



An AI-Enhanced Bibliometric Analysis of Customer Feedback and Hotel Performance in Hospitality

Análise Bibliométrica Assistida com Inteligência Artificial sobre o Feedback dos Clientes e o Desempenho Hoteleiro

Marta Morgado Neves 

Instituto Universitário de Lisboa (ISCTE-IUL), ISTAR, Lisboa, Portugal, Marta_Sofia_Neves@iscte-iul.pt

Nuno António 

NOVA Information Management School (NOVA IMS), Universidade Nova de Lisboa, Lisboa, Portugal, nantonio@novaims.unl.pt

Sérgio Moro 

Instituto Universitário de Lisboa (ISCTE-IUL), ISTAR, Lisboa, Portugal, and The University of Jordan, Amman, Jordan, Sergio.Moro@iscte-iul.pt

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Abstract

In the digital era, customer feedback has evolved into a strategic asset influencing hotel performance, competitiveness, and investment decisions. This study reviews the relationship between online reviews and key performance indicators (KPIs) in the hospitality sector and proposes an AI-enhanced literature review framework. By integrating bibliometric analysis, Natural Language Processing (NLP), and Large Language Models (LLMs), the approach enables scalable, context-aware synthesis of research on customer perceptions and their financial implications. The findings show that customer feedback significantly influences hotel performance, particularly affecting pricing strategies, occupancy rates, and revenue outcomes. However, the literature remains heavily reliant on rating-based proxies and makes limited use of real operational data, thereby constraining the accuracy of financial assessments. Additionally, gaps persist in data integration, geographic representativeness, and the translation of feedback into actionable investment decisions. From a practical perspective, the results highlight the need for more advanced, data-driven frameworks that integrate textual feedback with financial metrics. The proposed methodology offers a replicable approach to support more accurate and strategically relevant analyses in hospitality management.

Keywords: Customer Feedback; Hotel Performance; Online Reviews; Artificial Intelligence; Investment Strategies; Bibliometric Analysis.

Resumo

Na era digital, o feedback dos clientes evoluiu para um ativo estratégico com impacto no desempenho, competitividade e decisões de investimento no setor hoteleiro. Este estudo analisa a relação entre as avaliações online e os principais indicadores de desempenho (KPIs) na hotelaria e propõe um enquadramento de revisão da literatura assistido por inteligência artificial. Ao integrar análise bibliométrica, Processamento de Linguagem Natural (NLP) e Modelos de Linguagem de Grande Escala (LLMs), a abordagem permite uma síntese escalável e contextualizada da investigação sobre perceções dos clientes e as suas implicações financeiras. Os resultados demonstram que o feedback dos clientes influencia significativamente o desempenho hoteleiro, afetando estratégias de preços, taxas de ocupação e receitas. Contudo, a literatura baseia-se predominantemente em métricas agregadas, com utilização limitada de dados operacionais reais, restringindo a precisão das análises financeiras. Adicionalmente, persistem lacunas na integração de dados, representatividade geográfica e na tradução do feedback em decisões de investimento acionáveis. Do ponto de vista prático, os resultados evidenciam a necessidade de abordagens mais avançadas e orientadas por dados, que integrem feedback textual com métricas financeiras. A metodologia proposta oferece uma abordagem replicável para suportar análises mais precisas e estrategicamente relevantes na gestão hoteleira.

Palavras-chave: Feedback dos clientes, Desempenho Hoteleiro, Avaliações Online, Inteligência Artificial, Estratégias de Investimento, Análise Bibliométrica.

1. Introduction

Tourism has established itself as one of the most dynamic and strategic sectors of the global economy, exerting a significant impact on the economic and social development of regions throughout history (Sharma et al., 2021). Initially an exclusive activity reserved for a privileged few (Speake et al., 2022), tourism has progressively become more accessible to the general population (Qiao et al., 2022), thereby fostering profound economic, social, and cultural transformations in the regions that depend on it (Gretzel et al., 2021; Thommandru et al., 2023).

By the 1990s, the digital revolution had begun to mark a new era for the sector (Wang et al., 2021), profoundly transforming how hospitality businesses interact with their customers (Pandey et al., 2023). The proliferation of digital platforms has provided a global audience not only with the ability to make reservations quickly and conveniently [60] but also to share their opinions, generating an unprecedented feedback dynamic (Helberger, 2020; Jiménez-Zarco et al., 2025). With a vast array of available options, consumer awareness has become a decisive factor in decision-making (Verma et al., 2017; López- Rodríguez & Forero, 2024; González-Pozo



et al., 2025), and online reviews have assumed a crucial role in shaping the reputation of hospitality establishments (Zhang et al., 2021; Chuang et al., 2024).

Beyond online reviews, digital customer feedback in hospitality is increasingly mediated by AI-enabled interaction systems, including chatbots and recommendation-oriented platforms (Xu et al., 2025). These technologies are reshaping how travellers search for, evaluate, and book hotel services, while simultaneously generating new forms of behavioural and conversational data (Malik et al., 2026). As a result, customer feedback should be understood as part of a broader digital ecosystem of customer–hotel interaction, rather than being limited exclusively to public review platforms.

This competitive environment, intensified by real-time access to information and the transparency of online reviews, has led to a substantial increase in competition within the hospitality sector (Ye et al., 2020). A hotel's online reputation, often shaped by customer reviews (Gretzel et al., 2021), has become a decisive factor in destination and accommodation choices (Pu et al., 2024; Křečková et al., 2025), with direct implications for financial performance and business sustainability (Xie et al., 2017).

Once seen as a satisfaction indicator, customer feedback is now viewed as a strategic data source (Aldunate et al., 2022). In-depth analysis of this information enables hospitality businesses to identify critical areas for improvement (Zhan et al., 2020) and provides essential insights for marketing strategy development and service optimisation (Kshetri et al., 2024). The ability to transform feedback into a competitive advantage has proven to be a key differentiator for companies seeking to thrive in a saturated, increasingly demanding market (Buccieri et al., 2023).

Despite the recognised value of customer feedback, businesses face a significant challenge: the investment required to ensure customer satisfaction is often constrained by budgetary limitations (Mainardes et al., 2023). In this context, it is essential for hospitality companies to accurately understand what customers value most and what needs improvement to maximise return on investment (Michopoulou et al., 2019). Despite its recognised importance, the existing literature lacks integrated approaches that connect customer feedback analysis to scalable, data-driven methodologies linking qualitative insights to financial performance metrics (Vives et al., 2018).

This article aims to conduct an in-depth analysis of the impact of customer feedback on hotel financial performance, with a particular focus on online reviews, which are considered a strategically relevant resource. Through a review of the existing literature, the study explores the evolution of customer feedback, which has, over time, transcended its initial role as a mere measure of satisfaction to become an indispensable tool for continuous service quality improvement and the optimisation of strategic decision-making.

To meet the objectives of this research, we propose a hybrid methodology that partially automates the systematic literature review (SLR) process by integrating bibliometric analysis, LLMs, and human validation. While recent advances have demonstrated the potential of AI, particularly LLMs, to accelerate stages such as abstract screening and thematic summarisation, its application remains fragmented and limited to isolated phases. As noted by Bolaños et al. (2024), most LLM-based tools "do not directly support specific SLR phases" and are not yet fully integrated into coherent review workflows. Our methodology is novel in combining macro-level bibliometric mapping, micro-level semantic filtering via GPT-4, and AI-driven thematic clustering, followed by manual validation. This integrated approach mitigates selection bias, improves reproducibility, and offers a more structured and semantically rich categorisation. The human-in-the-loop component further ensures interpretability and contextual alignment, refining AI outputs to match the nuances of hospitality and tourism research.

Using this methodology, the study systematically analyses selected articles from leading academic journals that explicitly examine the relationship between customer feedback and hotel performance, employing diverse research methodologies. The findings reinforce that the strategic use of customer feedback provides hotels with a substantial competitive advantage, simultaneously enhancing customer satisfaction and improving financial performance.

While acknowledging the limitations of existing studies, this research contributes both methodologically and empirically by demonstrating that a structured, AI-enhanced approach to literature review can accelerate knowledge discovery and refine industry best practices. Additionally, the article discusses future research directions in this field by identifying significant gaps in the current literature and proposing new methodological approaches. By addressing these gaps, future studies can provide a more comprehensive and in-depth understanding of the mechanisms through which customer perception shapes business performance and long-term success in the hospitality industry.

In this context, the study is guided by three interrelated research questions:

RQ1: How has the academic literature on customer feedback and hotel performance evolved over time, particularly in terms of publication trends, geographic distribution, and scientific influence?



RQ2: What are the dominant research themes linking customer feedback to hotel performance, and how are these themes conceptually interconnected?

RQ3: How have methodological approaches in this field evolved, particularly with the growing role of artificial intelligence and LLM-based techniques, and what are the main research gaps that continue to limit the integration of customer feedback into performance-oriented decision-making frameworks?

2. Methodological Innovation: AI-Enhanced Systematic Literature Review Framework

2.1 Rationale and Limitations of Traditional SLRs

A SLR is a rigorous and structured methodological approach aimed at mapping, critically evaluating, and synthesising existing knowledge on a specific topic. In contrast to narrative reviews, SLRs follow standardised protocols that ensure transparency and replicability and minimise bias (Bolaños et al., 2024; Marzi et al., 2024). Originally rooted in Evidence-Based Medicine, the SLR approach has since been adapted to disciplines such as management, hospitality, and tourism (Bolaños et al., 2024; van Dinter et al., 2021).

SLRs are valued for synthesising large bodies of knowledge, supporting evidence-based decisions and advancing research (Uta Schirpke et al., 2023). However, despite these strengths, traditional SLRs have become increasingly unsustainable in fast-evolving scientific domains, such as digital tourism, AI-enhanced service management, and customer experience analytics, where new studies emerge at an unprecedented pace (Bornmann et al., 2021).

SLRs are known for being resource-intensive and slow (Al-Zubidy et al., 2019), often taking over a year (Bolaños et al., 2024; Borah et al., 2017). This is critical in fast-changing fields like tourism, where AI and events like COVID-19 reshape research faster than reviews can keep up with, often rendering reviews obsolete upon publication.

Additionally, the exponential increase in global scientific production (Bornmann et al., 2021) further complicates the identification and selection of studies, making it challenging to balance comprehensiveness with analytical depth. The need for periodic updates, crucial in dynamic fields such as customer feedback analytics, makes the process even more labour-intensive, often requiring researchers to restart it from scratch for each update (Bornmann et al., 2015).

To address these challenges, research has increasingly focused on automating SLRs, leading to AI-based tools for screening and data extraction (Kharawala et al., 2021; Qusai Khraisha et al., 2024; Tóth et al., 2023). The introduction of LLMs has significantly enhanced SLR execution by accelerating the process and deepening analysis. These models reveal emergent themes and latent connections that are often missed in manual reviews (Fabio Dennstädt et al., 2024; Landschaft et al., 2024).

This convergence between systematic review protocols and AI-enhanced analysis represents both a methodological evolution and a paradigm shift in scientific knowledge synthesis. Integrating human expertise with machine intelligence enables faster, deeper, and more adaptive reviews, allowing literature syntheses to evolve into living documents that respond in real time to emerging evidence, particularly relevant in fields like hospitality management and customer experience, where timely insights are vital for strategic agility and investment decisions.

2.2 Proposed Hybrid Framework: LLM Augmentation + Human Expertise

Building on the limitations identified in traditional SLRs, this study proposes and applies a hybrid AI-enhanced systematic literature review framework specifically designed to address the analytical challenges of customer feedback analysis in the hospitality sector. This framework combines advanced bibliometric analysis, manual expert validation, and AI-assisted thematic categorisation with GPT-4, leveraging the complementary strengths of human interpretative reasoning and machine-learning scalability. The use of GPT-4 was motivated by its ability to process large volumes of unstructured textual data and identify latent semantic patterns, thereby supporting the study's objective of systematically mapping how customer feedback influences hotel performance across diverse research contexts.

The proposed framework comprises six distinct, sequential phases, as illustrated in Figure 1, each designed to maximise the depth, breadth, and analytical power of the review process. To enhance methodological transparency and replicability, the role of GPT-4 within the framework is explicitly defined. GPT-4 was used during the initial screening and thematic categorisation phases. In the screening stage, abstracts were evaluated based on semantic proximity to the research questions using structured prompts. In the thematic categorisation stage, GPT-4 was prompted to assign each abstract to a coherent thematic cluster, following predefined instructions (see Appendix A). Human validation was then applied to ensure conceptual consistency and to correct potential misclassifications.

The proposed framework aligns with the emerging paradigm of hybrid or hetero-intelligence approaches, which emphasise integrating human expertise and artificial intelligence to enhance analytical performance. In this context, human intelligence



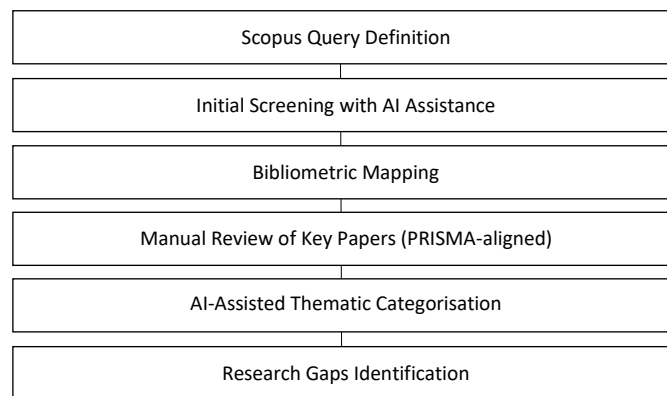
contributes domain knowledge, critical reasoning, and contextual interpretation, while AI systems provide scalability, consistency, and the ability to process large volumes of unstructured data.

This perspective is consistent with recent contributions that conceptualise hetero-intelligence as a collaborative system in which human and artificial intelligence interact to achieve superior outcomes compared to isolated approaches. For instance, recent studies propose structured hetero-intelligence frameworks that combine human judgment and LLM capabilities through sequential, replicable methodological steps, highlighting the importance of human oversight for ensuring robustness, contextual accuracy, and bias mitigation (Buitrago-Esquinas et al., 2024).

Similarly, in the context of tourism research, hetero-intelligence has been proposed as a methodological approach to address complex, multidimensional challenges by leveraging the complementary strengths of human and artificial intelligence. These approaches emphasise that, while LLMs are effective in processing information and generating insights, their limitations, particularly in contextual understanding and critical reasoning, require systematic human validation to ensure reliable outcomes (Buitrago-Esquinas et al., 2024).

Building on this perspective, the present study adopts a hybrid framework in which AI-driven semantic analysis is complemented by human validation, ensuring both scalability and interpretability. This integration enables a more structured, transparent, and reproducible literature review process while addressing the limitations of fully automated approaches.

Figure 1 - Hybrid SLR Framework - Combining Human Expertise & LLM Augmentation



Source: own elaboration.

1. **Scopus Query Definition:** A comprehensive search strategy was applied in Scopus, the leading abstract and citation database for peer-reviewed literature. The search criteria combined key terms related to customer feedback, hotel performance, and online reviews to ensure alignment with the study's scope.
2. **Initial Screening:** To refine the initial corpus, a combination of manual filtering and AI-assisted inclusion/exclusion was applied. Using GPT-4 to pre-screen abstracts based on semantic proximity to core research questions reduced noise and ensured thematic relevance.
3. **Bibliometric Mapping:** With the refined dataset, bibliometric techniques were employed to map scientific production, co-citation networks, geographic trends, and keyword co-occurrence patterns. This quantitative step provides a macro-level view of the evolution of research and highlights emerging or underexplored topics.
4. **Manual Review of Key Studies:** Informed by the bibliometric outputs, a targeted manual review was conducted, focusing on the most cited and thematically central papers, following PRISMA guidelines. This step preserves human interpretative depth, ensuring that contextual nuances, theoretical frameworks, and methodological rigour are critically evaluated.
5. **AI-Assisted Thematic Categorisation:** This is the framework's core methodological innovation. GPT-4 was prompted to analyse the full abstracts and generate thematic clusters, identifying recurring themes, methodological tendencies, conceptual overlaps, and latent research gaps. Unlike conventional keyword clustering, which relies on surface-level term frequency, LLM-based categorisation captures semantic relationships, even when terms are expressed in different ways across papers.



6. Research Gap Identification: Finally, the AI-generated thematic map was cross-validated against insights from manual reviews and bibliometric trends to synthesise the findings. This synthesis highlights not only what has been extensively researched but also areas where methodological weaknesses, geographical imbalances, or emerging topics reveal clear opportunities for future research.

This hybrid approach rests on the fundamental principle that human and machine intelligence excel in different, but complementary, tasks. Human researchers bring domain expertise, critical reasoning, and theoretical framing, while LLMs contribute scalability, semantic pattern detection, and algorithmic neutrality. By integrating the two, the review process benefits from interpretative depth and computational breadth, thereby minimising individual cognitive biases and accelerating knowledge discovery.

The proposed framework, though applied to hospitality, constitutes a scalable methodological contribution suitable for other fields with voluminous, rapidly evolving literature that requires both analytical depth and power. Feng et al. (2022) (Feng et al., 2022) demonstrated that AI models can achieve high recall (up to 0.928) in medical literature screening, though precision was lower (0.200), underscoring the need for human oversight to ensure relevance and contextual accuracy. Similarly, Chibwe et al. (2024) (Chibwe et al., 2024) evaluated GPT-4 in wastewater epidemiology, reporting near-perfect recall (1.00) and high precision (0.96), while stressing the importance of human intervention, especially for nuanced criteria like sampling locations. These findings justify the hybrid filtering used here, in which GPT-4 assists with pre-screening based on semantic proximity, while final inclusion decisions are manually validated to ensure accuracy and thematic coherence. This balance between automation and expert judgment enhances both efficiency and methodological rigour.

2.3 Article Selection Funnel Using the Hybrid SLR Framework

The article selection followed the Hybrid SLR Framework, ensuring a systematic and rigorous refinement of the literature.

The keyword query was developed iteratively, combining domain knowledge, key literature, and frequency analysis of terminology. The inclusion criteria were defined to ensure relevance and methodological rigour. Only peer-reviewed journal articles indexed in Scopus were considered. Scopus is a widely adopted academic database for retrieving relevant peer-reviewed scientific articles across many domains, including Tourism (Ramos et al., 2024). Studies were included if they explicitly examined the relationship between customer feedback (e.g., online reviews, ratings, or satisfaction measures) and hotel performance indicators. Articles focusing exclusively on other industries, lacking empirical or analytical contribution, or not addressing performance outcomes were excluded. Additionally, duplicates, non-English publications, and studies with insufficient methodological transparency were removed during the screening process.

To ensure coverage and sensitivity, it was structured around four thematic components: (1) customer feedback, (2) hospitality context, (3) performance dimensions, and (4) relational constructs, with synonymous terms and Boolean operators used to address lexical variation and maintain logical cohesion. The search query was executed in December 2024, and the results reflect the state of the literature at that time. Following implementation of the comprehensive search strategy, an initial query in the Scopus database yielded 406 documents. The complete search string and the corresponding number of results are presented in Figure 2.

Figure 2 - The search query used on Scopus

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("customer feedback" OR "guest feedback" OR "online review" OR "review rating" OR "guest rating" OR "customer satisfaction" OR "guest satisfaction") AND ("hotel" OR "hospitality industry" OR "lodging industry") AND ("performance" OR "business performance" OR "operational performance" OR "financial performance" OR "revenue management" OR "profitability" OR "RevPAR" OR "ADR" OR "occupancy rate") AND ("impact" OR "effect" OR "relationship" OR "association" OR "influence" OR "correlation" OR "causal analysis" OR "link" OR "relation")
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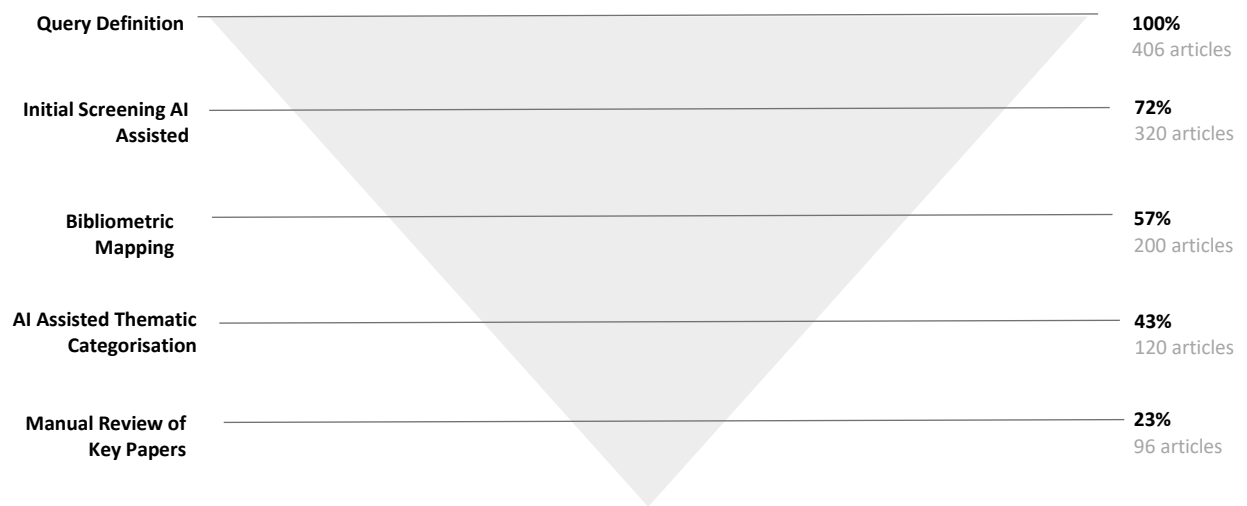
Source: own elaboration.

To ensure precision, an AI-assisted screening removed irrelevant studies, reducing the dataset to 320 articles (72%). Bibliometric analysis then identified co-authorship patterns and thematic clusters, allowing exclusion of less impactful studies, those with minimal contributions, limited citation influence, or lacking integration into the research discourse. This refinement resulted in 200 selected articles (57%), all with strong academic relevance and connections within the domain.



While the AI and bibliometric stages significantly reduced the volume and subjectivity of manual screening, a targeted manual review remained essential to assess methodological rigour, theoretical alignment, and contextual relevance, culminating in a curated set of 120 articles (43%). This step ensured that nuanced academic criteria, often beyond the reach of current LLMs, were adequately considered. Finally, AI-assisted thematic clustering, followed by manual refinement and validation, was used to structure the selected papers into dominant emerging themes, culminating in the final inclusion of 96 articles (23% of the initial dataset).

Figure 3 - Systematic Article Selection Funnel



Source: authors' own elaboration.

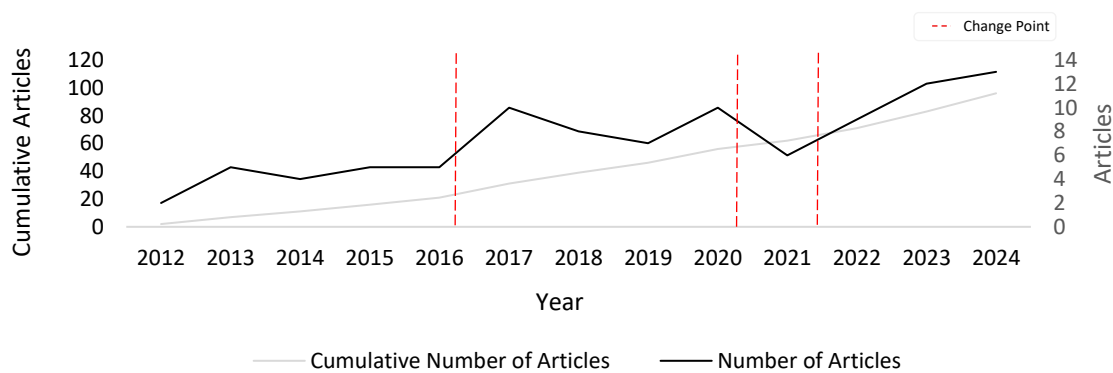
3. Results: Insights from the Hybrid AI-Enhanced Systematic Review

3.1 Bibliometric Perspective

As illustrated in Figure 3, this meticulous selection funnel ensured that only the most relevant, methodologically robust, and theoretically significant studies were considered, establishing a solid, high-quality foundation for the research.

A bibliometric analysis was conducted to examine the evolution and distribution of research on customer feedback and hotel performance. As shown in Figure 4, scientific production has increased steadily between 2012 and 2024, with more pronounced growth after 2016 and in the post-2022 period.

Figure 4 - Scientific Production by Year



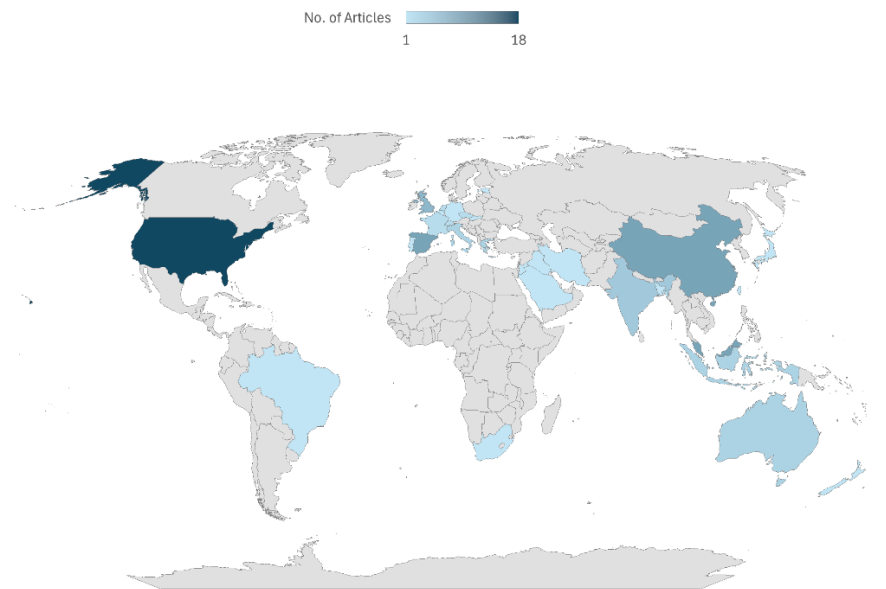
Source: authors' own elaboration.



A change point detection analysis identified several fluctuations in publication trends, particularly between 2018 and 2021, followed by a renewed increase after 2022, suggesting a re-emerging focus on customer experience and its role in hotel performance.

The geographical distribution of research on customer feedback and hotel performance reveals significant regional disparities in both scientific output and academic impact.

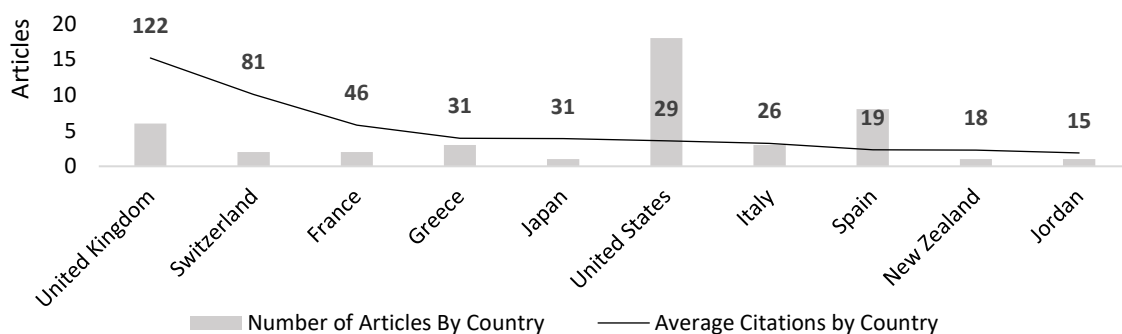
Figure 5 - Geographic distribution of published articles by country-based scientific production (2014-2024)



Source: authors' own elaboration.

As illustrated in Figures 5 and 6, certain countries demonstrate high research influence despite lower publication volumes, while others contribute extensively but have lower citation impact.

Figure 6 - Top 10 Countries by Average Citations: Number of Articles and Citation Average per Country



Source: authors' own elaboration.

Additionally, certain regions remain underrepresented, including New Zealand, Jordan, and Japan, highlighting geographical gaps in this research domain.

3.2 Mapping Research Themes

The integration of AI-assisted methodologies into systematic literature reviews has significantly enhanced the efficiency and comprehensiveness of research synthesis. In the domain of hospitality and customer feedback analysis, this approach has facilitated the identification of distinct yet interrelated research streams, elucidating emerging trends and persistent knowledge gaps.

Building on the AI-enhanced systematic literature review framework detailed in the preceding sections, this study employed a hybrid methodology to categorise fundamental themes in the hospitality research corpus. This categorisation process not only



captured the breadth of existing research but also uncovered latent connections between studies that might not have been immediately evident through traditional bibliometric approaches.

Six thematic clusters were identified using GPT-4 with a structured prompt that guided the model to develop coherent research themes organically. These clusters, which reflect the main research streams and their practical relevance, are summarised in Table 1, with the full prompt available in Appendix A to ensure reproducibility.

Table 1 - Thematic clusters identified by GPT-4 and their key research insights

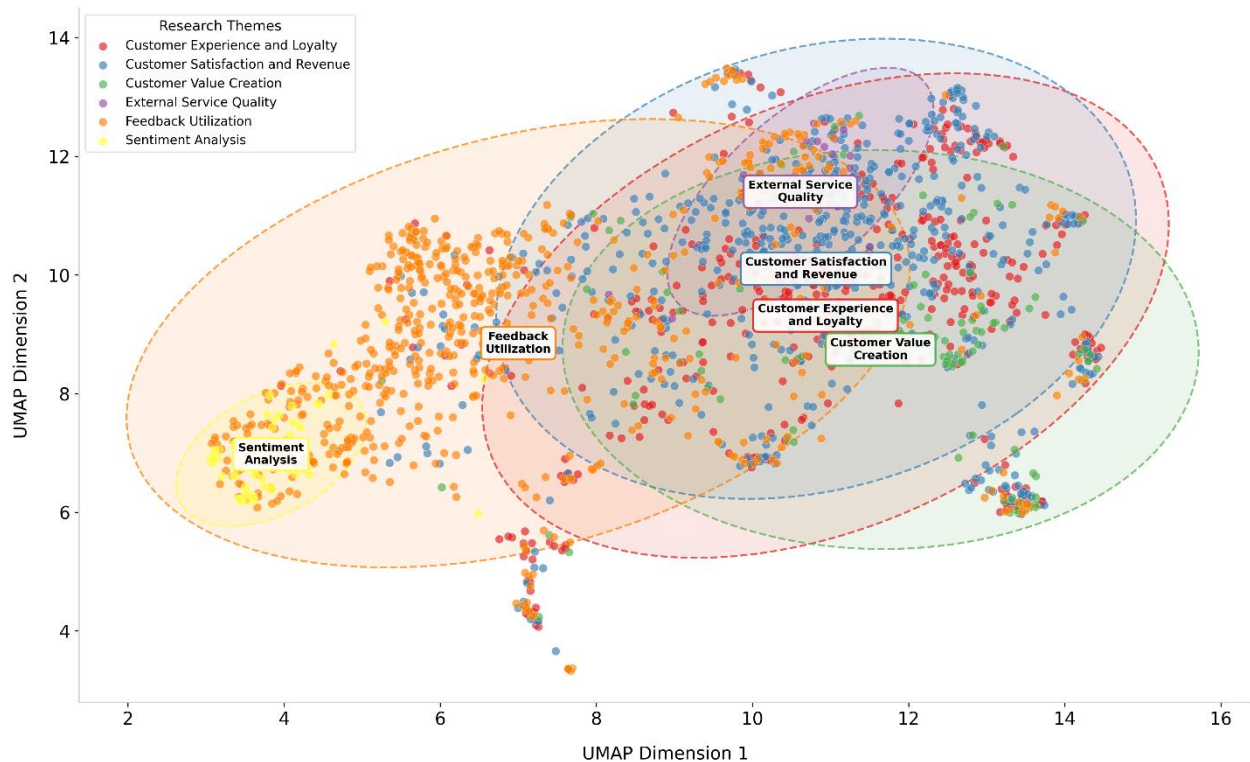
Cluster	Key Insights
Feedback Utilisation	General managers leverage customer feedback to enhance service quality by optimising training programs, refining operational procedures, and identifying patterns in complaints and praise to drive continuous improvement.
Customer Value Creation	Customer value is shaped by service innovation, cultural integration, and a deep understanding of guest preferences. This multi-phase process involves managers, employees, and guests and directly influences financial and customer-based performance.
Customer Satisfaction and Revenue	Studies establish a direct link between customer feedback and revenue growth, emphasising the role of service quality and customer perception in driving financial performance.
Sentiment Analysis	Text mining and sentiment analysis are widely used to extract actionable insights from customer reviews, revealing critical service attributes that influence satisfaction and purchasing behaviour.
Customer Experience and Loyalty	Research highlights psychological drivers of customer experience and the effectiveness of loyalty programs in enhancing guest retention, emphasising emotional engagement and personalised service.
External Service Quality	Studies assess service quality by focusing on key dimensions such as communication effectiveness, team responsiveness and operational efficiency, which are essential for customer retention and competitive differentiation.

Source: authors' own elaboration.

Expanding upon the thematic clusters identified in Table 1, Figure 7 provides a semantic visualisation that elucidates the interrelationships among research themes. Abstracts were encoded into a high-dimensional semantic space using the Sentence Transformer model ("all-MiniLM-L6-v2"), a state-of-the-art embedding technique for contextual representation. Subsequently, Uniform Manifold Approximation and Projection (UMAP) was employed to reduce dimensionality while preserving the data's intrinsic structure, yielding a two-dimensional mapping of the research landscape.



Figure 7 - Semantic Clustering of Research Themes Using Transformer-Based Embeddings and UMAP



Source: authors' own elaboration.

This visualisation provides an intuitive way to explore thematic proximities, illustrating how research topics cluster together based on shared concepts and methodologies. The semantic similarity among the clusters is highlighted in Figure 7, demonstrating that while distinct themes emerge, some degree of overlap is observable.

3.3 The Evolution of Methodologies and the Impact of AI

The study of customer feedback in hospitality has evolved from traditional qualitative analyses to AI-driven methodologies that offer deeper, data-driven insights. This chapter explores how advancements in machine learning, NLP, and semantic modelling have transformed the way research themes are identified and interpreted. The emergence of LLMs has further revolutionised this process, enabling automated, high-precision text analysis that uncovers complex thematic structures and evolving industry trends.

3.3.1 Conventional Paradigms and Established Methodologies

The relationship between customer feedback and financial performance has been widely studied in the hospitality sector, reflecting the growing role of digital platforms in shaping reputation and driving revenue. However, the evolution of these investigations reveals a methodological trajectory that, in many cases, has remained limited in its exploration of the qualitative dimensions of customer feedback. This literature review aims to trace this evolution, highlighting advancements, limitations, and opportunities for future research.

In the early 2010s, research predominantly relied on traditional econometric models to assess the impact of customer feedback on hotel financial performance. Studies such as that of Assaf et al. (2015) (Assaf et al., 2015) highlighted the importance of customer satisfaction and complaints as critical variables directly influencing the performance of hospitality businesses. However, these analyses were limited to quantitative metrics, such as numerical ratings and basic financial indicators, and did not explore the potential of textual reviews or consider the temporal evolution of feedback. While valuable for identifying statistical correlations, this quantitative perspective was overly static and overlooked the richness of textual reviews, limiting insights into the long-term impact of customer feedback on hotel performance.

3.3.2 The Emergence and Dominance of Review Platforms in the Digital Era

With the widespread adoption of platforms such as TripAdvisor and Booking, the relationship between customer satisfaction and financial performance has become increasingly complex. The volume of reviews now directly shapes consumer perception and has



made digital reputation a key driver of hotel profitability (Gao et al., 2020). Studies such as those by Ögüt et al. (2012) and Sayfuddin et al. (2021) (Ögüt et al., 2012; Sayfuddin et al., 2021) have demonstrated that a one-star increase in a hotel's rating can lead to a 2% to 3% growth in monthly revenue due to its signalling effect on potential customers. Additionally, price elasticity is influenced by online reviews, allowing highly rated establishments to charge higher rates than their direct competitors (Wang et al., 2015; Ye et al., 2012).

Studies indicate that consumers tend to place greater weight on negative experiences than on positive ones, a phenomenon known as the negativity effect in marketing (Lee et al., 2009). Numerous studies have shown that consumers not only rely heavily on online reviews when making decisions but also perceive negative feedback as more credible, often viewing it as more informative and authentic than positive reviews (Amos et al., 2021; Jin Ma et al., 2014). Even a small number of negative reviews can significantly impact a hotel's image and performance. Despite the consistency of these findings, the literature tends to rely heavily on aggregated rating effects, often overlooking heterogeneity across customer segments and contextual factors. As a result, the mechanisms through which online reviews influence decision-making and performance remain only partially understood.

3.3.3 Hotel Profiling and Market Differentiation: The Influence of Review Content and Volume

During this period, the literature began to differentiate the effects of customer satisfaction by hotel profile. Blal et al. (2014) and Wu et al. (2023) (Blal et al., 2014; Wu et al., 2022) observed that luxury hotels are more responsive to textual reviews, while economy hotels depend more on review volume to boost visibility and occupancy (De Pelsmacker et al., 2018; Melián-González et al., 2013). This distinction highlights different response patterns to customer feedback across hotel segments. However, this line of research remains largely descriptive and does not fully explain the underlying mechanisms driving these differences, limiting its ability to inform actionable managerial strategies.

Table 2 - Distinguishing the dependence on reviews in different types of hotels

Hotel Type	Sensitivity to Textual Reviews	Dependence on Review Volume
Luxury Hotels	High sensitivity to detailed textual reviews and sentiment. (Blal et al., 2014; Cho et al., 2023; Wu et al., 2022]	Less dependent on volume, more on review valence. (Blal et al., 2014)
Economy Hotels	Less sensitivity to detailed content. (Blal et al., 2014; Melián-González et al., 2013]	High dependence on review volume for visibility and occupancy. (De Pelsmacker et al., 2018; Melián-González et al., 2013)

Source: authors' own elaboration.

Furthermore, Xie (2017) and Xie et al. (2017) note that the negativity effect is not uniform, as negative reviews from reputable sources exert greater influence than those from anonymous users. This highlights the role of perceived credibility in shaping consumer responses to online feedback.

3.3.4 Advancements in Natural Language Processing and Machine Learning

With advancements in NLP and Machine Learning, research on customer satisfaction has shifted from aggregated numerical ratings to a more detailed exploration of textual review content. Studies such as those by Ažman et al. (2015) and Ažman et al. (2014) have demonstrated that the impact of satisfaction on performance is not linear but follows a U-shaped pattern.

Nevertheless, many models fail to capture the temporal dynamics of customer feedback, overlooking the possibility of dissatisfaction cycles that can have prolonged effects on occupancy rates, even after operational improvements (Kim et al., 2023; Roy, 2018). Moreover, many of these approaches rely on static datasets and fail to capture the dynamic, evolving nature of customer perceptions, thereby constraining their predictive capacity and limiting their applicability in real-time decision-making contexts.



3.3.5 The Transformative Role of Large Language Models

The rise of LLMs has significantly transformed how customer feedback is analysed and utilised in the hospitality industry, directly impacting the financial performance of establishments (Franco et al., 2023; Du Xishihui et al., 2024). Previously, the analysis of online reviews was limited to basic metrics such as valence and volume. However, recent advancements in AI have enabled more precise extraction of insights from unstructured textual data (Ruel et al., 2020).

One of the most significant advancements enabled by LLMs is their high precision in sentiment analysis and in extracting service quality dimensions from user-generated content. Recent studies demonstrate that these models exhibit remarkable capabilities in interpreting customer feedback, approaching the performance of human evaluators in sentiment classification (Falatouri et al., 2024). GPT has shown a high degree of agreement with expert analysis, highlighting its potential to detect linguistic nuances and subjectivities embedded in hotel reviews. These models have been applied to detect linguistic nuances and service quality dimensions in hotel reviews (Falatouri et al., 2024).

In addition, advanced techniques such as Aspect-Based Sentiment Analysis (ABSA) empower models like GPT-4o to provide nuanced, contextually aware interpretations of reviews, revealing dimensions previously difficult to discern, such as perceptions of staff hospitality, infrastructure quality, and service efficiency (Água et al., 2025).

Beyond sentiment analysis, LLMs such as T5, BART, GPT-3.5, and GPT-4 have shown strong capabilities in keyword extraction, feedback categorisation, and emotion detection, enabling the identification of service quality dimensions such as staff behaviour, infrastructure, and overall guest satisfaction (Água et al., 2025; Jeong et al., 2024; Nguyen et al., 2024). These approaches enable the systematic processing of large volumes of textual data and support the identification of recurring patterns in customer feedback.

Despite these significant advancements, the application of LLMs in hospitality research remains fragmented, with limited integration into unified analytical frameworks that directly connect customer feedback to financial performance. This highlights a critical gap between methodological innovation and practical implementation.

4. Discussion

4.1 Interpretation of Bibliometric Findings

The findings of this study provide a structured understanding of how the literature on customer feedback and hotel performance has evolved. From a bibliometric perspective, there is clear growth in scientific output, particularly after 2016 and in the post-2022 period, confirming the growing relevance of data-driven approaches in the hospitality sector. This evolution is closely linked to the expansion of digital platforms and the growing use of advanced analytical techniques for processing customer-generated content.

However, this expansion remains uneven. While some countries contribute more studies, others exert greater citation influence despite fewer publications, suggesting that the current body of literature is concentrated in specific academic and regional contexts. More importantly, the limited geographic diversity raises concerns regarding the generalizability of existing findings, highlighting the need for broader international contributions and more context-sensitive approaches in future research. Most notably, Latin America and Africa are clearly underrepresented, with the exceptions of Brazil and South Africa, suggesting that research in these regions is lagging in underdeveloped economies.

4.2 Interpretation of Thematic Clusters

At a conceptual level, the literature is organised around multiple interconnected research streams rather than a single dominant perspective, reflecting the multidimensional nature of hotel performance research. The central role of feedback utilisation highlights a shift from viewing customer feedback as a passive outcome toward recognising it as a strategic resource for operational and managerial decision-making.

The thematic clustering analysis emphasises this perspective by showing that research themes are not isolated but semantically interconnected. A particularly relevant finding is the central position of the "Feedback Utilisation" cluster, which connects multiple research streams, including service quality, customer experience, and performance optimisation. This positioning suggests that customer feedback is increasingly embedded within core business processes rather than treated as a descriptive metric.

The analysis also reveals differences in the internal structure of research themes. Clusters such as "Sentiment Analysis" exhibit high semantic cohesion, indicating a more methodologically consolidated research stream driven by text mining and AI-based



techniques. In contrast, clusters such as "Customer Value Creation" exhibit greater dispersion, reflecting a broader, more interdisciplinary conceptual scope that integrates perspectives from service innovation, customer behaviour, and strategic management.

Furthermore, the overlap between clusters suggests that key constructs, such as customer satisfaction, experience, loyalty, and revenue, are deeply interconnected. This reinforces the idea that hotel performance cannot be understood through isolated variables, but rather through integrated frameworks that capture the complexity of customer perceptions and their impact on business outcomes.

Taken together, these patterns suggest that the literature remains conceptually rich but unevenly consolidated, with some streams advancing through methodological standardisation while others remain more fragmented and exploratory.

4.3 Methodological Evolution

With respect to RQ3, the field has evolved from traditional quantitative approaches based on ratings and econometric models to more advanced AI-driven techniques capable of extracting insights from textual data. This transition reflects a broader shift from measuring customer satisfaction to interpreting the underlying dimensions of customer experience.

Early econometric models provided structured relationships between ratings and performance indicators, but were limited in capturing the richness and subjectivity of customer perceptions. The incorporation of textual analysis techniques, particularly sentiment analysis and ABSA, addressed this limitation by enabling the identification of specific service attributes and their contribution to satisfaction and dissatisfaction.

More recently, the adoption of machine learning and LLMs has significantly expanded analytical capabilities. These approaches enable a deeper semantic understanding of customer feedback and support the extraction of nuanced insights from large volumes of unstructured textual data. As a result, customer feedback analysis has evolved from a descriptive tool into a more predictive and strategically relevant component of hospitality analytics.

From a financial perspective, this evolution is particularly significant. Studies show that positive reviews, when effectively interpreted through advanced analytical models, are associated with higher conversion rates and revenue growth (Gîngioveanu et al., 2024; Marigliano et al., 2024), while the timely identification of negative sentiment contributes to mitigating losses in occupancy and pricing performance (Hsueh et al., 2024; Torres et al., 2014). This highlights the increasing importance of real-time, data-driven feedback analysis in supporting managerial decision-making.

The effectiveness of these approaches is closely linked to their ability to capture the complexity of customer experience. In this context, LLMs represent a paradigmatic advancement, as they overcome the limitations of traditional machine learning methods, which often rely on simplified sentiment classifications (Praveen et al., 2024). Instead, LLMs provide context-aware interpretations, enabling a more detailed understanding of how specific service attributes influence satisfaction and loyalty.

Beyond improving sentiment analysis, LLMs also enable a more sophisticated assessment of the relationship between customer feedback and financial performance. Their ability to process large-scale textual data in near real time allows organisations to monitor evolving satisfaction patterns and anticipate demand fluctuations, supporting more informed decision-making in areas such as pricing strategies and resource allocation (Ive Botunac et al., 2024). In contrast to conventional approaches that primarily signal trends, LLM-based methods can uncover latent patterns within customer evaluations, revealing underlying operational issues that may affect performance (Falatouri et al., 2024; Roumeliotis et al., 2024).

A key advantage of these models is their ability to integrate unstructured textual feedback with operational and financial metrics, enabling a more holistic understanding of the relationship between customer experience and hotel performance (Roumeliotis et al., 2024). This integration allows for the identification of strategic improvements with the greatest potential impact on profitability and competitive positioning (Praveen et al., 2024), which is particularly relevant in a highly dynamic and competitive hospitality environment (Lim et al., 2022).

Despite these advancements, several methodological challenges persist. A significant portion of the literature continues to rely on proxy indicators, limiting the ability to establish direct and robust relationships between qualitative customer feedback and financial performance metrics. Moreover, the integration of textual insights with operational and financial data remains underdeveloped, reducing the practical applicability of many models.

These findings suggest that future research should focus on developing more integrated analytical frameworks that combine qualitative and quantitative data sources to enable a more comprehensive understanding of how customer perceptions translate into measurable business outcomes in the hospitality sector.



4.4 Limitations and Next Generation Opportunities

Despite advances in customer feedback analysis, the literature remains hampered by several methodological and empirical limitations that constrain the robustness and practical applicability of its findings. A key issue is the scarcity of real, representative operational data, which leads many studies to rely on proxy measures to estimate the relationship between customer satisfaction and hotel performance (Jeong et al., 2022; Ridouan Nejari et al., 2023). While such approximations provide initial insights, they often fail to capture the complexity and subjectivity of guest experiences, limiting the accuracy of financial interpretations.

In addition, much of the existing research is based on temporally restricted datasets, overlooking the effects of seasonality, exogenous shocks, and broader market dynamics that significantly influence customer perceptions and business performance (Gîngioveanu Lupulescu et al., 2024; Zhang et al., 2021; Zhang et al., 2021). This lack of temporal depth reduces models' ability to capture dynamic patterns and weakens their predictive validity.

Another important limitation concerns the limited integration of contextual variables, particularly environmental and operational factors. For example, climatic conditions have been shown to influence customer satisfaction, yet they remain underexplored in most analytical frameworks (Mun et al., 2022; Rahman, 2024). Ignoring such variables reduces the explanatory power of existing models and restricts their applicability in real-world decision-making contexts.

Furthermore, the literature provides limited insight into how customer feedback is operationalised within hotels. While many studies emphasise the importance of feedback, few examine how it informs resource allocation, investment prioritisation, and strategic decision-making processes (Ridouan Nejari et al., 2023; Torres et al., 2014). This gap limits the translation of analytical insights into actionable managerial practices.

Finally, although the literature increasingly recognises the role of digital feedback, it remains largely focused on traditional online reviews and neglects emerging AI-mediated customer interactions. This narrow focus restricts the scope of analysis and overlooks new data sources that could enhance performance-oriented research.

5. Conclusion

The rapid transformation of the tourism and hospitality industry, driven by digitalisation, evolving consumer behaviours, and intensifying competition, has reinforced the strategic importance of customer feedback as a cornerstone for operational and financial decision-making. This systematic review demonstrates that the effective management of customer feedback, particularly online reviews, plays a decisive role in shaping consumer perception and directly influences key performance indicators such as pricing strategies, occupancy rates, RevPAR (Revenue per Available Room), and overall profitability. Moreover, the literature consistently highlights the asymmetric impact of feedback, with negative experiences exerting a stronger influence on customer decisions, underscoring the need for proactive, data-driven reputation management strategies.

The findings also reveal a clear methodological evolution in the field. The emergence of NLP and LLMs has significantly enhanced the capacity to extract meaningful insights from unstructured customer feedback, enabling more granular, context-aware, and predictive analyses. These technologies allow hotels to move beyond aggregate ratings and develop a deeper understanding of the specific service attributes that shape customer satisfaction and financial outcomes. In parallel, this study contributes methodologically by developing an AI-enhanced systematic literature review framework that integrates bibliometric analysis, LLM-assisted thematic clustering, and human validation. This hybrid approach provides a scalable and replicable methodology that improves analytical depth while reducing subjectivity, offering a valuable contribution to both academic research and applied contexts.

Overall, the findings directly address the research questions by demonstrating the literature's growing yet uneven evolution, the multidimensional and interconnected nature of research themes, and the ongoing methodological transition toward AI-driven approaches, while also highlighting persistent gaps in data integration and practical implementation.

Ultimately, advancing this field requires bridging the gap between analytical sophistication and practical implementation, ensuring that customer feedback analytics evolves from an interpretative tool into a core driver of data-driven decision-making and strategic value creation in the hospitality sector.

5.1 Implications and Recommendations for Hotels

The results of this study provide several relevant implications for hospitality practitioners. First, customer feedback should be treated as a strategic managerial asset rather than as a passive indicator of satisfaction. Hotels can leverage feedback data to systematically identify operational weaknesses, detect recurring service failures, and prioritise improvement initiatives with greater precision. Second, the findings suggest that relying solely on numerical ratings is insufficient to capture the complexity of customer



perceptions. Instead, hotels should adopt more advanced analytical approaches that can extract insights from textual reviews, enabling a deeper understanding of guest experiences and expectations.

Furthermore, the increasing availability of AI-based tools, including NLP and LLM-driven techniques, offers significant opportunities to enhance decision-making processes. These tools can support real-time monitoring of customer sentiment, facilitate the identification of emerging issues, and enable more informed adjustments in pricing strategies, service design, and resource allocation. The literature also indicates that the impact of customer feedback varies across hotel segments, suggesting that strategies should be tailored to specific market positioning and customer profiles. Overall, integrating feedback analytics into core business processes can strengthen competitiveness, improve service quality, and enhance long-term financial performance.

This is particularly relevant in investment-constrained environments, where the ability to prioritise improvements based on data-driven insights is a critical determinant of efficient resource allocation.

5.2 Future Research Agenda

Future research should prioritise the use of real, longitudinal, and high-frequency operational data to enable more accurate and direct assessments of the relationship between customer feedback and hotel performance. Moving beyond proxy indicators will be essential to strengthen both the validity and practical relevance of empirical findings.

There is also a need to develop integrated analytical frameworks that combine qualitative customer feedback with quantitative performance metrics, such as occupancy rates, ADR (Average Daily Rate), RevPAR, and profitability. Such approaches would allow for a more comprehensive understanding of how customer perceptions translate into measurable business outcomes.

Additionally, future studies should incorporate contextual variables, including seasonality, climatic conditions, and market dynamics, to improve the explanatory and predictive capacity of existing models. This would enable more realistic and adaptable analyses that better align with the complexity of hospitality environments.

Further research is also needed to explore how hotels operationalise customer feedback in practice, particularly regarding resource allocation and investment decision-making. Developing structured frameworks to translate feedback into strategic actions is a critical step toward bridging the gap between analysis and implementation.

Finally, in line with the sector's ongoing digital transformation, future research should extend beyond traditional online reviews to examine the role of emerging AI-based interaction systems, such as chatbots, recommender systems, and decision-support platforms. These technologies are increasingly shaping the customer journey and generating new forms of behavioural and conversational data, offering valuable opportunities for more advanced, dynamic performance analysis.

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Appendix A - Prompt Design for GPT-4-Based Thematic Clustering

You are assisting in a systematic literature review focused on customer feedback and its impact on hotel performance, including how such feedback informs investment strategies.

Your task is to analyse the abstract below and assign it to a thematic cluster, based on its main topic. The goal is to identify approximately six distinct and meaningful clusters across the entire dataset.

Instructions:

- Create a thematic cluster based on the content and focus of the abstract.
- Avoid generating overly specific or redundant clusters.
- Try to reuse existing cluster names you have already generated for previous abstracts, when appropriate.
- Only create a new cluster if the topic does not fit any of the previous ones.
- Aim for a final set of around six coherent and semantically distinct clusters across all abstracts.
- Clusters should be short, clear, and conceptually focused (e.g., "Customer Experience and Loyalty", not long descriptive phrases).

Abstract:

{abstract_text}

Output Format:

Abstract - Cluster: [Generated Cluster Name]