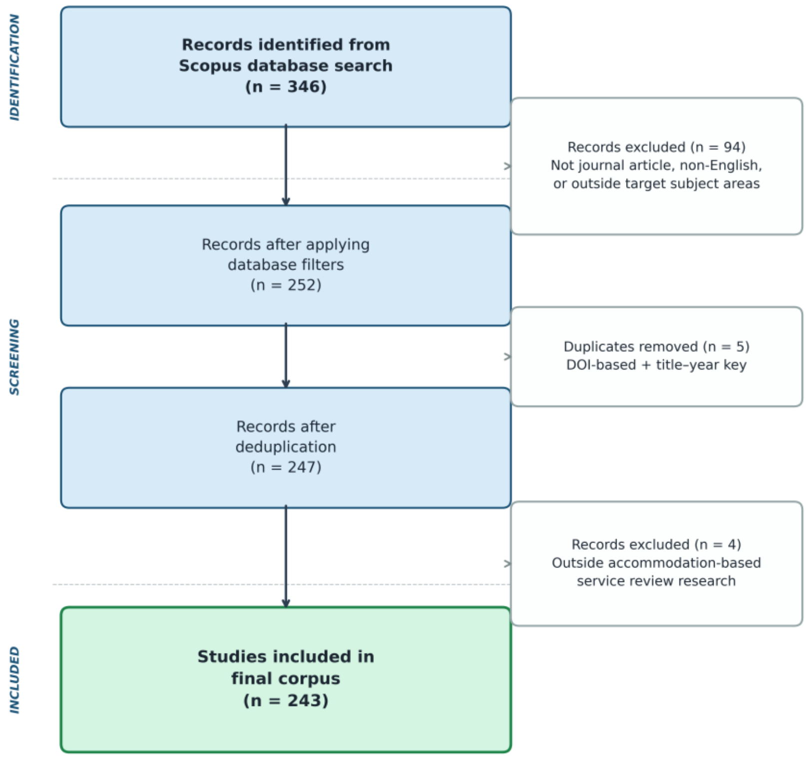

Figure 1: PRISMA Flow of Study Selection

Source: Authors' Work

Scopus served as the only bibliographic source. Its structured, exportable metadata is directly workable for reproducible bibliometric processing and downstream text mining. We searched on 9 February 2026, with a query built around four elements: the service construct, the accommodation context, the online review environment, and the text-mining method family. The final search string was:TITLE-ABS-KEY("service quality" OR SERVQUAL OR "service failure" OR "service recovery") AND TITLE-ABS-KEY(hotel* OR resort* OR "accommodation" OR "lodging") AND TITLE-ABS-KEY("online review*" OR "review mining" OR "user-generated content" OR UGC OR eWOM OR TripAdvisor OR Booking OR "Booking.com" OR Ctrip OR "携程") AND TITLE-ABS-KEY("topic model*" OR LDA OR STM OR "structural topic model" OR "text mining").

We retained journal articles only, in English, across four subject areas: Business, Social Sciences, Decision Sciences, and Computer Science. Of 346 records returned, 252 survived filtering and export. Figure 1 traces the screening sequence. After export, the data went into R. Deduplication ran twice: records with identical DOIs were removed first; a combined title-year key picked up what the DOI match missed, leaving 247 records. Of these, four were removed as outside accommodation-based service review research, giving a final corpus of 243 journal articles. Keeping database retrieval, deduplication, and eligibility screening as distinct stages makes each decision auditable, following established review practice (Page et al., 2021).

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Text analysis used five metadata fields per article: title, abstract, author keywords, index keywords, and source title. These were joined into a single text field per document. Records shorter than 80 characters after joining were dropped before modelling; sparse inputs destabilise LDA solutions. Preprocessing ran in R with quanteda 4.3.1 (Benoit et al., 2018): text was lowercased and stripped of punctuation, symbols, numbers, English stopwords, domain-specific stop terms, and URL fragments.

Two analytical tools were applied in sequence, not interchangeably. Bibliometric mapping came first, covering source concentration, keyword co-occurrence, and broad conceptual positioning. Topic modelling followed, moving past surface keyword clusters to the latent streams running through the corpus. Latent Dirichlet Allocation was estimated through the topicmodels package in R (Blei et al., 2003; Grün & Hornik, 2011), with K = 8 topics extracted by Gibbs sampling (iter = 3,000, burnin = 1,000, thin = 50). A K = 10 run served as a robustness check. K = 8 was retained because it gave the clearest separation between topics without collapsing thematically distinct streams, consistent with recent practice in tourism topic modelling (Kirilenko & Stepchenkova, 2025).

Frequency alone does not determine importance, so we compared topics on three dimensions: breadth, influence, and temporal movement. Topic prevalence was calculated as the mean document-topic proportion across the corpus:

$$Prevalence_k = \frac{1}{N}\sum_{d=1}^{N} \theta_{dk},$$

where N is the number of documents and θ_{dk} is the estimated proportion of topic k in document d. Topic influence was then examined using both citation-weighted impact and an age-adjusted citation percentile measure, while temporal change was assessed by tracing annual topic salience relative to each topic's own historical baseline. The point of these measures is not methodological display. It is to avoid a flatter reading of the literature in which frequency alone stands in for significance.

Combining these three layers allows the review to distinguish field structure, thematic content and topic-level importance. Bibliometric mapping supplies the structural view. Topic modelling identifies what the literature is about beneath the keyword surface. Impact and evolution assessment separate's themes that are merely frequent from those that are genuinely consequential. At that point the review moves from description to interpretation; a governance-oriented reading then becomes possible, because the literature can be examined for the service signals, response logics, and managerial routines it implicitly supports.

Findings

Corpus Profile and Field Development

Table 1 summarises the corpus profile and confirms that online review-based service quality research in hospitality and tourism has developed beyond a narrow niche into a broader and more methodologically mixed field. The dataset contains 243 journal articles published between 2005 and 2026, distributed across 116 sources and written by 712 unique authors.

The 243 articles produced 1,280 author keywords and 994 index keywords—a descriptor-to-document ratio high enough to suggest thematic branching rather than random dispersion. Adjacent streams are forming around a stable service-review core rather than pulling the field apart. Earlier hospitality overviews that used topic modelling noted a similar tendency, though they stopped at structural mapping and did not separate thematic breadth from scholarly influence (Zheng et al., 2023; Grljević, 2025).

Table 1: Corpus Profile

Metric	Value
Documents (N)	243
Timespan (years)	2005–2026
Sources (journals)	116
Authors (unique)	712
Author appearances	815
Avg. authors per document	3.35
Author keywords (DE): total	1280
Author keywords (DE): avg per document	5.27
Index keywords (ID): total	994
Index keywords (ID): avg per document	4.09
Total citations (TC)	8430
Avg. citations per document	34.69
References (CR): total	2431
References (CR): avg per document	10

Source: Authors' Work

Output was limited in the early years, picked up after 2015, and accelerated again after 2019. The 2026 count is lower because the year was incomplete at the time of retrieval. What is more relevant than volume is the source structure: publication has remained concentrated in hospitality journals even as the analytical vocabulary has grown more computational. Methods have been added to a service-management base rather than displacing it. Recent service-quality review work finds a similar pattern—AI and analytics appear as extensions of longer-running managerial concerns, not standalone novelties (Olawuyi & Kleynhans, 2025).

Major Conceptual Patterns in the Literature

Figure 2 maps the temporal distribution of the 20 most frequent author keywords across the review period. Keywords associated with the service management core—online reviews, service quality, service failure, service recovery—appear from the early years and maintain consistent presence through 2026. Computational and analytical terms—machine learning, natural language processing, big data—emerge predominantly after 2015 and strengthen toward the later years. Nothing in this distribution suggests displacement. The computational vocabulary arrived on top of a service-management base that was already there—not as a replacement for it. Recent work on AI in tourism confirms the same tendency (Li, 2025; Zhang et al., 2026).

The keyword distribution makes one thing plain: there is no replacement story here. The core questions—how guests experience service, how management responds, how quality is signalled and perceived—have not been displaced by sentiment analysis or deep learning. They

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have been supplemented. That supplement matters, but it does not rewrite what the review-based service quality literature is fundamentally about.

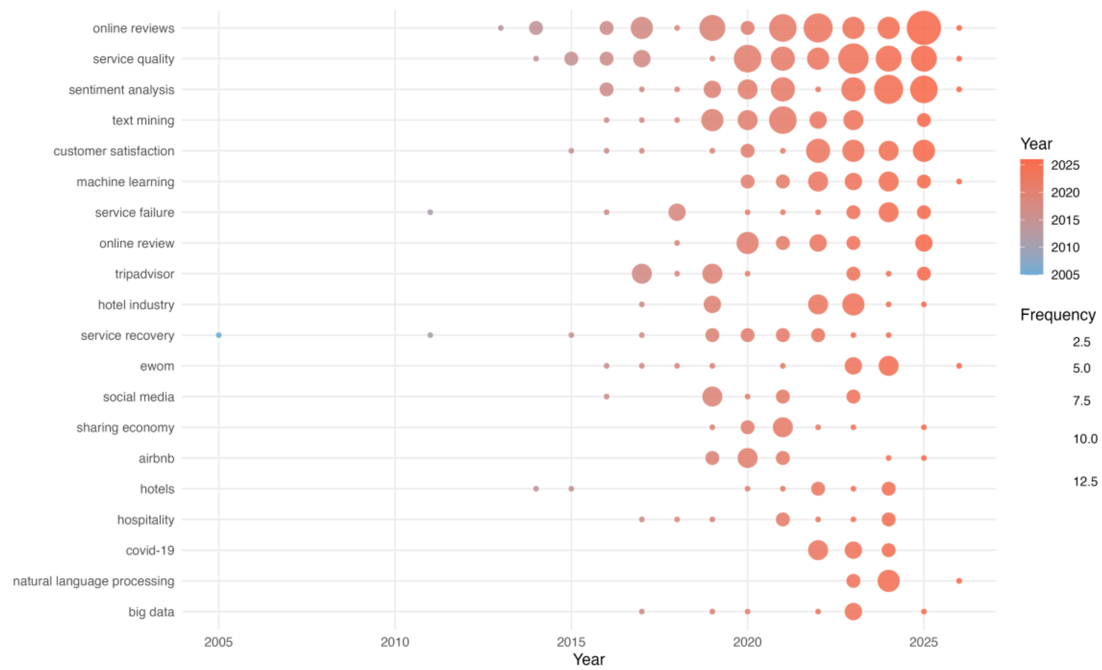

Figure 2: Temporal Distribution of the 20 Most Frequent Author Keywords (2005–2026)

Note: Bubble size represents annual keyword frequency; colour indicates publication year from 2005 (blue) to 2025 (red/orange). Keywords are ranked by total frequency across the review period.

Source: Authors' Work

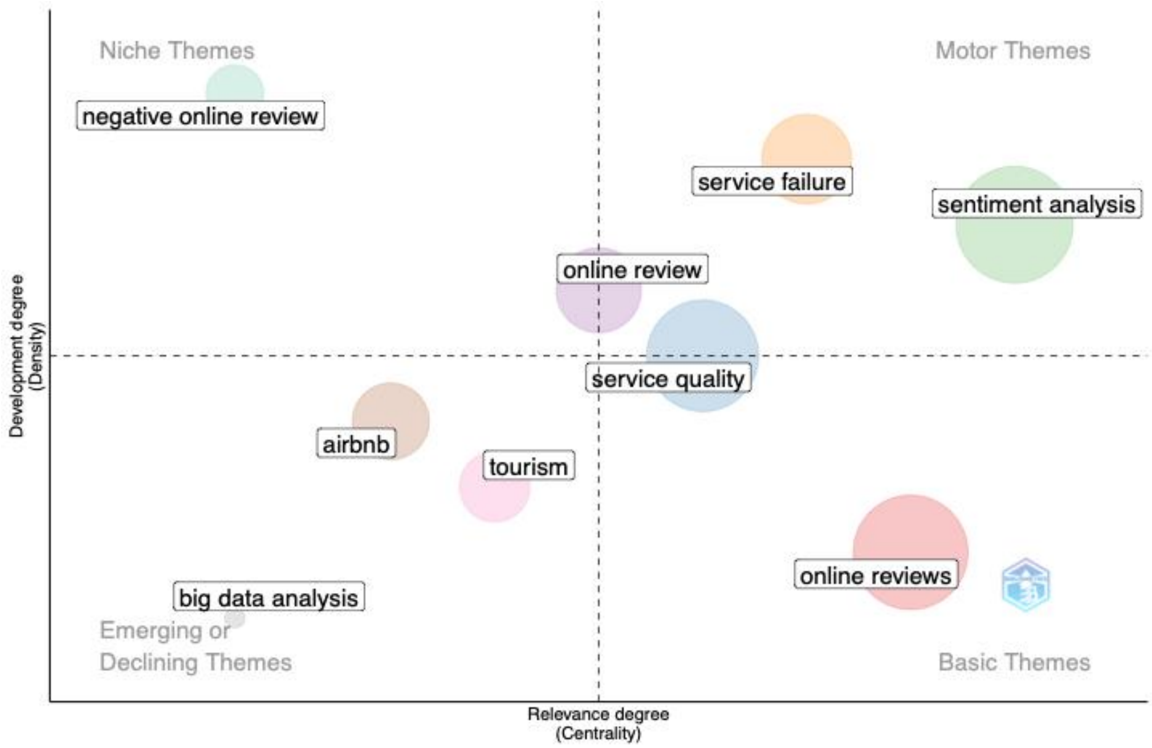

Figure 3: Thematic Map of Author Keywords

Note: The map positions themes according to centrality and density, distinguishing basic themes, motor themes, niche themes, and emerging or declining themes.
Source: Authors' Work

Figure 3 adds the field's internal hierarchy. Online reviews and service quality fall into the basic-theme quadrant. These are not specialised topics. They are the infrastructure of the literature. Sentiment analysis and service failure appear as motor themes. That position is more revealing. Service failure has moved beyond being a shared concern of the field and become one of the main sites where the literature now generates sharper and more operational governance logic. This fits earlier work by Sparks and Browning (2011) on managerial responses and later justice-oriented studies such as Olson and Ro (2020), but the thematic map shows that the issue is no longer just recurrent. It is productive. Negative online review is more bounded, while big data analysis remains less settled. Airbnb is visible, but not equally central. Centrality and dynamism, in short, do not line up across the field.

Thematic Structure of the Field

Four functional domains emerge from the latent structure of the corpus. The eight-topic solution does not produce one dominant block and several trivial leftovers. Topic prevalence is narrow, ranging from 11.52% to 13.61%, meaning several streams have expanded together. The field is not flat, though. Table 2 shows the differences clearly once prevalence and impact are read side by side.

Table 2: Latent Topic Taxonomy, Prevalence, and Impact

Topic	Topic label	Prevalence (%)	Impact (θ-weighted TC)	Top terms	Representative articles (Top 3)
T1	Review information and rating signals	12.45	36.13	information, ratings, managers, travelers, can, positive, studies, also, important, internet, business, system	1. Shen et al. (2021), Assessment of indoor environmental quality in budget hotels 2. Lata and Rana (2021), Determinants of consumers' online review adoption for hotel bookings 3. Tarkang et al. (2022), Website quality and information-task-fit in electronic word of mouth
T2	AI/ML-driven service analytics	12.39	33.16	data, learning, using, performance, machine, big, used, techniques, analytics, based, proposed, wellness	1. Yadegaridehkordi et al. (2021), Customer segmentation in eco-friendly hotels using machine learning 2. Yan et al. (2024), Optimizing tourism service quality using deep learning in 5G multimedia environments 3. Alsayat (2023), Customer decision-making based on big social data using machine learning

Topic	Topic label	Prevalence (%)	Impact (θ-weighted TC)	Top terms	Representative articles (Top 3)
T3	Knowledge mapping and social media stream	12.78	36.62	value, social, different, behavior, consumer, implications, design, media, purpose, consumers, limited, methodology	1. Nusair et al. (2019), A bibliometric analysis of social media in hospitality and tourism research 2. Azer and Alexander (2018), Conceptualizing negatively valenced influencing behavior 3. Park et al. (2016), Analyzing Twitter to explore perceptions of Asian restaurants
T4	NLP/LLM-enabled review understanding	12.34	28.25	sentiment, framework, insights, improve, using, industry, language, analyze, feedback, show, platforms, luxury	1. Ho et al. (2024), ChatReview: A ChatGPT-enabled framework for domain-specific review analysis 2. Hsueh and Hsu (2026), A GPT-based framework for visitor experience analysis 3. Botunac et al. (2024), Fine-tuning versus prompt engineering in hospitality review classification
T5	Guest experience and quality perceptions	12.56	31.67	guests, experiences, industry, content, guest, experience, perceptions, tourists, tripadvisor, user-generated, overall, group	1. Ali et al. (2023), Quality attributes and guest perceptions in Norwegian green hotels 2. Sann et al. (2020), Online complaining behavior across cultural background and hotel class 3. **Arici et al. (2023), Big data analytics and customer satisfaction with green hotel service quality**
T6	Service failure and recovery	13.61	40.93	negative, response, failure, management, responses, recovery, effect, intention, managerial, effects, perceived, justice	1. Olson and Ro (2020), Company responses to negative online reviews 2. S and Anusree (2016), Severity, agreement, webcare, and hotel booking intentions in negative online reviews 3. Qiu et al. (2018), Managing face in service failure

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Topic	Topic label	Prevalence (%)	Impact (θ-weighted TC)	Top terms	Representative articles (Top 3)
T7	Satisfaction/ attribute modelling under shocks	12.35	36.96	satisfaction, attributes, covid-19, impact, industry, modeling, word, new, perception, pandemic, latent, key dimensions,	1. Hussain et al. (2023), Tourism satisfaction, service quality, and destination loyalty 2. Kim et al. (2023), Asymmetric effects of multi-attributes on customer satisfaction during COVID-19 3. Grechyn and McShane (2021), Customer satisfaction with Wi-Fi speed in Australian hotels
T8	Sharing economy accommoda tion and SERVQUA L	11.52	33.04	accommodati on, airbnb, theory, sharing, factors, economy, elsevier, based, theoretical, servqual, sustainable	1. Wang and Yu (2021), Sustainable consumption behavior in the sharing economy 2. Liu et al. (2025), An FMEA decision support model for hotel risk assessment using online reviews 3. Liu et al. (2025), Reforming the SERVQUAL model for accommodation sharing services

Note: Prevalence refers to the average topic proportion across documents. Impact refers to the topic-weighted citation influence. Representative articles are the highest-ranked documents within each topic.
Source: Authors' Work

The first domain is managerial response, anchored by T6 (Service failure and recovery) and backed by T1 (Review information and rating signals). T6 leads the taxonomy on both dimensions: 13.61% prevalence and a citation impact of 40.93. Justice theory and face management supply the conceptual vocabulary. Replying to a negative review is not primarily a communication task—it is a fairness test. Guests assess whether a response is procedurally and interactionally adequate, not just whether one arrived (Olson & Ro, 2020; Qiu et al., 2018). Trust and webcare were already central concerns in earlier work (S & Anusree, 2016). What has not been settled is how to design the reply to itself: whether the text reads as genuine or templated, how quickly it was sent, and whether the tone fits the complaint type all affect whether guests accept it as sufficient (Ku et al., 2024; Tran et al., 2025).

The second domain is experience-evaluation, covering T5 (Guest experience and quality perceptions) and T7 (Satisfaction/attribute modelling under shocks). The more notable figure here is T7's: at 12.35% prevalence, its impact score of 36.96 sits above T5's 31.67 despite a nearly identical corpus share. Disruptions force guests to reprioritise service attributes in ways that routine monitoring was not built to detect, and that is what accounts for the gap. Hussain et al. (2023) track these dynamics at the broader tourism-satisfaction level; Kim et al. (2023) document how hotel attribute weights shifted asymmetrically during COVID-19. Grechyn and McShane (2021) provide a narrower instance—a single service attribute taking on unexpected salience under conditions of disrupted digital expectations. Classical service-quality measurement treats guest priorities as relatively stable inputs; the evidence from T7 complicates that assumption.

The third domain is computational-analytical, covering T2 (AI/ML-driven service analytics) and T4 (NLP/LLM-enabled review understanding). What distinguishes this domain is not its size—both topics carry corpus shares near 12%—but the gap between T4's recent output growth and its citation weight. T4 lands at 28.25 on impact, the lowest number in the taxonomy, despite its fast upward trajectory. T2 sits at 33.16 and has had longer to convert output into citations. Yadegaridehkordi et al. (2021) and Alsayat (2023) illustrate what that consolidation looks like: AI/ML tools tied to recognisable managerial decisions, tested with enough rigour to attract follow-on work. T4 is not there yet. Ho et al. (2024) on ChatReview and Hsueh and Hsu (2026) on GPT-based visitor experience analysis are its current frontier. Alharbi et al. (2025) and Zhang et al. (2025) note that trust, task fit, and interpretability are still open questions, not settled ones.

The fourth domain is contextual extension, represented by T8 (Sharing economy accommodation and SERVQUAL) and part of T3 (Knowledge mapping and social media stream). T8 has the smallest corpus share of any topic (11.52%) but an impact score of 33.04—higher than T4 and T5. Wang and Yu (2021) and Liu et al. (2025b) form its core; Liu et al. make the specific argument that SERVQUAL requires recalibration under accommodation-sharing conditions. Nusair, Butt, and Nikhashemi (2019) situate this within the broader opening of hospitality review research beyond traditional hotel contexts through social media. T3 does not belong exclusively to this domain: its top terms span social influence, consumer behaviour, and knowledge mapping, making it a cross-cutting stream that surfaces across multiple thematic contexts rather than anchoring any single one. Volume and influence diverge in this domain: the corpus share is small, but the intellectual return per study is not.

The taxonomy does not produce a flat hierarchy. T6 carries the most combined weight on prevalence and citation impact. T4 shows the widest gap between recent visibility and accumulated scholarly influence. T8 is small by prevalence but produces a stronger citation return per study than its corpus share would suggest.

Topic Influence and Thematic Evolution

Figure 4 plots topics by prevalence and citation impact. T6 occupies the high-prevalence, high-impact zone alone. The work on service breakdown, recovery logic and managerial response runs deeper than any other stream in the corpus. Sparks and Browning (2011) and Xie et al. (2014) established this direction early, linking hotel reviews to trust repair and complaint handling in work that has been repeatedly built upon. The impact data do not produce a surprise—they confirm what the depth of the earlier literature already implied.

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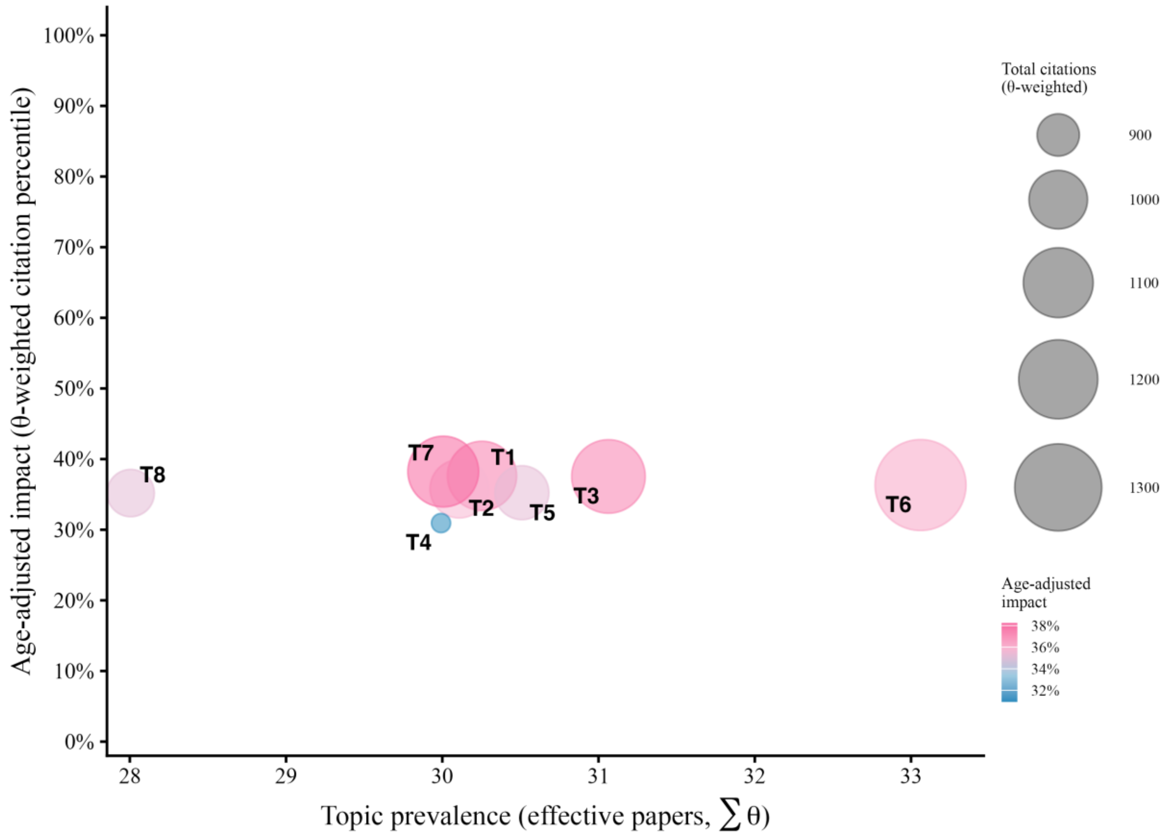

Figure 4: Topic Impact Landscape

Note: Bubble size represents topic-weighted citation influence, and colour indicates age-adjusted topic impact.
Source: Authors' Work

T8 falls in a second zone—lower prevalence, but influence that competes with larger topics. Platform-mediated accommodation alters the service setting and quality criteria simultaneously, which explains why a corpus share of 11.52% still produces an impact score of 33.04. Wang and Yu (2021) document this from the sharing-economy side; Liu et al. (2025b) go further, arguing that SERVQUAL itself requires adjustment for accommodation-sharing contexts. T3 sits nearby in the distribution, from a more meta-analytical angle.

T4 stands apart in one respect: 12.34% of the corpus but an impact score of 28.25, the lowest in the taxonomy. AI and LLM studies in hospitality are being produced faster than they are accumulating citation weight. Part of this is a publication-lag effect—recent work has had less time to build references than topics that established themselves a decade earlier. But T6 and T8 built their citation weight over time in ways T4 has not yet replicated. Li (2025) and Zhang et al. (2026) both documents continued output growth in generative AI and AI-supported hospitality contexts; neither demonstrates that this output has yet produced the same depth of citation return as the older service-management topics.

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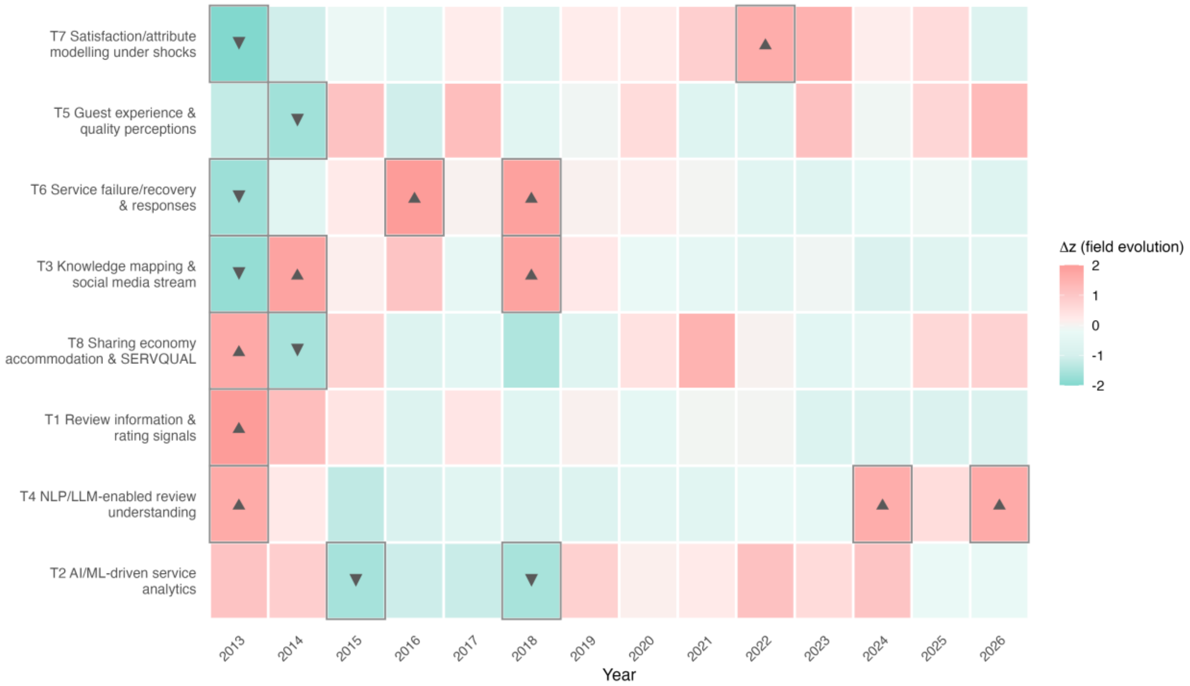

Figure 5: Topic Evolution Dynamics

Note: Positive and negative values indicate strengthening and weakening in standardised topic salience over time.
Source: Authors' Work

Figure 5 plots standardised topic salience by year. T6's line rises early and then levels off—stable before the corpus entered its main growth phase. T7 traces a spike that is narrow in time and concentrated around the disruption period, then subsides. T4 and T2 both trends upward in the later years, with T4's trajectory steeper. Reading the chart left to right: the managerial topics front-loaded their influence, and the computational topics are back-loading theirs. The service core was already established when the computational layer began growing, and the two sets of topics have followed different time paths through the field.

A Review-Based Framework for Service Quality Monitoring and Response

Table 3 draws the taxonomy into something more directly applicable. The topics are not all operationally relevant in the same way: T6 and T1 point toward complaint monitoring and response design; T2 and T4 toward analytical tools for handling review volume at scale; T8 toward sector-specific considerations for sharing-economy properties. Those distinctions are the table's point: each thematic stream maps to something a hospitality operation would actually track and act on.

Table 3: A Review-Based Framework for Service Quality Monitoring and Response in Hospitality

Topic	Theory anchor	Monitoring signal	Action lever	Evaluation metric
T1 Review information	Signaling; information diagnosticity	Rating variance; sudden drops;	Align web/app cues; verify key claims;	Conversion ↑; helpfulness ↑; mismatch-

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environment & rating signals		helpfulness ratio; "mismatch" mentions	badges/photos/policies; fix info gaps	complaint share ↓
T2 AI/ML-driven service analytics	Analytics capability; data-driven decisions	Negativity/churn risk score; segment drift; anomaly alerts	ML triage + routing; dynamic staffing; targeted recovery/marketing	AUC/F1 (or RMSE) ↑; time-to-intervention ↓; repeat issues ↓
T3 Social media & H&T knowledge mapping	Diffusion/social influence; agenda-setting	Sentiment momentum; share velocity; KOL-triggered spikes	Social listening rules; escalation; community moderation; rapid FAQ response	Sentiment recovery time ↓; diffusion rate ↓; qualified engagement ↑
T4 Advanced NLP & LLM-enabled review understanding	Sensemaking; human–AI collaboration	Aspect sentiment; emerging themes; cross-lingual risk	LLM-assisted aspect triage; human-in-loop checks; owner routing; evidence summaries	Aspect F1 ↑; analyst hours ↓; response latency ↓; false alarms ↓
T5 Guest experience & quality attribute perceptions	Expectation–confirmation; experience economy	Attribute negatives (cleanliness/check-in/green); segment gaps	Fix weak attributes; close promise–delivery gap; verifiable green cues	Attribute satisfaction ↑; positive mentions ↑; overall rating ↑
T6 Service failure, recovery & managerial responses	Justice theory; service recovery	Severe low-star + injustice language; delayed/templated replies	Webcare SLA; empathy/accountability scripts; compensation + escalation	Resolution rate ↑; rating rebound ↑; secondary negatives ↓
T7 Satisfaction/attribute modelling under shocks	Crisis management; attribution	Attribute-importance drift (hygiene/safety); asymmetry; volatility spikes	Prioritise assurance attributes; flexible policies; transparent risk comms	Cancellation ↓; satisfaction stability ↑; loyalty/repurchase ↑
T8 Sharing economy accommodation & SERVQUAL adaptations	SERVQUAL/e-SERVQUAL; platform governance	SERVQUAL gaps; host-risk mentions; rating variance	Standards/audits; dispute handling; host training; risk screening	Disputes ↓; response time ↓; variance ↓; dimension scores ↑

Note: The framework links major thematic streams in the literature to theory anchors, monitoring signals, action levers, and evaluation metrics. It is intended as a literature-based synthesis rather than a field-validated operational model.
Source: Authors' Work

What T6 and T1 describe is closest to what most hospitality operations already do in some form—tracking severe complaints, watching for fairness-related language in reviews, checking whether replies went out on time. The problems T5 and T7 point to are less comfortable: not whether the hotel said something back, but whether the service itself is drifting away from guest expectations, and whether a disruption has permanently shifted what those expectations are. T2 and T4 are different again—their value lies in processing volume, not in knowing which attributes matter most. T8 adds a practical qualification: a platform-mediated property draws different quality signals from a conventional hotel, and the same review data cannot be read the same way across both. Response design, response satisfaction, and AI-assisted review handling each cut across more than one of these uses (Ku et al., 2024; Tran et al., 2025; Zhang et al., 2025).

Two hundred and forty-three articles produce findings that are individually useful but hard to apply as a whole—they are not organised for practitioners, and no single paper covers the full range. Table 3 does something the 243 papers had not been arranged to do before: it translates the corpus into a form that a hospitality manager could work from without having read all of them. Whether the specific connections between what the literature identifies and what a working team should actually measure hold in practice depends on context and requires empirical testing. No prior synthesis had assembled this structure.

Nothing in this table has been piloted in an actual hotel or tourism operation. The connections between what the literature identifies and what a working team would measure and act on remain to be tested. Some of what the corpus suggests will translate without much adjustment; other parts will meet operational constraints that 243 published studies cannot anticipate. That is a real limitation—but it does not make the synthesis less worth attempting. Review research in hospitality has accumulated enough material to support a provisional framework of this kind, even though researchers have rarely drawn one out in these terms.

Discussion

Theoretical Contribution

The argument advanced here is narrower than most review-paper conclusions. For most of its history, hospitality research read reviews as a record: what guests reported, what they felt, how satisfaction tracked against benchmarks (Litvin et al., 2008; Cantallops & Salvi, 2014; Chen & Law, 2016). That reading is not wrong. It just stops too early. Reviews are also material—actionable signals that can be sorted, prioritised, and routed to wherever response capacity is available. That is what changes when the question shifts from what reviews say to what should be done about them. The methodological contribution is more contained. Counting how often a topic appears in a corpus is not the same as measuring its scholarly influence, and a topic that expanded recently is not the same as one that has generated durable citation weight. Running bibliometric mapping alongside LDA and age-adjusted impact captures those distinctions together; neither analysis alone would pick them up (Zheng et al., 2023).

Prevalence, scholarly influence and temporal momentum refuse to collapse into one ranking, and that refusal is useful. No organisation can watch every signal with equal intensity. Not every topic deserves intervention. The impact and evolution results, read this way, amount to a logic for deciding what comes first.

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Managerial Implications for Hospitality and Tourism Practice

Hospitality managers gain most by treating online review management as a layered governance routine rather than an ad hoc response activity. Domains that are both prevalent and influential, service failure and recovery above all, belong in standing dashboards and response protocols. Targeted triggers suit the specialised-but-influential domains. New AI capability deserves adoption in small doses, under observation. And the routine has to learn from itself. Response timeliness, complaint reduction, rating recovery and issue-detection quality are all measurable, and worth measuring, because a review system pays off only when signal processing shows up as service improvement (Palese et al., 2021; Li, 2025).

T6 is where the routine should anchor. Service breakdowns, managerial responses and recovery justice have the prevalence and citation weight to earn standing dashboards, response-time standards, escalation rules and post-recovery evaluation. T8 wants the opposite treatment. Small footprint, competitive impact: watch it closely wherever platform accommodation operates and skip the permanent dashboard. Prevalence determines how wide routine attention must reach; impact tells you what happens when that reach falls short. Some themes belong on standing dashboards; others run on trigger-based escalation or context-specific monitoring.

A third category holds topics where strategic weight has outrun consolidation—T4 again. Its impact is low today, but multilingual review environments, aspect-level risk diagnosis and high-volume text interpretation all pull in its direction. Experiment selectively here rather than institutionalise wholesale; human-in-the-loop summarisation, multilingual clustering and evidence-linked routing make sensible first moves. The temporal findings argue for the same adaptive stance. T6 deserves long-run institutionalisation. T2 and T7 need periodic recalibration. T4 is best grown in stages. None of this should be static; different thematic zones are best updated at different rhythms (Zheng et al., 2023; Palese et al., 2021; Zhang et al., 2025).

Limitations and Future Research

Some boundaries apply. The corpus comes from one database, Scopus, and from English-language articles only; relevant work indexed elsewhere, or published in other languages, will have been missed. The taxonomy depends on modelling decisions too. Different preprocessing, vocabulary trimming or topic numbers would redraw parts of the map, so we treat it as an interpretable representation, not a fixed one. The framework in Table 3 carries its own caveat: it is built from synthesis, and its practical value is untested in organisational settings so far (Palese et al., 2021; Zhang et al., 2025).

The most pressing extension is prospective testing. Whether the signal-action-metric logic in Table 3 actually sharpens monitoring, speeds response and improves recovery can only be settled in real hospitality settings, under the attention constraints managers face. Two methodological extensions also apply: replication with a multi-database and multilingual corpus would test whether the thematic structure holds beyond Scopus and English-language publishing, and comparison with newer embedding-based or generative topic-modelling approaches would show whether they produce materially different topic boundaries.

Conclusion

The 243 articles examined here map a structured but internally differentiated field. Bibliometric mapping, latent topic modelling, topic-level impact assessment and thematic evolution analysis each reveal a different face of the same literature: a stable service-quality core that has drawn in computational analytics, platform-based accommodation contexts and language-oriented interpretive approaches without losing its original orientation.

Prevalence, scholarly influence and temporal momentum do not move together, and that divergence is the analytical result. The field has no single organising agenda—it has a layered structure: durable cores, specialised streams, emerging analytical fronts. That structure is also the governance argument. Review systems are not just repositories of customer feedback; they are running signals for service monitoring, intervention prioritisation and adaptive response.

Two takeaways, then. The field has a structured map: a broad, methodologically diverse literature sorted into streams of differing influence and momentum. And the map works as more than a reading list, because once its themes are tied to monitoring signals, action levers and evaluation metrics, it becomes a governance logic for hospitality and tourism management. Whether that logic improves monitoring, response and recovery in practice is an empirical question. Answering it means prospective testing, in real organisations, under the attention constraints managers actually face.

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